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Location Privacy Protection in Social Networks

by

Mohammad Reza Nosouhi

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Certificate of Authorship/Originality

I, Mohammad Reza Nosouhi declare that this thesis, is submitted in fulfilment of the requirements for the award of Doctor of Philosophy, in the School of Computer Science at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

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List of Publications

Journal Papers

J-1. MR. Nosouhi, K. Sood, S. Yu, M. Grobler, “PASPORT: A Secure and Private Location Proof Generation and Verification Framework”, *IEEE Transactions on Computational Social Systems*, vol. 7, Issue 2, pp. 293–307, Apr 2020. Available online at: `https://ieeexplore.ieee.org/document/8967030`

J-2. MR. Nosouhi, S. Yu, W. Zhou, and M. Grobler, “Blockchain for Secure Location Verification”, *Journal of Parallel and Distributed Computing*, vol. 136, pp. 40–51, Feb 2020. Available online at: `https://www.sciencedirect.com/science/article/abs/pii/S074373151930320X`

J-3 L. Cui, Y. Qu, MR Nosouhi, S. Yu, J.W. Niu, and G. Xie, “Improving Data Utility Through Game Theory in Personalized Differential Privacy”, *Journal of Computer Science and Technology*, vol.34, pp. 272–286, 2019. Available online at: `http://jcst.ict.ac.cn/EN/10.1007/s11390-019-1910-3`

Conference Papers

C-1. MR. Nosouhi, S. Yu, K. Sood, and M. Grobler, “HSDC–net: Secure Anonymous Messaging in Online Social Networks”, *IEEE TrustCom*, 2019. Available online at: `https://ieeexplore.ieee.org/document/8887315`

C-2. MR. Nosouhi, S. Yu, M. Grobler, Y. Xiang, and Z. Zhu, “SPARSE: Privacy–Aware and Collusion Resistant Location Proof Generation and Verification”, *IEEE GLOBECOM*, 2018. Available online at: `https://ieeexplore.ieee.org/document/8647933`

C-3. MR. Nosouhi, Y. Qu, S. Yu, Y. Xiang, and D. Manuel, “Distance –Based Location Privacy Protection in Social Networks”, *International Telecommu-*

nications Network and Applications Conference, 2017. Available online at: https://ieeexplore.ieee.org/document/8215390

C-4. MR. Nosouhi, V. H. Pham, S. Yu, Y. Xiang, and M. Warren, "A Hybrid Location Privacy Protection Scheme in Big Data Environment", *IEEE GLOBECOM*, 2017. Available online at: https://ieeexplore.ieee.org/document/8254987

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ABSTRACT

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Social networks have become more ubiquitous due to new advances in smartphone technology. This has provided an opportunity for social network service providers to utilise location information of users in their services. For example, Facebook Places, Foursquare and Yelp are popular social networks that mostly rely on utilising users' location data in their services. They offer a variety of useful services, from location recommendations to nearby friend alerts. However, protecting location privacy of users is still an open challenge for social network service providers. It has been shown that hiding real identity and choosing a pseudonym does not guarantee to protect a user's privacy since privacy may be invaded by analysing position data only. This is really a big issue since other private information of users can be revealed by analysing their location data (e.g., home address, health condition, interests, etc.).

In this study, we investigate the location privacy issue of social networks and propose several solutions. We classify the proposed solutions into three categories based on the selected approaches, i.e. (i) differential privacy-based, (ii) cryptography-based, and (iii) anonymity-based solutions. We first study the approach in which differential privacy is utilised to preserve privacy of users. In this regard, we develop Distance–Based Location Privacy Protection mechanism (DBLP2), a customisable location privacy protection approach that is uniquely designed for social network

users. It utilises the concept of social distance to generalise users' location data before it is published in a social network. The level of generalisation is decided based on the social distance between users.

Secondly, we study cryptography-based methods for location privacy protection in Location–Based Services (LBS) and social networks. In this domain, we propose three cryptography-based and privacy–aware location verification schemes to preserve location privacy of users: (i) Privacy–Aware and Secure Proof Of pRoximiTy (PASPORT), (ii) Secure, Privacy–Aware and collusion Resistant poSition vErification (SPARSE), and (iii) a blockchain–based location verification scheme. These schemes prevent location spoofing attacks conducted by dishonest users while protect location privacy of users. To the best of our knowledge, majority of the existing location verification schemes do not preserve location privacy of users.

Thirdly, we investigate anonymity as another approach to preserve users' privacy in social networks. In this regard, we first study the relevant protocols and discuss their features and drawbacks. Then, we introduce Harmonized and Stable DC–net (HSDC–net), a self–organizing protocol for anonymous communications in social networks. As far as we know, social networks do not offer any secure anonymous communication service. In social networks, privacy of users is preserved using pseudonymity, i.e., users select a pseudonym for their communications instead of their real identity. However, it has been shown that pseudonymity does not always result in anonymity (perfect privacy) if users' activities in social media are linkable. This makes users' privacy vulnerable to deanonymization attacks. Thus, by employing a secure anonymous communication service, social network service providers will be able to effectively preserve users' privacy.

We perform extensive experiments and provide comprehensive security and privacy analysis to evaluate performance of the proposed schemes and mechanisms.

Regarding the DBLP2 mechanism, our extensive analysis shows that it offers the optimum data utility regarding the trade–off between privacy protection and data utility. In addition, our experimental results indicate that DBLP2 is capable of offering variable location privacy protection and resilience to post processing. For the SPARSE scheme, our analysis and experiments show that SPARSE provides privacy protection as well as security properties for users including integrity, unforgeability and non–transferability of the location proofs. Moreover, it achieves a highly reliable performance against collusions. To validate performance of the PASPORT scheme, we implement a prototype of the proposed scheme on the Android platform. Extensive experiments indicate that the proposed method can efficiently protect location–based applications against fake submissions. For the proposed blockchain–based scheme, our prototype implementation on the Android platform shows that the proposed scheme outperforms other currently deployed location proof schemes. Finally, our prototype implementation of the HSDC–net protocol shows that it achieves low latencies that makes it a practical protocol.

In summary, this research study focuses on developing new mechanisms for preserving location privacy of social network users. This is done through different approaches. Moreover, extensive effort is made to make the current location–related schemes and protocols privacy–aware. In this regard, several solutions in the form of scheme, mechanism, and protocol are introduced and their performance is evaluated. The results of this research work have also been presented in seven papers published in peer-revewied journals and conferences.

Keywords: anonymous communications; customizable differential privacy; data privacy; DC–net; location privacy; location–based services; location proof; social distance; social networks.

Chapter 1

Introduction

1.1 Background

Social networks have become a very popular communication plaftform due to the various attractive services and facilities that they offer to their users. Since their introduction in the mid–1990s, social networks such as Facebook, Twitter and LinkedIn have been exponentially growing every year in terms of active users and revenue. According to the latest statistics [1], Facebook had 2.41 billion monthly active users as of the second quarter of 2019 while it had only 100 million in August 2008. Moreover, its revenue has grown from USD 0.4 million in 2004 to USD 17.6 billion in 2019. This rapid and continuous growth of social networks indicates that they have become a dominant method for people to connect and share information on the Internet.

Social networks have become more ubiquitous due to new advancements in smartphone technology. Consequently, most social media time is now spent on mobile devices. According to a comScore report, Instagram users spend 98% of their screen time on their mobile devices rather than on desktops [2]. This figure is 86% for Twitter users. Thus, an opportunity has been provided for social network service providers to utilise users' location information in their services. As a result, new mobile social networks and Location–Based Services (LBS) have been introduced in the past few years. For example, Facebook Places, Foursquare and Yelp are popular social networks that base their services on the users' location data. They offer useful services, from location recommendations to nearby friend alerts. In LBS, real–time position data of a mobile user is utilised to provide his/her requested information such as the nearest ATM, restaurant or a retail store. LBS have become one of the most attractive mobile applications these days. Based on the market reports, the number of downloads of LBS apps from different app stores has been more than 7.5 billion downloads in 2019 [3].

However, protecting users' location privacy is a significant challenge for social networks. Location privacy is very important because users' location data can be used to obtain other private information about them. For example, personal interests, health status and political tendency may be related to the places visited by a user. Even if a user's real name or ID is hidden or pseudonyms are used, it has been shown that privacy may be invaded by analysing position data only [4], [5]. In this case the user's location data can be correlated with public information about the user to reveal his/her identity. For example, an adversary who has access to users' spatiotemporal data can reidentify a user if he knows that the user spends time in a coffee shop every day and uses a specific online service at the same time. In another example, users' location data can identify a person as a potential cancer patient if he/she has frequently visited a medical centre for cancer treatment. Therefore, using pseudonyms cannot guarantee users' location privacy by itself [5].

To address this issue, new location privacy preserving mechanisms should be developed to prevent any undesired publication of users' spatiotemporal data in social networks. Although some efforts have been made in these directions, location privacy is still an open issue in social networks [6], [7]. This study aims to investigate different approaches for preserving users' privacy in social networks. We first study the approach in which Differential Privacy [8], [9] is utilised for privacy protection. In this regard, we develop Distance–Based Location Privacy Protection mechanism (DBLP2) which is a customisable location privacy protection mechanism designed for use in social networks. It utilises the concept of social distance to design a customisable location privacy protection scheme in which a user's location data is generalised before it is published in a social network. The level of generalisation is decided based on the social distance between users. For this reason, we extend the standard Differential Privacy framework in the proposed mechanism to offer variable privacy protection.

Secondly, as another approach, we investigate cryptography–based solutions and methods for location privacy protection in Location–Based Services (LBS) and social networks. We propose three cryptography–based and privacy–aware location verification schemes to preserve location privacy of users: (i) Privacy–Aware and Secure Proof Of pRoximiTy (PASPORT), (ii) Secure, Privacy–Aware and collusion Resistant poSition vErification (SPARSE), and (iii) a blockchain–based location verification scheme.

Thirdly, we investigate anonymity as another approach to preserve users' privacy in social networks. In this domain, we propose a dummy–based location privacy protection scheme for LBS [10]. In dummy–based schemes [11–16], in addition to the user's real location, some fake location data (dummies) are sent to the Location–Based Service Provider (LSP) by the user as a service enquiry. This prevents an adversary who has access to the LSP's resources from distinguishing the user's real location. Furthermore, we introduce Harmonized and Stable DC–net (HSDC–net), a self–organizing protocol for anonymous communications in social networks. In social networks, privacy of users is generally preserved using pseudonymity, i.e., users select a pseudonym for their communications instead of their real identity. However, it has been shown that pseudonymity does not always result in anonymity (perfect privacy) if users' activities in social media are linkable. This makes users' privacy vulnerable to deanonymization attacks. Thus, by employing a secure anonymous communication service, social network service providers will be able to effectively preserve users' privacy.

1.2 Problem Statement

Recently, due to the advances in the smartphone technology and positioning systems, there has been the emergence of a variety of location–based applications and services [17–20] such as activity–tracking applications, location–based services, database–driven cognitive radio networks (CRNs), and location–based access control systems. In these applications, mobile users submit their position data to a location–based service provider (LBSP) to gain access to a service, resource, or reward. These applications are very popular due to the useful services they offer. According to recent business reports, the market value of location–based services (LBS) was USD 20.53 billion in 2017 and is anticipated to reach USD 133 billion in 2023, with an expected annual growth rate of 36.55% [21].

However, location privacy is a critical issue for these applications and services. This is because other private information of users can be revealed by analysing their location data (e.g., home address, health condition, personal interests, etc.). As a result, users of location–based social networks are concerned that their location privacy is breached by service providers or third–party entities. Moreover, when users share their location data in social networks, they may be uncomfortable because their location privacy can be breached by other users. This may result in a large degradation of the network utility because in this case, users may behave more conservatively and keep their information local.

To address these issues, many research efforts have been made and several solutions proposed so far. However, the existing solutions for privacy protection in social networks have some critical problems. In this regard, we identified three issues, i.e. *dependency on user collaboration*, *binary access control*, and *low efficiency of data utility* that are presented and discussed in the next section. These problems result in significant privacy concerns for social network users.

To summarise, the following is the problem statement of this research work:

To develop new secure and efficient privacy–preserving schemes and mechanisms for users of location–based social networks through three approaches, i.e. (i) differential privacy, (ii) cryptography, and (iii) anonymity approaches.

We also investigate the application scenarios of each approach. Different aspects of the location privacy problem that each approach addresses will also be discussed. In the next section, we present three research questions that are resulted from the problem statement of this thesis.

1.3 Research Questions

In this subsection, we present the research questions resulted from the problem statement.

- Research question (1): *Is it possible to develop a privacy–preserving mechanism that (i) does not rely on users' collaboration, (ii) is flexible in terms of social distance between users, and (iii)) achieves an optimum level of data utility?*

In this regard, differential privacy [8–9] is a promising tool to address this question. It provides a flexible and efficient platform for developing new secure privacy–preserving mechanisms.

- Research question (2): *Can we utilise cryptography–based techniques and solutions to develop a privacy–aware and collusion–resistant location proof scheme for users of location–based social networks?*

In the second part of this research work, we investigate cryptography–based solutions to protect location–based applications and services [17–20] against location spoofing attacks while location privacy of users is preserved. In these applications, mobile users submit their position data to a location–based service provider (LBSP) to gain access to a service, resource, or reward.

- Research question (3): *Can we address the existing issues of DC–net and develop a new efficient anonymous communication protocol to provide anonymity in social networks?*

In social networks, lack of anonymous group messaging service is tangible. To the best of our knowledge, no social network provider offers such a service. Using this service, users can create groups in social media and anonymously publish their opinions (see [37–39] for some example applications). To offer anonymity, several anonymous communication networks (ACNs) have been proposed so far. Among these protocols, the Dining Cryptographers network (DC–net) [49] is one of the most popular protocols that guarantees protection against traffic analysis attacks. However, DC–net suffers from three critical issues that reduces its practicality. This builds the third part of the research work presented in this thesis.

1.4 Research Objectives

This section presents the targets of this research study. The following three main objectives are defined for this study.

i. Develop a customisable location privacy protection mechanism based on the differential privacy framework that is uniquely designed for use in social networks.

ii. Develop cryptography–based privacy–preserving location verification mechanisms for location–based social networks.

iii. Design and develop anonymisation schemes for users of social networks based on the Dining Cryptographers network (DC–net) approach.

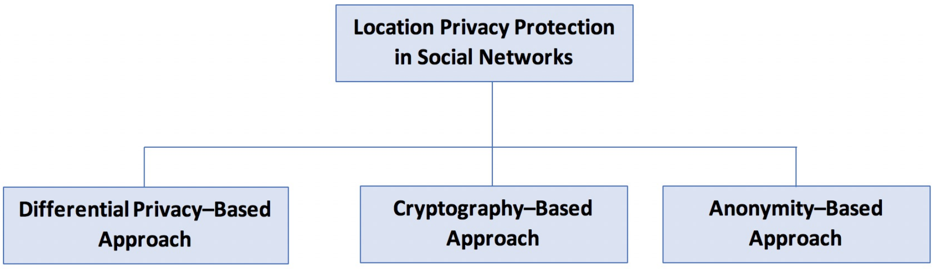

Location Privacy Protection in Social Networks
Differential Privacy–Based Approach
Cryptography–Based Approach
Anonymity–Based Approach

Figure 1.1 : Research Objectives

To achieve the mentioned objectives, a comprehensive literature review should be performed in each of the three targeted subtopics. In addition, extensive experiments should be conducted to assess performance of the proposed mechanisms and ensure that they can successfully address the identified problems of the current privacy protection mechanisms in social networks. Fig. 1.1 shows how the three research objectives are related to each other.

1.5 Scientific Contributions

In this section, the main scientific contributions of this research study are presented. They are categorised based on the three main topics covered in this thesis, i.e., differential privacy–based, cryptography–based, and anonymity–based approaches for privacy protection in social networks (see Table 1.1). For the first approach, we have the following contributions:

- Using the concept of effective distance, we propose a weighted graph model for social networks to measure the social distance between users.
- By customising the standard differential privacy framework, we introduce a customisable and distance–based location privacy protection mechanism (DBLP2) for social network users.

For the second approach that is covered in this research study, the following

Table 1.1 : List of Contributions

Approach	**Contribution**	**Objective**	**Paper**
Differential Privacy–Based Approach	Proposed a weighted graph model for social networks.	For social distance measurement	[133]
	Introduced DBLP2 mechanism.	To preserve location privacy of social networks' users	[133]
Cryptography–Based Approach	Proposed SPARSE scheme.	For private location proof generation and verification	[93]
	Introduced PASPORT scheme.	For private location proof generation and verification	[131]
	Developed P-TREAD distance bounding mechanism.	For secure and private proximity checking	[131]
	Proposed a blockchain–based location proof scheme.	For private location proof generation and verification	[130]
Anonymity–Based Approach	Proposed a filtering technique for Location-Based Services.	To eliminate the spatiotemporal correlation problem in LBS	[10]
	Identified short stability as a drawback of the DC-net protocol.	To make DC-net a reliable and practical protocol	[132]
	Proposed HSDC-net protocol.	For anonymous communication	[132]

contributions are listed:

- We propose SPARSE, a secure and privacy–aware distributed location proof scheme for mobile users. Our security analysis shows that SPARSE achieves the necessary properties of a secure and private location proof system.

- We design PASPORT, a secure, privacy–aware and collusion–resistant location proof scheme for mobile users.

- To privately perform the procedure of proximity checking, we propose P–TREAD and integrate it into PASPORT.

- We propose a blockchain–based, secure, and privacy–aware scheme for LP generation and verification in which mobile users generate LPs for each other.

Regarding the last approach, i.e. anonymity in social networks, the contributions of this research work are as follows:

- A new filtering technique is presented to eliminate the spatiotemporal correlation problem in LBS applications.
- We prove that the "short stability" is a drawback of the DC–net protocol.
- We further improve SDC–net and propose HSDC–net, a collision avoiding and accountable protocol for anonymous communications.

In the next section, we present the structural organization of the thesis.

1.6 Thesis Organization

This thesis is organised as follows:

- *Part I*: We investigate the differential privacy–based approach in Part I. We first present a comprehensive literature review and some preliminaries in Chapter 2. Efforts have been made to identify and present the related research issues and directions. In Chapter 3, the research methodology for Customisable Location Privacy Protection in Social Networks is presented. The results of our analysis and experiments are presented and discussed in Chapter 4.
- *Part II*: In the second part of the thesis, we investigate the cryptography–based approach and propose some privacy–preserving schemes based on cryptographic algorithms and techniques. We first present the relevant literature review and some preliminaries in Capter 5. Then, in Chapter 6, we introduce *Privacy–Aware and Secure Proof Of pRoximiTy* (PASPORT) and present the

results of our analysis and experiments. Our second proposed scheme, i.e. *Secure, Privacy–Aware and collusion Resistant poSition vErification* (SPARSE), is introduced in Chapter 7. Finally, in Chapter 8, we introduce the *blockchain–based location verification scheme* and present the results of our experiments.

- *Part III*: In the last part of the thesis, we investigate the anonymity–based approach and introduce two solutions for privacy protection. Firstly, in Chapter 9, we present some related work and preliminaries. Then, in Chapter 10, our first anonomity–based solution, i.e. *Harmonized and Stable DC–net* (HSDC–net), is introduced. Finally, in Chapter 11, our second anonomity–based solution is introduced and its performance is evaluated and discussed.
- *Chapter 12*: This chapter summarises the thesis and highlights key investigations.

1.7 Conclusion

Social networks have recently become one of the most popular platforms for communications. They have been exponentially growing every year in terms of active users and revenue. Moreover, the recent advances in the smartphone technology and positioning systems have made social networks more ubiquitous. This has resulted in the emergence of a variety of location–based applications and services. In these applications, mobile users submit their position data to a location–based service provider (LBSP) to gain access to a service, resource, or reward. However, preserving users' location privacy is still a big challenge for social networks due to the recent development of the data analysis and mining technologies. Location privacy is very important for users because other private information about users can be obtained by knowing their location data.

In the next chapter, we present an extensive literature review about the research questions addressed in this thesis. We first review the research studies relevant to customisable location privacy in social networks. Then, we present a literature review of the anonymity issue in social networks. Finally, we explore the location verification schemes in location–based social networks by giving an overview of the existing location proof schemes and discussing their pros and cons.

Part I

Differential Privacy–Based Approach

Chapter 2

Literature Review and Preliminaries

2.1 Introduction

The recent advances in smartphone technology and positioning systems has enabled social network service providers to offer a variety of location–based applications and services for their users. In these applications, real–time location data of mobile users is utilised to provide requested information or access to a resource or service. The variety of useful services offered by these applications has made them very popular [14], [17–19]. However, preserving location privacy of users is a big challenge for the service providers since users share their location data either with other users or with a service provider.

This chapter presents a literature review on the current privacy preserving techniques and solutions in social networks. This includes the privacy preserving mechanisms proposed based on the popular differential privacy framework. We also discuss the current location privacy preservation mechanisms proposed for Location–Base Services (LBS) and Geo–Social Networks (GeoSNs). In this regard, K–Anonymity, Dummy–Based, and Cryptography–Based schemes are reviewed.

Moreover, this chapter presents some preliminaries as the foundation for the next chapter. After briefly reviewing the concept of differential privacy and the Laplace mechanism, we introduce the necessity of customising the adjacency relation defined in the standard differential privacy to match its definition with the location domain.

2.2 Literature Review

Privacy protection in social networks has been comprehensively studied by Abawajy et al. [59] to present a comprehensive survey of the recent developments in social networks' data publishing. They have analysed different privacy risks and attacks in social media along with the presentation of a threat model. They have also quantified and classified the background knowledge which is used by adversaries to violate users' privacy. In addition, Fire et al. [60] presented some strategies and methods in privacy preserving social network data publishing through a detailed review of different security and privacy issues. They have reviewed a range of existing solutions for these privacy issues along with eight simple–to–implement recommendations which can improve users' security and privacy when using these platforms [13].

A few location privacy protection mechanisms have been proposed based on differential privacy. In [64], a perturbation technique based on differential privacy was introduced to achieve geo–indistinguishability for protecting the exact location of a user. This technique adds random Laplace–distributed noise to users' location in order to sanitize their location before publishing. A differentially private hierarchical location sanitization (DPHLS) approach has been proposed for location privacy protection in large–scale user trajectories. The approach provides a personalised hierarchical mechanism that protects a user's location privacy by hiding the location in a dataset that includes a subset of all possible locations that might be visited in a region [65]. By doing this, the level of location randomisation is reduced, hence, the amount of noise required for satisfying differential privacy conditions is minimized.

Another research study in the differential privacy field has been conducted in [66] to consider the problem of releasing private data under differential privacy when the privacy level is subject to change over time. In spite of other works that consider privacy level as a fixed value, they have studied cases in which users may wish to relax their privacy level for subsequent releases of the same data after either a re–evaluation of the privacy concerns or the need for better accuracy. For this reason, the authors have presented a mechanism whose outputs can be described by a lazy Markov stochastic process to analyse the case of gradual release of private data.

Some other research studies have recently been done on the location privacy of Geo–Social Networks (GeoSNs) users [61], [67–69]. GeoSNs are a variety of social networks by which users can find their favourite events, persons or groups in a specific region or identify popular places by comparing how many people have already checked–in at different places. This is done by utilising users' location data which have been shared by them in that region. In fact, GeoSNs combine location recommendation services (such as services offered by location–based services) with social network functionality [10], [69]. In other words, they can be viewed as location–based social networks which connect people in a specific region based on their interests.

In [69] different GeoSNs were classified into three categories Content–Centric, Check–In Based and Tracking–Based according to the services they offer. In addition, the main privacy issues that threaten user location privacy were identified. Moreover, the authors of [67] have studied techniques that sanitize users' location data based on differential privacy framework before publishing them as location recommendations in GeoSNs. Moreover, to enhance the accuracy of the location recommendations, they have identified some effective factors which improve data accuracy.

In [68] a location–privacy–aware framework is offered to publish reviews for local business service systems. The proposed framework publishes reviews based on utility to achieve two main goals, maximizing the amount of public reviews which users

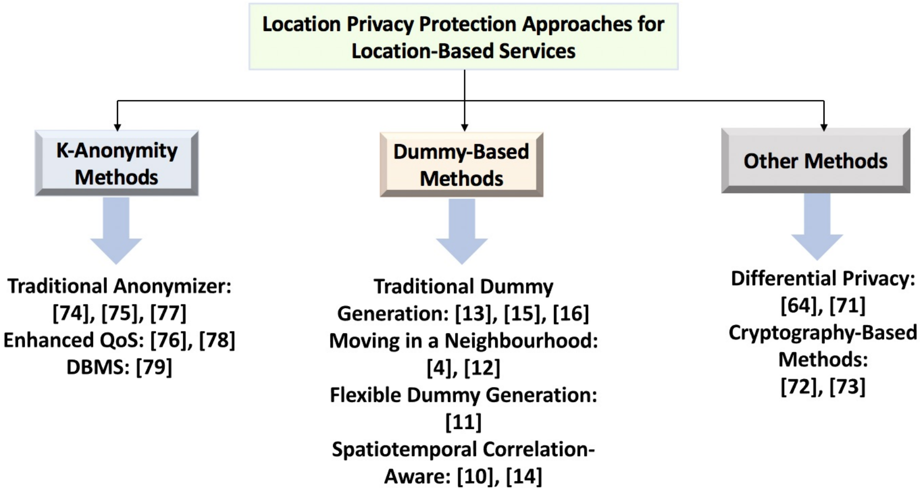

Location Privacy Protection Approaches for Location-Based Services
K-Anonymity Methods
Dummy-Based Methods
Other Methods
Traditional Anonymizer: [74], [75], [77]
Enhanced QoS: [76], [78]
DBMS: [79]
Traditional Dummy Generation: [13], [15], [16]
Moving in a Neighbourhood: [4], [12]
Flexible Dummy Generation: [11]
Spatiotemporal Correlation-Aware: [10], [14]
Differential Privacy: [64], [71]
Cryptography-Based Methods: [72], [73]

Figure 2.1 : Methods for location privacy protection in location–based services

share and having the maximum number of businesses that obey the proposed public principle. Moreover, in [70], the differential privacy framework has been adopted to the context of location–based services to quantify the level of indistinguishability in the users' location data. Their proposed scheme is a symmetric mechanism that injects noise to the real location of the user through a noise function to obfuscate the user's location before its submission. They have also analysed the mechanism with respect to location privacy and utility.

One of the latest papers on the location privacy of GeoSNs users is [61] in which the importance of users' awareness of the outcomes of sharing their locations in GeoSNs along with the resultant privacy threats were discussed. Moreover, a feedback tool has been designed to enable users to realize the level of threat related to the disclosure of their location data. To evaluate the effectiveness of the proposed feedback tool, they have conducted a user study which confirms the necessity of users' location privacy awareness.

Prior work on privacy issue of Location–Based Services has mostly focused on K–Anonymity and Dummy–Based methods although some efforts have recently done on other techniques such as Differential Privacy [64], [71] and Cryptography–Based [72–73] schemes.

K–Anonymity efforts [74–78] require a trusted third–party server which is called an anonymizer, between users and LSP. The anonymizer receives service requests from a user and enlarges its location into a region (cloaking region) so that it contains the locations of $K - 1$ other users as well as location of the requesting user. Therefore, the adversary cannot identify the requesting user among other $K - 1$ users. The advantage of these methods is that the communication cost between users and anonymizer is reduced, however, they suffer from decreased QoS because when there are not enough users near the requested user, the anonymizer has to increase the radius of cloaking region, hence, the increased processing times results in a greater service latency. To solve this problem, some efforts have been done in [76] and [78] to increase QoS. In these papers the area of cloaking region is minimized by using footprints–historical locations of other users.

Although the mentioned efforts have solved the low QoS problem, they still rely on a trusted third–party anonymizer which is a disadvantage for these schemes. To address this issue, a K–Anonymity privacy protection scheme has been proposed in [79] which does not rely on a trusted anonymizer between users and LSP. However, this method still requires a DataBase Management System (DBMS) to operate.

Several dummy–based location privacy schemes [4], [12–16] have been proposed so far for location privacy protection. In all of them users send their location data including noise (some fake location data or dummies) to LSP directly. Thus, there is no need for a trusted anonymizer. In [4] and [12], two dummy generation algorithms have been presented, Moving in a Neighbourhood and Moving in a Limited Neighbourhood. In these algorithms, the first dummy set is selected randomly but next dummies are generated in a neighbourhood of the previous position of the dummies. Moreover, a cost reduction technique was proposed in [4] to limit the communications overhead caused by sending dummies.

However, generating dummies at random or through a fixed rule can not provide flexible location privacy for users. Hence, in [11], a Privacy–Area Aware scheme is proposed based on a flexible dummy generation algorithm in which dummies are generated according to either a virtual grid or circle. This approach provides configurable and controllable dummy generation by which it is possible to control the user's location privacy. A disadvantage of this method is that it does not consider nature of the region. For example, some dummies may be generated in an unlikely location for a user (e.g., in a river). To solve this problem in [12] a Dummy–Location Selection (DLS) method has been proposed to prevent the adversary from exploiting side information such as a region map. This is done by carefully selecting dummies based on the entropy metric.

However, in [14] it has been showed that when a user adopts one of the aforementioned dummy–based methods, the adversary can identify some dummies with a minimum correct ratio of 58% by means of the spatiotemporal correlation between neighbouring location sets. Therefore, they have proposed a Spatiotemporal Correlation–Aware privacy protection scheme in which correlated dummies are filtered out and only uncorrelated dummies are sent to LSP. However, this method can protect user's location privacy under some conditions only and if the adversary estimates the threshold angle which is used to filter space correlated dummies, he will be able to identify dummies or even the user's real location.

2.3 Preliminaries

This section presents some preliminaries that is required as the foundation for the next chapter. We first review the concept of differential privacy and the Laplace mechanism. Then, we discuss the necessity of customising the adjacency relation defined in the standard differential privacy to match its definition with the location domain.

2.3.1 Differential Privacy

Differential privacy [8] is a privacy preserving framework that enables data analysing bodies to promise privacy guarantees to individuals who share their personal information. In fact, differentially private mechanisms can make users' private data available for data analysis, without needing data clean rooms, data usage agreements or data protection plans [9]. More precisely, a differentially private mechanism that publishes users' private data provides a form of indistinguishability between every two adjacent databases. Here, "adjacent" means that they differ only in a single record. However, as you see later, we will extend the concept of "adjacency" to the location domain.

Definition [8]: The randomised mechanism $\mathcal{A}$ with domain H is $\epsilon-$differential private if for all $S \subseteq Range(\mathcal{A})$ and for all adjacent $x, y \in H$ (i.e. $||x-y||_1 \leq 1$) we have

$$Pr[\mathcal{A}(x) \subseteq S] \leq e^{\epsilon} Pr[\mathcal{A}(y) \subseteq S],$$

where ϵ is the privacy level which is a positive value and denotes the level of privacy guarantees such that a smaller value of ϵ represents a stricter privacy requirement. In other words, for a smaller ϵ, the mechanism makes any adjacent data x and y more indistinguishable, i.e. for a small value of ϵ, with almost the same probability, the published $\mathcal{A}(x)$ and $\mathcal{A}(y)$ are placed in the same region S. However, for a large ϵ, this probability is much higher for $\mathcal{A}(x)$ than $\mathcal{A}(y)$ which makes them more distinguishable. Therefore, mechanism $\mathcal{A}$ can address privacy concerns that individuals might have about the release of their private information. Note that differential privacy is a definition, not an algorithm [9]. In other words, we can have many differentially private algorithms for a privacy scenario and a given ϵ.

2.3.2 Laplace Mechanism

One of the most popular mechanisms developed based on the differential privacy framework is the Laplace mechanism [9], [64], [97] in which Laplace–distributed noise is added to users' private data to make it $\epsilon-$differentially private.

Laplace Mechanism [9]: Given the private data $x \in H$, the Laplace mechanism is defined as:

$$\mathcal{A}_L(x, \epsilon) = x + N,$$

where, N is Laplace–distributed noise with scale parameter $1/\epsilon$ and zero mean, i.e.,

$$N \sim Lap(0, \frac{1}{\epsilon})$$

The probability density function for N is:

$$f_N(n) = \frac{\epsilon}{2}\, e^{(-\epsilon|n|)}, \tag{2.1}$$

where ϵ denotes the privacy level required by the user. The Laplace distribution is a symmetric version of the exponential distribution. According to its probability density function, with high probability, the Laplace mechanism generates much stronger noise for small values of privacy level and vice versa [9], [64], [97].

In this research work, we consider the set of private data $H \subseteq R^2$ since our target is to protect users' location data which is assumed as $L =< latitude, longitude >$ where $latitude, longitude \in R$ are GPS coordinates in the ranges $[-90, 90]$ and $[-180, 180]$ respectively. Moreover, the adjacency relation defined in the standard differential privacy should be customised, since we need a mechanism for publishing location data which guarantees that *adjacent* locations are indistinguishable to some extent. For this reason, we will customise the adjacency relation definition later in the next section in order to use differential privacy framework in location domain.

2.4 Conclusion

In this chapter, we reviewed the existing literature on the current privacy preserving techniques and solutions in social networks and reviewed the advantages and disadvantages of each solution. It is concluded that differential privacy, as a promising framework, can be employed to develop reliable and efficient privacy preserving mechanisms in social networks.

Moreover, this chapter presented some preliminaries as the foundation for the next chapter. In this regard, the concept of differential privacy and the Laplace mechanisms were presented. Moreover, we discussed the necessity of customising the adjacency relation defined in the standard differential privacy to match its definition with the location domain.

In the next chapter, we introduce the Distance–Based Location Privacy Protection (DBLP2) mechanism for users of social networks. It provides customisable location privacy protection by which social network users can customise their privacy settings according to their social distance to other users.

Chapter 3

Customisable Location Privacy Protection in Social Networks

3.1 Introduction

In this chapter, we propose the Distance–Based Location Privacy Protection (DBLP2) mechanism for users of social networks. The proposed mechanism preserves users' location privacy at an individual level based on their social distances. It returns a customised response through the differential privacy mechanism whenever a user requests to access another user's location information. In the proposed mechanism, closer relationships bring more accurate location information. The primary distinguishing characteristic of DBLP2 is that it provides a flexible location privacy protection framework for social network users which overcomes the identified disadvantages. Moreover, DBLP2 improves data utility by generating responses with optimal accuracy and providing privacy–aware access rights for different users. Our extensive analysis shows that it offers the optimum data utility regarding the trade–off between privacy protection and data utility. In addition, our experimental results indicate that DBLP2 is capable of offering variable location privacy protection and resilience to post processing.

We first present the background in the next section. Then, in Section 3.3, our proposed DBLP2 mechanism is introduced. Finally, Section 3.4 summarises this chapter.

3.2 Background

Social networks have recently become a popular online communication platform. According to the latest statistics [1], Facebook had more than 2.41 billion monthly active users in 2019 while it had only 100 million in 2008. This rapid and continuous growth of social networks indicates that communication on them has become a prominent method for people to connect and share information on the Internet. Furthermore, people even use these services for their business promotion, such as advertising and marketing activities. Furthermore, social networks have become more ubiquitous due to the new advances in smartphone technology [6], [7]. This has provided an opportunity for social network service providers to utilise location information of users in their services. For example, Facebook Places, Foursquare and Yelp are popular social networks that mostly rely on utilising users' location data in their services. They offer a variety of useful services, from location recommendation to nearby friend alerts.

However, a big challenge for social networks is how to protect location privacy of users. This challenge has become one of the most important issues in social media due to the existing structure of social networks that enables an adversary to track movements of users [6], [7]. For example, a new Chrome extension called Marauder's Map has been developed that enables Facebook users to easily track movements of other users and plot them on a map with an accuracy of around one meter [55]. It uses the location data that users have shared in Facebook Messenger chats. Moreover, different methods have been proposed for user location inference based on users' tweets [56–58]. This is a significant issue since other private information of users can be revealed by analysing their location data (e.g., home address, health condition, interests, etc.).

To address these privacy issues, social network service providers offer some built–

in tools enabling users to decide on their own privacy preferences. In addition, different methods have been proposed to protect user location privacy in social networks and Geo–Social Networks (GeoSNs) [61], [65], [67], [68]. However, these tools and methods introduce additional problems that may lead to further privacy leakage as follows.

Firstly, current solutions rely on user collaboration while some users may not be competent enough to collaborate in such processes. Moreover, some users are not even aware that social networks have been equipped with these privacy protection tools. They might customise their default privacy settings only after their privacy is violated [59], [60]. Secondly, the mentioned privacy protection tools and methods are not efficient enough to protect different users' privacy requirements [60], [61]. Specifically, they are not flexible in terms of social distance between users and rigidly divide users to be either friends or strangers [62]. These privacy protection tools look at the level of privacy protection as a rigid binary function, while in reality, we treat privacy differently against different relationships. Although differential privacy [8], [9] is the dominant tool used for privacy protection, it cannot offer customised privacy protection in its current form. Finally, applying rigid privacy policies keeps users information local and limits data utility for public [62], [106].

To address the aforementioned problems, in the next subsection, we propose the Distance–Based Location Privacy Protection (DBLP2) mechanism. The proposed mechanism protects location privacy of social network users based on their social distances. We define social distance as a measurement index of social relationship which indicates the intimacy of users based on their interactions in the social network. In the next section, we present the preliminary knowledge of the related topics.

3.3 The Proposed DBLP2 Mechanism

In this section, the proposed DBLP2 mechanism is presented. Firstly, we present the system architecture and propose a graph model for social networks. Then, we discuss how social distances are converted to privacy levels. Finally, we present the proposed customisable differential privacy framework. The designed mechanism is independent of user collaboration and improves the utility of social networks. In other words, it satisfies the following properties:

Flexible privacy: The system must generate $\epsilon(d_{ij})$–differential private responses, where d_{ij} is the social distance between user u_i and u_j. Thus, the privacy level ϵ must be a function of social distances.

Independent of user collaboration: The system must embrace the whole responsibility of users' privacy protection regardless of whether users collaborate with the system or not. Therefore, by default, the system must perform a standard distance–to–privacy function for each user to obtain the required privacy levels against other users. Competent users can customise this function based on their own requirements.

Optimal accuracy: Responses generated by the system must be as accurate as possible regarding the trade–off between privacy protection and data utility. Therefore, to preserve data utility, the level of location generalisation must be kept to a minimum, i.e., the system needs to minimise the expected squared error $\| L_{ij} - L_i \|^2 \ \ (i, j \in V)$, where L_i is the real location of user u_i and L_{ij} is an approximation of L_i generated by the system for sending to user u_j.

In the next section, we present system architecture of the proposed DBLP2 mechanism.

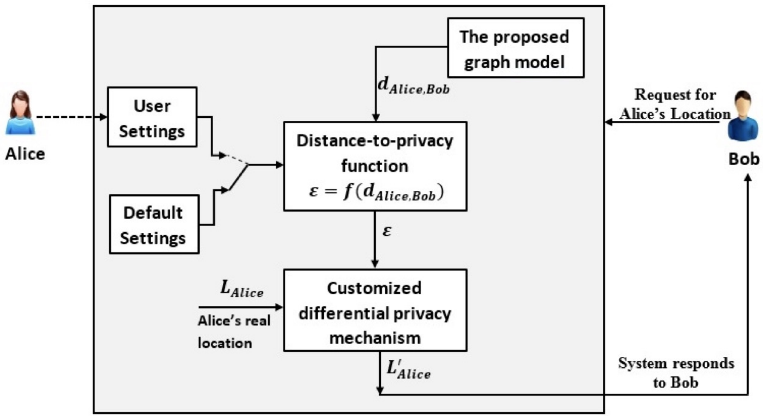


Figure 3.1 : The proposed DBLP2 system architecture.

3.3.1 System Architecture

In this work, we assume the social network service provider as a centralised trusted entity that is in charge of keeping users' raw private location data, calculating the social distances and executing our proposed DBLP2 mechanism.

Fig. 3.1 shows the proposed system architecture. As you see, when Bob sends a request for Alice's Location data, firstly, using their social distance, i.e. $d_{Alice,Bob}$, the privacy level ϵ that Alice requires against Bob is obtained. The required privacy level ϵ is calculated by a distance–to–privacy function f. Default or Alice settings have a critical role to convert $d_{Alice,Bob}$ to ϵ. Since function f can be different for different users (depending how important location privacy is for the user), it must be customisable by users based on their requirements. The default settings are designed based on the behaviour of incompetent users. As you will see in this section, these default settings model a moderate behaviour which most users have in social networks in terms of privacy protection. Obviously, Alice can personalise these settings based on her privacy protection requirements.

Finally, using a customised differential privacy mechanism, an appropriate amount of noise (regarding the obtained privacy level ϵ) is injected to Alice's real location (L_{Alice}) and the sanitised location L'_{Alice} is generated for offering to Bob. In the next subsections, details of the mentioned stages are discussed.

3.3.2 Graph Model

We model social networks by a directed and weighted graph $G = (V, E)$ in which nodes represent social network users and edges define social relations between users. Therefore, if user u_i has $|u_i|$ friends in her friend list, node u_i is connected to a set of $|u_i|$ neighboring nodes. Now suppose the graph has $|V| = N$ nodes and for each edge $(i, j) \in E$ we assign a weight w_{ij} which represents the social distance between user u_i and u_j. As we discussed in Section 1, in most cases, a social network user has different social distances from other users who are in her friend list. For example, although a family member and a colleague of her can both be in her friend list, she is more comfortable with the family member than the colleague in terms of privacy concerns. Hence, we believe that weighted graphs are more appropriate models for social networks rather than unweighted graphs because they enable us to model different social distances by weighted edges.

Moreover, we adopt a directed graph to model the network instead of undirected because we believe that social relations between users are not necessarily symmetric. In other words, two friends in a social network might have different feelings about each other. For example, although Bob regards himself as very close to Alice, she may consider some privacy protection settings against Bob. We call this attribute *friendship asymmetry* in social networks. A directed graph model allows us to analyze privacy protection requirements for each user separately. Therefore, for any given users u_i and u_j, equations $d_{ij} = d_{ji}$ and $w_{ij} = w_{ji}$ are not necessarily true.

Using the proposed graph model, the social distance d_{ij} can be obtained. For this reason, we extend the effective distance definition [98], [99] to obtain the dis-

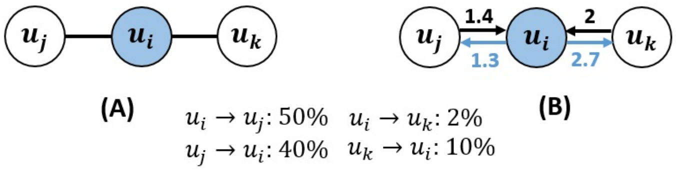

u_j
u_i
u_k
(A)
u_j
1.4
1.3
u_i
2
2.7
u_k
(B)
$u_i \rightarrow u_j$: 50%
$u_j \rightarrow u_i$: 40%
$u_i \rightarrow u_k$: 2%
$u_k \rightarrow u_i$: 10%

Figure 3.2 : A simple example showing three users of a social network modelled by a simple graph.

tance between friend users (neighbor nodes in the graph) in the social network (or equivalently w_{ij} where $(i, j) \in E$). However, other methods and techniques for social distance measurement [100–103] can be integrated into the DBLP2 mechanism.

The extended effective distance from the two neighbor nodes u_i and u_j is defined as

$$e(i, j) = 1 - log(p_{ij}),$$

where p_{ij} is the percentage of user u_i's messages which have been sent to user u_j, (i.e., $0 < p_{ij} \leq 1$) and is calculated by equation 3.1:

$$p_{ij} = \frac{m_{ij}}{\sum_{k=1}^{|u_i|} m_{ik}} \quad , \tag{3.1}$$

where m_{ij} is the number of messages that user u_i has sent to user u_j and $|u_i|$ is the cardinality of user u_i (the number of u_i's friends).

The concept of effective distance reflects the idea that a small value of p_{ij} or equivalently a small number of messages exchanged between user u_i and u_j results in a large distance between them, and vice versa. Therefore, for each edge $(i, j) \in E$ we adopt

$$w_{ij} = e(i, j), \tag{3.2}$$

as the effective weight that represents the social distance between two friend users u_i and u_j.

A simple example is illustrated in Fig. 3.2 which shows how effective weights are applied to the nodes of a social network graph. As you see, 50% of user u_i's messages has been sent to u_j (i.e., $P_{ij} = 0.5$) while she has sent only 2% of her messages to u_k. Therefore, after calculating effective weights for each friend using equation 3.2 and applying them to the graph, Fig. 3.2(B) is obtained. You see that u_i has a smaller distance to u_j (1.3) than u_k (2.7). The friendship asymmetry attribute is also considered in our model (Fig. 3.2(B)) which makes the social network graph a directed graph.

By applying effective weights to the whole network's graph, we are able to calculate the distance between non–friend users. For this reason, we just need to add individual effective weights on each path between two non–neighbor nodes and find the path with the minimum additive effective weights, i.e.

$$d_{ij} = min(\sum_{l=1}^{K_p} w_l^p) \quad ,$$

where w_l^p is the effective weight of the lth edge on the pth path between node u_i and u_j and K_p is the the number of edges that make path p.

Different methods have been proposed to find the shortest path between a pair of nodes in graphs [100–103]. Since the purpose of this section is not to offer an algorithm for the shortest path problem, we just assume that we have the distance between any pairs of nodes in the network.

3.3.3 Converting Social Distances to Privacy Levels

Before injecting noise to a user's location data, we need to quantify her privacy level against other users in a social network since we need to design a system with flexible (variable) privacy level. Hence, we adopt the social distance as a determinant factor to obtain different privacy levels that a user requires against other users.

To discuss how social distances are mapped to privacy levels, we assume f is a

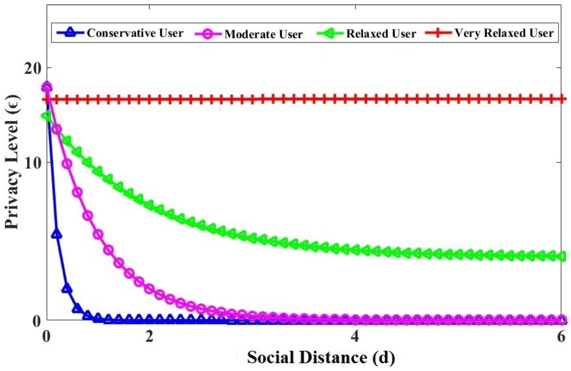


Figure 3.3 : An example of four users with different privacy protection requirements.

function which converts social distance between user u_i and u_j, i.e. $d_{ij}(i, j \in V)$, to a privacy level $\epsilon(d_{ij})$. The following properties can be considered for a standard function f in social networks.

- f is a decreasing function since the standard differential privacy definition specifies that a larger value of ϵ represents a more relaxed privacy level (or equivalently a small social distance) and vice versa. Thus, there is always an inverse relationship between d_{ij} and privacy level ϵ. The slope of these inverse changes depends on the user behavior in terms of privacy protection, thus, it can be different for each user.

- For large distances ($d \rightarrow \infty$), ϵ must be near zero ($\epsilon \rightarrow 0$). This means a tight privacy constraint for strangers who are far from a user in the network.

- For small distances, i.e. $d \rightarrow 0$, ϵ must be a relatively large value ($\epsilon >> 1$) which represents a loose privacy constraint for a user's close friends in the network.

Different functions can be defined with the mentioned properties. For example, an exponential function f in the following can be adopted to convert social distances to privacy levels.

$$f(d_{ij}) = e^{(a-bd_{ij})} \ , \tag{3.3}$$

where, $a, b > 0$ are regression coefficients used to calibrate the formula. However, function f can have different properties for different users (dependant on how privacy is important for each user). For example, a user might be very conservative and only allows her family members and close friends to see her location. On the other hand, there are always some social network users with minimal privacy concerns (see Fig. 3.3). Hence, a single function f can not satisfy privacy requirements of all users with different privacy protection requirements. Therefore, users should be able to customise f based on their own requirements.

However, to make the system independent of user collaboration, we consider the behavior of the moderate user shown in Fig. 3.3 as a standard model and adopt its function as the standard function f for all users. Those users who want to customise this function can change the related settings. For example, by applying constants c_1, c_2 and c_3 to the mentioned function f (equation 3.3), we obtain the following function f'.

$$\epsilon = f'(d_{ij}) = c_1 + e^{(c_3 - c_2 d_{ij})} \tag{3.4}$$

where $c_1, c_2, c_3 \geq 0$. A default value is defined by the system for constants c_1 to c_3 to create the standard function. However, each user is able to customise the function by changing the appropriate settings. Therefore, all four groups of users introduced in Fig. 3.3 are covered through a single function.

3.3.4 Customisable Differential Privacy

After discussing how social distances are converted to appropriate privacy levels, we are ready now to present the noise injection mechanism for the DBLP2 system. We adopt the differential privacy framework (see Section 3.1) because of its verified privacy guarantees [8], [9]. The target is to randomise a user's real location such that there must always be a minimum level of indistinguishability for an adversary between the user's real location and any other location which is adjacent to it. This level of indistinguishability is varied inversely with the privacy level ϵ, i.e. a large value of privacy level ϵ (smaller social distances equivalently) results in a lower level of indistinguishability and vice versa. However, for the sake of data utility, unnecessary randomisation must be avoided such that a balance between data utility and the level of privacy protection must be kept regarding the trade–off between data utility and privacy protection.

Since the proposed mechanism publishes location data, we customise the adjacency relation defined in the standard differential privacy in order to use differential privacy framework in the location domain. This is shown in Definition 1.

Definition 1. *Adjacency relation:* Locations L and L' are considered adjacent if the distance between them is less than a predefined value D, i.e.

$$||L - L'||_2 \leq D$$

Using Definition 1 we customise the standard definition of differential privacy to our needs. For this reason, we present the concept of $(D, \epsilon)-$location privacy in Definition 2.

Definition 2. $(D, \epsilon)-$*location privacy:* Suppose $L \in R^2$ be a user's private location and $L' \in R^2$ is adjacent to L, (i.e. $||L - L'||_2 \leq D$). Mechanism $\mathcal{A} : R^2 \rightarrow R^2$ is $(D, \epsilon)-$location private if for any $S \subseteq Range(\mathcal{A})$ we have

$$ln(\frac{Pr[\mathcal{A}(L) \in S]}{Pr[\mathcal{A}(L') \in S]}) < \epsilon$$

Intuitively, if an adversary wants to infer L, the distinguishability between L and any adjacent location L' that he selects is limited by ϵ. In other words, all adjacent locations L' have an equal chance to be placed in the region where $\mathcal{A}(L)$ is located. Therefore, the level of distinguishability is determined by the privacy level ϵ. To simplify the notions, in the rest of this section, we simply use notion "$\epsilon-$differential privacy" instead of "$(D, \epsilon)-$location privacy".

Now suppose $L_i \in R^2$ is the GPS coordinates of user u_i's real location, i.e. $L_i =< L_i^{(1)}, L_i^{(2)} >$. If $d_{ij} \in R_+$ is the social distance between user u_i and u_j, then using equation 3.5, mechanism $\mathcal{M} : R^2 \to R^2$ generates response L_{ij} that user u_j receives as an approximation of user u_i's location.

$$L_{ij} = \mathcal{M}(L_i, \epsilon(d_{ij})) = L_i + N(\epsilon(d_{ij})), \tag{3.5}$$

where $\epsilon(d_{ij})$ is the privacy level required by user u_i against user u_j and N is a two–dimensional Laplace–distributed random variable with scale $\epsilon(d_{ij})$.

From equation 3.5 it is concluded that the accuracy of the response L_{ij} depends on the amount of injected noise $N(\epsilon(d_{ij}))$. The noise level itself is determined by the privacy level ϵ (which is the scale of N's distribution) because the probability density function of the Laplace distribution (see equation 2.1) states that a smaller amount of noise is generated with high probability for larger values of ϵ and vice versa. Therefore, since ϵ is an inverse function of d_{ij}, we can say that the system generates a more accurate response for friends with smaller social distance (or larger privacy level equivalently) while casual friends and strangers receives more generalised responses.

We already mentioned three properties for the system, i.e. *flexible (variable) privacy*, *independent of user collaboration*, and *optimal accuracy.* Regarding the first property, we can say that the system offers variable privacy because users with different social distances from a specific user receive responses with different accuracy. This accuracy has an inverse relation with the social distance between the users. Therefore, the system provides a variable privacy protection tool for social network users to preserve their location privacy against a spectrum of users (from family members and close friend to strangers). Moreover, it is independent of user collaboration. The reason is that, the system always considers a default privacy protection plan for all users by taking function f' with a default value for constants c_1 to c_3. Therefore, there is always a default privacy plan for each user even if she is not aware of such a privacy protection tool.

After the distance to privacy function is determined, the noise injection mechanism is executed independent of user collaboration. This is applied even to incompetent users who can not collaborate with privacy protection systems due to different reasons (e.g. lack of sufficient language or computer skills) or are not aware of privacy violation risks in the social network until their privacy is violated.

Regarding the third property (i.e. *optimal accuracy*), we analyze the accuracy of system responses in terms of squared errors in the next section.

3.4 Conclusion

In this chapter, we proposed DBLP2, a distance–based location privacy protection system for social network users by extending differential privacy framework. It addresses the three problems from which the current privacy protection solutions suffer. Firstly, it works independent of user collaborations such that a standard privacy protection plan is considered by default for all the network users which works without users cooperation. However, users can customize their default plan based on their own privacy protection policy. Secondly, the accuracy of the proposed system's responses has an inverse relation with the social distance between users. Thus, the system provides a flexible (variable) privacy protection tool for social network users rather than a rigid binary privacy protection mechanism. Finally, the proposed system improves the utility of social networks because of the following reasons. (1) It generates privacy–aware responses with the optimum accuracy regarding the trade–off between privacy protection and data utility. (2) The system allows stranger visitors who compute global statistics and obtain privacy–aware location information about users while in the existing social networks they are rejected firmly from gathering statistics by restricting access rights.

In the next chapter, we present a comprehensive system analysis and performance evaluation of the proposed DBLP2 mechanism to assess its performance in terms of achieving the optimum accuracy and resistance against privacy attacks.

Chapter 4

Results

4.1 Introduction

In this chapter, we first present a comprehensive system analysis to show that the proposed DBLP2 mechanism achieves the optimum accuracy and is resistant against privacy attacks. Furthermore, we evaluate the system performance regarding the four types of users discussed in the previous section, i.e. conservative user, very relaxed user, relaxed user, and moderate user. Finally, we assess the immunity of the proposed system against collusion attacks.

4.2 System Analysis

This section analyzes the performance of the system from accuracy and security perspectives. First, we assess accuracy of the responses generated by the system to ensure that it offers optimal utility. Next, the system immunity against privacy attacks is assessed. Our analysis shows that the system offers optimal accuracy which depends on ϵ only. In addition, from a security point of view, the results of our analysis indicate that the proposed system is resilient to post processing and collusion attacks.

Accuracy: It is vital for a privacy protection system to keep a balance between data utility and the level of privacy protection. To maintain data utility, the system must preserve the accuracy of privacy–aware responses. For this reason, the optimal amount of noise should be injected to the users' private location regarding the trade–off between privacy protection and data utility. In other words, the noise magnitude must not be more than what is required for privacy protection.

In the proposed mechanism, the accuracy of response L_{ij} can be measured by squared error Δ_{ij} as

$$\Delta_{ij} = ||L_{ij} - L_i||_2^2 \qquad i, j \in V,$$

where a smaller error represents more accuracy. By using equation 3.5 we have

$$\begin{bmatrix} L_{ij}^{(1)} \\ L_{ij}^{(2)} \end{bmatrix} = \begin{bmatrix} L_{i}^{(1)} \\ L_{i}^{(2)} \end{bmatrix} + \begin{bmatrix} N_1(\epsilon(d_{ij})) \\ N_2(\epsilon(d_{ij})) \end{bmatrix},$$

where $L_{ij}^{(k)} \in R$ $(k = 1, 2)$ are the GPS coordinates of response L_{ij} and $N_k(\epsilon(d_{ij}))$ $(k = 1, 2)$ are independent and identically distributed random variables, i.e.

$$N_k \sim Lap(0, \epsilon(d_{ij})) \qquad \forall i, j \in V, \; k = 1, 2$$

Therefore, the squared error Δ_{ij} is obtained as

$$\Delta_{ij} = N_1^2(\epsilon(d_{ij})) + N_2^2(\epsilon(d_{ij})) \;\; i, j \in V$$

$N_1^2 + N_2^2 = \Delta$ corresponds to a circle with radius $\sqrt{\Delta}$, for cumulative distribution function of Δ. Therefore, we have

$$F_\Delta(\delta) = Pr[\Delta \le \delta] = Pr[(N_1^2 + N_2^2) \le \delta]$$
$$= \int_{-\sqrt{\delta}}^{\sqrt{\delta}} \int_{-\sqrt{\delta - n_2^2}}^{\sqrt{\delta - n_2^2}} f_{N_1,N_2}(n_1, n_2) dn_1 dn_2.$$

Since N_1 and N_2 are independent and identically distributed we have

$$f_{N_1,N_2}(n_1, n_2) = f_{N_1}(n_1) f_{N_2}(n_2) = \frac{\epsilon^2}{4} e^{-\epsilon(|n_1| + |n_2|)}.$$

Therefore,

$$F_\Delta(\delta) = \int_{-\sqrt{\delta}}^{\sqrt{\delta}} f_{N_2}(n_2) \int_{-\sqrt{\delta - n_2^2}}^{\sqrt{\delta - n_2^2}} \frac{\epsilon}{2} e^{-\epsilon |n_1|} dn_1$$
$$= \frac{\epsilon}{2} \int_{-\sqrt{\delta}}^{\sqrt{\delta}} (1 - e^{-\epsilon \sqrt{\delta - n_2^2}}) e^{-\epsilon |n_2|} dn_2$$

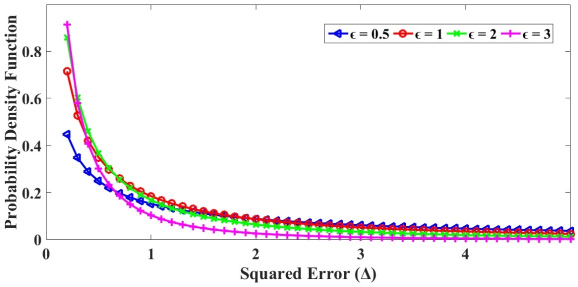


Figure 4.1 : Probability density function for generalised gamma distribution.

By taking differentiation, we obtain the probability density function (PDF) of Δ as

$$f_{\Delta}(\delta) = \frac{d}{d\delta} F_{\Delta}(\delta) = \frac{\epsilon}{2\sqrt{\delta}} e^{-\epsilon\sqrt{\delta}} \tag{4.1}$$

From equation 4.1 it is derived that Δ has generalised gamma distribution [126] with scale parameter $1/\epsilon^2$, expected value $2/\epsilon^2$ and variance $20/\epsilon^4$. This means that the random variable Δ depends only on ϵ, i.e. for larger values of ϵ (equivalently, smaller social distances), with high probability, a smaller Δ is offered and vice versa (see Fig. 4.1). Therefore, the accuracy of the responses L_{ij} is determined by the privacy level ϵ only and they have a direct relation, i.e. any increase in ϵ results in a more accurate response. This is exactly what the mechanism needs to satisfy: *flexible (variable) privacy* and *optimal accuracy*, as we discussed in the previous section.

Security: In the following, we analyze the proposed system's performance against privacy attacks. For this reason, we first show that the system is immune to post processing. In other words, if an adversary has no additional knowledge about a user's real location, he cannot make the system's responses less private by performing computation on the output of the system. Next, we prove that the proposed system is resilient against collusion attacks in which a group of users collaborate and share their received responses to obtain a more accurate approximation.

Proposition 1. *(Resilience to post processing):* If $\mathcal{M} : R^2 \to R^2$ is the proposed mechanism which preserves ϵ–differential privacy, then for any function $f : R^2 \to R^2$, the composition $f \circ \mathcal{M} : R^2 \to R^2$ also preserves $\epsilon-$ differential privacy.

Proof: Assume location L' is adjacent to L, i.e. $||L' - L|| \leq D$ (see definition 1) and $S' \subset R^2$. By defining $S = \{l \in R^2 : f(l) \in S'\}$ and because $\mathcal{M}$ is a $\epsilon-$differential private mechanism we have

$$Pr[f(\mathcal{M}(L)) \in S'] = Pr[\mathcal{M}(L) \in S] \leq e^{\epsilon} Pr[(L') \in S']$$

Therefore, according to the definition of S we obtain

$$Pr[f(\mathcal{M}(L)) \in S'] \leq e^{\epsilon} Pr[f(\mathcal{M}(L')) \in S']$$

which means $f \circ \mathcal{M}$ is also $\epsilon-$differential private.

Resilience to post processing is a common advantage of mechanisms that adopt the differential privacy framework [9], [127]. It guarantees that after the system publishes an $\epsilon-$differential private response, an adversary without any additional knowledge on the private data cannot increase privacy loss and make it less private [128].

Therefore, the proposed mechanism is resilient to post processing. This makes it immune to privacy attacks that rely solely on post processing. Moreover, we proof that the proposed mechanism is also resilient to collusion attacks in which a group of users combine their responses to make a more accurate approximation. In practice, an adversary can create multiple fake accounts in the social network and establish such a colluding group.

Theorem 1. *(Resilience to collusions):* Consider a group of K users $C \subseteq V$ who collaborate and share their response $\mathcal{M}(l_i, \epsilon(d_{ij})) = l_{ij}(j = 1, 2, \ldots, K), (i \in V)$ to obtain $l_c^{(i)}$. If l_{ij} be an $\epsilon(d_{ij})-$differentially private response, then $l_c^{(i)}$ is $(max_{j \in C} \epsilon(d_{ij}))-$differentially private.

Proof: from equation 3.5 we have

$$\begin{bmatrix} l_{i1} \\ l_{i2} \\ . \\ . \\ . \\ l_{iK} \end{bmatrix} = l_i + \begin{bmatrix} N(\epsilon(d_{i1})) \\ N(\epsilon(d_{i2})) \\ . \\ . \\ . \\ N(\epsilon(d_{iK})) \end{bmatrix},$$

where l_i is the private location of user u_i. We sort the responses $L_{ij}(j = 1, 2, \ldots, K)$ such that

$$\epsilon(d_{i1}) < \epsilon(d_{i2}) < \ldots < \epsilon(d_{iK}),$$

which means l_{iK} is the most accurate response among $l_{ij}(j \in C)$. To obtain $l_c^{(i)}$, the adversary combines K received responses l_{ij}. Therefore,

$$l_c^{(i)} = \sum_{j=1}^{K} w_j l_{ij} = \sum_{j=1}^{K} w_j (l_i + N(\epsilon(d_{ij}))),$$

where w_j is the weight considered for response j in the combination process. For simplicity we assume $w_j(j \in C)$ are equal, i.e.

$$w_j = \frac{1}{K} \quad j = 1, 2, \ldots, K.$$

Therefore,

$$l_c^{(i)} = l_i + \frac{1}{K} \sum_{j=1}^{K} N(\epsilon(d_{ij}))$$

By defining $N(\epsilon(d_{ij})) = N_{ij}$ we have

$$l_c^{(i)} = l_i + \frac{1}{K} \sum_{j=1}^{K} [N_{iK} + \sum_{m=j+1}^{K} (N_{im-1} - N_{im})].$$

Since $l_i + N_{iK} = l_{iK}$ we obtain

$$l_c^{(i)} = l_{iK} + \sum_{j=1}^{K} \sum_{m=j+1}^{K} (N_{im-1} - N_{im}) \tag{4.2}$$

From equation 4.2 we can say that $l_c^{(i)}$ consists of two parts. First, $\epsilon_{iK}-$differential private l_{iK} which is the most accurate response in C since $\epsilon_{iK} = max_{j \in C}\ \epsilon_{ij}$ and second, a noise section. Since N_{im-1} and N_{im} are independent Laplace– distributed random variables, $(N_{im-1} - N_{im})$ has also Laplace distribution. Therefore, we can consider $\phi = \sum_{j=1}^{K} \sum_{m=j+1}^{K} (N_{im-1} - N_{im})$ as Laplace-distributed noise added to l_{iK}. In conclusion, we can say that $l_c^{(i)}$ is the $\epsilon_{iK}-$differential private response l_{iK} which has been post processed by function $g(x) = x = \phi$, i.e.

$$l_c^{(i)} = g(l_{iK}) = g(M(l_i)) = l_{iK} + \phi.$$

According to proposition 1, mechanism $\mathcal{M}$ is immune to post processing, hence, $l_c^{(i)}$ is also $\epsilon_{iK}-$differential private. Therefore, the result of any collusion attack is equivalent to a $(max_{j \in C}\ \epsilon(d_{ij}))$–differential private response which means no more accuracy is obtained. Consequently, there is no need for additional privacy preserving noise when multiple users ask for a user's private location.

4.3 Performance Evaluation

In this section, we evaluate the performance of our proposed DBLP2 system. Firstly, we evaluate the proposed system's performance regarding the four types of users discussed in the previous section. Finally, we assess the immunity of the proposed system against collusion attacks.

Variable Privacy: To evaluate the system performance in terms of variable privacy, a single user scenario is considered in which the user's location privacy is protected against a variety of users. For this reason, we assess the magnitude of the injected noise for a spectrum of users (i.e. from family members and close friends to casual friends and strangers). To model this scenario, we increase the social distance d from 0 to ∞ and obtain the related privacy level ϵ using the function introduced in equation 3.4. Then, for each value of the obtained privacy level ϵ, the magnitude

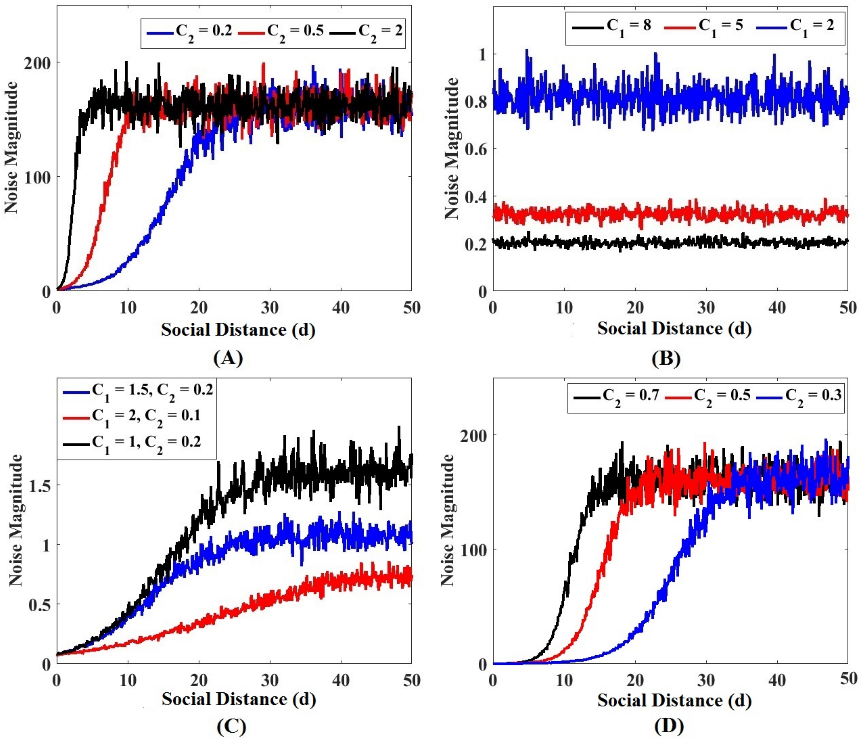


Figure 4.2 : The magnitude of the injected noise for a (A) conservative user, (B) very relaxed user, (C) relaxed user, and (D) moderate user.

of the injected Laplace noise is calculated.

As discussed in Section 3.2.2, by selecting the appropriate values for constants c_1, c_2 and c_3, the distance to privacy function f' can model the behavior of different users in choosing a privacy protection policy. Therefore, we adopt this function for the experiments to convert social distances to privacy levels. In this regard, the behavior of the four types of users introduced in Section 3.2.2 are modeled using this function by selecting the suitable values for c_1, c_2 and c_3. Finally, based on the privacy levels obtained, the related noise magnitude is calculated. The results of our experiments are shown in Fig. 4.2.

For the first type of user, i.e. the conservative user, the result (see Fig. 4.2 (A)) shows that the amount of injected noise is largely increased when the social distance is raised above zero. This means that the system generates responses with high accuracy for the user's family members and close friends (who have small social distance) while other users receive a totally inaccurate response. We performed the experiments for three different values of constant c_2 to see the effect of this parameter. As you see, c_2 determines the threshold social distance at which a tight privacy protection (required by the user) starts. In other words, c_2 represents how a user is conservative. We have also selected $c_1 = 0$ and $c_3 = 0.1$ in this case (c_1 must be zero for this type of user).

Fig. 4.2 (B) shows the result for a very relaxed user ($c_2 = c_3 = 0$). In this case, c_1 determines a high privacy level (relaxed privacy) which the user selects against all the other users. As you see, the system always generates a very small noise regardless of the social distance (a relatively accurate response for all the other users). The level of this noise is determined by c_1. In other words, for larger c_1 (higher privacy level) a more accurate response is generated. You can realise the difference between the system responses generated for the first and second type of users (Fig. 4.2 (A) and (B), respectively), if you compare the amount of the noise generated for each category. Moreover, the amplitude of the changes in the amount of generated noise is higher for a smaller c_1. The reason is that the variance of the generated Laplace noise is $2/\epsilon^2$. Thus, the variance is increased as c_1 is decreased.

The noise magnitude for the third type of user, i.e. the relaxed user, is shown in Fig. 4.2 (C) for different values of c_1 and c_2 ($c_3 = 3$ is selected in this case). The noise magnitude for this type of user is almost the same as what we have in Fig. 4.2 (B) (notice the amount of noise magnitude in Fig. 4.2 (B) and Fig. 4.2 (C)). The only difference is that in this case, the user requires less privacy protection for small social distances while in the second type, there is no difference between different social distances in terms of privacy protection.

Finally, for the last type of users, i.e. the moderate user, which we propose her

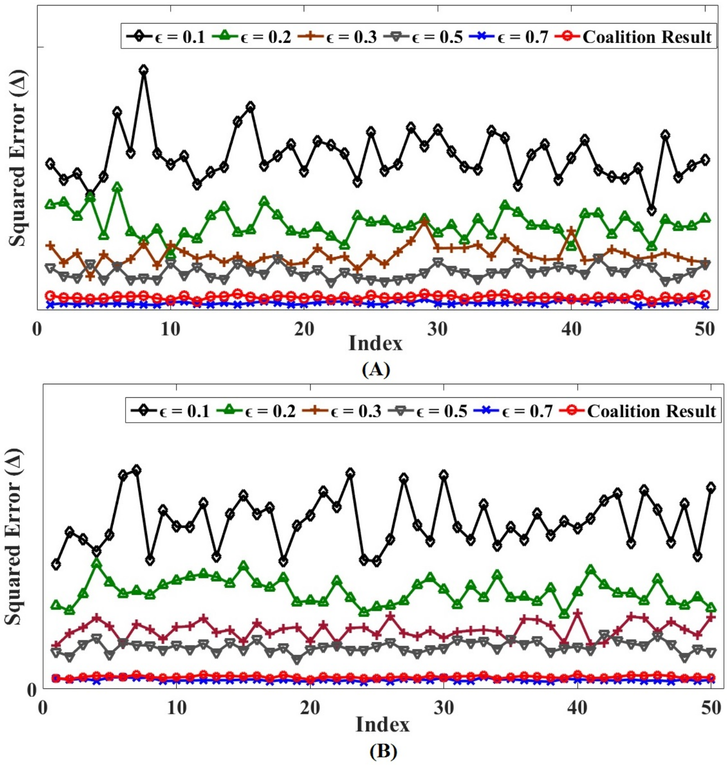


Figure 4.3 : The result of a collusion attack in which five users with different social distances from the victim have shared their response to obtain a more accurate location data.

behavior as the standard behavior, the result is shown in Fig. 4.2 (D) for different values of c_2 ($c_1 = 0, c_3 = 3$). As you see, for small social distances, the system generates accurate responses (the noise magnitude is very small) while the level of accuracy is gradually increased as the social distance gets bigger. The constant c_2 determines the slope of this increment such that for a bigger c_2, the noise magnitude is increased with a higher rate.

Collusion Attacks: In this part, we consider a collusion attack in which five users share their received responses to obtain a more accurate approximation of the victim's location. In practice, an adversary can establish such a colluding group by creating five fake accounts in the social network. We assume that these five users have different social distances from the victim. In other words, the victim has different privacy levels $\epsilon_1, \epsilon_2, \ldots, \epsilon_5$ against these five users. Hence, they receive responses with different accuracy as well, i.e. the user with the largest ϵ (smallest social distance) receives the most accurate response and vice versa. We compare the accuracies of these responses and the collusion outcome to see if there exists any motivation for an adversary to perform a collusion attack or not. In order to have a better picture of the system performance, we have performed the experiments 50 times for each user and obtained the squared error Δ of the five responses and the outcome of the collusion in each iteration. You can see the result in Fig. 4.3.

As will be discussed in section 5.1, the resultant squared error is a random variable with the generalised gamma distribution. Therefore, as Fig. 4.3 shows, a different error has been obtained for a specific user for separate experiments. In addition, the amplitude of these changes is higher in a response with a lower ϵ. The reason is that the variance of the squared error Δ, i.e. $20/\epsilon^4$, is larger for a lower ϵ. Moreover, as we expect, the accuracy of each response only depends on the privacy level $\epsilon(d)$. Consequently, in each iteration, the user with the lowest ϵ has received the response with the largest error and vice versa.

You see in Fig. 4.3 that the outcome of the collusion attack is almost the same as the most accurate response and has never been more accurate than it. This confirms the results of our analysis in the previous subsection which states that the result of any collusion attack is equivalent to a $(max_{j \in C}\ \epsilon(d_{ij}))$–differential private response. Consequently, there is no logical motivation for an adversary to conduct such a collusion attack since no additional benefit can be gained.

Moreover, regarding the combination process of the responses, Fig. 4.3 (A) shows the result of the experiments when the same weights have been considered for the responses, i.e. the responses have equal share in creating the collusion result.

However, the results shown in Fig. 4.3 (B) is for a case in which the responses have been combined with different weights. As you see, the same result has been obtained in both cases which confirms that the combination process does not affect the immunity of the system against collusion attacks.

4.4 Conclusion

In this chapter, we presented the results of our analysis and performance evaluation of the proposed DBLP2 mechanism. The proposed mechanism returns a customised response through the differential privacy mechanism whenever a user requests to access another user's location information. Moreover, DBLP2 improves data utility by generating responses with optimal accuracy and providing privacy–aware access rights for different users. Our extensive analysis shows that it offers the optimum data utility regarding the trade–off between privacy protection and data utility. In addition, our experimental results indicate that DBLP2 is capable of offering variable location privacy protection and resilience to post processing.

In the next part of the thesis, we explore the crytography–based approach for privacy preserving in social networks. In this regard, three diffrent cryptography–based solutions are introduced and their performance is analysed and evaluated.

Part II

Cryptography–Based Approach

Chapter 5

Literature Review and Preliminaries

5.1 Introduction

In recent years, advancements in smartphone technology and positioning systems have resulted in the emergence of location–based applications and services such as activity–tracking applications, location–based services (LBS), database–driven cognitive radio networks (CRNs), and location–based access control systems. In these services, mobile users' real–time location data is utilised by a location–based service provider (LBSP) to provide users with requested information or access to a resource or service. These applications are fast growing and very popular due to the range of useful services they offer [14], [17–19].

However, it is possible for dishonest users to submit fake check–ins by changing their GPS data. To clarify and highlight the fake location submission issue consider LBSPs like Yelp and Foursquare that may offer some rewards (such as gift vouchers) to users who frequently check in at specific locations. This creates an incentive for dishonest users to submit fake check–ins by manipulating their GPS data. For example, in a research study, Zhang et al. [26] found that 75% of Foursquare check–ins are false and submitted by dishonest users to obtain more rewards. Furthermore, in database–driven CRNs, malicious users can submit fake locations to the database to access channels which are not available in their location [23, 25, 32].

In this chapter, we highlight and review the existing location verification schemes. These schemes are also called location proof (LP) schemes in the literature. Moreover, we present some preliminaries as the foundation for the next three chapters.

5.2 Literature Review

In this section, we review the literature on location proof (LP) schemes. They are generally categorised into two groups depending on the system architecture: centralized and distributed. In the centralized schemes, a trusted fixed wireless infrastructure, usually a WiFi access point, is employed to check the proximity of mobile users and generate LPs for them. On the other hand, in the decentralized schemes, this task is done by ordinary mobile users who act as witnesses and issue LPs for each other. This makes their implementation easier and cheaper than the centralized mechanisms. In this section, we review the related literature on each category separately.

5.2.1 Centralized Schemes

In this approach, a central trusted node such as a wireless access point is utilised to generate LPs for users in a specific site. The idea of employing wireless access points as location proof generators was introduced by Waters et al. [83] for the first time. They measure the round–trip signal propagation latency to decide on the proximity of a user to a trusted access point referred to as the location manager. However, the proposed scheme is vulnerable against relay attacks and specifically against Terrorist Frauds. In other words, their algorithm lacks a mechanism by which the location manager ensures that the received ID is really for the user who has submitted the LP request.

To address this issue, Saroiu et al. [84] proposed a technique in which the access point broadcasts beacon frames consisted of a sequence number. To obtain an LP, users must sign the last transmitted sequence number with their private key and send it back to the access point along with their public key (the access point broadcasts beacons every 100 milliseconds). This makes the system resistant against Terrorist Frauds since the malicious prover does not have enough time to receive the sequence number from the adversary, sign and send it back to the adversary. However, the proposed algorithm has privacy issues because users must reveal their identity publicly. Javali et al. [85] have used the same idea to make their algorithm resistant against relay attacks. They also utilise the unique wireless channel characteristics, i.e., channel state information (CSI) to decide on users' proximity. The proposed scheme consists of three entities, i.e., Access Point, Verifier and Server which makes the system expensive. In addition, the user's identity is revealed publicly which might cause privacy issues. Table 5.1 presents a comparison of these LP schemes.

5.2.2 Distributed Schemes

In the distributed scenarios, users collaborate with the system to generate LPs. In other words, users act as witnesses for each other. The main advantage of this approach is that there is no need for a trusted access point to issue LPs. Therefore, this type of systems can be used in locations where users are far from a trusted entity. APPLAUS introduced by Zhu et al. [86] is one of the pioneer research works on distributed location proof systems. In APPLAUS, mobile devices use their short–range Bluetooth interface to communicate with their nearby devices who request an LP. To preserve users' location privacy, they need to select a set of M pseudonyms and change them periodically. These pseudonyms are considered as users' public keys which are required to be registered with a trusted Certificate Authority (CA) along with the associated private keys. However, changing pseudonyms regularly creates a high level of computation and communication overhead. In addition, the users are required to generate dummy LPs as well.

Davis et al. proposed a privacy–preserving alibi (location proof) scheme in [87] which has a distributed architecture. To preserve users' location privacy, in the introduced scheme, their identity is not revealed while an alibi is being created. Thus, only a judge with whom a user submits his/her alibi can see the user's identity.

Table 5.1 : Comparision of LP Schemes

LP Scheme	**Features**	**Advantages**	**Disadvantages**
Waters *et al.* [83]	Round–trip signal propagation delay is measured to decide on device proximity	Privacy–aware Lightweight	Vulnerable to P–P collusions
Javali *et al.* [85]	No DB mechanism is used Utilises channel state information (CSI) to decide on users proximity	Resistant to P–P collusions Fast	Privacy issue Expensive for implementation
Saroiu *et al.* [84]	Access point broadcasts sequence numbers periodically Provers sign the last transmitted sequence number to request an LP	Resistant to P–P collusions	Privacy issue
VeriPlace [92]	To obtain a final LP, a user needs to get an intermediate LP from a trusted access point	Privacy–aware	Needs three types of trusted entities run by separate parties
STAMP [90]	An entropy–based trust model is used to address P–W collusions	Supports location granualrity	Vulnerable to P–P collusions (the broaken Bussard–Bagga DB protocol is employed)
APPLAUS [86]	Provers adopt different pseudonyms and change them periodically	Privacy–aware	High communication overheads High computation overheads
Alibi [87]	Provers' ID is revealed only when they choose to submit their alibi to a judge	Privacy–aware Lightweight	Vulnerable to collusion attacks
Link [89]	A group of local users collaboratively verify a prover's location	Resilient to situations when there is not enough neighbour devices	Privacy issue
SPARSE [93]	No DB mechanism is used for secure proximity checking	Resistant to P–P collusions Privacy–aware	Prevents P–W collusions only in crowded scenarios
PROPS [88]	Group signatures and ZKP are used to make provers anonymous	Efficient and privacy–aware	Vulnerable to P–W collusions

However, collusions and other security threats have not been considered in the paper.

In the distributed solutions, Prover–Witness collusions are possible because witness devices are not always trusted. A witness device can issue an LP for a dishonest user while one of them (or both) is not located at the claimed location. This is one of the major challenges of these schemes. For example, in PROPS which has been proposed by Gambs et al. [88], Prover–Witness collusions have not been discussed although it provides an efficient and privacy–aware platform for users to create LPs for other users.

To the best of our knowledge, there is no efficient and reliable solution proposed in the literature to resolve the Prover–Witness collusions issue with a high level of reliability even though some significant efforts have been made so far. For example, in LINK introduced by Talasila et al. [89] a group of users collaboratively verify a user's location upon his/her request sent through a short–range Bluetooth interface. It is assumed that there is a trusted Location Certification Authority (LCA) to which the verifying users (located in the vicinity of the requesting user) send their verification messages. Then, the LCA checks validity of the claim in case of a Prover–Witness collusion. This is done by checking three parameters: the spatiotemporal correlation between the prover and verifiers, the trust scores of the users, and the history of the trust scores. However, it does not detect and prevent Prover–Witness collusions with a high level of reliability. Moreover, in the LINK scheme, users' location privacy has not been considered in the scheme design since a user needs to broadcast his/her ID to the neighbour verifiers.

STAMP introduced by Wang et al. [90] is another example in which an entropy–based trust model is proposed to address the Prover–Witness collusions issue. This method is also unable to provide the necessary reliability to detect Prover–Witness collusions. In addition, to address Terrorist Frauds, STAMP employs the Bussard–Bagga protocol [91] as the distance bounding protocol which has already been shown to be unsafe [94–96]. Moreover, the computation time required by STAMP to create an LP is long when users have a large private key [90].

Although different novel methods have been introduced so far, each of them has its own constraints, i.e., privacy issues [85], [84], [89], vulnerability against collusions [83], [86–90], high level of communication and computation overheads [86], and expensive implementation [85], [92]. The scheme proposed in [93] prevents Prover–Witness (P–W) collusions only in crowded scenarios.

5.3 Preliminaries

In this section, we first review distance bounding (DB) protocols and present the security attacks that these protocols might experience. These attacks are a threat for location proof systems as well because most LP schemes employ a DB protocol for proximity checking. Following this, we review TREAD and discuss the need of TREAD modification. Furthermore, we present an overview of the blockchain technology and review the three diferent types of blockchains. Since we introduce a blockchain–based LP scheme in chapter 8, it is needed to review the basic concepts of blockchain systems first. Following this, we present some of the design challenges that we need to address in this part of our research work.

Distance–Bounding Protocols

Distance–bounding protocols [91], [96], [109–111], were introduced by Brand *et al.* [112] to determine an upper bound on the distance between a prover and a verifier, whilst at the same time, the prover device authenticates itself to the verifier. In other words, DB protocols aim to provide authenticated proximity proofs in order to prevent some security attacks. Despite some implementation challenges, in the future, DB protocols will be employed by bank payment companies and car manufacturers due to recent advances [96].

All DB protocols work based on the fact that RF signals do not travel faster than light. First, the verifier sends a challenge bit and the prover replies promptly by sending the corresponding response regarding the received challenge bit. This procedure is called *fast bit exchange* in the literature. Then, the verifier measures the related round–trip time (RTT) which must be less than a specified threshold. This threshold is obtained by computing RTT_{max} that is related to the maximum allowed distance to the prover and is obtained through the following equation:

$$RTT_{max} = \frac{2d_{max}}{C} + t_o \ ,$$

where d_{max} is the maximum allowed distance, C is the speed of light, and t_o is an overhead time that is added to cover the computation time [95]. This process is repeated n rounds with n different challenge bits (where n is the length of prover's private key). Finally, the verifier either accepts or rejects the prover's claim.

In addition to the proximity checking, the verifier must authenticate the neighbor prover at the same time. Otherwise, an adversary can collude with a remote malicious prover and perform the *fast bit exchange* mechanism on behalf of the remote prover. In this regard, there are some security attacks that a well–designed DB protocol must be resistant against. In the literature, the following security threats have been identified so far [96]. These attacks threat an LP scheme as well since most of the LP schemes employ a DB protocol as their core function.

Distance Frauds: In a distance fraud, a malicious prover tries to convince an honest verifier that his physical distance to the verifier is less than what it really is (see Fig. 5.1 (a)). This attack can occur if there is no relationship between challenge bits and response bits and the malicious prover knows the time at which the challenge bits are sent. In this case, the malicious prover can send each response bit before its challenge bit is received.

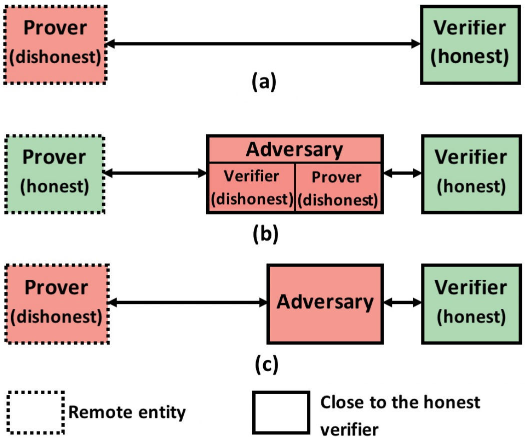


Figure 5.1 : Distance–bounding protocols are generally exposed to three types of security attacks: (a) Distance Fraud, (b) Mafia Fraud, and (c) Terrorist Fraud.

Mafia Frauds: In this attack, an adversary tries to convince an honest verifier that a remote honest prover is in the vicinity of the verifier. The adversary in this attack can be modeled by a malicious prover that communicates with the honest verifier and a malicious verifier who interacts with the honest prover (Fig. 5.1 (b)). The car locking system is a good example to understand this type of attacks where an adversary tries to open a car's door by convincing the reader unit that the key is close to the car.

Terrorist Frauds: In this attack, a remote malicious prover colludes with an adversary who is close to an honest verifier to convince the verifier that he/she is in the vicinity of the verifier (see Fig. 5.1 (c)). Although in their collusion, they never share private information (e.g., private key) with each other, it is still possible that they establish a very fast communication tunnel between themselves and the adversary relays the verifier's message to the malicious prover who can sign and send it back to the adversary for submission. Therefore, just a simple assumption that users never share their private key can not protect the system against this type of attacks.

Table 5.2 : Comparision of the success probability of different security threats for some well–known DB protocols

DB Protocol	**Distance Frauds**	**Mafia Frauds**	**Terrorist Frauds**
Swiss–Knife [110]	$(3/4)^n$	$(1/2)^n$ to 1	$(3/4)^{\theta n}$
Gambs *et al* [111]	$(3/4)^n$	$(1/2)^n$	1
Bussard–Bagga [91]	1	$(1/2)^n$	1
privDB [119]	$(3/4)^n$	$(1/2)^n$	1
SKI [118]	$(3/4)^n$	$(2/3)^n$	$(5/6)^{\theta n}$
Fischlin–Onete [109]	$(3/4)^n$	$(3/4)^n$	$(3/4)^{\theta n}$

Moreover, there is another attack called *Distance Hijacking* introduced by Cremers *et al* [113]. They believe this attack is an extension of distance frauds which is very close to Terrorist Frauds as well. In a distance hijacking attack, a remote malicious prover tries to provide wrong information about his distance to an honest verifier by exploiting the presence of one or multiple honest provers.

To address the mentioned attacks, different DB protocols have been introduced so far [91], [109–111], [114–119]. However, each protocol has its own constraints (for more detail refer to [94–96], [108]). For example, the popular Bussard–Bagga protocol (introduced by Bussard *et al* [91] to address the Terrorist Frauds) was proven insecure by Bay *et al* [94–96]. Table 5.2 compares some well–known DB protocols in terms of vulnerability against the mentioned security threats and frauds. In this table, the success probability of the most common security threats have been shown. n indicates the number of rounds in the DB process and θ is a parameter related to a Terrorist Fraud such that it is difficult to prevent from the exhaustive searches that are done to recover θn bits (see [95] and [108] for more details).

As we see in the table, most of the DB protocols are vulnerable to at least one security attack. Moreover, the two fraud–resistant protocols, i.e. SKI [118] and

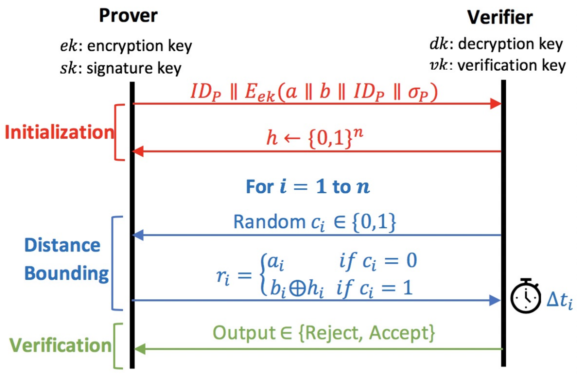


Figure 5.2 : Message exchange diagram for TREAD

Fischlin–Onete [109], need a large n to provide sufficient reliability which makes the DB process slow since the process is performed for n rounds.

TREAD

TREAD is a secure and light–weight DB protocol proposed by Avoine *et al* [108] to address the aforementioned problems. In TREAD, a novel idea has been deployed to make the protocol resistant to Terrorist Frauds: if a dishonest prover colludes with another user to conduct a Terrorist Fraud, he can be easily and unlimitedly impersonated by the accomplice later. This risk is not easily taken by any rational prover.

Assuming there is a prover device in the vicinity of a trusted verifier who have secretly shared the encryption/decryption key pair ek and dk, and the signature/verification key pair sk and vk, TREAD is performed in three phases, i.e. *Initialization*, *Distance Bounding*, and *Verification* (see Fig. 5.2).

1) *Initialization:* In this phase, the following activities are performed by the prover and verifier devices:

Prover: The prover device generates two random bit–strings a and b from the uniform distribution on $\{0,1\}^n$, computes the signature $\sigma_P = \mathcal{S}_{sk}(a||b||ID_P)$ and

Table 5.3 : List of Cryptographic Notations

Notation	Description
$\|\|$	Concatenation
$\mathcal{S}_{ent}(m)$	Signature of entity *ent* on message m
$E_{ent}(m)$	Encryption of message m using public key of entity *ent*
Loc	GPS coordinates related to the prover's Location
ID_P	The prover's identity
ID_W	The witness's identity
$\oplus$	XOR operation

the encrypted message $e = E_{ek}(a||b||ID_P||\sigma_P)$ where ID_P is the prover's ID (see Table 5.3 for a list of notations). Then, it sends $e||ID_P$ to the verifier.

Verifier: Upon receiving $e||ID_P$, the verifier device decrypts e using the decryption key dk and checks the prover's signature σ_P using the verification key vk to see if it is correct. If σ_P matches the prover's signature, the verifier generates a random bit–string h from the uniform distribution on $\{0,1\}^n$ and sends it to the prover.

2) *Distance Bounding:* In this phase, the prover and verifier devices start to perform the n–stage fast bit exchange process :

Verifier: In stage $i, (i = 1, 2, \dots, n)$, the verifier picks a random bit c_i, sends it to the prover and starts its timer.

Prover: Upon receving c_i, the prover immediately computes the following bit $r_i =$ and sends it back to the verifier:

$$r_i = \begin{cases} a_i, & \text{if} \quad c_i = 0 \\ b_i \oplus h_i, & \text{if} \quad c_i = 1 \end{cases}$$

Verifier: When r_i is received by the verifier device, it stops the timer and records its value Δt_i. Then, it performs stage $i+1$ until all the n stages are done after which it goes to the verification phase.

3) *Verification:* In this phase, the verifier device checks all the received r_i for $i = 1, 2, \ldots, n$ to see if they have been correctly computed based on h_i, c_i, a_i and b_i (the last two bits received in the initialization phase). Then Δt_i must be less than the predefined threshold RTT_{max} for $i = 1, 2, \ldots, n$.

Finally, the prover's request is accepted if the above checkings are successfully passed for all n stages.

As we see, in case of a Terrorist Fraud, a dishonest prover (located far from the verifier) not only has to provide the accomplice with his σ_P and e, but also his random bit–strings a and b. Otherwise, the accomplice is unable to correctly respond to the challenge bits c_i in the DB phase. This enables the accomplice to easily impersonate him later using a, b, σ_P, and e. See [108] for a comprehensive security analysis on TREAD.

TREAD Modification

In spite of the security guarantees that TREAD offers, it needs some amendment before we make use of it in our proposed architecture. In the following, we show how the prover's location privacy is negatively affected, if TREAD is integrated into PASPORT without any customization.

In TREAD, the prover's ID is sent to a neighbor verifier (which is assumed to be trusted) through a short–range communication interface. Due to PASPORT's decentralized architecture, the trusted verifier is located far away from the prover. Instead, a witness device (which is untrusted from a privacy point of view) collects the prover's data and performs the DB procedure. Thus, the prover's ID is sent to the witness devices in the form of a plain text message if we integrate TREAD into PASPORT without any modification. This breaches the prover's location privacy.

Hence, it is necessary to modify TREAD and make it a privacy–aware DB protocol.

Note that prover anonymity can be offered by TREAD if group signatures are used [108]. However, they guarantee provers' anonymity up to group level only. Since we do not want to use group signatures in the PASPORT's architecture, in the next section, we propose a private version of TREAD, i.e. P–TREAD, by which a prover device can anonymously broadcast its LP request for neighbor witnesses while he/she benefits from the TREAD security guarantees.

5.3.1 Blockchain Overview

A blockchain system is a tamper–proof and tamper–apparent ledger that is digitally implemented using a distributed approach without requiring a central storage system. It can also be implemented in such a way that no central authority is required to operate and maintain the whole system. The distributed ledger consists of users transactions that are cryptographically signed by them. A group of transactions create a *block*. Thus, the distributed ledger is made of blocks of transactions. Users generate their transactions and broadcast them in the network where they can be read by verifiers for verification. A verifier can be either an ordinary user (in public blockchains) or an authorized user or entity (in private and consortium blockchains). Once a transaction is verified, it is added to a new block. After a new block is issued (added to the ledger), it is computationally infeasible to tamper its transactions [121], [122]. The reason is that each block contains the hash of its previous block. This links every block to its previous block which results in having a chain of blocks.

Generally, blockchains can be divided into the following three categories based on their permission model, which determines who can operate and maintain the system (e.g., generate a new block).

- Public blockchains: In a public blockchain system, any user can verify transactions and generate a new block. This type of blockchain systems is also called permissionless blockchain in which the system allows anyone to join the network with both read and write permissions. Bitcoin is an example of a public blockchain.

- Private blockchains: In private blockchains, only specific users or entities can verify transactions and generate a new block. In other words, the system is controlled by an organization that manages access permissions. Thus, not all the users have access to the detail of the transactions stored in the ledger.

- Consortium blockchains: These systems are actually private blockchains that are employed by a group of organizations. A consortium blockchain is considered as a semi-decentralized blockchain that usually adopts a hybrid access method. Quorum and Corda are two examples of consortium blockchains.

It is proposed that the LP scheme proposed in this research work is implemented as a public blockchain system. This has several advantages including complete decentralization (independent of a trusted third party), full transparency of the public ledger, more security (due to use of incentivized validation that results in more miners contributing to validations), and self–sustainability. However, depending on the application scenario, the proposed scheme can be implemented as a private or consortium blockchain as well.

5.3.2 Design Challenges:

Blockchain technology has created a great opportunity to design decentralized systems for different applications. However, some novel features of a blockchain–based architecture introduce a number of design challenges for our work. For example, recording users' location data in a public ledger contradicts their location privacy.

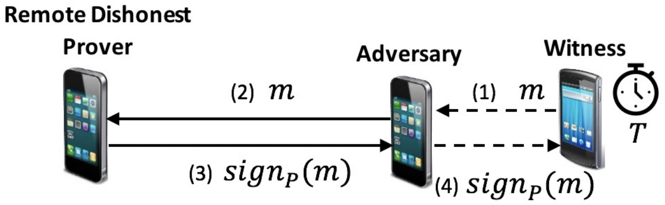


Figure 5.3 : An example of P–P collusions.

Moreover, regardless of the blockchain architecture, there are different security and privacy challenges for LP generation and verification that must be addressed. In this section, these design challenges are presented in three different categories, i.e., *Security*, *Privacy*, and *Application–related* challenges. We also present a countermeasure for each design challenge which is used in the proposed scheme to address the challenge.

Security Challenges

- *Prover–Prover (P–P) collusions*: In P–P collusions (also known as Terrorist Frauds), a distant malicious prover colludes with an adversary who is located in the vicinity of an honest witness (see fig. 5.3). During the attack, the adversary pretends to be the distant prover and submits an LP request with the witness on behalf of the malicious prover. To detect P–P collusions, we adopt a time–limited approach in which a witness generates a random number m and sends it to the prover through a short–range communication interface. Then, only a short period of time T is given to the prover to sign m and send it back to the witness. If the witness receives the response after the period T, it rejects the prover's request to generate an LP. Thus, in the case of a P–P collusion, an adversary does not have enough time to relay m to the remote dishonest prover and obtain his signature. Note that this approach assumes that users never share their private key with each other. Therefore, the adversary cannot sign m on behalf of the remote prover.

- *Prover–Witness (P–W) collusions*: In this collusion scenario, a dishonest witness colludes with a distant malicious prover and issues a fake LP for him. P–W collusions are the most difficult challenges to address in this area of research. To the best of our knowledge, no reliable and effective solution has been offered in the literature so far to address these attacks. In this research work, we adopt a novel mechanism to address P–W collusions in which an attacker (a dishonest witness who wants to generate a fake LP for a remote dishonest prover) is forced to change his attack to a P–P collusion attack. Therefore, the P–W collusion is detected since the proposed scheme detects P–P collusions through the presented time–limited approach.

Privacy Challenges

To design an LP system using the blockchain architecture, one possible approach is that we record users' plaintext spatiotemporal data in a public ledger. However, this approach contradicts users' location privacy because their spatiotemporal data is shown publicly. In addition, it has been shown that even if users hide their real identity (which is common in blockchain systems) it is still possible to identify a user by analyzing the history of his/her spatiotemporal data [14], [106]. Thus, adopting a pseudonym by users cannot guarantee their location privacy.

To address this challenge, we adopt a novel approach in which users commit to their spatiotemporal data before they create a transaction. These commitments are then added to the transaction and will be stored in the public ledger after verification:

$$C_{(P,ST)} = Commit(ST, r), \tag{5.1}$$

where $ST = (Loc, Time)$ is the spatiotemporal data of the user (prover) and r is a random nonce generated by him/her for the commitment to ST.

When a user submits a location claim with a LBSP, he/she opens the commitment by sending r to the LBSP. Therefore, if the user loses this r, his/her location claim will not be confirmed by the LBSP. This is similar to a user wanting to spend his/her Bitcoin money (in Bitcoin, users cannot spend the money in their wallet if their private key is lost). Therefore, it is infeasible to obtain the history of a user's spatiotemporal data by analyzing his/her transactions stored in the public ledger.

Application–Related Challenges

In this subsection, we present two critical challenges that may result in negative impacts on the performance of LP schemes if not addressed.

- *Challenge 1*: A big challenge for our decentralized scheme lies in how we can convince mobile users to act as a witness since they generally tend to reject requests to generate LPs if there is not enough incentive for them (for example, to save on battery consumption). To address this problem, we integrate an incentive mechanism into our proposed LP scheme to reward users who collaborate with the system with a specific amount of cryptocurrency. The LBSPs can make this currency valuable by exchanging them for rewards, badges and benefits that they are currently providing to their users (see [26] and [84] for more details and examples). Moreover, other businesses such as insurance companies and government agencies that might utilize LPs of their customers can contribute to make the currency more valuable. This creates the necessary incentive for mobile users and verifiers to collaborate with the system.

- *Challenge 2*: Speed is another challenge for an LP system that needs to be addressed. As far as we know, the majority of the LP schemes which have been proposed in literature so far utilize a DB protocol to check the proximity of a prover to a witness. This not only requires some hardware changes on mobile devices, but also makes the LP generation process slow when users adopt a long private key [85] since a prover device must respond to m challenge messages that a witness sends to it, where m is the size of the prover's private key. This process is called *fast–bit–exchange* in literature.

In the proposed system design, we do not adopt a DB protocol to check the proximity of a prover to a witness. Instead, the time–limited mechanism (discussed in the security challenges) enables the witness to check whether the prover is really located in its vicinity or not. This makes the LP generation process much faster than the current solutions.

5.4 Conclusion

In this chapter, we reviewed the existing literature on the current location verification solutions in location–based social networks and reviewed the advantages and disadvantages of each solution. It is concluded that although different LP schemes have been introduced so far, they suffer from at least one of the following problems: location privacy issue, vulnerability against collusions, high level of communication and computation overheads, and expensive implementation.

Moreover, this chapter presented some preliminaries as the foundation for the next chapter. In this regard, we reviewed distance bounding (DB) protocols and presented the security attacks that these protocols might experience. Following this, we reviewed TREAD as a promising distance bounding protocol and discuss the need of TREAD modification. Furthermore, we presented an overview of the blockchain technology and review the three diferent types of blockchains. Finally, we presented some of the design challenges that we need to address in this part of our research work.

In the next chapter, we introduce our first location proof scheme, i.e. Privacy-Aware and Secure Proof Of pRoximiTy (PASPORT) scheme. which performs LP generation and verification for mobile users in a secure and privacy–aware manner. The proposed scheme provides the integrity and non–transferablity of generated LPs.

Chapter 6

PASPORT: Secure and Private Location Proof Generation and Verification

6.1 Introduction

Recently, there has been a rapid growth in location–based systems and applications in which users submit their location information to service providers in order to gain access to a service, resource or reward. We have seen that in these applications, dishonest users have an incentive to cheat on their location. Now, we present some examples to highlight relevant issues in these applications.

- A significant percentage of Foursquare check–ins are fake and created by dishonest users to obtain in–system rewards (such as gift vouchers) offered to users who frequently check–in at specific locations [26]. LBSPs like Yelp and Foursquare offer some rewards (such as gift vouchers) to their users who frequently check–in at specific locations. This encourages dishonest users to submit fake check–ins by manipulating their GPS data. In a research study, Zhang *et al* [26] found that almost 75% of Foursquare check–ins are false and submitted by dishonest users to obtain more rewards.

- In the current online rating and review applications, users' real location is not verified which enables them to submit fake positive or negative reviews for their own business or their rivals, respectively [27–28]. Online ratings and reviews have a significant impact on the revenue of businesses. Thus, dishonest users have an incentive to create either fake positive or negative reviews for their own business or their rivals, respectively [26]. Specifically, using the new crowdsourcing platforms like Mechanical Turk [28], it is less challenging to create a large number of fake reviews. Unfortunately, in the current online rating and review platforms, users' real location is not verified which enables them to submit fake reviews.

- Activity–tracking applications such as RunKeeper and Endomondo enable users to monitor their physical activities like running or cycling and share their location–based activities with the service providers and other users in social networks [24]. Using these applications, users share their location–based activities with the service providers and other users in social networks. To encourage users, the service providers offer different incentives for them such as vouchers, discounts, or awards [29–31].

- CRNs [23], [25], [32], as a typical LBS, are an efficient solution for the spectrum management issue in large–scale IoT systems [23]. In this approach, to increase spectrum utilisation, available frequency channels in a specific area are offered to unlicensed radio users located at the region when the channels are not occupied by licensed users. These networks are vulnerable to location spoofing attacks since malicious users can submit fake locations to the database to access channels which are not available in their location. This may cause severe signal interference for the neighbour primary users [23], [33].

- In location–based access control applications [34–36], attackers can gain unauthorized access to a system or resource by submitting fake location claims.

- In activity–tracking applications, insurance companies may offer health insurance plans in which customers are offered discounts if they have a minimum level of physical activity [24], [29–31]. This creates an incentive for dishonest users to cheat on their location data.

Unfortunately, no effective protection mechanism has been adopted by service providers against these fake location submissions. This is a critical issue that causes severe consequences for these applications. Motivated by this, we propose three location verification schemes in this section to address the problem, i.e., (1) Privacy-Aware and Secure Proof Of pRoximiTy (PASPORT), (2) Secure, Privacy–Aware and collusion Resistant poSition vErification (SPARSE), and (3) a blockchain–based location verification scheme. Using PASPORT, users submit a location proof (LP) to service providers to prove that their submitted location is true. PASPORT has a decentralized architecture designed for ad hoc scenarios in which mobile users can act as witnesses and generate location proofs for each other. It provides user privacy protection as well as security properties, such as unforgeability and non–transferability of location proofs. Furthermore, the PASPORT scheme is resilient to Prover–Prover collusions and significantly reduces the success probability of Prover–Witness collusion attacks. To further make the proximity checking process private, we propose PTREAD, a privacy–aware distance bounding protocol and integrate it into PASPORT. To validate our model, we implement a prototype of the proposed scheme on the Android platform. Extensive experiments indicate that the proposed method can efficiently protect location–based applications against fake submissions.

6.2 Background

The recent advances in the smartphone technology and positioning systems has resulted in the emergence of a variety of location–based applications and services [17–19] such as activity–tracking applications, location–based services, database–driven cognitive radio networks (CRNs), and location–based access control systems. In these applications, mobile users submit their position data to a location–based service provider (LBSP) to gain access to a service, resource, or reward. These applications are very popular due to the useful services they offer. According to recent business reports, the market value of location–based services (LBS) was USD 20.53 billion in 2017 and is anticipated to reach USD 133 billion in 2023, with an expected annual growth rate of 36.55% [21]. However, LBSPs are vulnerable to location spoofing attacks since dishonest users are incentivized to lie about their location and submit fake position data [22–26].

Now, we present some examples to highlight relevant issues in these applications. In the current online rating and review applications, users' real location is not verified which enables them to submit fake positive or negative reviews for their own business or their rivals, respectively [27], [28]. Further, in CRNs [23], [25], [32], malicious users can submit fake locations to the database to access channels which are not available in their location. This may cause severe signal interference for the neighbour primary users [23], [33]. In location–based access control applications [34–36], attackers can gain unauthorized access to a system or resource by submitting fake location claims. In activity–tracking applications, insurance companies may offer health insurance plans in which customers are offered discounts if they have a minimum level of physical activity [24], [29–31]. This creates an incentive for dishonest users to cheat on their location data. Thus far, with these examples, it is clear that preventing fake location submissions in these applications is still an open challenge.

To protect these applications against location spoofing attacks, a number of location proof (LP) schemes have been proposed. Using these mechanisms, a mobile device (called a *prover* in the literature) receives one or more LPs from its neighbour devices when it visits a site. The prover then submits the received LPs to the LBSP as a location claim. The LBSP checks the submitted LPs and either accepts or rejects the user's claim. LP schemes are categorized into two groups depending on the system architecture: *centralized* or *distributed*. In the centralized mechanisms [83–85], [92], a trusted wireless infrastructure (like a WiFi access point) is employed to generate LPs for mobile users. In the distributed schemes [86–90], [93], mobile users act as witnesses and generate LPs for each other. The latter approach is useful for scenarios in which there is no wireless infrastructure at the desired locations or it is expensive to employ a large number of access points (APs) for different locations.

In our extensive literature review and to the best of our knowledge, we observed that all the current LP schemes suffer from at least one key drawback. Firstly, some of these schemes are vulnerable to *Prover–Prover (P–P)* collusions [83], [87], [90]. In this attack, a remote malicious prover colludes with a dishonest user (located at a desired site) to obtain an LP. The dishonest user submits an LP request to the neighbor witness devices on behalf of the remote prover. This security threat is called *Terrorist Fraud* in the literature [91] (see the next subsection for more details). Secondly, none of the current distributed schemes offer a reliable solution for *Prover–Witness (P–W)* collusions. In this attack, a dishonest user acts as a witness for a remote malicious prover and generates a fake LP for him [90]. Note that this security threat is specific to the distributed LP schemes only since witnesses are not trusted in this type of scheme while in the centralized mechanisms, LPs are issued by a trusted entity only. Finally, in some schemes, location privacy has not been considered [84], [85], [89], i.e., users broadcast their identity for neighbour devices or a third party server during the LP generation or submission process.

In addition, there are other challenges with the current schemes such as high level of communication and computation overheads [86], and expensive implementation [85], [92]. As far as we know, no LP scheme has been introduced to address all these challenges at the same time.

Motivated by this, to address these key concerns, we propose a distributed LP scheme, PASPORT, which performs LP generation and verification for mobile users in a secure and privacy–aware manner. The proposed scheme provides the integrity and non–transferablity of generated LPs. To make PASPORT resistant to P–P collusions and perform private proximity checking, we develop a privacy–aware distance bounding (DB) protocol P–TREAD and integrate it into PASPORT. P–TREAD is a modified version of TREAD [108], a state of the art and secure distance bounding protocol without privacy consideration. Our customization does not affect TREAD's main structure and features. Thus, PASPORT benefits from its security guarantees. By employing P–TREAD as the distance bounding mechanism, a malicious prover colluding with an adversary can easily be impersonated by the adversary later. Generally, users do not take such a risk by initiating a Prover–Prover collusion. In addition, to resolve the P–W collusions issue, we propose a witness selection mechanism that randomly assigns the available witnesses to the requesting provers instead of allowing them to choose the witnesses themselves. We show that by adopting this mechanism, a P–W collusion can be conducted with only a negligible success probability if LBSPs create sufficient incentives for users to act as witnesses and generate LPs for provers.

6.3 PASPORT: The Proposed Scheme

In this section, we present our proposed scheme for secure LP generation and verification. *Firstly*, we present the framework and its entities. *Secondly*, we present the trust and threat model which we have considered in our work. *Following this*, we introduce P–TREAD. *Finally*, the full framework of the PASPORT scheme is presented.

6.3.1 Architecture and Entities

The proposed system architecture is shown in Fig. 6.1. As we see, the system has a distributed architecture and consists of three types of entities, i.e., Prover, Witness and Verifier. A *Prover* is a mobile user who requires to prove his/her location to a verifier. A *Witness* is the entity that accepts to issue an LP for a neighboring

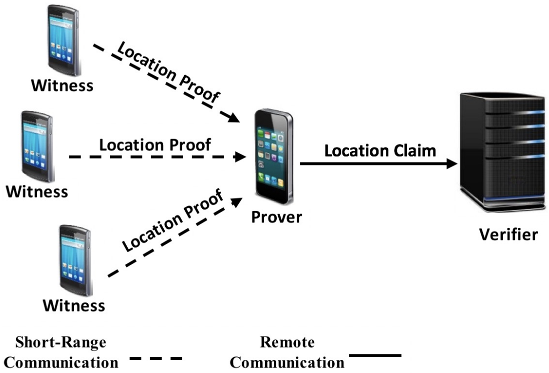


Figure 6.1 : The proposed system architecture.

prover upon request. We assume service providers create sufficient incentives for mobile users to become a witness and certify other users' location. In PASPORT, we consider witnesses as mobile users.

Finally, a *Verifier* is the unit who is authorized by the service provider to verify LPs claimed by provers. We assume provers communicate with witnesses through a short–range communication interface such as Wi-Fi or Bluetooth. This short–range communication channel is supposed to be anonymous such that users can broadcast their messages over it without revealing their identifying data such as IP or MAC address.

6.3.2 Trust and Threat Model

We assume mobile users are registered with the service provider. Each user has a unique public–private pair key stored on his/her mobile device and certified by a Certification Authority (CA). Users' identity is determined through their public key and we assume users never share their private key with other users because they do not give their mobile devices to others [85], [90], [92]. Thus, in a collusion scenario, we suppose a malicious prover never goes that far to provide another party with his/her private key. We also assume all the messages exchanged between the entities might be eavesdropped by passive eavesdroppers. In the following, we discuss the trust and threat model for each entity individually.

Prover. It is assumed that the prover makes an effort to obtain false LPs. This can be done through different scenarios in which a prover might (a) try to provide the witnesses with fake information about his/her location to convince them to generate LPs for him/her, (b) manipulate the LP issued for him/her to change its location or time field, (c) attempt to steal an LP issued for another user and use it for him/herself, and (d) collude with other users (provers or witnesses) to obtain LPs. Moreover, we assume provers try to obtain the identity of witnesses.

Witness. A witness might collude with a prover to generate a fake LP for him/her. In addition, a witness may try to deny an LP which has been issued by him/herself. Witnesses are assumed to be curious about the provers' identity.

Verifier. We suppose the verifier is trusted and never leaks users' identity and their spatiotemporal data. It is assumed that the verifier keeps a regularly updated list of witnesses who are present at the given location and have accepted to generate LPs for other users. The verifier accepts the LPs issued by these witnesses only. We suppose service providers create necessary incentives to encourage selfish users to collaborate with the system. Otherwise they might not generate LPs to save their battery power or reduce their communication costs.

Regarding collusions, we consider both Prover–Prover and Prover–Witness collusions in our threat model as it can be directly derived from the above assumptions. In the next subsection, we introduce the proposed privacy–aware DB protocol P–TREAD.

6.3.3 P–TREAD

In this subsection, we present P–TREAD, a modified version of TREAD, for private proximity checking in the PASPORT architecture.

As discussed in the Preliminaries subsection, to protect users' privacy, we need to customize TREAD in such a way that provers can anonymously submit an LP request to neighbor witnesses. For this reason, in P–TREAD, we limit a witness' role to only collecting (not verifying) the required data from the prover (the verification is performed by the remote trusted verifier). All the privacy–sensitive data are encrypted by the prover and sent to a witness who signs and sends them back to the prover as an LP. Then, after the claim (received LP) is submitted to the verifier by the prover, verification of the claim can be performed by the trusted verifier in the next phase. We divide the whole procedure into two phases, (a) data collection and LP generation, and (b) authentication and verification.

Phase 1. Data collection & LP generation. In this part of the protocol, the initialization phase of TREAD is performed with the following exceptions:

- The prover device does not send ID_P to the witnesses as a plain text message (it only sends e to the witnesses).
- e is computed by the prover device using the verifier's public key. Therefore, the witnesses can not decrypt it and deanonymize the prover. We assume that the verifier publishes its public key for the users. Moreover, every user has registered a public/private key pair with the verifier.
- The witness devices do not check the prover's signature σ_P since the prover must be anonymous (in addition, they can not decrypt e and obtain the signature). Later, σ_P will be checked by the verifier in the next phase.

Then, the DB procedure is performed similar to the DB phase of TREAD by which the prover's responses r_i to challenge bits c_i ($i = 1, 2, \ldots, n$) are collected. After data collection is finished, the witness device creates the following LP and sends it to the prover:

$$LP = E_{Verifier}(m_2||\mathcal{S}_{Witness}(m_2))$$

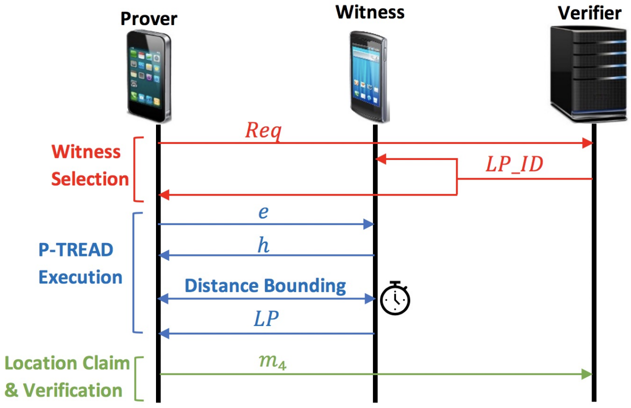
where $m_2 = r||c||h||e||ID_W||Loc||time$ and ID_W is the witness ID. Note that the prover can not see ID_W since it is encrypted using the verifier's public key. This preserves location privacy of the witnesses as well. Finally, the prover submits the following message with the remote verifier:

$$LP^{'} = E_{Verifier}(LP||a||b||ID_P)$$

In other words, the witness collects the required information from the prover (e and r), creates message LP, and sends it to the prover for submission. In this phase, the witness can not see the prover's identity as it has been encrypted by the verifier's public key in message e.

Phase 2. Authentication & verification. In this phase, the verifier authenticates the prover based on the received $LP^{'}$ and verifies the validity of the LP issued by the witness. To do this, it first decrypts $LP^{'}$ using its private key and extracts LP, a, b, and ID_P. Then, it checks the following:

- The signature σ_P placed in message e must match the prover's signature based on ID_P.
- The received ID_Ps placed in e and $LP^{'}$ must match.
- The witness signature on message m_2 must match the signature associated with ID_W.
- The two $a||b$s placed in the messages e and $LP^{'}$ must match.
- The received response r must match $r^{'}$ where $r^{'}$ is obtained based on the received a, b, h, and c bit–strings.



$$Req = E_{Verifier}(ID_P \parallel Loc)$$
$$e = LP\_ID \parallel E_{Verifier}(m_1 \parallel \mathcal{S}_{Prover}(m_1))\ , m_1 = a \parallel b \parallel ID_P \parallel Loc$$
$$LP = E_{Verifier}(m_2 \parallel \mathcal{S}_{Witness}(m_2)), m_2 = r \parallel c \parallel h \parallel e \parallel ID_W \parallel Loc' \parallel time$$
$$m_4 = E_{Verifier}(LP_1 \parallel LP_2 \parallel \cdots \parallel LP_K \parallel a \parallel b)$$

Figure 6.2 : Message flow between the three entities of the proposed scheme.

If all the above checks are successfully passed, the prover's location claim is accepted by the verifier.

As we see, by using P–TREAD, a prover can anonymously request an LP from neighbor witnesses while the main structure of TREAD is preserved which brings security guarantees for users. In the next subsection, we integrate P–TREAD into our main LP scheme, i.e. PASPORT, to perform secure and private device proximity checking.

6.3.4 The Workflow of PASPORT Framework

The proposed LP scheme consists of three main phases: *Initialization*, *Location Proof Generation*, and *Location Claim and Verification*.

1) Initialization: In this phase users register with the system and the Certification Authority certifies users' public–private key pairs. Moreover, the verifier creates a Witness Table in which it keeps the identity and location of mobile users who accept to be a witness. This table is regularly updated as witnesses sign on or off at every site. Furthermore, for every registered user in the system, the verifier records a list of provers for which the user generates an LP. These lists are used by the verifier to select which witnesses are qualified to generate LPs for a specific prover. This is done to prevent Prover–Witness collusions.

2) Location Proof Generation: This phase is run in two stages: *Witness Selection* and *P–TREAD Execution* (see Fig. 6.2).

2.1) Witness Selection: In this stage, the prover submits an LP request to the verifier. Upon receiving the prover's request, the verifier selects K witnesses form its Witness Table to generate LPs for the prover. This is done to neutralize Prover–Witness collusions because in this case, the prover does not have control over the witness selection process. However, to further protect PASPORT against prover–witness collusions, we integrate an entropy–based trust model as a supplementary method into the witness selection mechanism. Using this trust model, a trust score is computed by the verifier for every available witness device w based on its LP generation history and the number of LPs that w and the prover have issued for each other in the past. If the obtained score is above a threshold, the device is selected to witness for a requesting prover. The following step by step activities are performed in this stage:

i. **Prover**: First, the prover sends the following message Req to the verifier to inform it that he/she wants to start requesting an LP. This message can be sent to the verifier through the prover's Internet connection.

$$Req = E_{Verifier}(ID_P \| Loc)$$

ii. **Verifier**: Upon receiving the prover's message, the verifier extracts all the witnesses who have recently (in a reasonable period of time) proved that they are in an acceptable distance to location *Loc* from its Witness Table (this acceptable distance is defined depending on the application). Then, K witnesses are selected among the shortlisted witnesses using the proposed trust model. These K witnesses are then qualified to generate LPs for this prover. If there are not enough qualified witnesses, the verifier suspend this request until the necessary number of qualified witnesses become available. Then, the verifier generates a unique ID for this LP (LP_ID) and sends it to the selected witnesses and the prover as well.

2.2) P–TREAD Execution: In this stage, the prover starts to perform the P–TREAD protocol.

i. **Prover**: The prover generates two n–bit random numbers a and b, and then computes the following message e and broadcasts it through the predefined short–range communication interface (WiFi or Bluetooth).

$$e = LP\_ID \| E_{Verifier}(m_1 \| \mathcal{S}_{Prover}(m_1)) \ ,$$

where

$$m_1 = a \| b \| ID_P \| Loc$$

ii. **Witness**: A witness upon receiving e, extracts the LP_ID and compares it with the one received from the verifier. If they are not same, it discards e. Otherwise, it generates an n–bit random number h and sends it to the prover.

iii. **Prover**: The prover computes ($z_i = b_i \oplus h_i$) for $i = 1, 2, \ldots, n$ and sends an *Ack* to the witness.

iv. **Witness**: The witness starts an n–stage time sensitive DB process by generating a random bit c_i at each stage i and sending it to the prover. It also starts a timer immediately after sending c_i.

v. **Prover**: Upon receiving c_i, the prover instantly sends the following response r_i to the witness:

$$r_i = a_i.\bar{c}_i + z_i.c_i$$

vi. **Witness**: The witness stops the timer when the response r_i is received from the prover. The timer must show a time less than the predefined threshold $\frac{2d_{max}}{C} + t_o$, where d_{max} is the maximum allowable distance between the prover and the witness, C is the speed of light, and t_O is the overhead time required by the prover to compute the response bit r_i upon receiving c_i. If all the n responses are received in the correct time, the witness issues the following location proof and sends it to the prover:

$$LP = E_{Verifier}(m_2 \| \mathcal{S}_{Witness}(m_2)) \ ,$$

where

$$m_2 = r \| c \| h \| e \| ID_W \| Loc^{'} \| time$$

For timer values larger than this threshold, the witness generates the following location proof:

$$LP = E_{Verifier}(m_3 \| \mathcal{S}_{Witness}(m_3)) \ ,$$

where

$$m_3 = ID_W \| reject$$

As we see, we adopt the *sign–then–encrypt* model to compute PASPORT messages. This protects the privacy of provers (witnesses). The reason is that if the more common *encrypt–then–sign* model is chosen, a witness (prover) can check the signature on e (on LP) with the public keys of all the users and find the prover's (witness') identity. Moreover, by using this method, eavesdroppers never infer the users' identity.

3) Location Proof Claim and Verification: Upon receiving LPs from all the K witnesses, the prover concatenates them in message m_4 and sends it to the verifier.

$$m_4 = E_{Verifier}(LP_1 \| LP_2 \| \ldots \| LP_K \| a \| b)$$

The verifier checks the received location proofs and either accepts or rejects the prover's claim. First, it decrypts each witness's location proof and message e using its private key. Then, it computes $r_i^{'} = a_i.\bar{c}_i + (b_i \oplus h_i).c_i$ for $i = 1, 2, 3, \ldots, n$ regarding the received a, b, c, and h. If $r_i^{'} \neq r_i$, the verifier rejects the prover's claim. Otherwise, the following checks are performed by the verifier:

- Is the witness with identity ID_W among the witnesses which have been qualified by the verifier in the Witness Selection stage?
- Are the two ID_Ps extracted form Req and m_1 the same?
- Are prover's and witnesses' signatures on m_1 and m_2 correct regarding ID_P and ID_Ws respectively?
- Is Loc in an acceptable range of $Loc^{'}$?
- Is *time* in an acceptable range of the current time?
- Are the two $a \| b$ s received in the messages m_1 and m_4 the same?
- Is $K - K_R \geq T$ correct? Where K_R is the number of rejected location proofs and T is a threshold which is defined depending on the application.

Assuming the prover's location claim passes all the above checks successfully, the verifier accepts the prover's claim.

6.3.5 Witness Trust Model

To further protect PASPORT against prover–witness collusions, we integrate an entropy–based trust model into the PASPORT witness selection mechanism. Using this trust model, the verifier computes a trust score for a witness device based on its LP generation history. If the obtained score is above a threshold, the device is selected to witness for a requesting prover. In fact, a witness device receives a low score if it has issued many LPs for that prover. Thus, the prover device is prevented from receiving its LPs from a small group of witnesses only.

We adopt an entropy–based approach to measure the trust scores. In information theory, entropy represents the average amount of information that we get from a message produced by a stochastic source of data. It works based on the fact that when a low–probability message is received, it carries more information than when the source of data produces a high–probability message [120]. Thus, it is a suitable measure of the level of diversity and randomness that a prover device should have in the list of its witnesses. In other words, when a higher entropy is obtained for a witness device, it is more likely that it has generated LPs for a diverse range of provers rather than for a small group of prover devices.

Consider w is a witness device that has already issued at least one LP for N prover devices $p_1, p_2, \ldots, p_N$. Assume $A(w, p_i)$ is a percentage of the past LP transactions between w and p_i out of w's total past LP transactions. The entropy of w is obtained using the following equation.

$$e_w = -\sum_{i=1}^{N} A(w, p_i) log(A(w, p_i))$$

We define $S(w, p_i)$ as the trust score of device w to be selected as a witness for the prover device p_i.

$$S(w, p_i) = \frac{e_w e_{p_i}}{1 + B(w, p_i)}$$

where $B(w, p_i)$ is the number of LPs that w and p_i have issued for each other in the past out of their total number of LP transactions.

As a result, in the witness selection phase, the verifier selects those devices with the highest trust score. This prevents the system from selecting a witness who may have a connection with the prover and has already issued several LPs for the prover. Moreover, using this model, possible prover–witness collusions can be detected and prevented by the system because a prover device who has received majority of its LPs from a small group of witnesses is more likely to collude with these witnesses.

6.3.6 PASPORT Usability

Since PASPORT has a decentralized architecture, it relies on the collaboration of mobile users to generate location proofs for each other. Note that users usually need to have an LP for crowded public places (e.g., shopping centers). This mitigates the concerns about the number of available witnesses. However, mobile users may refuse to collaborate with the system in order to save their battery power or reduce their communication costs. To address this issue, service providers should create sufficient incentives for mobile users to collaborate with the system and certify other users' location. In this regard, we propose two approaches to overcome the issue.

i. Location–based service providers can incentivize mobile users to collaborate by offering them some rewards, badges and benefits that they are currently providing to their users (see [26] and [84] for more details and examples). These rewards can be granted to mobile devices based on their contribution in the network, e.g., the number of LPs that they have generated for other users in a given time period. Moreover, other businesses such as insurance companies and government agencies that might utilize LPs of their customers can contribute to make the rewards more valuable. This creates the necessary incentive for mobile users to collaborate with the system.

ii. The second approach is to integrate an incentive mechanism into the proposed scheme, e.g., using a blockchain architecture that remunerate users with a given amount of a cryptocurrency. Since PASPORT is a decentralized scheme, the distributed architecture of blockchains is an appropriate platform to address this issue. This encourages mobile users to collaborate with the system and respond to other users' LP requests.

Thus, by applying the incentive policies on the proposed scheme and encouraging mobile users, a sufficient number of witness devices are become available for the verifier to select.

6.4 Results

In this section, we first present our security and privacy analysis. Then, the results of our experiments are presented and discussed.

6.4.1 Security and Privacy Analysis

We perform a comprehensive security and privacy analysis to show that PASPORT achieves the necessary security and privacy properties of a secure and privacy–aware LP scheme described in [24] and [30].

1. Resistance to Distance Frauds: In PASPORT, distance frauds are prevented by the time sensitive DB process (performed in stages 2–2–d, 2–2–e and 2–2–f) which is performed via a short–range communication interface. Moreover, the existence of the random number h ensures us that $a_i \neq b_i \oplus h_i$. Otherwise (if the witness does not send h and the prover responds just with $r_i = a_i.\bar{c}_i + b_i.c_i$), a remote malicious prover can simply select $a = b$ and send $r_i = a_i = b_i$ before it receives the challenge bit c_i (in this case r_i does not depend on the challenge bit c_i). Thus, for a remote malicious prover the only way to have his fake location verified is colluding with a dishonest prover or witness. As we see in this section, PASPORT is resistant to Prover–Prover collusions and reduces the success probability of Prover–Witness collusions to a negligible value.

2. Unforgeability: It is not feasible for a malicious prover to create a location proof himself without proving his location to a qualified witness. The reason is that the verifier checks each qualified witness' ID with their signature on m_2. Since users do not share their private key with each other, the malicious prover can not create the witness' signature on m_2 even if he knows the identity of each qualified witness. Moreover, an adversary who tries to forge another user's location proof will not be successful because he does not have the victim's private key to sign m_1. Furthermore, if a location proof is created by a dishonest witness W' who has not been selected as a qualified witness, it will be easily detected by the verifier by comparing the identity of W' with all the qualified witnesses' identity.

3. Non–Transferability: Suppose an adversary wants to use a location proof which has been issued for prover P. Even if the adversary knows the prover's ID, i.e., ID_P, he still does not have the random numbers a and b to create m_4 and submit his claim. Note that random numbers a and b have been encrypted using the verifier's public key. Thus, neither the adversary nor the witness can see them. Moreover, the presence of *time* in m_2 makes it infeasible for the prover device P to give its location proof along with ID_P, a and b to another device for later submissions. In this case, the prover can not change *time* because it has been signed by the witness' private key and encrypted using the verifier's public key.

4. Resistance to Mafia Frauds: Suppose an adversary A wants to perform a Mafia Fraud on prover P and witness W who are both honest. Suppose A consists of (or is modeled by) a witness $\bar{W}$ and a prover $\bar{P}$. Even if we assume that $\bar{W}$ obtains message e by communicating with P, it is not feasible for $\bar{p}$ to fool W using e. The reason is that $\bar{P}$ must successfully perform the DB process by sending response bits r_i to W. This requires the total knowledge of random numbers a and b which P never sends them to $\bar{W}$. Moreover, A does not gain any further knowledge about a and b by pretending to be different witnesses (for example n malicious witness

$\bar{W}_1$, $\bar{W}_2$, ..., $\bar{W}_n$). This is because P generates different numbers a and b whenever he/she performs P–TREAD. In other words, for different witnesses, different $a\|b$ is generated. Therefore, PASPORT is resistant to Mafia Frauds.

5. Resistance to Terrorist Frauds (Prover–Prover collusions): Suppose a remote malicious prover P colludes with an adversary A which is close to an honest witness W to obtain a fake LP. In this attack, A must send message e to W and perform DB process on behalf of P. To perform this attack, P helps A by generating message e and sending it to A. In addition, P has to send the random numbers a and b to A as well. Otherwise, A can not respond to challenge bits c_i in DB process and the attack is defeated. However, if P sends $a\|b$ to A, he can easily impersonate P later for as many times as he wants. Therefore, the prover must select one between performing the attack and being impersonated. In fact, in PASPORT, the cost of a Prover–Prover collusion is increased to such a level that no rational prover accepts its risk.

6. Resistance to Sybil Attacks: In a Sybil attack, an adversary tries to control or influence a peer–to–peer network by creating multiple fake identities. There are a number of countermeasures that can be adopted to make PASPORT resistant to Sybil attacks.

i. **Identity Verification:** Since PASPORT is a permissioned peer–to–peer network (rather than a permissionless network, e.g., Bitcoin), all users' identities are verified before they are authorized to access the system. This can be supported by forcing users to perform a two–factor authentication process when they register to the network. For example, users may be asked to provide a security code sent to their mobile phone or email address. In this case, the network rejects to create a new account if a duplicate mobile phone number or email address is provided by the adversary. This makes a Sybil attack non–economic for malicious users since they have to provide many SIM cards or email addresses to proceed with the attack. Alternatively, users may need to sign up using individual email addresses or social network profiles, e.g., Facebook accounts. Furthermore, in a specific time interval, no more than a specific number of accounts may be allowed to be created using a single IP address.

ii. **Unequal Reputation:** A supplementary technique to prevent Sybil attacks is to consider different levels of reputation for different accounts. Using this technique, witness devices associated with the accounts with an older creation date receive more reputation and their testimony is highly accepted. Newly–created accounts must remain active for a specific period before they become eligible to witness. This limits the power of new accounts. Therefore, creating many new accounts does not result in any advantage for a Sybil attacker against other older reputable accounts.

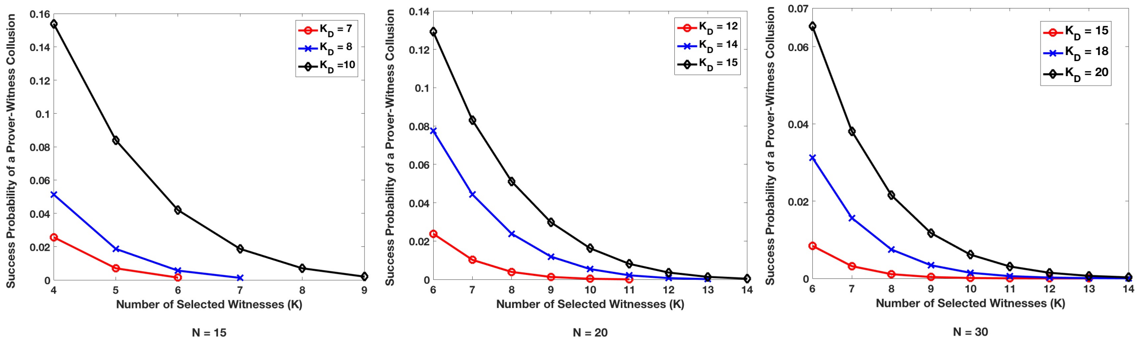
iii. **Cost to create an identity:** To prevent malicious users from creating multiple fake accounts, the network may consider a small cost for every user that wants to join the network. In this case, the cost to create a single account is small. However, the total cost to create many identities is higher than the reward or benefit that the attacker receives after successfully conducting the Sybil attack. Note that it is more important to make it expensive for an attacker to create and control multiple accounts in a short period of time rather than just creating a new account. In other words, considering a cost for identity creation should not restrict honest users from joining the network. In fact, the amount of cost should be selected in such a way that creating many accounts becomes non–economic comparing to the benefits that the attacker receives.

7. Resistance to Witnesses Collusions: Witnesses might collude to obtain an honest prover's e and $a||b$ to impersonate P later. Since P generates different random numbers a and b each time he/she communicates with a witness, the colluding witnesses do not gain more information than what they could obtain without collusion.

8. Preventing Prover–Witness Collusions: In PASPORT, using the witness selection mechanism, the verifier qualifies some witnesses to generate LPs for a prover. A list of these qualified witnesses is kept and linked to the LP_ID by the verifier. Later, in the claim verification phase, the verifier rejects those location proofs generated by unqualified witnesses. Therefore, a malicious prover can not select a specific witness to generate an LP for him.

Let's consider a case in which a remote malicious prover P colludes with some dishonest witnesses which are present at the desired location. We assume K_D is the number of these colluding witnesses who have not generated an LP for P before in a specific period of time. Now, suppose $N > K_D$ is the total number of witnesses who have accepted to collaborate with the system at this location (including the dishonest witnesses) and have not generated an LP for P since a specific time. Note that creating necessary incentives for the witnesses by the service provider can make N a large number. In PASPORT, a location claim is accepted if there are at least T valid (non–rejected) location proofs associated with the claim. Thus, for $K_D \leq T$ the attack is definitely defeated. If $T \leq K_D \leq K$ and x is the number of dishonest witnesses who have been qualified and selected by the verifier, the success probability of a Prover–Witness collusion is obtained through the following equation:

$$\begin{aligned} P_{success} &= P(x \geq T) \\ &= P(x = T) + P(x = T+1) + \ldots + P(x = K_D) \\ &= \sum_{j=T}^{K_D} P(x = j) = \frac{\sum_{j=T}^{K_D} \binom{K_D}{j}\binom{N-K_D}{K-j}}{\binom{N}{K}} \end{aligned}$$



N = 15

N = 20

N = 30

Figure 6.3 : Success probability of a Prover–Witness collusion for different values of K_D and system parameters.

Note that the malicious prover has to collude with the witnesses who are physically present at the location. This makes it very difficult to have a large K_D. However, we assume he can select $K_D \geq K$. In this case, if $T = K$ is selected by the system, we have:

$$P_{success} = P(x = T) = \frac{\binom{K_D}{K}}{\binom{N}{K}} = \frac{K_D!(N-K)!}{N!(K_D-K)!}$$

Fig. 6.3 shows the collusion success probability for different K_D and system parameters. As we see, if $K \geq 0.5N$ is selected, the success probability of a collusion is always less than 0.03. In STAMP [25], a similar LP scheme, the system will detect collusions with a 0.9 success rate if a malicious prover P colludes with 5% of all the users. Note that in STAMP, P can select any user to collude with, no matter where he/she is located. In PASPORT, if P colludes with approximately 50% of the witnesses who are physically present at the desired location and have not generated an LP for him before, the system can prevent this collusion with a success rate better than 0.97. Obviously, the second situation which offers a better prevention rate is much tougher for P to fulfill. Therefore, with carefully chosen parameters, PASPORT provides a more reliable solution for Prover–Witness collusions than what is proposed in STAMP.

9. Resistance to Distance Hijacking: In distance hijacking attacks [38], a remote malicious prover H tries to fool an honest witness W on their mutual distance by using the involuntary help of an honest prover P which is close to W. Suppose H initiates the protocol by sending Req to the verifier. Upon receiving the related LP_ID, H must broadcast his message e_H through a short–range interface but he is not physically close enough to the qualified witnesses to do so. Thus, the attack can not proceed. Even if we assume that H broadcasts e_H for the witnesses, the attack is defeated. The reason is that in this attack it is assumed that P responds to W's challenge bits in the DB process since H is remote. However, the honest prover P is not aware of random numbers a_H and b_H by which H has already created e_H. Instead, P replies to W with his/her own response bits r_i computed using P's random numbers a_P and b_P in the message e_P. This causes W to generate the LP based on e_P other than e_H. Therefore, if H uses the generated LP to submit his claim with the verifier, this claim will be rejected since the signature on m_1 (in e_P) does not match with H's identity. If H sends his $a_H \| b_H$ to P beforehand, the Distance Hijacking attack converts to a Terrorist Fraud in which P colludes with the remote malicious prover. As we discussed before, PASPORT is resistant to Terrorist Frauds as well.

10. Prover Location Privacy: The prover's ID appears in messages Req, m_1 and m_4. These messages are encrypted by the verifier's public key. Thus, the verifier is the only entity who can identify the prover and neither the witnesses nor an eavesdropper can see the prover's ID. As we discussed before, the *sign–then–encrypt* model improves PASPORT's ability to preserve user's location privacy.

11. Witness Location Privacy: Since a witness device encrypts its ID using the verifier's public key, it is not feasible for the prover or an eavesdropper to identify the witness. Also, users' signatures do not reveal their identity because of the employed *sign–then–encrypt* model.

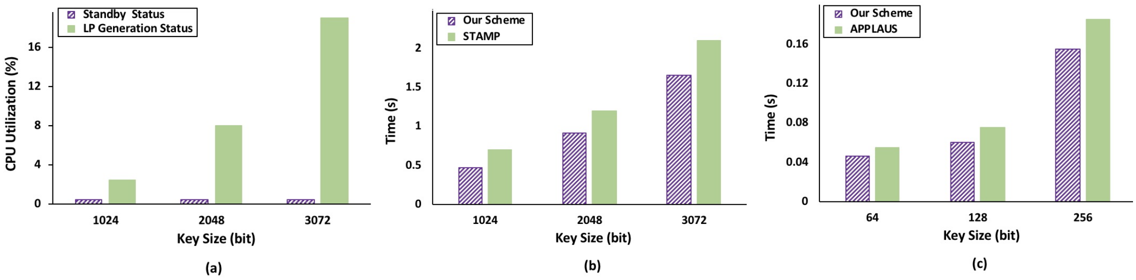


Figure 6.4 : (a) CPU usage for different key sizes. (b) and (c) Time required for LP generation in our scheme, STAMP [25], and APPLAUS [26] under different key sizes. In APPLAUS, the authors have not implemented their scheme for key sizes larger than 256.

12. Resistance to Eavesdropping: In PASPORT, the prover and witness encrypt their messages with the verifier's public key. Therefore, an eavesdropper gains nothing by listening to their communications. Only LP_ID is sent without encryption that has no value by itself. Moreover, obtaining message e without the total knowledge of random numbers a and b does not enable an eavesdropper to impersonate the prover later. In addition, since PASPORT provides non–transferability, an eavesdropper can not make a claim with an eavesdropped LP issued for another user.

6.4.2 Performance Evaluation

To study the feasibility of the proposed scheme, we implemented a Java prototype of the proposed scheme on the Android platform. Our experiments were performed on two Android mobile devices: (1) a LG G4–H818P equipped with a Hexa–Core 1.8 GHz processor, 3 GB of RAM, and running Android OS 5.1, acting as a prover, and (2) a Sony Xperia Z1 equipped with a Quad–Core 2.2 GHz processor, 2 GB of RAM, with Android OS 4.4.4, acting as a witness. We adopted Bluetooth as the communication interface between the mobile devices and conducted the tests in both indoor and outdoor environments. Each measurement shown in this section

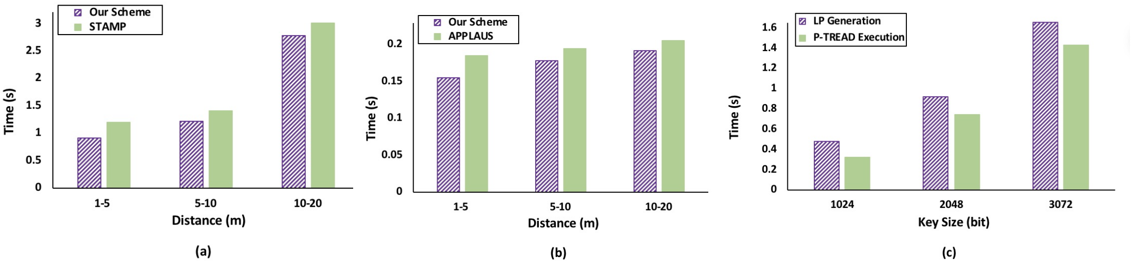


Figure 6.5 : (a) and (b) Time required for LP generation over different physical distances. The shown measurements are for the key sizes 2048 for (a) and 256 for (b). (c) P–TREAD distance bounding protocol takes most of the time required for LP generation.

has been obtained by averaging the results of 10 independent tests. We used RSA key pairs for encryption and SHA1 as the one–way hash function to compute users' signatures. Since the LP verification phase is performed by the verifier server that has a high level of storage and computational power, we focus our experiments on the P–TREAD Execution phase that is performed by mobile devices with limited resources.

During the application runtime, we measured the CPU utilization of the implemented code by installing a monitoring application that reports the amount of CPU usage of the processes running on the device. As we see in Fig. 6.4 (a), the CPU usage for a user in standby mode is almost 0.5% and independent of the key size. However, due to heavy computations required for encryption and signature calculations in the LP generation phases, the average CPU usage increases to 2.5%, 8%, and 19% for key sizes 1024, 2048, and 3072, respectively.

We also recorded the amount of time that PASPORT requires to generate an LP after the prover device receives LP_ID from the verifier. We compared the results to the decentralized schemes STAMP [25] and APPLAUS [26]. Fig. 6.4 (b) and 6.4 (c) show the results for different key sizes (in APPLAUS, the authors have not implemented their scheme for key sizes larger than 256). As expected, longer times were recorded for larger key sizes. The reason is that the DB phase is performed for n challenge bits. Thus, for larger values of n, it takes longer for the DB phase to be performed. As the figures show, PASPORT provides faster responses than similar schemes. The reason is that in STAMP and APPLAUS, the Bussard–Bagga DB protocol is used for provers' proximity checking while in PASPORT, we integrate P–TREAD into the scheme to perform this job that is a more lightweight protocol regardless of its security advantages over the Bussard–Bagga protocol. Unlike P–TREAD, in the Bussard–Bagga protocol, different commitment and decommitment computations are needed to be performed by the prover and witness devices, respectively. Moreover, STAMP requires to perform at least two commitment calculations in order to provide location privacy [25]. In APPLAUS, to preserve users' location privacy, they need to select a set of M pseudonyms and change them periodically. This creates a high level of computation and communication overhead.

To evaluate the impact of physical distance between the mobile users on LP generation, we conduct our experiments for different distances and compare the results to the performance of STAMP and APPLAUS (see Fig. 6.5 (a) and 6.5 (b), respectively). As we see, for longer distances, the required time for PASPORT to generate an LP increases since higher communication latencies occurring in this case. Note that distance only affects the Bluetooth communication latency and does not change the amount of time required for computations performed in mobile devices.

Finally, Fig. 6.5 (c) shows what percentage of the time required for LP generation is taken by the P–TREAD Execution phase. As we see, most of this time is taken by the DB protocol since it requires multiple Bluetooth transmissions. As we discussed before, this time is increased for larger key sizes. As a result, the selection of key size has a critical impact on the scheme's performance. Although larger key sizes provide stronger security, they impose more computational and storage overheads.

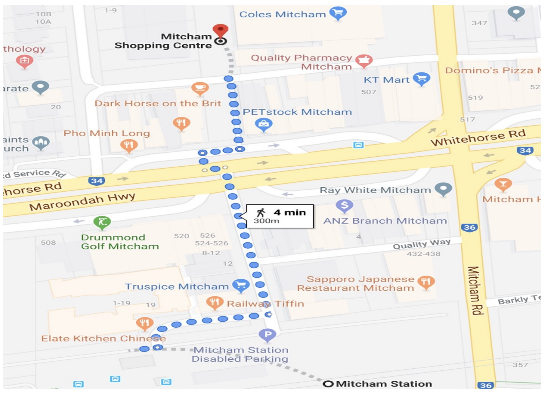


Figure 6.6 : Outdoor path for the mobility tests (300 meters).

We also performed some experiments for the scenario in which multiple witness devices participate in the LP generation process. To evaluate the effect of device mobility, we performed the outdoor experiments while the prover and witness devices were moving with an average speed of 1.2 m/s . Fig. 6.6 shows the 300 m outdoor path that we used for the mobility test. During the mobility test, an average distance of 7 m was maintained between the prover and witness devices. Fig. 6.7 (a) and (b) show the time required by five different witness devices to generate LPs for a single prover device in indoor and outdoor environments, respectively. We noticed an average increase of 8% in the latency of LP generation for the indoor environment. This is due to signal attenuations, absorptions and reflections caused by indoor elements such as walls, windows, and furniture. However, it does not have a significant impact on the system performance. Therefore, PASPORT performs well in indoor environments. It is expected that PASPORT shows a better performance if users communicate using WiFi as it provides more coverage distance than Bluetooth.

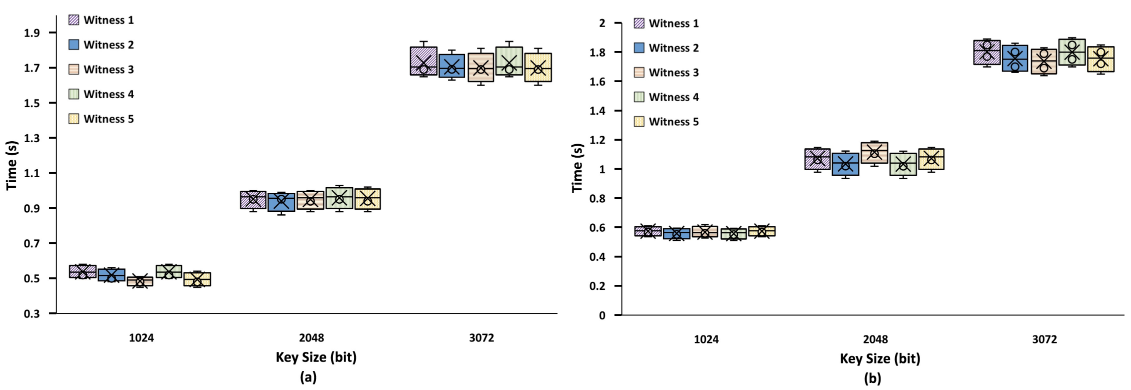


Figure 6.7 : Time required for LP generation when multiple witness devices are involved. (a) outdoor and (b) indoor environments.

6.5 Conclusion

In this chapter, we studied the location verification issue in social networks and proposed PASPORT, a secure and privacy–aware scheme for LP generation and verification. The proposed scheme has a decentralized architecture suitable for ad–hoc applications in which mobile users generate LPs for each other. To address Terrorist Frauds, we developed a distance bounding protocol P–TREAD, that is a private version of TREAD, and integrated it into PASPORT. Using P–TREAD, a dishonest prover who established a P–P collusion with an adversary can easily be impersonated by the adversary later. Thus, no logical user takes such a risk by initiating a P–P collusion. Furthermore, we employed a witness selection mechanism to address P–W collusions. Using the proposed mechanism, available witnesses are randomly assigned to requesting provers by the verifier. This prevents malicious provers from choosing the witnesses themselves.

In the next chapter, we introduce our second LP scheme, i.e. Privacy–Aware and collusion Resistant poSition vErification scheme (SPARSE). Similar to PASPORT, it has a distributed architecture designed to generate privac–aware location proofs for mobile users.

Chapter 7

SPARSE: Privacy–Aware and Collusion Resistant Location Proof Generation and Verification

7.1 Introduction

In this chapter, we propose the Secure, Privacy–Aware and collusion Resistant poSition vErification scheme (SPARSE) which provides secure and private LP generation and verification for mobile users. SPARSE has a distributed architecture designed for ad–hoc scenarios in which mobile users generate location proofs for each other. In the proposed scheme, we do not employ a DB protocol for protection against Terrorist Fraud. Instead we adopt a time–limited approach to make SPARSE resistant to these attacks. This introduces two advantages. Firstly, the speed of LP generation becomes independent of the length of the users' private key. Secondly, the costs of the system implementation is reduced since implementing a DB protocol requires some hardware changes on mobile devices [85]. Moreover, to address Prover–Witness collusions, we do not allow provers to choose their witnesses. Instead, the system performs a witness selection mechanism by which some witnesses are chosen and qualified to generate LPs for a specific prover. We show that by using this method, if the service provider creates necessary incentives for users to collaborate with the system and generate LP for each other, the success probability of these collusions is negligible.

Since we do not integrate any distance bounding protocol into SPARSE, it becomes an easy–to–implement scheme in which the location proof generation process is independent of the length of the users' private key. We provide a comprehensive

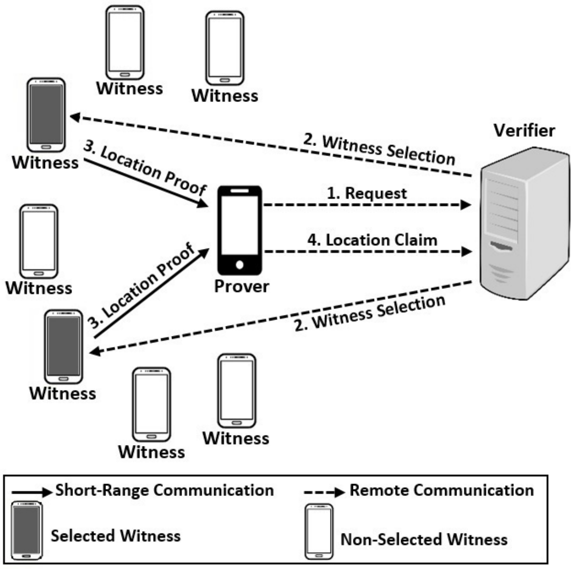


Figure 7.1 : The system architecture of SPARSE Scheme

security analysis and simulation which show that SPARSE provides privacy protection as well as security properties for users including integrity, unforgeability and non–transferability of the location proofs. Moreover, it achieves a highly reliable performance against collusions.

7.2 The SPARSE Scheme

Fig. 7.1 presents the proposed system architecture. As you see, SPARSE has a distributed architecture and consists of three types of entities:

Prover: A mobile user who wants to prove his/her location to a verifier.

Verifier: The entity that is authorized to assess and verify the provers' location proofs.

Witness: A mobile user who has accepted to generate a LP for his/her neighbor provers.

In the following we present some assumptions regarding our threat and trust model:

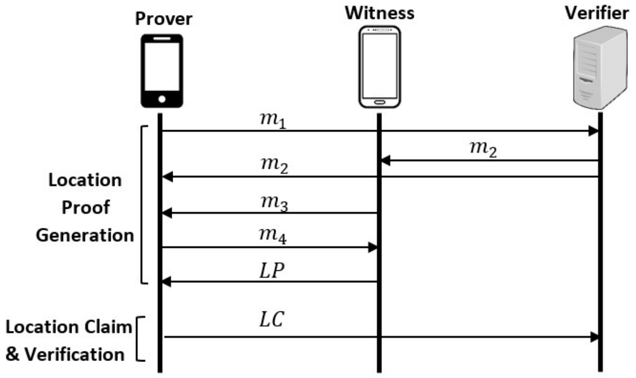


Figure 7.2 : Message exchange diagram for the proposed scheme.

– Users (provers and witnesses) send their messages to each other via their short–range communication interfaces such as WiFi or Bluetooth.

– To obtain a fake LP, dishonest provers might provide the witnesses with fake information about their location or change the contents of a LP generated for him/her or another user. They might also collude with other users (provers or witnesses) to achieve their goal.

– Users never share their private key with each other [85], [90], [92].

– Witnesses are assumed to be untrusted. Thus, they may collude with a remote dishonest prover and issue a fake LP for him/her. Moreover, both provers and witnesses are untrusted from a privacy point of view.

– The verifier is supposed to be a trusted entity which does not publish users' identity and their data.

Now, we introduce our proposed location proof scheme, SPARSE. It is executed in two separate phases: *Location Proof Generation*, and *Location Claim & Verification* (see Fig. 7.2). Refer to table 7.1 for a short description about the cryptographic notations that are used in this paper.

1) Location Proof Generation:

Table 7.1 : List of Notations

Notation	**Description**
$\|\|$	Concatenation symbol
$\mathcal{S}_u(m)$	Signature of user u on message m
$E_{ent}(m)$	Encryption of message m using public key of entity ent
Loc	GPS coordinates related to the prover's location
$Loc^{'}$	The witness's location
$time$	The current time
ID_P	The prover's ID
ID_W	The witness's ID

a. Prover: The prover starts the protocol by sending the following message m_1 to the verifier to inform it that he/she wants to submit a location claim.

$$m_1 = E_{Verifier}(Req\|\mathcal{S}_{Prover}(Req)),$$

where $Req = ID_P\|Loc$ is the prover's request.

b. Verifier: Upon receiving m_1, the verifier randomly selects K witnesses among those who are present at Loc. Then, it generates a unique ID for this location proof (ID_{LP}) and sends it to the prover and selected witnesses.

c. Witness: After receiving ID_{LP}, a selected witness generates a random sequence number rs and broadcasts the following message m_3 through its predefined short–range communication interface (Bluetooth or WiFi) for a period T (e.g., 100 ms).

$$m_3 = ID_{LP}\|rs$$

After this time, another rs is generated and broadcasted in a similar way. This process is repeated until the witness receives a response from the prover.

d. Prover: When the prover device receives m_3, it first ensures that the ID_{LP} is the same as the one already received from the verifier. Otherwise, it just discards m_3 and continues to listen to the channel. If they are same, the prover must immediately compute message m_4 and send it to the witness:

$$m_4 = ID_{LP} \| rs \| E_{Verifier}(rs \| \mathcal{S}_{Prover}(rs))$$

e. Witness: Upon receiving m_4, provided that the ID_{LP} in m_4 is the same as the current location proof ID, the witness checks to see whether this rs is the last sequence number that had been broadcasted by itself. If it is, the witness generates the following location proof LP and sends it to the prover.

$$LP = E_{Verifier}(m_5 \| \mathcal{S}_{Witness}(m_5)),$$

where $m_5 = m_4 \| Loc^{'} \| time \| ID_W$. Otherwise, the following *null* LP is sent to the prover:

$$LP = E_{Verifier}(m_5 \| \mathcal{S}_{Witness}(m_5)),$$

where $m_5 = null \| ID_W$.

2) Location Claim & Verification:

a. Prover: The prover generates the following location claim LC using the K received LPs from the K selected witnesses and submits it with the verifier:

$$LC = E_{Verifier}(m_6 \| \mathcal{S}_{Prover}(m_6)),$$

where $m_6 = LP_1 \| LP_2 \| \ldots \| LP_K \| ID_P$.

b. Verifier: After the verifier receives the LC, it checks the following items:

- Are the two ID_Ps received through messages m_1 and LC the same?
- Is the prover's signature on m_6 correct regarding the claimed ID_P?

- For each $LP_i, (i = 1, \ldots, K)$:
  - Is the witness with identity ID_W among the selected witnesses?
  - Is the witness signature on m_5 correct regarding the ID_W?
  - Are $time$ and Loc in an acceptable range of the current time and Loc' respectively?
  - Are the two random sequences rs in m_4 same?
- Is the number of non–*null* LPs greater than a predefined threshold K_T?

If all the above checks are passed successfully, the verifier accepts this LC. Otherwise, the prover's claim is rejected.

7.3 Results

This section presents our security and privacy analysis and discisses the results of our experiments.

7.3.1 Security and Privacy Analysis

In this section, a comprehensive security and privacy analysis is presented to show that SPARSE achieves the fundamental security and privacy properties of a secure and privacy–aware location proof system described in [87], [88] and [92].

Resistance to Distance Frauds: In a distance fraud, a malicious prover tries to convince an honest witness (or a verifier) that his physical distance to the witness (or verifier) is less than what it really is. In SPARSE, the prover must sign and encrypt the random sequence rs in a limited time T over a short–range communication interface. If a malicious prover is not located in the communication range of the witness, he/she can not proceed with the attack. Thus, for him/her the only way to get the fake location verified is to collude with another user. In this section, we analyze the SPARSE performance against collusions separately.

Unforgeability: We consider several scenarios: If a dishonest prover wants to generate a LP by himself (without proving his proximity to a selected witness), the verifier will detect this. Note that the verifier checks the received ID_W with the signature on m_5. Since users do not share their private key, this prover can not compute the witness signature on m_5 even if he knows the identity of each selected witness. Moreover, if a malicious user wants to forge another user's LP, again the prover will detect it. The reason is that he must sign messages m_1 and m_6 using the victim's private key which is not accessible for him. Furthermore, if a malicious witness who is not among the selected witnesses wants to generate a LP for a prover, the issued fake LP is detected by the verifier.

Non–Transferability: If a malicious user wants to submit a LP which has been generated for another prover P, the verifier will find it because P's signature is on rs which does not match with the attacker's ID. Note that the attacker can not see and manipulate the LP's contents since it has been encrypted using the verifier's public key. Even if he knows the P's ID and wants to impersonate P by submitting his request using a new m_1, he must forge the P's signature which is unlikely without having the P's private key. Moreover, the presence of *time* in m_5 makes it impossible for him to use this LP later.

Resistance to Mafia Frauds: In this attack, an adversary tries to convince an honest witness that an honest prover is in the vicinity of the witness while he/she is not really (readers can refer to [91] and [94] for detailed information about *Mafia Frauds*). We assume an adversary A is going to perform a *Mafia Fraud* on a remote prover P and witness W who are both honest. We model A with a witness $\bar{W}$ and a prover $\bar{P}$. The time–limited process performed in stages 1.d and 1.e prevents $\bar{P}$ from sending rs to $\bar{W}$ for obtaining the P's signature on it because there is not much time to do so. If this process takes longer than T, the witness will send another rs which invalidates the previous rs. Thus, the attack is defeated.

Prover & Witness Location Privacy: Since all the messages that contain the prover's and witness' ID are encrypted with the verifier's public key, they can only be seen by the verifier. Moreover, we have employed the *sign–then–encrypt* model to generate SPARSE messages. This makes it infeasible for a curious entity or an eavesdropper to check the prover's or witness signature with the public key of all the users and find their identity.

Resistance to Terrorist Frauds (Prover–Prover collusions): In this attack, a remote malicious prover colludes with an adversary who is close to an honest witness to convince the witness that he/she is in its vicinity. Now, imagine an adversary A that is close to an honest witness W wants to collude with a remote dishonest prover P and answers to W's challenges on behalf of P. In this case, A must send rs to P to sign and encrypt it and then sends it back to A for submission with W. However, there is not enough time for them to do so because the validity of this rs is only for a short period T. After this time, the witness will broadcast a new rs and reject all the messages m_4 which have the previous rs. Thus, SPARSE is resistant to this type of attacks.

Resistance to Prover–Witness Collusions: Upon receiving a specific prover's request, it is the verifier that selects some witnesses to generate LPs for him/her. Later, in the Location Claim & Verification phase, the verifier rejects any LPs generated by witnesses not selected by the verifier. Thus, the prover is not permitted to collect a LP from any witness he/she likes. This makes it very difficult for a malicious prover to set up a successful *Prover–Witness* collusion. In this case, he has to increase the size of his collusion group to improve his chances of winning. In other words, he must collect at least K_T non–null LP to become successful. More precisely, if there are at least K_T colluding witnesses among the K selected witnesses, the attack will succeed. However, we show that this happens with a negligible probability. For this reason, suppose the malicious prover is colluding with K_C dishonest witnesses which are located at his desired location L. We assume N is the number of all witnesses present at L (including the dishonest witnesses) and x is the number of the colluding witnesses who are selected by the verifier to generate LP. Obviously, for $K_C < K_T$ we have $P_s = 0$, where P_s is the attack success probability. For $K_T \leq K_C < K$ we have:

$$\begin{aligned} P_s &= P(x \geq K_T) \\ &= P(x = K_T) + P(x = K_T + 1) + \ldots + P(x = K_C) \\ &= \sum_{j=K_T}^{K_C} P(x = j) = \frac{\sum_{j=T}^{K_C} \binom{K_C}{j}\binom{N-K_C}{K-j}}{\binom{N}{K}} \end{aligned}$$

Note that the malicious prover must collude with the witnesses who are physically present at L. This makes it too difficult to have a large K_C, specifically, for the applications where performing a large size collusion is too expensive. However, we assume he can select $K_C > K$. In this case, if $K_T = K$ is selected by the system, we have:

$$P_s = P(x = K_T) = \frac{\binom{K_C}{K}}{\binom{N}{K}} = \frac{K_C!(N-K)!}{N!(K_C-K)!}$$

Simulation results show that P_s is negligible if system parameters are carefully chosen (see the previous section for more details). Specifically, for large values of N, the attack is defeated with a high probability. Note that if the service provider creates enough incentives for the witnesses to collaborate with the system, we will have a large N. Therefore, SPARSE can significantly reduce the success probability of these collusions.

7.3.2 Performance Evaluation

In this section we evaluate the performance of SPARSE against *Prover–Witness* collusions. We adopt the same configuration with which STAMP [90] performance has been evaluated. Total number of users is set to 1000 and we suppose an average of 5% of these users are present at each location. Moreover, the threshold $K_T = K$

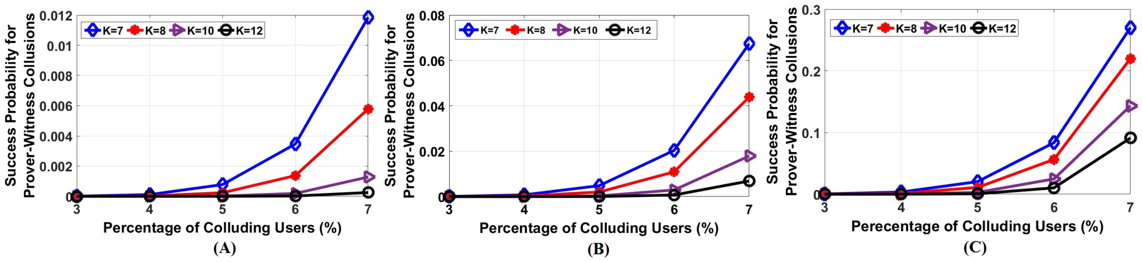
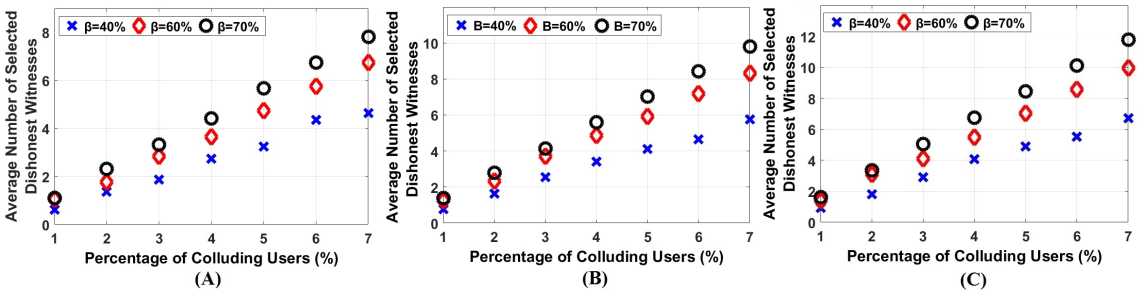


Figure 7.3 : The success probability of Prover–Witness collusions. (A) $\beta = 40\%$ (B) $\beta = 60\%$ and (C) $\beta = 80\%$

is adopted which means no null LP is accepted by the verifier. It is also assumed that the malicious prover sets up a collusion group of size K_C which is varied from 1% to 7% of all the users. An aggregation rate β is allocated to each collusion group which represents the percentage of colluding users who are located at the desired location during the time at which the attack is performed. Thus, $\beta = 0.7$ means that 70% of colluding users are present at the given location during the attack.

Fig. 7.3 shows the success probability of *Prover–Witness* collusions for different values of β and K. As you see, the attack has a maximum success probability of 0.012 and 0.07 for $\beta = 40\%$ and 60% respectively when 7% of users collude with the malicious prover. This means that the system can prevent *Prover–Witness* collusions with the minimum success rates 0.988 and 0.993 for the mentioned situations. Even if 80% of colluding users are located at the intended location (i.e. $\beta = 80\%$) and the malicious prover colludes with 5% of users, the system prevents the attack with the success rates 0.98, 0.99, 0.997, and 0.999 for $K = 7$, 8, 10, and 12, respectively while in STAMP the maximum success rates 0.95, 0.92 and 0.65 have been achieved for different collusion tendencies when 5% of users collude. In fact, STAMP has a relatively poor performance against provers with a low collusion tendency. This is because they decide on the users' LP transaction history. Thus, for the malicious provers who have a diverse transaction history, STAMP does not



(A) (B) (C)

Figure 7.4 : The average number of colluding witnesses that are selected by the verifier for (A) $K = 8$ (B) $K = 10$ and (C) $K = 12$

offer a reliable performance (e.g. with a collusion tendency 0.2, STAMP achieves a collusion detection rate 0.65 when 5% of users collude with the malicious prover). However, SPARSE reaches the prevention success rates better than 0.98 regardless of the prover's past LP transactions. You can also see in Fig. 7.4 the average number of colluding witnesses who are selected by the verifier for different values of K and β. As you see, the number of selected dishonest witnesses are less than K which means that even for $\beta = 70\%$ and with 6% colluding users, the scheme is resistant to these collusions if K_T is chosen close to K.

7.4 Conclusion

In this chapter, we introduced SPARSE, a distributed location proof system for mobile users. The main distinguishing characteristic of the proposed system is that it provides a solution for the Terrorist Fraud and Prover–Witness collusions, the two issues from which the current distributed location proof systems suffer. Moreover, we have not employed the traditional distance bounding protocols. This not only results in fast location proof generation by the witnesses (because they become independent of the length of users' private key), but also provides an easy–to–implement system architecture.

In the next chapter, we introduce our third LP scheme which is a blockchain–

based scheme for location proof generation and verification. It utilises the unique features of the blockchain technology to provide a decentralized secure and privacy–aware scheme for location proof generation and verification.

Chapter 8

Blockchain for Secure Location Verification

8.1 Introduction

In this section, we utilise the unique features of the blockchain technology to design a decentralized scheme for location proof generation and verification. In the proposed scheme, a user who needs a location proof (called a prover) broadcasts a request to the neighbor devices through a short–range communication interface, e.g. Bluetooth. Those neighbor devices that decide to respond (called witnesses) start to authenticate the requesting user. In the proposed scheme, mobile users act as witnesses for a user (prover) that requests an LP in their physical proximity. Witnesses start to authenticate the prover and if the prover is successfully authenticated, a transaction is created based on the proposed blockchain framework. The transaction (that holds the prover's LP data) is then broadcast onto a peer–to–peer network over the internet where it can be picked up by verifiers for further verification. Finally, the verified transaction is stored in a time–stamped public ledger accessible for LBSPs. To preserve users' location privacy, they cryptographically commit to their spatiotemporal data before it is inserted into a transaction. Later, they open the commitment when they submit a location claim with an LBSP.

To prevent distance frauds, all the communications between prover and witness devices are performed through a short–range communication interface like Bluetooth. Moreover, we integrate an incentive mechanism into the proposed scheme whereby witnesses and verifiers are rewarded by a small amount of cryptocurrency. This incetivizes them to collaborate with the system rather than ignoring provers' requests to save power on their device. In the proposed blockchain framework, transactions are created using a secure and privacy–aware method. They hlod provers' commitment to their spatiotemporal data and the information related to witnesses and verifiers' rewards. However, they do not contain any data that identifies a prover. A group of transactions forms a block which is identified by a unique header generated by a cryptographic hash function. Each block contains hash of the previous block, therefore, all blocks are inherently linked. This makes the ledger (that holds users' LPs) immutable and irreversible. Moreover, employing the decentralized blockchain architecture enables us to benefit from the power of consensus, while the conventional LP schemes are performed by a central thirdparty entity.

Upon successful authentication, a transaction is generated as a location proof and is broadcast onto a peer–to–peer network where it can be picked up by verifiers for the final verification. Our security analysis shows that the proposed scheme achieves a reliable performance against Prover–Prover and Prover–Witness collusions. Moreover, our prototype implementation on the Android platform shows that the proposed scheme outperforms other currently deployed location proof schemes.

8.2 The Proposed Architecture

The proposed scheme is executed in three stages, discussed next. Fig. 8.1 shows the message exchange diagram of the proposed scheme. We explain the scheme step by step based on the computations and operations that each entity performs.

1) LP Request Submission

Prover. In the first stage, the prover generates the following message m_1 and broadcasts it to the surrounding witness devices through a predefined short–range communications interface:

$$m_1 = \bar{m}_1 \| r \ ,$$

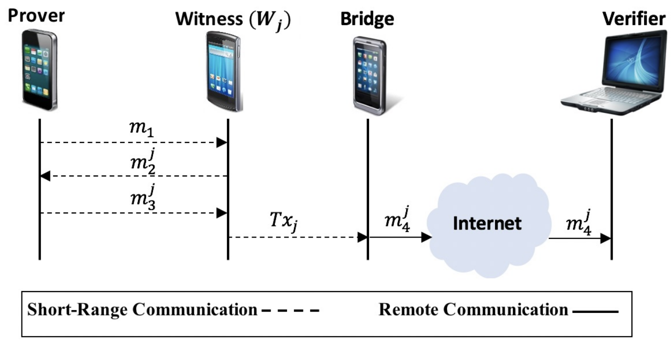


Figure 8.1 : Message exchange diagram of the proposed scheme

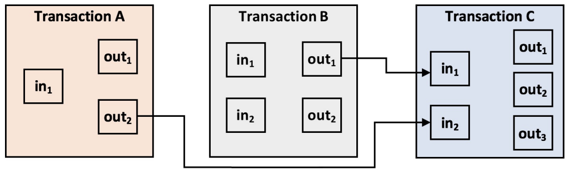


Figure 8.2 : In the proposed scheme, each transaction can have different inputs and outputs.

where $\bar{m}_1 = ID_P \| H(Prev\_Tx) \| Index \| Rew \| C_{(P,ST)}$.

In $\bar{m}_1$, ID_P is the prover's ID (public key), $H(Prev\_Tx)$ is the hash of the prover's previous unspent transactions containing the outputs that the prover wants to spend now (see Fig. 8.2 and 8.3), $Index$ specifies the index of that output (it indicates how the prover has received this cryptocurrency that he/she wants to spend), and $C_{(P,ST)}$ is the prover's commitment to his/her spatiotemporal data.

As you see, the prover sends the random nonce r to the witness because the witness must be able to open the commitment $C_{(P,ST)}$ to ensure that it is the same with the current location. This prevents dishonest provers from committing to a different location data and obtaining an LP for it.

Rew in the above message is the amount of reward that the prover is willing to pay to a witness and a bridge. This reward cannot be less than a predefined

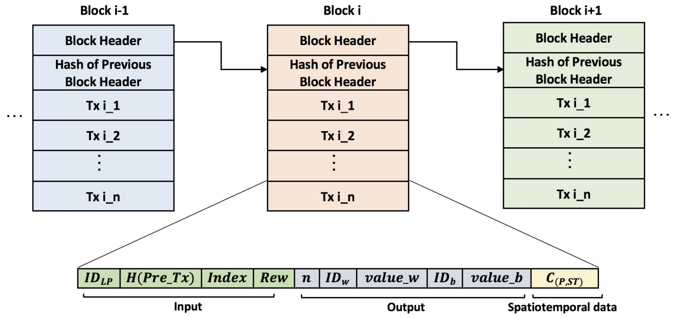


Figure 8.3 : Block creation and transaction structure in the proposed scheme.

minimum amount Rew_{min}. The minimum reward amount is set to provide additional protection against P–W collusions where a malicious witness is forced to change his attack to a P–P collusion (see Section 6 for more detail). Without the predefined minimum amount, the malicious witness can broadcast a m_1 message on behalf of a remote dishonest prover and add a very low reward amount to the Rew field to decrease the incentive of other witnesses to issue an LP for this request. Thus, in this case, the attack can proceed with a higher chance of success.

2) Tx Generation and Submission

Witness. Upon receiving m_1, a witness (let us say $w_j, j = 1, 2, \ldots, J$ where J is the number of witnesses that reply to the prover's request) opens the commitment $C_{(P,ST)}$ to check whether the spatiotemporal data inserted by the prover matches the current location and time or not. If they are the same, w_j sends the following message m_2^j to the prover and starts a timer. This is done after the prover device acknowledges that it is ready to receive the challenge message m_2^j. This prevents any disorder in execution of the mechanism since J different witnesses want to send their challenges message to the prover:

$$m_2^j = LP_j \| Sign_{w_j}(LP_j), \quad j = 1, 2, 3, \ldots, J$$

where $LP_j = \bar{m}_1 \| n_j \| ID_{w_j} \| ID_b$ in which n_j is a random number generated by w_j

ID_{w_j} and ID_b are the identity of the witness and selected bridge, respectively. Note that each device knows the ID of the currently serving bridge that has been elected by users.

Prover. When the prover device receives each m_2^j, it immediately signs it using its private key and sends the following message m_3^j to w_j:

$$m_3^j = m_2^j \| Sign_P(m_2^j) \| \quad j = 1, 2, 3, \ldots, J$$

By signing m_2^j (which is an LP), the prover consents that he/she rewards Rew to the witness, selected bridge, and verifier. For simplicity, we assume their share is equal, however this assumption can be removed by adding two fields $value\_w$ and $value\_b$ next to the ID_{w_j} and ID_b respectively, to specify their share. The difference between Rew and $value\_w + value\_b$ is considered as the verifier's reward (same as the payment mechanism in Bitcoin).

Witness. Upon receiving m_3^j, witness w_j stops the timer and checks to see whether it was received in the predefined period of time T. T is a system parameter and must be carefully designed such that it only provides the prover with an opportunity to sign m_2^j, and send it back to w_j (in the next section, we propose some practical values for T based on our experimental results). Thus, with a carefully selected T, in case of a P–P collusion, an adversary does not have such an opportunity to relay m_2^j to a remote dishonest prover and receive his signature.

If m_3 is received in time, w_j creates the following transaction Tx_j and broadcasts it through its short–range communication interface to be delivered to the selected bridge. Other mobile users that are located between the witness and bridge discard the transaction if they have not already received the prover's request message m_1. Otherwise, they broadcast it such that it finally reaches the bridge. As you will see in the next section, this technique enables the proposed scheme to prevent P–W collusions.

$$Tx_j = m_3^j \| Sign_{w_j}(m_3^j), \quad j = 1, 2, \ldots, J$$

Note that w_j does not have to check the prover's signature on m_2^j since a verifier (that has more power and computational resources) can do it later in the *Tx Verification* phase. You will further see in the *Tx Verification* phase that a verifier randomly selects the Tx issued by one of the J witnesses to add to the chain.

If m_3^j is not received in time, or the signature on m_2^j is not correct, w_j broadcasts the following transaction Tx_j onto the peer–to–peer network on the internet:

$$Tx_j = m_3^j \| Nack \| Sign_{w_j}(m_3^j \| Nack)$$

Thus, in case of a P–P collusion, the $Nack$ transaction informs the verifiers on the internet that a collusion is taking place.

The selected bridge. Upon receiving $Tx_j, j = 1, 2, \ldots, J$, the selected bridge device checks it to make sure its ID has been correctly inserted. It also discards the additional copies of a transaction that might be received. Then it signs Tx_j using its private key and broadcasts the following result onto the peer–to–peer network using its internet interface:

$$m_4^j = Tx_j \| Sign_b(Tx_j)$$

3) Tx Verification

A Tx can be verified by any verifier in the network. A verifier plays a similar role to a miner in Bitcoin. Upon receiving $m_4^j, j = 1, 2, \ldots, J$, a verifier starts to perform the following checks:

- The prover signature on m_2^j matches the prover's public key, i.e. ID_P.

- The witnesses' signatures on LP_j and Tx_j messages match their ID.
- The bridge signature on m_4^j is correct.
- Rew is equal or less than the output value of the prover's unspent transactions (indicated by $H(Prev\_Tx)$ and $Index$).
- At least J_1 non–$Nack$ transactions received for this LP that pass the above checks.

Moreover, if the output value in the prover's previous transaction (indicated by $index$ in Fig. 8.3) is greater than Rew, the difference is considered as the last output of the current Tx and goes to the prover's wallet. Thus, in this case, the prover can use this Tx later as an unspent transaction.

If all the above checks are passed, the verifier randomly selects one of the J transactions and adds it to the current block that he/she is creating (see Fig. 8.3). Blocks are identified by a unique header created by a cryptographic hash function. Each block is linked to the previous blocks since the hash of the previous block is stored in every block. This makes the ledger immutable and irreversible.

Regarding the consensus algorithm, we adopt the Proof of Stake (PoS) approach instead of the Proof of Work (PoW) method. In PoS, a random selection process is used by the network to determine which node is the generator of the next block. This selection process is performed by considering a combination of different parameters, e.g., the wealth of each node, the age of stakes, and different randomization factors [121]. Those nodes who want to participate in the block generation process must lock a specific amount of their coins into the network. This is considered as their bond or stake that determines their chances to be selected as the next block validator (larger stakes result in higher chances). Some randomization techniques are also integrated into the selection mechanism to randomize it and prevent the wealthiest nodes to take control of the network. Dishonest validator nodes lose their stake if they do not perform the protocol honestly (i.e., not to verify a fraudulent transaction).

PoS has several advantages over PoW and adopting PoS as the consensus algorithm makes the block generation faster and more energy–efficient. For example, it is a much greener consensus mechanism since block creators need to consume a lot of energy in the PoW approach. Unlike the PoW approach, in PoS the block generators do not need to compete to solve difficult energy–consuming puzzles. Therefore, the time required for block generation only depends on the computational power of the block generator, i.e., the block generator only needs to verify the block's transactions and computes header of the block. In PoW, however, miners have to spend additional time to solve difficult puzzles as well. In addition, PoS provides more security regarding the 51% attack [123].

Similar to the Bitcoin setup, we propose two types of nodes in the network, i.e., *lightweight* and *full nodes*. Full nodes can store a copy of the entire ledger (all the blocks and transactions). Thus, there can be many backups of the public ledger in the network. Location–based service providers have the required incentive to play the role of a full node in the network since they benefit from the system a lot. Moreover, they have more storage resources to store a copy of the entire ledger. On the other hand, lightweight nodes (i.e., ordinary users) does not have to store the whole blockchain. These nodes can access and explore the ledger using the access services offered by the full nodes. These services are actually similar to the Simplified Payment Verification (SPV) service offered in Bitcoin [124]. Thus, lightweight nodes can create or verify a transaction without having to download the entire ledger.

8.3 Results

This section presents our security and privacy analysis and discisses the results of our prototype implementation.

8.3.1 Security and Privacy Analysis

In this section the security and privacy of the proposed scheme are discussed.

Location Privacy: In the proposed scheme, a prover commits to his/her spatiotemporal data before requesting an LP. Thus, instead of the plaintext spatiotemporal data, this commitment is stored in the public ledger. This makes the prover's location data publicly inaccessible. However, as discussed before, when the prover wants to submit a location claim with a LBSP, he/she opens the commitment by sending the random nonce r to the service provider. In the following, we provide a detailed analysis on the proposed technique to show how it preserves users' location privacy.

We make use of unforgeable cryptographic commitments to keep submitted locations private in the public ledger. To perform this technique, users commit to their spatiotemporal data before they create a transaction:

$$C_{(P,ST)} = Commit(ST, r) = g^r v^{ST},$$

where $ST = (Loc; Time)$ is the spatiotemporal data of the prover and $r \in \{0, 1, \ldots, q-1\}$ is a random nonce generated by the prover for commitment to ST. g and v are selected from the subgroup of G of order q in Z_p^*, where q and p are pre–determined values such that q divides $p - 1$.

As discussed in Section 5, $C(P, ST)$ is added to a transaction and will be stored in the public ledger after verification. When the prover wants to submit a location claim with a LBSP, he/she opens the commitment by sending r and ST to the service provider who can confirm $C(P, ST) = g^r v^{ST}$. Using the above commitments, the proposed technique achieves two essential security properties:

i. **Binding Property:** A prover cannot change the submitted location anymore. Thus, when the commitment is opened at a later stage by an LBSP, the revealed location data is really what the prover has already committed to. In other words, the prover cannot find another nonce $\bar{r}$ such that it results in the same commitment value $C(P, ST)$ considering a different spatiotemporal data $\bar{ST} \neq ST$.

Proof: If a prover P commits to ST and can later open the commitment as $\bar{ST} \neq ST$, then we have:

$$g^r v^{ST} = g^{\bar{r}} v^{\bar{ST}},$$

or equivalently:

$$\log_g(v) = \frac{r - \bar{r}}{\bar{ST} - ST}$$

This means that the prover could calculate the discrete logarithm $\log_g(v)$ that contradicts the fact that discrete logarithms are computationally infeasible to calculate.

Hiding Property: When a user's commitment is added to the public ledger, it is infeasible to open it unless the prover shares the random nonce r.

Proof: Similar to the encryption with one–time pad, v^{ST} and consequently ST, are perfectly hidden in $g^r v^{ST}$ because g^r is a random element of G. Thus, it is computationally infeasible for an adversary to obtain ST without the knowledge of r.

Therefore, the provers' private spatiotemporal data are not revealed to the public even though they are stored in a public ledger. However, the provers can open their commitments by sharing the random nonce r with the related service provider.

Resistance to Distance Frauds: This attack is performed by a single attacker, i.e. a malicious prover who is far from a desired location L. During the attack, the malicious prover attempts to convince the honest witnesses (located at L) that his physical distance to them is less than what it really is. In the proposed architecture, mobile users perform the proposed scheme by running an application that communicates with other devices through a short–range communication interface. In other words, witness devices only listen for any incoming LP requests using their short–range communication interface. This makes it impossible for a distant malicious prover to perform a distance fraud.

Resistance to Terrorist Frauds (P–P collusions): The detection of P–P collusions is commonly performed by witnesses and a verifier. When a witness device receives a prover's LP request, it performs the presented time–limited mechanism in which the prover is given a short period of time T to sign message m_2^j (generated by the witness $w_j, j = 1, 2, \ldots, J$) and send it back to the witness. In case of a P–P collusion, an adversary who is conducting the attack has only two options to choose from, since he does not have the prover's private key:

(a) The adversary relays m_2^j to the remote dishonest prover to obtain his signature. This process takes a period of time $T^{'} = 2t_c + t_p$ where t_c and t_p are the communication and processing times, respectively. In this case, the witness receives the response after $T^{''} = T + 2t_c$ approximately. Hence, the attack is detected by the witness because $T^{''}$ is definitely greater than T. In the next subsection, we propose some practical values for T based on our implementation results.

(b) The adversary signs m_2^j himself (using his own private key). In this case, the verifier who checks the signatures will detect this in the Tx verification phase. Note that checking the signature could also be done by the witnesses. However, it is more efficient to make a verifier responsible for this duty because it has more power and computational resources than a witness device (as signature checking requires heavy computations to be performed).

Moreover, utilizing the random number n_j makes m_2^j a random message. This prevents the adversary from guessing m_2^j and relaying it to the prover in advanced to have his signature ready to send back to the witness.

Resistance to P–W collusions: The proposed architecture has been designed in such a way that a malicious witness who is going to perform a P–W attack is forced to change his attack to a P–P collusion. To clarify this, let us consider a malicious witness W who colludes with a dishonest prover P to generate a fake LP for him. For this reason, W creates a fake transaction Tx_W and based on his situation performs one of the following:

1) W broadcasts the fake transaction through its short–range communication interface for the elected bridge to receive and broadcast it onto the peer–to–peer network on the internet. The local mobile users (including the bridge) who receive Tx_W broadcast it only if they have already received an LP request (message m_1) with the same ID_P. Since the prover's ID_P is not published in the P-W collusion scenario, the fake transaction Tx_W is prevented from being published to the potential verifiers on the internet. Consequently, Tx_W is not added to the public ledger. This forces the witness to locally publish the ID_P by broadcasting an LP request message m_1. In this case, we can say that the attack is changed to a P–P collusion in which an adversary (W in this scenario) broadcasts an LP request on behalf of a remote prover. As we discussed in the previous analysis, the proposed scheme is resistant to P–P collusions. Therefore, P–W collusions are prevented by the scheme as well.

2) W broadcasts the fake transaction Tx_W onto the peer–to–peer network himself (instead of broadcasting it to be received by a legitimate bridge). In this case, W does not have to be located at the desired location. To be successful, W needs to insert another ID along with its associated signature into the transaction as a

bridge ID and signature, respectively. Since each mobile device may only have one ID, three mobile devices must be involved in the attack at this stage (P, W, and a bridge). However, in the verification phase, verifiers need to receive at least J_1 non–$Nack$ transactions related to this LP (this is one of the requirements that a verifier checks before adding a transaction to a block). Hence, in this case, a malicious prover needs to collude with $J_1 + 1$ mobile devices to conduct a successful attack (totally $J_1 + 2$ mobile devices must be involved in the attack). This can be more expensive for the malicious prover than the reward or benefit that the LBSP provides specifically when J_1 is a large number. Note that users usually need to have an LP for crowded public places. Thus, there is no concern about the number of available witnesses. Specifically, by integrating the incentive mechanism into the proposed scheme, mobile users have enough incentive to respond to other users' LP requests. Therefore, a large J_1 can be adopted by the system to make the attack non–economic for malicious provers. Moreover, LBSPs can look at the history of LPs that have been issued for a prover to determine if a specific group of witnesses always issue LPs for this prover.

To make the scheme more resistant against P–W collusions, verifiers can adopt a random J_1 in a specific range. Therefore, the dishonest prover does not know what collusion group size he must adopt, making it more challenging to conduct an attack.

Non–Transferability: In the proposed scheme, a transaction added to a block can only be used by its owner, i.e. the prover. The reason is that it is signed by the prover, hence, if a dishonest prover provides another user with his random nonce r, the user cannot claim an LP with the LBSP using this Tx. Therefore, the prover signature makes a Tx non–transferrable.

8.3.2 Implementation Results

To study the feasibility of the proposed scheme, we implemented a Java prototype of the proposed scheme on the Android platform. Our experiments were performed on two Android mobile devices: (1) a LG G4–H818P equipped with a Hexa–Core 1.8 GHz processor, 3 GB of RAM, and running Android OS 5.1, acting as a prover, and (2) a Sony Xperia Z1 equipped with a Quad–Core 2.2 GHz processor, 2 GB of RAM, with Android OS 4.4.4, acting as a witness.

We adopted Bluetooth as the communication interface between the mobile devices and conducted the tests in both indoor and outdoor environments. Each measurement shown in this section has been obtained by averaging the results of 10 independent tests. We used RSA key pairs for encryption and SHA1 as the one–way hash function to compute users' signatures. Since the Tx verification phase is performed by verifiers that use desktop or laptop computers with a high level of storage and computational power, we just focus our experiments on *Request Submission*, *Proximity Checking*, and *Tx Generation* phases that are performed by mobile devices with limited resources. The implemented code occupies only 64 KB of data memory. Moreover, during the application runtime, less than 1% of the available memory is used. We also recorded the CPU utilization of the code by installing a monitoring application that reports the amount of CPU usage of the processes running on the device. As you see in Fig. 8.4 (a), the CPU usage for a user in the standby mode is almost 0.5% and independent of the key size. However, due to heavy computations required for signature and commitment calculations in the LP generation phases, the average CPU usage increases to 3%, 10%, and 24% for key sizes 1024, 2048, and 3072, respectively.

We measured the amount of time that the proposed scheme requires to generate an LP after the prover device broadcasts m_1. We compared the results to the

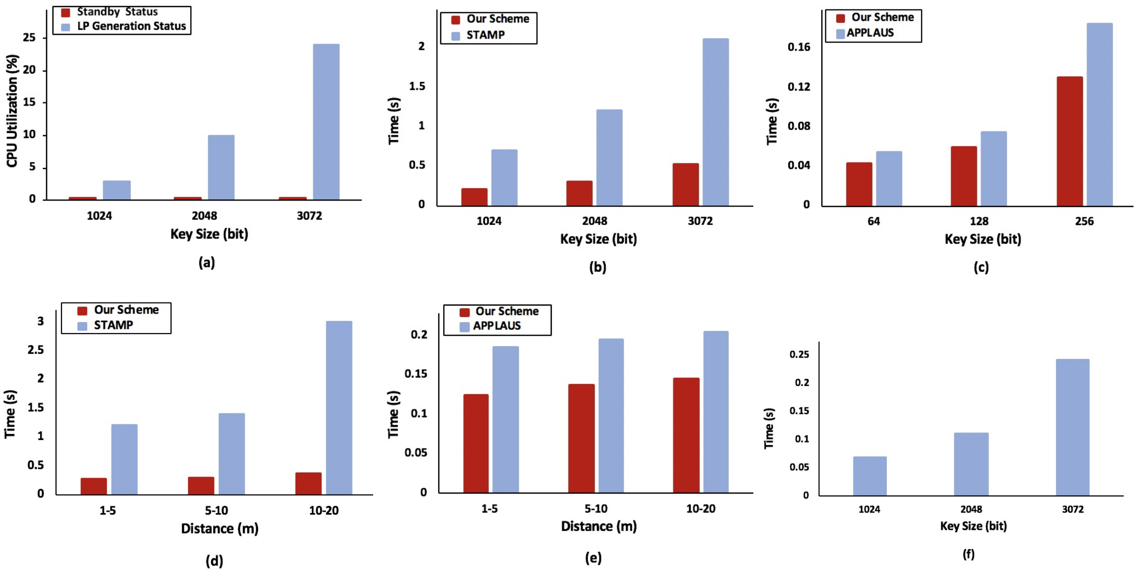


Figure 8.4 : (a) CPU usage for different key sizes. (b) and (c) Time required for LP generation in our scheme, STAMP, and APPLAUS under different key sizes. (d) and (e) Time required for LP generation over different physical distances. (f) Time required for Tx generation after a witness receives message m_3.

decentralized schemes STAMP [90] and APPLAUS [86]. Fig. 8.4 (b) and 8.4 (c) show the results for different key sizes (in APPLAUS, the authors have not implemented their scheme for key sizes larger than 256). As you see, our proposed scheme is faster than STAMP by an order of magnitude. The reason is that we have not adopted a DB protocol to check the prover's proximity to the witness while in STAMP, the Bussard–Bagga DB protocol is used to perform this job. As discussed in before, adopting a DB protocol makes an LP generation scheme slow specifically when users select a long private key.

To evaluate the impact of physical distance between mobile users on LP generation, we conduct our experiments for different distances and compare the results to the performance of STAMP and APPLAUS (see Fig. 8.4 (d) and 8.4 (e), respectively). Compared to them, our scheme's Bluetooth communications have a smaller

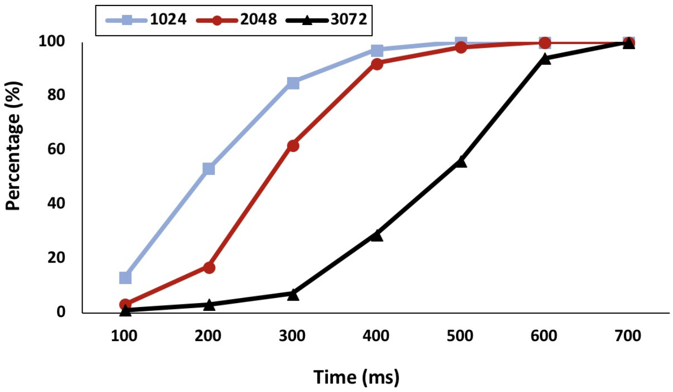


Figure 8.5 : The percentage of LP requests that successfully pass the P–P collusion detection test for different values of T.

share in the amount of time required to generate an LP (the number of Bluetooth communications is lower in our scheme since it does not run a DB protocol). Thus, the level of dependency on physical distance is much lower in our scheme. Note that distance only affects the Bluetooth communication latency and does not change the amount of time required for computations performed in mobile devices.

We also examined the computational time required for the witness device to generate a transaction. The results are shown in Fig. 8.4 (f) for different key sizes. As you see, key size has a negative impact on Tx generation latency because the only heavy operation that the witness device needs to perform in the Tx generation process is signature computation.

Finally, to obtain the optimum value for parameter T, we changed it from 100 to 700 ms by steps 100 ms (see Fig. 8.5) and recorded the percentage of LP requests that passed the P–P collusion detection test. We found that T can be approximately set to 400, 500, and 700 ms for the key sizes of 1024, 2048, and 3072, respectively. These are close to the maximum amount of time that an ordinary device requires to respond to the challenge message sent by a witness device located in its vicinity. If a small value is selected for T, slow mobile devices will fail to sign the challenge message and send it back to the witness in the given time T. Therefore, a specific tolerance can be considered for mobile devices with a slower CPU speed. However, increasing T can provide a malicious prover with the opportunity to successfully conduct a P–P collusion attack.

8.4 Conclusion

In this chapter, we proposed a blockchain–based, secure, and privacy–aware architecture for LP generation and verification. The target of the proposed scheme is to prevent dishonest mobile users from submitting fake check–ins and location claims with LBSPs. It relies on the collaboration of mobile devices that generate an LP for other mobile devices. We also integrated an incentive mechanism into the proposed scheme to reward mobile users who collaborate with the system. The main strengths of the proposed architecture are the following: (1) It does not require a central trusted authority to operate due to employing the blockchain decentralized architecture. (2) It has reliable performance against P–P and P–W collusions to which the majority of the current schemes are vulnerable. (3) Our prototype implementation shows that the LP generation procss in the proposed scheme is faster than the existing schemes due to employing a faster mechanism for proximity checking. (4) It preserves users' location privacy as they commit to their spatiotemporal data before it is published and added to the public ledger. Thus, it is not possible to infer a user's location data by exploring the public ledger.

In the next chapter, we explore anonymity of users in social networks and propose Harmonised and Stable DC–net (HSDC–net), a self–organising protocol for anonymous communications in social networks. We also present the results of our prototype implementation that shows HSDC–net achieves low latencies and can be efficiently integrated into social network applications.

Part III

Anonymity–Based Approach

Chapter 9

Literature Review and Preliminaries

9.1 Introduction

In the last part of this thesis, we investigate anonymity as another approach to provide privacy in social networks. As far as we know, social networks do not offer publicly available anonymous group messaging. If these services are employed by social network service providers, users can be able to create a group in social media and anonymously post their opinions. For example, consider a group of journalists; each journalist wishes to publish some secret government information that he/she obtained from a confidential source. Using an anonymous communication protocol, they can create a group in social media and anonymously publish their posts without the risk of prosecution (see [37–39] for more example applications). Note that the protocol not only needs to hide the origin of each post, but it must also be resistant against traffic analysis to prevent a government agency or an ISP from identifying the message publishers by monitoring and analysing the journalists' traffic in the network.

To offer anonymity, several anonymous communication networks (ACNs) have been proposed so far such as onion routing [40], AN.ON [41–42], and Tor [43]. These solutions work based on mixnet [44], a basic anonymous communication protocol. However, to guarantee users' anonymity, they need access to a set of geographically distributed servers (or mixes) such that at least some of them are trusted [45]. In addition, mixnet–based networks cannot provide the necessary protection against traffic analysis attacks [37], [46–48]. These attacks can be conducted by powerful adversaries like large ISPs who can monitor users' traffic in the network [46]. Dining Cryptographers network (DC–net) [49] is another anonymous communication protocol that guarantees protection against traffic analysis attacks. Unlike mixnet, DC–net is completely performed by the users themselves and does not require any proxy. However, DC–net suffers from three critical issues that reduce its practicality. Firstly, there is a collision possibility issue. Users' messages are exposed to corruption due to possible collisions. In DC–net, every user publishes a vector of data that has N elements (positions or slots) where N is the number of users in the group who want to anonymously publish a message. It requires every user to place his/her message in a unique slot where other users must insert their keys XORed together. Any deviation from this procedure makes all the users' messages unrecoverable. Secondly, DC–net is vulnerable to disruptions and Denial of Service (DoS) attacks since a malicious user can disrupt the protocol by sending irrelevant bit–streams in each of the N slots.

Finally, DC–net is able to provide anonymity only for a few protocol cycles. We name this issue the Short stability problem. To the best of our knowledge, no previous research work has identified this flaw in the DC–net performance. We prove that it is feasible to infer the origin of each message, after users published their messages for at least three protocol cycles.

9.2 Literature Review

In this section, we present a brief review of the literature on anonymous communication protocols. Prior significant research work in this area started in the early 1980s when Chaum presented mixnet [44]. In mixnet, users' encrypted messages are batched together and successively relayed into the network after they are decrypted and shuffled by a set of proxies (named as mixes). Several extensions of the mixnet protocol have been proposed so far such as onion routing [40], Tor [43], An.On

[42], and Mixminion [80]. However, these protocols require that users' messages are passed through a series of proxies which results in high latency and makes them vulnerable to traffic analysis [81]. Moreover, they are vulnerable to active attacks and disruptions which break the anonymity guarantees and cause protocol jamming, respectively [46], [52], [82]. In addition, mixnet–based protocols offer anonymity as long as at least one mix in the network executes the protocol honestly.

Beside the original mixnet, Chaum introduced DC–net as another option towards anonymous communication [49]. DC–net is a distributed and non–interactive protocol that allows a group of users to anonymously publish their messages in a single broadcast round. It provides users with secure anonymous communication if the protocol is executed honestly. However, DC–net suffers from three critical issues that make it impractical [38–39], [50–52].

To address the DC–net problems, a number of DC–net extensions have been introduced. Dissent [38] focuses on addressing traffic analysis and DoS attacks to which mixnet and DC–net protocols are vulnerable. For this reason, the authors of Dissent have proposed a mechanism to trace disrupting (misbehaving) users. This is called accountability in the literature. However, in Dissent, the employed shuffling mechanism imposes a delay at the start of each round that makes the protocol impractical for delay–sensitive applications [52].

Herbivore [39] is another anonymous group messaging protocol that provides anonymity by dividing a large group of network users into smaller DC–net subgroups. In fact, in Herbivore, the size of user groups is reduced in order to limit the attack surface. This enables the protocol to provide only small sizes of anonymity sets.

Although DC–net–based protocols have a decentralized and non–interactive structure, a few numbers of server–based protocols have also been proposed in the literature. For example, Wolinsky et al. [82] suggest a client/server architecture to achieve a high level of scalability. In their proposed protocol many untrusted clients anonymously publish their messages through a smaller and more trusted set of servers. The protocol offers traffic analysis resistance and strong anonymity, provided that there is at least one honest server. However, the proposed disruptor tracing procedure is too costly. To solve this issue, public–key cryptography and zero–knowledge proofs are used in Verdict [46] to infer and exclude any misbehaviour before it results in a disruption. However, no security analysis has been presented in the paper to proof its security. Riffle [47] is another server–based protocol proposed in this area of research. It consists of a small set of servers that provide anonymity for a group of users. However, it still relies on at least one trusted proxy server.

Prior work on privacy issue of Location–Based Services has mostly focused on *K–Anonymity* and *Dummy–Based* methods although some efforts have recently done on other techniques such as *Differential Privacy* [9], [64] and *Cryptography–Based* [72–73] schemes.

K–Anonymity efforts [74–78] require a trusted third–party server which is called an anonymizer, between users and LSP. The anonymizer receives service requests from a user and enlarges its location into a region (cloaking region) so that it contains the locations of K-1 other users as well as location of the requesting user. Therefore, the adversary cannot identify the requesting user among other K-1 users. The advantage of these methods is that the communication cost between users and anonymizer is reduced, however, they suffer from decreased QoS because when there are not enough users near the requested user, the anonymizer has to increase the radius of cloaking region, hence, the increased processing times results in a greater service latency. To solve this problem, some efforts have been done in [76–78] to increase QoS. In these papers the area of cloaking region is minimized by using footprints–historical locations of other users.

Although the mentioned efforts have solved the low QoS problem, they still rely on a trusted third–party anonymizer which is a disadvantage for these schemes. However, in [5] a K–Anonymity privacy protection scheme has been proposed which doesn't rely on a trusted anonymizer between users and LSP. But their method still requires a DataBase Management System (DBMS) to operate.

Several dummy–based location privacy schemes [4], [12], [13–16] have been proposed so far for location privacy protection. In all of them users send their location data including noise (some fake location data or dummies) to LSP directly. Thus, there is no need to a trusted anonymizer. In [4] and [12], two dummy generation algorithms have been presented, *Moving in a Neighbourhood* and *Moving in a Limited Neighbourhood*. In these algorithms, the first dummy set is selected randomly but next dummies are generated in a neighbourhood of the previous position of the dummies. Also, a cost reduction technique was proposed in [4] to limit the communications overhead caused by sending dummies. However, generating dummies at random or through a fixed rule can not provide flexible location privacy for users. Hence, in [11], a Privacy–Area Aware scheme is proposed based on a flexible dummy generation algorithm in which dummies are generated according to either a virtual grid or circle. This approach provides configurable and controllable dummy generation by which it is possible to control the user's location privacy. But a disadvantage of this method is that it doesn't consider nature of the region. For example, some dummies may be generated in places which are unlikely for a user to be there (e.g., in a river). To solve this problem in [13] a Dummy–Location Selection (DLS) method has been proposed to prevent the adversary from exploiting side information such as a region map. This is done by carefully selecting dummies based on the entropy metric.

But in [14] it has been showed that when a user adopts one of the aforementioned dummy–based methods, the adversary can identify some dummies with a minimum correct ratio of 58% by means of the spatiotemporal correlation between neighbouring location sets. Therefore, they have proposed a Spatiotemporal Correlation–Aware privacy protection scheme in which correlated dummies are filtered out and only uncorrelated dummies are sent to LSP. But this method can protect user's location privacy under some conditions only and if the adversary estimates the threshold angle which is used to filter space correlated dummies, he will be able to identify dummies or even the user's real location.

9.3 Preliminaries

This section presents the foundation for the next sections. After briefly reviewing DC–net protocol, we introduce its drawbacks and explain why it requires modifications.

9.3.1 DC–net Overview

DC–net [49] is a distributed and non–interactive protocol proposed to provide anonymous communications for a group of users who wish to anonymously publish their messages in the group. Its title comes from the example by which Chaum explained his proposed protocol:

Three cryptographers sit around a table in a restaurant to have dinner. They are informed by a waiter that someone has anonymously paid their bill. The payer can be one of them or the bill might have been paid by the NSA (National Security Agency). They respect each other's right to make an anonymous payment, but they are curious to see if NSA has paid the bill. Thus, they perform the following protocol:

For all pairs, two cryptographers share a secret bit by tossing an unbiased coin behind their menu such that only those two cryptographers see the result. Thus, cryptographer A, for example, has two secret bits k_{AB} and k_{AC} that have been shared

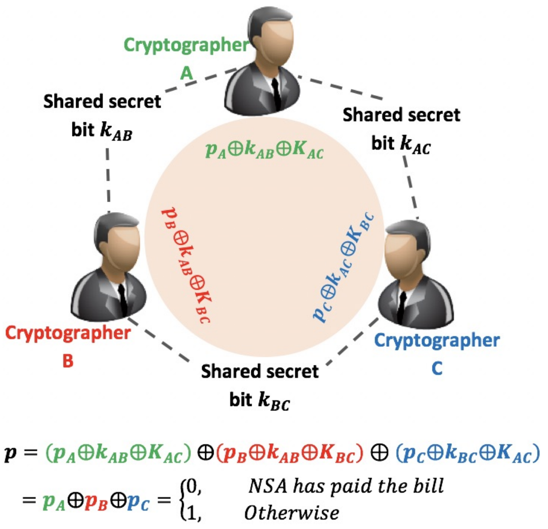

Cryptographer
A
Shared secret
bit k_{AB}
Shared secret
bit k_{AC}
$p_A \oplus k_{AB} \oplus K_{AC}$
$p_B \oplus k_{AB} \oplus K_{BC}$
$p_C \oplus k_{AC} \oplus K_{BC}$
Cryptographer
B
Cryptographer
C
Shared secret
bit k_{BC}
$p = (p_A \oplus k_{AB} \oplus K_{AC}) \oplus (p_B \oplus k_{AB} \oplus K_{BC}) \oplus (p_C \oplus k_{BC} \oplus K_{AC})$
$= p_A \oplus p_B \oplus p_C = \begin{cases} 0, & \text{NSA has paid the bill} \\ 1, & \text{Otherwise} \end{cases}$

Figure 9.1 : The Dining Cryptographers network in a simple example.

with cryptographer B and C, respectively (see Fig. 9.1). Then, if a cryptographer has paid the bill, he XORs his shared keys with bit 1. Otherwise, the XOR operation is performed with bit 0. In both cases, each cryptographer announces his result. If the three published results are XORed together, the result bit is 0 if NSA has paid their bill. If one of the cryptographers has paid the bill, the result is 1.

This basic protocol has been extended to multiple users in [125]. Let's consider N users $u_1, u_2, u_3, \ldots, u_N$ who wish to anonymously publish some L–bit messages $\mathbf{m}_i$ $(i = 1, 2, \ldots, N)$. Assume that each pair of users (u_i, u_j) shares an L–bit key $\mathbf{k}_{ij}(w)$ in a set–up phase where $\mathbf{k}_{ij}(w) = \mathbf{k}_{ji}(w)$ for $i, j, w \in \{1, 2, \ldots, N\}$. Moreover, in this phase, every user computes the following *XORed Keys* (XK) vector:

$$\mathbf{X}_i = [\mathbf{x}_i(1) \;\; \mathbf{x}_i(2) \;\; \mathbf{x}_i(3) \;\; \ldots \;\; \mathbf{x}_i(N)],$$

where

$$\mathbf{x}_i(w) = \oplus_{\substack{j=1 \\ j \neq i}}^{N} \mathbf{k}_i j(w), \quad w = 1, 2, \ldots, N. \tag{9.1}$$

After the set–up phase, users can broadcast their messages by performing the following steps:

(1) Every user u_i randomly selects a slot (position) $s_i \in \{1, 2, \ldots, N\}$ in his/her $\mathbf{X}_i$ vector.

(2) The XK vector $\mathbf{X}_i$ is converted to $\mathbf{Y}_i$ by replacing $\mathbf{x}_i(s_i)$ with $\mathbf{m}_i \oplus \mathbf{x}_i(s_i)$. Then, $\mathbf{Y}_i$ is published.

Since $\oplus_{i=1}^{N}\mathbf{x}_i(w) = 0$ for $w = 1, 2, \ldots, N$, if users have selected different positions, we have:

$$\oplus_{i=1}^{N}\mathbf{Y}_i = \mathbf{M}^{'},$$

where $\mathbf{M}^{'}$ is the users' messages vector $\mathbf{M} = [\mathbf{m}_1 \quad \mathbf{m}_2 \quad \mathbf{m}_3 \ldots \mathbf{m}_N]$ in which the elements have been shuffled. We define $\mathbf{M}^{'}$ as the *Shuffled Messages Vector* (SMV) since we need to refer to this vector frequently.

Therefore, the users' messages are published for the group in such a way that the origin of each message is anonymous.

9.3.2 DC–net Drawbacks

Although DC–net offers strong anonymity, it suffers from some critical issues:

- *Collision possibility*: In DC–net, it is assumed that the users select different slots (or positions) in the XK vector $\mathbf{X}_i$. However, if two users u_i and u_j place their messages in the same slot (i.e., $s_i = s_j$ are selected by them), $\mathbf{m}_i \oplus \mathbf{m}_j$ is recovered in the $\mathbf{M}^{'}$ vector at the final stage that makes both $\mathbf{m}_i$ and $\mathbf{m}_j$ unrecoverable (note that in this case, one element of $\mathbf{M}^{'}$ is obtained as $\mathbf{0}$).
- *Vulnerability against disruptions* (security issue): DC–net works well only when users execute the protocol honestly. The protocol is jammed if a malicious user, for example, fills $\mathbf{Y}_i$ with some random bits and publishes it. In this case none of the users' messages is successfully recovered.

Apart from that, we identified another critical issue, i.e. short stability, in the

DC–net performance which is discussed in the next subsection.

9.3.3 The Short Stability Issue

We noticed that DC–net provides anonymity only for a few protocol cycles. After users publish their messages for at least three cycles, it is possible to infer the origin of each message by analysing vectors $\mathbf{Y}_i$ published in the previous three cycles by the users. To clarify this, consider the following example:

DC–net is performed by a group of four users u_1, u_2, u_3, and u_4 who want to publish some 5–bit messages. They publish $\mathbf{Y}_i^{(1)}, \mathbf{Y}_i^{(2)}$, and $\mathbf{Y}_i^{(3)}$ $(i = 1, 2, 3, 4)$ in the first three protocol cycles. Suppose the XK vector for user u_1 is $\mathbf{X}_1 =$ [11000 10100 00110 10110], and for these three cycles, he/she selects slots 2, 4, and 1 in the XK vector $\mathbf{X}_1$ to XOR his/her messages $\mathbf{m}_1^{(1)} = 10011, \mathbf{m}_1^{(2)} = 11001$, and $\mathbf{m}_1^{(3)} = 10101$, with $\mathbf{X}_1$ components, respectively. Thus, for the published vector $\mathbf{Y}_1$ we have:

$$\mathbf{Y}_1^{(1)} = [11000\ \ 00111\ \ 00110\ \ 10110]$$

$$\mathbf{Y}_1^{(2)} = [11000\ \ 10100\ \ 00110\ \ 01111]$$

$$\mathbf{Y}_1^{(3)} = [01101\ \ 10100\ \ 00110\ \ 10110]$$

By analysing these three vectors, the XK vector $\mathbf{X}_1$ is easily obtained. Intuitively, if different slots are selected by the user u_1, for a specific $w \in \{1, 2, 3, 4\}$, $\mathbf{x}_1(w)$ is the element in the set $\{\mathbf{y}_1^{(l)}(w)\}$ $(l = 1, 2, 3)$ that has been repeated at least twice. Having $\mathbf{X}_1$, the other users are able to compute $\mathbf{X}_1 \oplus \mathbf{Y}_1^{(j)}$ and identify u_1 as the publisher of $\mathbf{m}_1^{(1)}$, $\mathbf{m}_1^{(2)}$, and $\mathbf{m}_1^{(3)}$. If the same slot is chosen for at least two cycles, the elements of the above set are totally different (assuming there are different messages in each cycle). In this case, this slot is identified as the one in which the user has XORed his/her message during at least two of these cycles.

9.4 Conclusion

In this chapter, we reviewed the existing literature on anonymity and reviewed the advantages and disadvantages of different anonymous communication protocols. It is concluded that .

Moreover, this chapter presented some preliminaries as the foundation for the next chapter. In this regard, the concept of differential privacy and the Laplace mechanisms were presented. Moreover, we discussed the necessity of customising the adjacency relation defined in the standard differential privacy to match its definition with the location domain.

In the next chapter, we introduce our anonymity–based solution, i.e. Harmonized and Stable DC–net (HSDC–net) for privacy preservation in social networks. HSDC–net is a self–organizing protocol for anonymous communications that enables users of social networks to anonymously publish their messages.

Chapter 10

Anonymity in Social Networks

10.1 Introduction

While hiding the contents of users' messages has been successfully addressed before, the anonymization of message senders remains a challenge, specifically if users do not trust their ISP. To resolve this challenge, several solutions have been proposed so far. Among these solutions, the Dining Cryptographers network protocol (DC–net) provides the strongest anonymity guarantees. However, DC–net suffers from two critical issues that makes it impractical: (1) collision possibility, (2) vulnerability against disruptions and DoS attacks. Moreover, we noticed a third critical issue during our investigation: (3) DC–net users can be deanonymized after they publish at least three messages. In other words, anonymity is provided only for a few cycles of message publishing. In this paper, we propose Harmonized and Stable DC-net (HSDC–net), a self–organizing protocol for anonymous communications. In our protocol design, we first resolve the short stability issue and obtain SDC–net, a stable extension of DC–net. Then, we integrate the Slot Reservation and Disruption Management sub–protocols into SDC–net to overcome the collision and security issues, respectively. Our prototype implementation shows that HSDC–net achieves low latencies that makes it a practical protocol.

In the next section, we present our anonymity–based solution, i.e. Harmonized and Stable DC–net (HSDC–net) for privacy preservation in social networks.

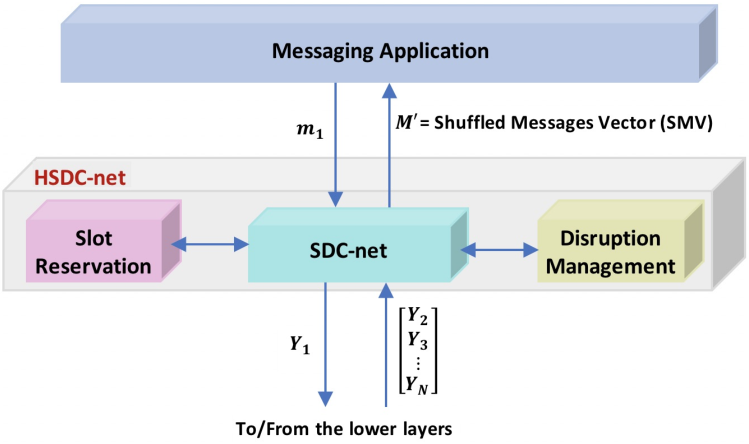


Figure 10.1 : HSDC–net system architecture.

10.2 HSDC–net: Secure Anonymous Messaging in Online Social Networks

In this section, we describe the proposed HSDC–net protocol and present the Disruption Management sub–protocol. At the end of this section, we discuss how HSDC–net supports multiple reservations.

10.2.1 Protocol Description

Suppose a group of N users who want to anonymously publish their messages in the group. Assume they all use a simple messaging application that does not offer anonymity. We add HSDC–net (as a separate and independent module) to the messaging application to make it an anonymous message exchanging application (see Fig. 10.1). In this scenario, HSDC–net delivers the SMV to the messaging application in which the other users' messages are placed in such a way that the origin of each message is anonymous.

The proposed protocol is performed in three phases (1) *Initialization*, (2) *Scheduling*, and (3) *Message Publishing* (MP). In the scheduling phase, after the protocol initialization, the available N slots are anonymously allocated to the users. Then, they publish their messages by continuously executing the MP phase. In the following, we present each phase individually and in the order that they are performed.

Initialization

In this phase, all the N users in the group execute an initialization algorithm individually. Considering user u_1, this algorithm takes as input the user vector $U = [u_2 \ \ u_3 \ \ldots u_N]$ and generates the following items in collaboration with the users specified in U:

- A matrix of pairwise symmetric keys $\mathbf{K}_1^{(0)} = \begin{bmatrix} \mathbf{K}_{12}^{(0)} \\ \mathbf{K}_{13}^{(0)} \\ \cdots \\ \mathbf{K}_{1N}^{(0)} \end{bmatrix}$,

  in which $\mathbf{K}_{1j}^{(0)} = [\mathbf{k}_{1j}^{(0)}(1) \ \ \mathbf{k}_{1j}^{(0)}(2) \ \ldots \ \mathbf{k}_{1j}^{(0)}(N)]$, where $\mathbf{k}_{1j}^{(0)}(w)$, $(w = 1, 2, \ldots, N)$ is an L–bit secret symmetric key that u_1 shares with u_j $(j = 2, 3, \ldots, N)$ to use in slot w.

- Vector $R_1 = [r_{12} \ \ r_{13} \ \ldots r_{1N}]$, where r_{1j} is a random integer number shared secretly between users u_1 and u_j.

Moreover, by executing this algorithm, each user u_i signs the following two items using his/her private key and sends them to user u_j $(j = 1, 2, \ldots, N, j \neq i)$ (we assume every user has adopted a public/private key pair and already published his/her public key in the network):

- The jth row of matrix $\mathbf{K}_i^{(0)}$ (i.e., $\mathbf{K}_{1j}^{(0)}$ for user u_1).

- The jth element in R_i (i.e., r_{ij}).

We will use these signatures for disruption management.

Scheduling Phase

In this phase, every user u_i performs the SR sub–protocol that is executed in the following steps:

(1) u_i creates vector $\mathbf{S}_i = [\mathbf{S}_i(1) \;\; \mathbf{S}_i(2) \ldots \mathbf{S}_i(N)]$, in which every element consists of L zero bits (i.e., $\mathbf{S}_i(w) = \mathbf{0}$ for $w = 1, 2, \ldots, N$).

(2) Two random integer numbers l and n are selected by u_i in $[1, L]$ and $[1, N]$, respectively. Then, the lth bit in $\mathbf{S}_i(n)$ is set to 1 to obtain $\mathbf{S}_i^{'}$ (assuming $\mathbf{S}_i^{'}$ is a single bit–stream, it has only a single bit 1 in the position $l + (n-1)L$).

(3) u_i computes and publishes the following vector $\mathbf{Z}_i$:

$$\mathbf{Z}_i = [\mathbf{Z}_i(1) \;\; \mathbf{Z}_i(2) \ldots \mathbf{Z}_i(N)],$$

where $\mathbf{Z}_i(w) = [\oplus_{\substack{j=1 \\ j \neq i}}^{N} \mathbf{k}_{ij}^{(0)}(w)] \oplus \mathbf{S}_i^{'}(w)$,$w = 1, 2, \ldots, N$.

(4) Upon receiving $N-1$ vector $\mathbf{Z}_j$ ($j = 1, 2, \ldots, N, j \neq i$) from the other users (who performed the same procedure), u_i computes vector $\mathbf{V} = [\mathbf{V}(1) \;\; \mathbf{V}(2) \ldots \mathbf{V}(N)]$, in which $\mathbf{V}(w) = \oplus_{i=1}^{N} \mathbf{Z}_i(w)$. Note that $\mathbf{V}(w) = \oplus_{i=1}^{N} \mathbf{S}_i^{'}(w)$ because the terms related to the pairwise keys are cancelled out when they are XORed together. Thus, if we consider vector $\mathbf{V}$ as a single bit stream, it shows all the 1 bits set by the users (in step 2) placed in their primary positions (see Fig. 10.2). (5) u_i computes the hamming weight of $\mathbf{V}$, i.e., $H = Hamming(\mathbf{V})$ that indicates how many bits 1 exist in $\mathbf{V}$. Based on the obtained H, two situations are supposable:

- If $H = N$, there is no collision and every user has selected a unique slot. In this case, (considering $\mathbf{V}$ as a single bit stream) u_i highlights his/her selected 1 (set in step 2) in $\mathbf{V}$, keeps all the 1s and removes all the 0s of $\mathbf{V}$ (Fig. 10.2). This results in a bit stream of size N in which all the N bits are 1. In this bit stream, the bit number associated with the position in which the highlighted bit 1 has been placed is the slot assigned to u_i.

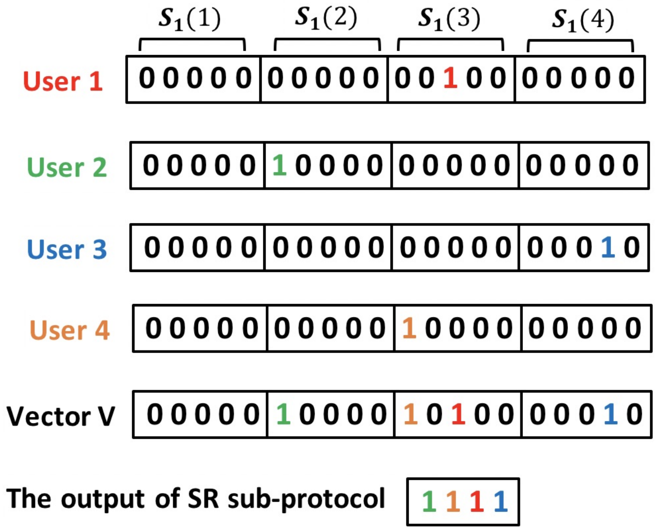


Figure 10.2 : A simple illustration of SR performance.

- If $H \neq N$, it means two or more users have selected the same random numbers l and n in step 2. In this case, the SR sub–protocol needs to be restarted. However, to protect users against the DC–net short stability issue, we need to change the users' pairwise keys. To do this, every user u_i changes his/her symmetric keys $\mathbf{K}_i^{(0)}$ to $\mathbf{K}_i^{(1)}$ by adding r_{ij} to all the elements in the jth row of $\mathbf{K}_i^{(0)}$, $(j = 1, 2, \ldots, N, j \neq i)$. Using this technique, users can non–interactively obtain a new set of pairwise keys without imposing any further communication overhead.

As you see, we consider $\mathbf{S}_i^{'}$ as a single LN–bit vector in which every bit represents a slot. By doing this, the N users have LN slots to select from instead of only N slots. This can reduce the probability of collision to a negligible level if L is a relatively large number.

Message Publishing (MP) Phase

After the N available slots of SMV are allocated to the N users in the scheduling phase, every user u_i can anonymously publish his/her messages. This can be done by performing the original DC–net protocol. However, as discussed before, the short stability issue must be addressed first. For this reason, we propose Stable DC–net (SDC-net) that addresses this issue.

Stable DC-net (SDC-net): In SDC–net, users change their pairwise keys before they start a new round of the MP phase (publishing a new message is done with a new set of pairwise keys). This makes the elements of $\mathbf{Y}_i^{(p)}$ dissimilar for different rounds ($p = 0, 1, 2, \ldots$).

Suppose u_i wants to publish his/her message $\mathbf{m}_i^{(p)}$ in round p of the MP phase. To change his/her pairwise keys, u_i simply adds r_{ij} (which has been secretly shared with user u_j in the initialization phase) to all the elements in the jth row of $\mathbf{K}_i^{(p-1)}$ ($j = 1, 2, \ldots, N, j \neq i$). This results in $\mathbf{K}_i^{(p)}$ which is a set of different keys in comparison to $\mathbf{K}_i^{(p-1)}$. Therefore, by applying a different set of keys in equation 9.1, a different XK vector $\mathbf{X}_i$ is obtained in each round of MP that makes $\mathbf{Y}_i^{(p)}$ completely dissimilar to $\mathbf{Y}_i^{(p-1)}$. Note that, the new sets of pairwise keys are obtained by the users without imposing any further communication overhead to the protocol.

Now, let's return back to explain the MP phase. In round p of this phase, user u_i publishes message $\mathbf{m}_i^{(p)}$ by invoking algorithm $SDC - net(U, \mathbf{K}_i^{(p)}, \mathbf{m}_i^{(p)}, slt_i)$. This algorithm takes as input, the vector U of $N - 1$ users, matrix of pairwise keys $\mathbf{K}_i^{(p)}$, user's message $\mathbf{m}_i^{(p)}$, and the slot number assigned to u_i. The output of this algorithm is the $\mathbf{Y}_i^{(p)}$ vector that its elements are obtained using equation 10.1 and 10.2:

$$\mathbf{y}_i^{(p)}(w) = \oplus_{\substack{j=1 \\ j\neq i}}^{N} \mathbf{k}_{ij}(w),\ \ for \ \ w = 1, 2, \ldots, N, w \neq slt_i, \tag{10.1}$$

and

$$\mathbf{y}_i^{(p)}(slt_i) = \mathbf{m}_i^{(p)} \oplus (\oplus_{\substack{j=1 \\ j\neq i}}^{N} \mathbf{k}_{ij}(slt_i)) \tag{10.2}$$

Similar to DC–net, every user is able to obtain the SMV by XORing the received

$N-1$ vector $\mathbf{Y}_j^{(p)}$ $(j=1,2,\ldots,N, j\neq i)$ with his/her own vector $\mathbf{Y}_i^{(p)}$, i.e.:

$$SMV^{(p)} = \oplus_{i=1}^{N}\mathbf{Y}_i^{(p)} \tag{10.3}$$

As we mentioned before, users' messages are shuffled in SMV such that the origin of each message is unknown.

Disruption Management

As we discussed before, the original DC–net protocol is jammed if one or more users perform dishonestly. Since misbehaviours of dishonest users are inherently unavoidable, protecting DC–net against disruptions and jamming attacks is difficult and imposes additional time and communication overheads on the protocol [46], [52]. Therefore, creating accountability is a good solution to address this issue.

After a disruption is detected (if the users' messages in SMV have been corrupted), assuming the disruption is detected in round p, the following steps are performed by every user u_i who detects the disruption:

1) u_i publicly informs other users that his/her message in slot slt has been corrupted (note that revealing slt does not jeopardize u_i's anonymity since other users cannot see his/her real message which has been corrupted).

2) Upon receiving u_i's announcement, other users publish the set of their keys related to this slot, i.e., u_j $(j=1,2,\ldots,N, j\neq i)$ publishes $\{\mathbf{k}_{jl}^{(p)}(slt)\}_{\substack{l=1\\ l\neq j}}^{N}$.

3) Every user u_j checks the other users' published keys to see if a user (say u_l) has published a key different than their shared pairwise key $\mathbf{k}_{jl}^{(p)}$.

4) If u_j (in step 3) finds that user u_l has published a key different than their shared pairwise key (i.e. $\mathbf{k}_{jl}^{(p)}$), he/she announces u_l's identity as the disruptor. To support his/her claim, u_j publishes u_l's signature on the real $\mathbf{k}_{jl}^{(p)}$ and r_{jl} received during the initialization phase.

5) u_i computes $D_j = \oplus_{\substack{l=1 \\ l \neq j}}^{N} \mathbf{k}_{jl}^{(p)}(slt)$ for $j \neq i$.

6) If $D_j \neq \mathbf{Y}_j^{(p)}(slt)$, u_j's identity is published by u_i as the disruptor. Other users can also confirm this by computing D_j and comparing it with $\mathbf{Y}_l^{(p)}(slt)$.

7) The messaging application is notified by sending the identity of the disruptor(s).

After the identity of disruptor(s) is publicly announced, the users can resume the protocol, this time by excluding the disruptor(s). To do this, they need to update their matrix of pairwise symmetric keys $\mathbf{K}_i^{(p)}$ by eliminating the row(s) associated with the disruptor(s). However, they do not need to perform the initialization phase and set up new pairwise keys as the previous keys are still valid.

Multiple Reservations

In HSDC–net, it is possible that a user reserves more than one slot in the scheduling phase. The reason is that during the scheduling phase, the users have LN slots to select from which is much larger than the number of users in the group, i.e. N, specifically, if L is a large number. This is an advantage for users with a high activity rate that need to publish more messages during a single cycle. To reserve B slots ($B > 1$) when performing the SR sub–protocol, a user needs to repeat step 2 of SR for B times. Note that in this case, the users' XK vectors and SMV have $N + A(B - 1)$ elements (or slots), where A is the number of users who reserve B slots. On the other hand, it is required to consider an upper limit on the number of slots that every user can reserve. This protects the protocol from performance degradation caused by collisions.

10.3 Results

This section presents a comprehensive security analysis of the proposed HSDC–net protocol and discusses the results of our prototype implementation.

10.3.1 Security Analysis

In this section, we show how the proposed protocol performs against different security threats. The target of these security threats can be either deanonymizing users' messages or disrupting the protocol performance.

DoS attacks on SR sub–protocol: Suppose a malicious user u_D reserves many slots by setting the majority (or all) of vector $\mathbf{Z}_D$'s bits to 1. This results in many collisions during the scheduling phase. According to our experimental results, using the SR sub–protocol, the maximum number of SR restarts is 2, which can be considered as a threshold to decide on a DoS attack. When a DoS attack is detected during the scheduling phase, the DM sub–protocol is invoked which outputs the identity of disruptor(s). Then, after u_D is excluded from the list of peers, the honest users can resume the protocol.

Collusions: Consider N_C colluding users $(u_{c,1}, u_{c,2}, \ldots, u_{c,N_C})$ who want to deanonymize the messages of a specific user u_v. For this reason, they join the group of which u_v is a member, such that the final group size is N $(N > N_C)$. Moreover, the N_C colluding users share their matrix of pairwise keys (i.e., $\mathbf{K}_i^{(0)}$) along with their random vector R_i. To deanonymize u_v's messages in round p, they need to compute u_v's XK vector $\mathbf{X}_v^{(p)}$, compare it with the received $\mathbf{Y}_v^{(p)}$, and obtain $\mathbf{m}_v^{(p)}$. They can compute $A_1(w) = \oplus_{j=1}^{N_C} \mathbf{k}_{v,j}^{(p)}(w)$ $(w = 1, 2, \ldots, N)$ since they have already shared their matrix of pairwise keys and random vector R. Thus, by using Equation 9.1, they start to build $\mathbf{X}_v^{(p)}$:

$$\mathbf{x}_v^{(p)}(w) = \mathbf{A}_1(w) \oplus \mathbf{A}_2(w), \quad w = 1, 2, \ldots, N,$$

where $\mathbf{A}_2(w) = \oplus_{j=N_C+1}^{N} \mathbf{k}_{v,j}^{(p)}(w)$.

As you see, they need to have $A_2(w)$ to obtain each $\mathbf{x}_v^{(p)}(w)$ for $w = 1, 2, \ldots, N$. However, computing $A_2(w)$ requires the knowledge of pairwise keys $\mathbf{k}_{v,j}^{(p)}$ $(j = N_C + 1, N_C{+}2, \ldots, N)$ shared between u_v and the non–colluding users $(u_{N_C+1}, u_{N_C+2}, \ldots, u_N)$.

Hence, the attack is defeated since $A_2(w)$ is unknown to the colluding users. Furthermore, by employing a group entry control mechanism (like the one proposed in [39]), we can prevent malicious users from setting up large size collusion groups.

Node Failures: Suppose user u_o becomes offline while the protocol is being performed. This prevents the other users from computing SMV using Equation 10.3 because u_o is no longer broadcasting his/her vector $\mathbf{Y}_o$. In this case, the remaining users can easily exclude u_o and resume the protocol. To do this, assuming u_o is disconnected at round p, every user u_i needs to exclude his/her keys shared with u_o (i.e. $\{\mathbf{k}_{io}^{(p)}(w)\}_{\substack{w=1 \\ w \neq i}}^{N}$) from Equations 10.1 and 10.2 before computing his/her $\mathbf{Y}_i$ vector. In other words, the users must remove the row associated with u_o from their matrix of pairwise symmetric keys $\mathbf{K}_i^{(p)}$ to be able to perform the next rounds of the protocol. However, they do not need to perform the initialization phase and set up new pairwise keys as the previous keys are still valid.

10.3.2 Performance Evaluation

In this section, we evaluate the performance of HSDC–net and present the results of our prototype implementation. In our evaluations, we consider Twitter, Facebook Messenger, and Instagram. We conducted our experiments based on the maximum number of characters per message allowed in these applications. For Twitter, the maximum number of characters in a tweet has recently increased from 140 to 280 characters. However, this value is 500 and 2000 characters for Instagram and Facebook Messenger, respectively. We considered 2 bytes of data per character on average, as UTF–8 coding system is used by these applications.

Implementation

We developed a prototype implementation of HSDC–net to evaluate its deployment in microblogging applications. The implementation is written in *Python* and

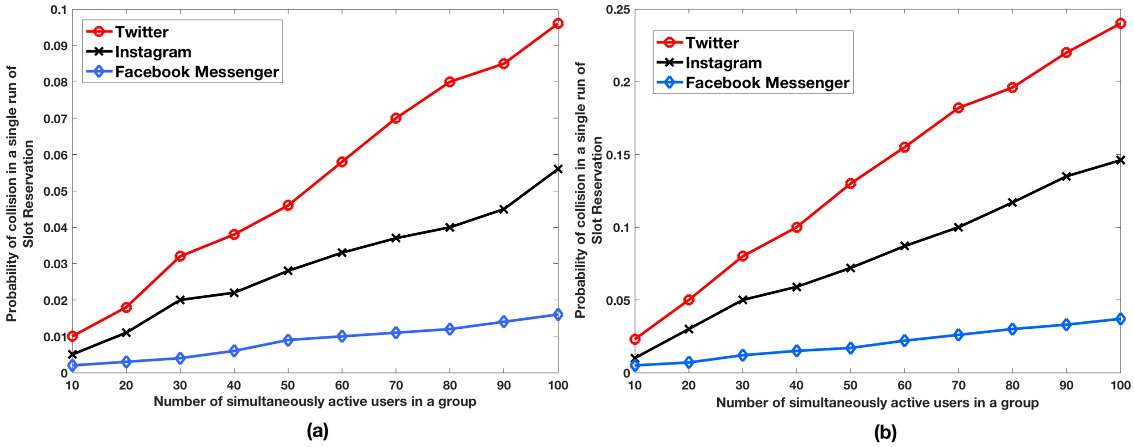


Figure 10.3 : Probability of collision after a single run of SR for (a) $B = 3$ and (b) $B = 5$.

uses OpenSSL 1.1.0 for eliptic curve DSA signatures and PKI operations. We used the Deterlab [63] infrastructure to test the prototype under realistic network conditions. Deterlab provides a shared testbed for distributed protocols and enables us to easily change network topology and node configurations.

Setup: The testbed topology that we used in Deterlab consists of three 100 Mbps LANs with 10 ms latency between the core switches and clients. The three LANs are connected together using 10 Mbps links with 20 ms latency. We executed the protocol for 5 to 50 clients. Two types of client machines were used for the experiments: 3GHz Intel Xeon Dual Core with 2GB of RAM and 2.13 GHz Intel Xeon CPU X3210 Quad Core with 4GB of RAM.

Evaluation

Collisions: Fig. 10.3 shows the probability of collision for different values of the number of simultaneously active users and the scheduling overhead efficiency factor B. Collisions are more likely to occur for larger values of B that shows a sensible trade–off between collision probability and the efficiency factor B. Note that the values of collision probability shown in the figures have been obtained based on only

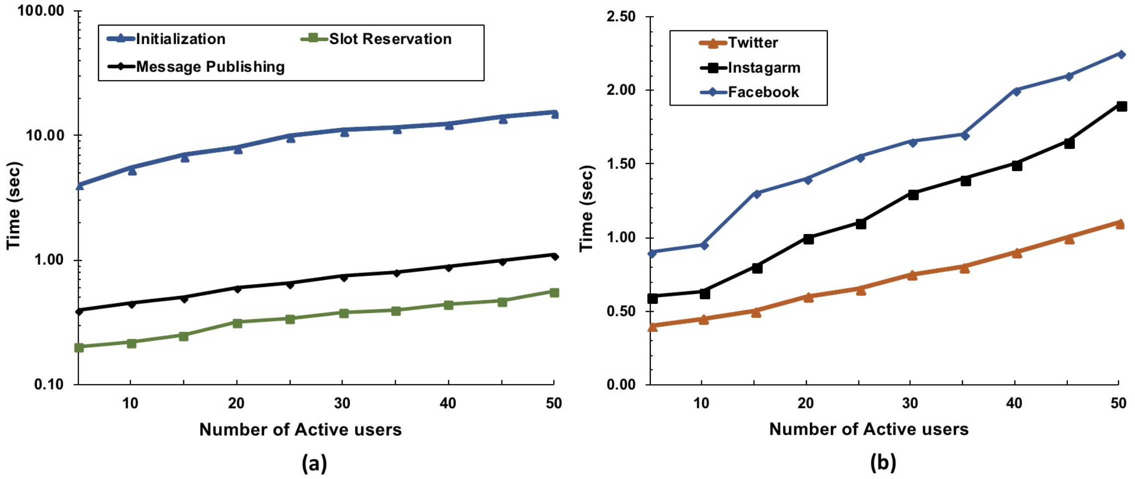


Figure 10.4 : (a) Time required to initialize the protocol, reserve a slot, and perform one cycle of anonymous message publishing. (b) End–to–end latency to publish an anonymous post.

a single run of the scheduling phase. However, we noticed that even for larger values of B, almost 100% of the slots for the next B MP cycles are successfully allocated in at most two runs of the scheduling phase.

Latency: Fig. 10.4 (a) shows the time required to perform the three phases of HSDC–net. In this figure, the shown results are for the scenario in which the clients publish messages of length 560 bytes (the maximum size of a single tweet on average). Large values of N result in larger XK vectors that make the system slower. Note that the illustrated time required for performing the message publishing phase includes the time needed for a single run of the SR sub–protocol. For example, considering $N = 50$, it takes 1.1 sec for the clients to anonymously publish a tweet in the group. 0.56 sec of this time is spent on the slot reservation phase. The end–to–end latency to publish an anonymous post is illustrated in Fig. 10.4 (b) for Twitter, Instagram, and Facebook Messenger. Twitter has the quickest responses since it has the smallest XK vector.

The time required to reserve B slots in a single run of the SR sub–protocol is

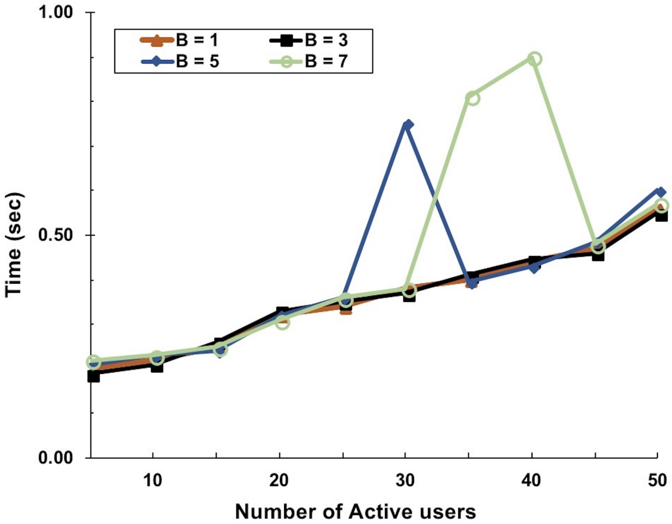


Figure 10.5 : Time required to reserve B slots in a single run of SR for different values of B

shown in Fig. 10.5. As the figure indicates, for $B = 1$ and $B = 3$ only a single run of SR is required to reserve B slots. However, some collisions have occurred for $B = 5$ and $B = 7$ in larger values of N that caused the SR sub–protocol to be restarted.

Finally, in Fig. 10.6, the end–to–end latency of HSDC–net and some of the most well–known anonymity protocols are compared. As you see, HSDC–net outperforms Dissent [38] and Verdict [46] protocols in terms of speed. The reason is that the SR and MP phases in HSDC–net are performed using simple and lightweight operations i.e. XOR and SUM. However, in Dissent and Verdict, heavy–duty tasks are performed for public–key encryption/decryptions and zero–knowledge proofs. Note that the latency of HSDC–net will be shorter if we have $B > 1$ because in this case only a single run of SR is required for B consecutive cycles of message publishing.

Communication overhead: We also examined the maximum possible size of the XK vector for Twitter, Facebook Messenger, and Instagram. Considering 50 users who publish their messages simultaneously in a group, the maximum size of an XK vector is obtained 27, 49, and 195 KB, for these applications, respectively.

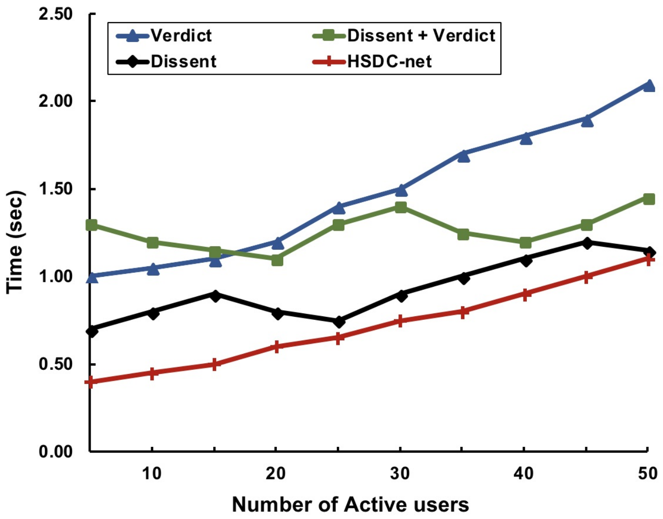


Figure 10.6 : End–to–end latency to anonymously publish a tweet for HSDC–net and some well–known anonymity schemes.

These values are quite practical since they are in range of the average size of an ordinary email that is 75 KB. Note that, realistically, N is the number of users that want to simultaneously publish their messages not the maximum number of a group's members. Thus, the real group size can be much larger than N.

10.4 Conclusion

In this chapter, we reviewed the anonymity issue in social networks and proposed HSDC–net, a self–organizing and accountable protocol for anonymous communications. It addresses the three issues from which the original DC–net protocol suffers, i.e., short stability, collision possibility, and vulnerability to disruptions. We first extend DC–net to Stable DC–net (SDC–net) to solve the short stability issue. To address the collision issue, we integrated the Slot Reservation sub–protocol into SDC–net, by which users can reserve slots before they start to publish their messages. Our experimental results show that the probability of collisions are significantly reduced. Finally, to handle disruptions, we proposed Disruption Management sub–protocol and integrated it into SDC–net.

In the next chapter, we introduce our second anonymity–based solution for privacy preservation in location–based services and social networks.

Chapter 11

A Hybrid Location Privacy Protection Scheme in Big Data Environment

11.1 Introduction

In this chapters we explore location privacy in location–based services (LBS) and proposes a hybrid location privacy protection scheme for users. Indeed, location privacy is a significant challenge of LBS. Particularly, by the advantage of big data handling tools that are easily available, huge location data can be managed and processed easily by an adversary to obtain user private information from LBS. So far, many methods have been proposed to preserve location privacy of users in these services. Among them, dummy–based methods have various advantages in terms of implementation and low computation costs. However, they suffer from the spatiotemporal correlation issue when users submit consecutive requests. In this chapter, we investigate this issue and propose a practical dummy–based location privacy protection scheme to address it. The proposed method filters out the correlated fake location data (dummies) before submissions. Therefore, the adversary can not identify the user's real location. Evaluations and experiments show that our proposed filtering technique significantly improves the performance of existing dummy–based methods and enables them to effectively protect the user's location privacy in the big data environment.

11.2 Background

With the recent huge advance in technology, we are now facing the age of big data. According to the IBM report* we create 2.5 quintillion bytes of data every day, and 90% of the data in the world today has been created in the last two years alone. This data comes from sensors, social media sites, emails, digital pictures and videos, and different mobile applications. Among these applications, Location-Based Services (LBS) have a significant and growing impact on big data since they produce a large number of location data every day [104–105]. These location data have three dimensions, personal, spatial and temporal, indicating a user's location at a specific time. Location–Based Service Provider (LSP) uses these data to provide information, such as the nearest ATM, restaurant, or a retail store.

However, a significant challenge for LBS is how to protect users location privacy. Since LSPs store location data of users, it is feasible that an adversary at LSP obtains private information about a user by analysing her position data. Even if a user's name or ID is hidden or pseudonyms are used, it has been shown that privacy may be invaded by analysing position data only [4], [106]. Hence, it is necessary to develop a location privacy preserving system to prevent LSPs from obtaining the user's real location.

Many methods have been proposed to achieve this goal [4], [12], [75–76], [79]. These methods can be categorized in different ways. In [79], they have been categorized as *Spatial Anonymization*, *Obfuscation*, and *Private Retrieve* methods. However, in [14] they have been classified from a different point of view as *Dummy–based*, *K–Anonymity*, *Differential Privacy* and *Cryptography–based* methods. Regardless how we classify them, they all have a common goal: to protect user's location privacy while at the same time user benefits from advantages of the service.

*https://www.ibm.com/software/data/bigdata/what-is-big-data.html

Each of the aforementioned methods has its own strengths and weaknesses. But among them, dummy–based methods have drawn the attention of researchers due to their unique features ([4], [12], [10–11], [14–16]). In dummy-based methods, in addition to the user's real location, some fake location data (dummies) are sent to LSP by the user as a service enquiry. This prevents the adversary from distinguishing the user's real location. LSP then provides the requested information to the user, who can easily extract her own required information among them and ignores the others. The most important advantage of dummy–based methods is that they do not rely on a trusted third party anonymizer. Moreover, users do not need to encrypt the requests. Thus, there is no need to share a key between the LSP and users.

However, for some LBS in which users send requests continuously, such as route navigation applications, it has been shown that dummy–based methods suffer from a crucial restriction, which has been named as the *spatiotemporal correlation issue* [14]. When a user sends consecutive service queries, there is always two types of correlation between neighbouring location sets, i.e., space and time correlations. In Fig. 11.1, we show an example of these correlations. As we can see in the diagram, there are two consecutive location data, each one consisted of the user's real location and four dummies. Although dummy D'_3 in the second location set is geographically close to other dummies and the user's real location, it isn't reachable in the request time interval since there is a river between them. Hence, the adversary can exploit this time correlation and identify it as a fake location data. Moreover, you can see that D'_4 is not in the same direction with other dummies and the real location. Thus, the adversary can identify it as a dummy because it is separated from the trajectory, especially when we consider more consecutive requests.

Experiments in [14] indicated that the existing dummy–based schemes can protect user location privacy with no more than 42% success ratio when users send consecutive requests. To solve the mentioned problem, a spatiotemporal correlation–

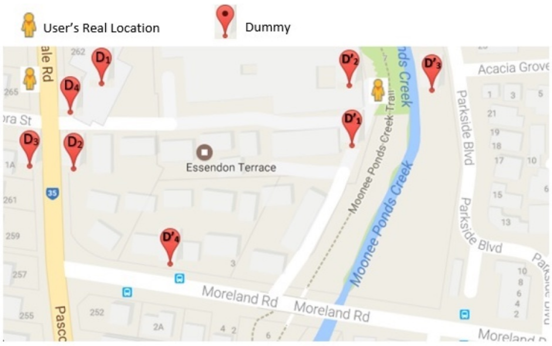


Figure 11.1 : The concept of Spatiotemporal correlation issue between 2 neighbouring location sets.

aware scheme has been proposed in [14], in which correlated dummies are identified and prevented from transmission to LSP. This makes the neighbouring submitted location sets uncorrelated. Therefore, the adversary can't increase the probability of distinguishing the real location by identifying dummies and ignoring them.

The proposed scheme in [14] has well identified and addressed the spatiotemporal correlation issue. However, the scheme can only solve the problem under some conditions. To solve this issue, a new filtering technique is presented in this chapter which enables users to filter out spatiotemporal correlated dummies. It works with the existing dummy–based methods to generate initial candidate dummies. Then, it examines the generated dummies in terms of time and space correlations and filters out the corrolated ones. It guarantees that only uncorrelated dummies are submitted to the LSP. Unlike [14], our proposed technique can prevent the adversary from identifying dummies without the limitations which [14] has while enjoys all of its advantages.

11.3 Assumptions and Definitions

Table 11.1 summarizes the notations to be used throughout the chapter. The system architecture that we adopt is a client–server model (see Fig. 11.2) in which

Table 11.1 : Summary of Notation

Symbol	**Meaning**
K_i	User location privacy requirement number
l_i^j	jth dummy generated at ith service request
l_i^r	User's real location at ith request
T_i	Time at which ith location is sent to LSP
L_i=$\{l_i^1$, l_i^2,. . . , $l_i^{K_i-1}$, $l_i^r\}$	Location set at ith service request
$< l_{i-1}^r$, $l_i^r >$	The real movement path

no trusted third–party is required. LSP is assumed to be untrusted and knows what location privacy protection algorithm the user runs. Also, we assume that LSP has enough public side information about the requesting region (e.g., he has a detailed map of the region), therefore, he can utilize the spatiotemporal correlation between neighbouring location sets to identify the user's real location.

At ith service request, the algorithm generates K_i-1 dummies, (l_i^1, l_i^2 ,. . . , $l_i^{K_i-1}$), and the location set L_i is formed by adding the user's real location l_i^r to dummies. Then, as we can see in Fig. 11.2, L_i is submitted by the user to LSP at time T_i . LSP processes the request and sends the requested information back to the user including K_i service query results. Finally, the user picks up her own query result and ignores the others.

11.3.1 User's Location Privacy Requirement

If we define K_i as the parameter which reflects the user's location privacy requirements, then the adversary must not be able to identify the user's real location with a probability greater than $1/K_i$. We define this as the minimum User's Location Privacy Requirement (ULPR). Therefore, in order to satisfy it, the user must

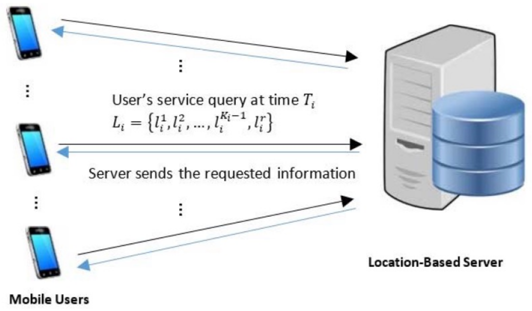

User's service query at time T_i
$L_i = \{l_i^1, l_i^2, \ldots, l_i^{K_i-1}, l_i^r\}$
Server sends the requested information
Location-Based Server
Mobile Users

Figure 11.2 : Our proposed system architecture. Unlike K–Anonymity methods, there is no need to have a trusted third–party anonymizer.

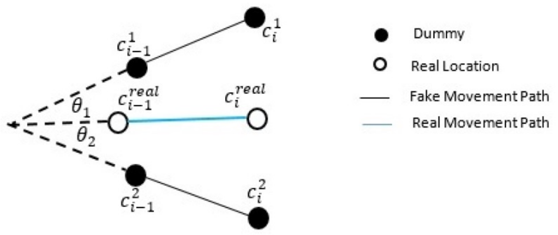


Figure 11.3 : An example of two neighbour location sets at time T_{i-1} and T_i.

send at least K_i-1 uncorrelated dummies with the real location to LSP.

11.3.2 Analysis of a Correlation–Aware Scheme

The spatiotemporal correlation–aware privacy protection scheme presented in [14] uses a Direction similarity filter to make sure that all dummies are in the same direction with the real movement path, and hence are not correlated in terms of space. To do this, the algorithm filters out those fake movement paths which have an angle with the real movement path larger than a threshold, which is designed as follows:

$$\forall l_i \in L_i, \exists l_{i-1} \in L_{i-1} : \angle[(l_{i-1}, l_i), (l_{i-1}^r, l_i^r)] \leq \sigma_A \ , \tag{11.1}$$

where symbol $\angle$ denotes the angle between the fake and real movement paths and σ_A is a threshold angle defined by the user.

The problem here is that if an adversary chooses σ'_A so that $\sigma'_A{<}2\sigma_A$ (the adversary doesn't know σ_A since it is a user–defined value), the algorithm cannot satisfy the minimum ULPR, because if the adversary calculates the angle between any pair of the movement paths, he can identify those pairs which have an angle larger than σ'_A as the fake movement paths. For example, in Fig. 11.3 the angle between 2 fake movement paths is $\theta_1{+}\theta_2$. According to (1), both θ_1 and θ_2 are smaller than σ_A, so we have

$$\theta_1 + \theta_2 \leq 2\sigma_A \tag{11.2}$$

Therefore, if the adversary chooses σ'_A so that $\sigma'_A{<}2\sigma_A$, then he concludes that both movement paths are fake because the angle between them is larger than the threshold and none of them can be the real movement path. In such cases the minimum ULPR is not satisfied because some dummies are identified by the adversary, and he can distinguish the user's real location with a probability greater than $1/K_i$. Hence the scheme proposed in [14] works for $\sigma'_A{>}2\sigma_A$ only.

In the next section, our new filtering technique is presented which simulation results show that it can successfully solve this problem.

11.4 The Hybrid Scheme

Our proposed scheme can work with any existing dummy generation methods. After dummies generated, they are passed through a three–stages filter to eliminate the spatiotemporal correlated dummies and hence satisfy the minimum ULPR (by submitting at least $K_i - 1$ uncorrelated dummies with the real location to LSP). We have chosen the last stages of our proposed filter same as Time Reachability and In–degree/Out–degree filters presented in [14]. But we have developed a new filtering technique for the first stage.

11.4.1 Direction Filter

This is the first filter that dummies are applied to. The goal of this filter is to eliminate the spatial correlation between neighbouring location sets. This is done by the direction filter which makes sure that each dummy has at least one movement path in the same direction with the real movement path. Therefore, there are at least $K_i - 1$ spatially uncorrelated dummies at the output of this stage. The filtering rule is defined as

$$\begin{cases} \forall l_i \in L_i, \exists l_{i-1} \in L_{i-1} : \\ \theta_{min} \leq \angle[(l_{i-1}, l_i), x\ axis)] \leq \theta_{max} \\ \forall l_{i-1} \in L_{i-1}, \exists l_i \in L_i : \\ \theta_{min} \leq \angle[(l_{i-1}, l_i), x\ axis)] \leq \theta_{max}, \end{cases} \tag{11.3}$$

where θ_{min} and θ_{max} are calculated through (4):

$$\begin{cases} \theta_{max} = (j+1)\frac{2\pi}{K_i}; \\ \theta_{min} = j\frac{2\pi}{K_i} \end{cases} for\ \ j\frac{2\pi}{K_i} \leq \theta_i^r \leq (j+1)\frac{2\pi}{K_i} \tag{11.4}$$

$j = 0, 1, 2, \ldots, K_i - 1,$

where θ_i^r is the angle between the real movement path and x axis at ith service request and $[\theta_{min},\theta_{max}]$ is the angle range that selected dummies can have.

The algorithm not only checks the current dummies, but also checks the previous location data which have already submitted to the LSP. This is because all dummies in the previous location set must have at least one movement path with the same direction as the real movement path's direction. Otherwise the related dummy will be identified by the adversary as a detached point since there is no movement path leaves it in the same direction with other movement paths. Unlike [14], there is no need to use a user–defined parameter like σ_A which adds some side information to the adversary's knowledge.

11.4.2 Time Reachability Filter

After that space correlation between neighbouring dummies has been removed in the first stage, time reachability filter checks the reachable time of every possible movement path formed between the existing dummies and the previous location set. Every movement path which is unreachable in the request time interval $T_i - T_{i-1}$ is eliminated by this filter. Therefore, the adversary is no longer able to identify fake movement paths from their unusual reachable time. In fact, this filter guarantees that every dummy has at least one movement path which is reachable in the request time interval. Thus, all dummies which pass this filter and the user's real location have same entropy in terms of time reachability.

After this stage, there must be at least $K_i - 1$ dummies to satisfy the minimum (ULPR), otherwise (in case that more than $M - K_i + 1$ dummies are filtered where M is the total number of initial dummies) the dummy generation algorithm will be re–invoked to generate another initial dummy set and the algorithm will be restarted.

11.4.3 Detached/Hub Filter

This filter has the same structure as In–degree/Out–degree filter in [14] has. The dummies finally are applied to this filter to make sure that:

- There is at least one movement path for each dummy (there is no detached dummy which has no possible movement path starts from or ends at it).
- There is at least one dummy with larger number of movement paths than what the real location has. (If the real location has the most number of movement paths, it is identified by the adversary since it is a movement hub [14])

Again, at the end of this stage, we must have at least $K_i - 1$ dummies to satisfy the minimum ULPR. In fact, the last stage completes the performance of other two stages and if in any of the previous stages a dummy has been detached (due to eliminating its movement paths) or if the real location has become the movement hub, the detached/hub filter will sort it out and eliminate this additional information which can be exploited by the adversary to identify the user's real location.

11.5 Analysis on the proposed scheme

The adversary is assumed to be able to store and analyse the user's location data in order to obtain some private information about the user. We assume a location privacy protection scheme to be secure if it can satisfy the minimum ULPR.

If our scheme is adopted by a user to protect her location privacy, she submits her query to LSP includes her real location and at least $K_i - 1$ dummies. Since all dummies have already passed through direction, time reachability and detached/hub filters, there is no spatiotemporal correlation between the dummies, also, the movement paths formed by our proposed scheme are indistinguishable. In the other word, it can be said that:

1) For each dummy, there is at least one movement path which is reachable in the request time interval. So, totally, there are at least $K_i - 1$ different movement paths reachable in the request time interval. Hence, if the adversary wants to exploit any time correlation between neighbouring location data and choose one movement path as the real one, he will be successful with a probability of no more than $1/K_i$.

2) Through direction filter, only those dummies are selected to submit that at least one of their corresponding movement paths is in the same direction with the real movement path. Therefore, if the adversary tries to identify dummies by means of the space correlation between dummies, he has to choose one among K_i

uncorrelated location points which means the success ratio is not more than $1/K_i$.

So, our proposed scheme satisfies the minimum ULPR, hence, protects the user's location privacy effectively.

11.6 Performance Evaluation

11.6.1 Evaluation Setup

The algorithm has been implemented in Matlab on a Windows 7 laptop with 2.3 GHz Intel i5 CPU and 4GB memory. We use California Points of Interest[†] as a real dataset with 208,000 locations including restaurants, bars, shopping centers and hospitals. Also, we adopt the GridDummy algorithm [11] to generate dummies for consecutive requests over a real road map of Los Angeles city (source: TIGER/Line Files[‡]).

In our experiments, the user's location privacy requirement K is selected from the common range 3 to 20 and for simplicity we assume the user has same K_i in all the requests. Also, for each user we define a trajectory consisted of 11 real locations and 10 movement paths. The reachable time between consecutive locations are obtained from Google Map API.

We define the number of indistinguishable movement paths as the criteria to measure the level of location privacy protection. This is because the larger number of indistinguishable movement paths we have, the less likely the adversary can identify the user's real location among dummies.

[†] https://www.cs.utah.edu/ lifeifei/SpatialDataset.htm

[‡] https://www.census.gov/geo/maps-data/data/tiger-line.html

Table 11.2 : The Average number of dummy regenerations for different numbers of initial candidate dummies

Initial candidate dummies	**Average number of dummy regenerations**
$1.5K$	4
$2K$	1
$3K$	0
$4K$	0

11.6.2 Results

Fig. 11.4 shows the number of indistinguishable movement paths for each user location privacy requirement K. The baseline shows the minimum ULPR in which the adversary faces only K indistinguishable movement paths. As you see, our proposed algorithm has a significant distance with the baseline, especially in large amounts of K. For example, when K=20, the minimum ULPR is satisfied by only 20 indistinguishable movement paths. However, our proposed algorithm can form 98 indistinguishable movement paths on the average, which is much more than 18. Therefore, our proposed method always satisfies the minimum ULPR hence, protects the user's location privacy in consecutive requests with 100% success ratio.

Fig. 11.4 shows the case in which we have generated 1.5K dummies as the initial candidate dummies. The reason that we have not generated only K initial candidate dummies is that the algorithm may never be completed. In fact, in such cases, some of these K dummies are always filtered by the algorithm. Hence, we have less than K location data after filtering and consequently the algorithm is restarted continuously. Therefore, to guarantee the algorithm's convergence we must generate more than K initial candidate dummies. Also, choosing a larger number of initial

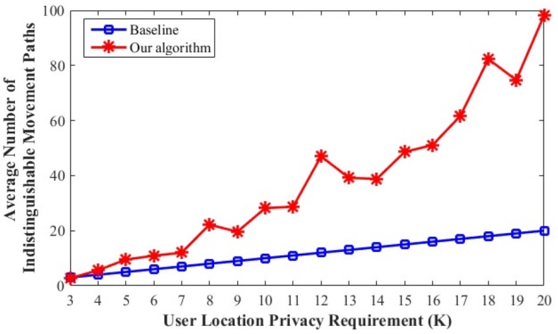


Figure 11.4 : Average number of indistinguishable movement paths for 1.5K initial candidate dummies.

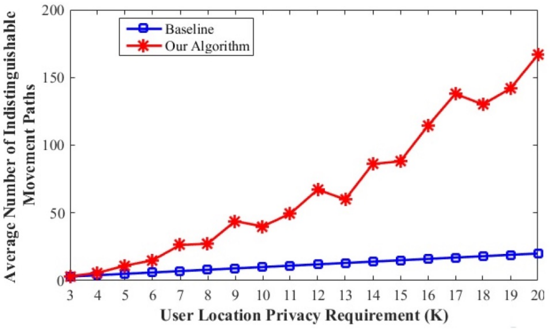


Figure 11.5 : Average number of indistinguishable movement paths for 3K initial candidate dummies.

candidate dummies causes more dummies at the output, thus more indistinguishable movement paths the adversary faces (Fig. 11.5) that means higher location privacy protection.

On the other side, by increasing the number of initial candidate dummies, the computation cost for filtering is increased though the number of dummy regenerations reduced. To find an optimum number of initial candidate dummies, we compare the average number of dummy regenerations for 1.5K, 2K, 3K and 4K number of initial candidate dummies in Table 11.2. As you see, by increasing the number of initial candidate dummies, the average number of dummy regenerations is reduced. This is obvious because if we have more initial candidate dummies it is more likely that we have at least K location data at the output and there is no need to regenerate dummies. But this decrease isn't significant from 2K to 3K an 4K. Thus, the optimum number for initial candidate dummies is 1.5K which is not too much to increase the computation cost and at the same time the number of dummy regenerations is in an acceptable level.

11.7 Conclusion

In this chapter, we proposed an enhanced filtering technique to improve the performance of dummy generation methods when users send consecutive requests in LBS applications. It eliminates the spatiotemporal correlation between neighbouring dummies before submitting them to the service provider. The proposed algorithm consists of 3 filters. Direction and Detached/Hub filters have been designed to eliminate the spatial correlation between neighbouring location sets. Moreover, Time filter eliminates those dummies which are correlated in time reachability factor. Security analysis show that our proposed scheme satisfies the minimum User's Location Privacy Requirement (ULPR). Also, experimental evaluations indicate that the proposed algorithm can significantly improve the user's location privacy by increasing the number of indistinguishable movement paths.

Chapter 12

Summary

12.1 Introduction

The recent advances in smartphone technology and positioning systems has enabled social network service providers to offer a variety of location–based applications and services for their users. In these applications, real–time location data of mobile users is utilised to provide requested information or access to a resource or service. However, preserving location privacy of users is a big challenge for the service providers since users share their location data either with other users or with a service provider.

In this regard, many research efforts have been made to address this issue. From our literature review, we found that differential privacy, as a promising framework, can be employed to develop reliable and efficient privacy preserving mechanisms in social networks. However, Anonymity and Cryptography–Based approaches have also been used in this domain. Each of the mentioned approaches has its own benefits and disadvantages as discussed in this thesis. In this chapter, we present a summary of the research work done in this study.

12.2 Conclusion

In this research study, we investigate the location privacy issue in social network and develop Distance–based Location Privacy Protection mechanism (DBLP2), a customisable location privacy protection approach that is uniquely designed for social network users. In DBLP2, the concept of social distance is utilised to generalise users' location data before it is published in a social network. The level of generalisation is decided based on the social distance between users. Furthermore, to preserve users' location privacy in location–based applications and services (the popular and fast growing social network applications), we propose three privacy–aware location verification schemes: (i) Privacy–Aware and Secure Proof Of pRoximiTy (PASPORT), (ii) Secure, Privacy–Aware and collusion Resistant poSition vErification(SPARSE), and (iii) a blockchain–based location verification scheme. They prevent dishonest users from conducting location spoofing attacks while protect location privacy of users. To the best of our knowledge, majority of the existing location verification schemes do not preserve location privacy of users.

Theoretical and experimental results show that DBLP2 mechanism provides the optimum data utility regarding the trade–off between privacy protection and data utility. In addition, our experimental results indicate that DBLP2 is offers variable location privacy protection and is resilience to post processing. Regarding the proposed SPARSE scheme, our analysis and experiments show that SPARSE provides privacy protection as well as security properties for users including integrity, unforgeability and non–transferability of the location proofs. Moreover, it achieves a highly reliable performance against collusions. To validate performance of the PASPORT scheme, we implement a prototype of the proposed scheme on the Android platform. Extensive experiments indicate that the proposed method can efficiently protect location–based applications against fake submissions. For the proposed blockchain–based scheme, our prototype implementation on the Android platform shows that the proposed scheme outperforms other currently deployed location proof schemes.

We also study the anonymity topic in social networks and utilise it as another solution to preserve users' privacy in social networks. In this regard, we

first study the relevant protocols and discuss their features and drawbacks. Then, we introduce Harmonized and Stable DC–net (HSDC–net), a self–organising protocol for anonymous communications in social networks. As far as we know, social networks do not offer any secure anonymous communication service. In social networks, privacy of users is preserved using pseudonymity, i.e., users select a pseudonym for their communications instead of their real identity. However, it has been shown that pseudonymity does not always result in anonymity (perfect privacy) if users' activities in social media are linkable. This makes users' privacy vulnerable to deanonymisation attacks. Thus, by employing a secure anonymous communication service, social network service providers will be able to effectively preserve users' privacy.

The proposed HSDC–net protocol addresses the three issues from which the original DC–net protocol suffers, i.e., short stability, collision possibility, and vulnerability to disruptions. We first extend DC–net to Stable DC–net (SDC–net) to solve the short stability issue. To address the collision issue, we integrated the Slot Reservation sub–protocol into SDC–net, by which users can reserve slots before they start to publish their messages. Our experimental results show that the probability of collisions are significantly reduced and they are totally avoided after at most two runs of SR. Finally, to handle disruptions, we proposed Disruption Management sub–protocol and integrated it into SDC–net. The results of our implementation show that HSDC–net achieves low latencies that makes it a practical protocol.

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