Using Hidden Markov Models to Improve Floor Level Localisation

Jean Kyle Alvarez*, Dinuka Abeywardena, Lei Shi and Sarath Kodagoda
Centre for Autonomous Systems, University of Technology, Sydney, Australia
{Jean.Alvarez, Dinuka.Abeywardena, Lei.Shi-1, Sarath.Kodagoda}@uts.edu.au

Abstract

The focus of this paper is on estimating the floor level of a robot/person moving in a multi-floor environment. It demonstrates how information about transitions between floors can be employed within a probabilistic framework to improve the accuracy of floor level estimation. This is achieved by combining a simple linear classifier with a Hidden Markov Model that captures the two basic motion patterns in a multi-floor environment: within-floor and between floors, switching from one to the other as floor transition events are detected. Through real-world experiments, we demonstrate the ability of this framework to produce accurate floor level estimates using only RSSI (Received Signal Strength Indicator) measurements, even when operating in an environment with as little as five WiFi access points per floor.

1 Introduction

Consider the need to localize and track robots or people navigating within multi-floor indoor environments. A system capable of achieving this has many potential applications including search and rescue, advertising, tracking tasks and resource management. Such a system could be developed in a hierarchical manner, first by considering only the floor level of the robot or person being tracked and then by considering exact location within that floor. For ease of reference we name the former floor level localization and the latter within-floor localization.

Both floor level and within-floor indoor localization has been extensively researched in the recent past using a variety of sensing modalities ranging from inertial sensors, laser distance sensors, pressure sensors, pedometers, vision sensors and WiFi access points. A system developed by [Iocchi *et al.*, 2007] have built multi-storey maps of buildings using a combination of laser range finders, IMUs and stereo cameras. The focus of this paper is on building a real-world, mobile, floor level localization system using wireless signals emitted from existing WiFi infrastructure of multi-floor buildings. We present a method to improve the accuracy of floor level localization by employing information about inter-floor transitions. We discuss how inter-floor transitions could be detected using WiFi signal strength information and how this information could be employed in a probabilistic manner to improve the accuracy of the SVM based floor level predictions when only a small number of access points are being considered. The key concept here is detecting and exploiting the floor transition events. If a floor transition event has not occurred, then there is a high probability that the person or robot being tracked is still in the same floor as before. If however a floor transition event has occurred, then there is low probability for the person or robot to be in the same floor as before and a high probability to be in a different floor.

This paper demonstrates that combining floor level transition information with WiFi signal strength measurements in a simple probabilistic framework can produce extremely accurate floor level predictions even when only a handful of WiFi access point are available or being considered. The rest of this paper is structured as follows. In Section 2 we present the application scenario that motivated the work in this paper. In Section 3 we discuss the related works. Section 4 details the methodology adapted in this paper and Section 5 the experiments and results. Section 6 concludes the paper with a summary of contributions and planned future work.

2 Motivation

The authors of this paper are a part of a team tasked with developing assistive robotic solutions to aid the elderly residents in an in-home care facility in NSW, Australia. Discussions with the facility carers revealed their need to allow increased liberties for residents while still being able to locate them when required should they get lost. A scenario where this is extremely important (and difficult to achieve using standard person tracking systems such as those employing GPS) is when the residents conduct their weekly visit to nearby shopping centres. One carer accompanies approximately 10 residents but most of the residents, especially those who suffer from minor dementia, are not allowed to roam freely in the shopping centre as they are often unable to find their way back to the designated meeting point at the end of the time period allocated for the visit. In the event that one or more of the residents have not made their way back to the designated meeting point, the carer has perform an exhaustive search of the shopping centre to locate the missing residents.

To mitigate the efforts of the carer and to enable increased mobility to the residents, it was decided to design a system that enabled the carers to limit their search as much as possible to the most probable locations of the missing residents. In the first iteration of the system, each resident and carer visiting the shopping centre would be provided a smart phone equipped with inertial sensors and a WiFi transceiver. While the inertial sensors can and are being used to design a within-floor localization system, it was decided to evaluate the utility of using only WiFi signal strength measurements to predict the floor level location of residents.

One may argue that inertial sensors are better suited for floor level predictions as they can be used to detect step climbing [Faulkner *et al.*, 2010]. However, here this was not the case as most of the elderly residents employ assistive walking devices and as such can only use the elevators to travel between floors. It should be noted that the floor level localization system described here is not specific to this particular application scenario, even thought it was the motivation for the system development. The goal of this paper is to demonstrate how the floor transitions events, irrespective of how they are detected, could be used to improve the floor level predictions and as we restrict our experiments to a specific way of floor transitions (using elevators). A more generic system that is capable of handling floor transitions using other methods such as stair cases and escalators could be constructed and is the focus of future work.

3 Related Work

Related work for this research varies from floor level localisation, various WiFi localisation techniques and the application of hidden Markov Models (HMM) in improving localisation accuracy. Preliminary research was conducted to see currently available results and relevant research to determine areas of improvement between techniques and to discover possible novelties within application.

3.1 Floor Level Localisation Techniques

Previous work has been done to track people inside an environment using IMUs (Inertial Measurement Units) [Feliz, 2009]. Newer developments in technology have even allowed indoor localization using a combination of smartphone IMUs and WiFi RSSI readings to within a reasonable degree [Liu *et al.*, 2014] by using a particle filter. The movement model is propagated by the IMU and the estimate improved by integrating it with WiFi RSSI to provide room-level accuracy. In terms of floor-level localisation, both of the previously mentioned only target single-floor applications. [Faulkner *et al.*, 2010] however has proven that altitude estimation is possible by attaching IMU sensors onto the user's boot heel and applying an extended Kalman filter to constrain velocities, pitch and roll to characterize and measure altitude errors. The current disadvantage to the implementation is that it functions by having the IMU attached to the user's heel which is very impractical within the context of aged-care and elderly users. However, it does seems highly likely that a floor level localisation using only a smartphone's IMU is possible and currently being investigated.

Floor level estimation has also been attempted using other sensors. [Xia, 2015] used the barometer sensor inside a smartphone to obtain altitude information. The results provided suggest that accurate floor level localisation would be difficult with their estimation algorithm as they obtained errors less than 5 meters in 90% of their readings. While not a bad result, it would not provide accurate enough results within a shopping centre. [Xia, 2015] Achieved slightly better results but required multiple barometer sensors and smartphones to achieve it. While promising, it does not seem that smartphone barometers are readily accurate enough to provide accurate floor level estimates.

3.2 WiFi Localisation

WiFi based localization is not a new topic and the theory behind using it has been around since 2004 [Serrano and Rodero, 2004]. The techniques behind WiFi localization has varied greatly from using simple RSSI fingerprinting [Navarro *et al.*, 2010] to more complicated approaches implemented by [Ferris *et al.*, 2006] who used Gaussian processes to model the Wifi

RSSI distribution.

Triangulation and propagation models have been found to be largely inaccurate due to the complexity of modelling the non-linearity of signal propagation [Ocana *et al.*, 2005]. As such fingerprint Wifi localization has remained the most popular method of indoor WiFi localization, with accuracy usually improved by implementing other techniques such as heirarchical models together with fingerprinting [Hernandez *et al.*, 2012]. Fingerprinting based localization is implemented by creating a radio map of a given area based on the RSSI data from various access points. A probability distribution of RSSI values for a given location are generated and act as a fingerprint for on-line measurements. As it is a relatively simple technique, many others have tried to improve on its implementation. [Chen *et al.*, 2008] implemented a rule-based localization method, [Li *et al.*, 2014] applied sparse SVMs and [Chen *et al.*, 2013] improved the algorithm by measuring double peak distributions. This method forms the basis of our implementation together with a linear SVM to provide initial floor estimates based on the WiFI radio map and hidden Markov model for improved localisation.

The previously mentioned study by [Ferris *et al.*, 2006] chose to use Gaussian processes mainly due to its robustness and ability predict signal strength measurements at arbitrary continuous locations. The WiFi RSSIs were modelled as a Gaussian process and localization was done using a particle filter. An interesting result was that the team achieved approximately 80% accuracy within 2 metres. This result included various levels, use of stairs and elevators. An area of concern however was that all training data was collected within 1 hour of the same day. [Huang *et al.*, 2011] Has also used Gaussian processes for WiFi GraphSLAM but at a single floor level implementation.

3.3 Hidden Markov Models in Wi-Fi Localisation

Hidden Markov models are not new in their application to WiFi based indoor localisation.[Chen *et al.*, 2008] applied a hidden Markov model to model a user's movement throughout the building along with various rule-based methods. Transition probabilities were developed around the probability of moving between rooms and corridors. While their implementation was limited to a single floor, room-based navigation, it provides good insight to expanding our floor-level, floor transition model into being able to model movement inside an entire building. [Hernandez *et al.*, 2014] Also applied HMMs to improve localisation accuracy. The team applied an heirarchical model that used an HMM at the top and used K Nearest Neighbours and an SVM as observations to the HMM. Their findings however indicate that the error reduction in implementing an SVM together with the HMM reduced error by only 1.57%. Our results would prove contrary, although our implementations differ in scope.

4 Methodology

Data for the WiFi localization was collected using a Sony Xperia Z3 Compact running Android version 5.1.1. The data was collected at Broadway Shopping Centre in Ultimo over various days, times and weather conditions to ensure robustness of the resulting model. Broadway Shopping Centre contains four floors of which the bottom three were the focus for the floor level localisation. To simulate the aged-care scenario, no stairs or escalators were used for travelling in between floors. Only elevators were allowed when conducting inter-floor travel.

The developed system runs two predictive models, an SVM and an HMM to provide a floor estimate within the building. Figure 1 gives a visual overview of the system. The first stage utilizes an SVM using the received signal strengths (RSSI) as features to provide an estimate on which class (floor level) the readings belong to. The resulting estimate from the SVM becomes the input to the HMM as the observed emission of the hidden model.

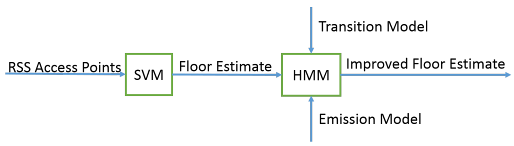

Figure 1: System Overview

The purpose of including the HMM is to improve on the estimate provided by the SVM classification by incorporating information about floor transitions. The SVM only relies on the most recent measurement of RSSI values and as such may produce incorrect estimates in certain areas of each floor such as open atrium areas where strong signals from access points in adjacent floors may be received. In certain other areas with strong physical separation between floors and a high concentration of access points, the floor level estimates from the SVM may have increased accuracy. The HMM can be thought of as a probabilistic accumulator of this information until a floor transition is detected at which point it enables a reset of the accumulated information.

4.1 Access Point Selection

As the WiFi structure of the building is unknown, a preliminary test was conducted by walking inside the building and recording all the available access points and their MAC addresses. Over 200 access points were visible in the building but their location within the building remains unknown. An advantage of using the RSSI fingerprinting localization technique is that the locations of the access points themselves are not necessary to provide location estimates.

A database of all available access points was built and used to select which access points were the most appropriate for floor classification. The access point list was filtered, removing any access points whose SSID were obviously not part of the building infrastructure or owned by a store i.e. personal mobile hotspots etc. The resultant list was then sorted to order which access points had the most signal strength variations over the three floors. As the system is envisaged to eventually run on a mobile platform, only the top fifteen access points were chosen for use in the SVM classification. This was to ease the number of calculations that need to be performed by the smartphone and save on battery life.

4.2 Support Vector Machine Classification

The open-source LIBSVM library was used to perform all the training and predicting of the SVM stage. As previously mentioned, the SVM uses the received signal strengths as features for classification. WiFi signal strengths were acquired every 3 seconds and the signal strengths of the 15 chosen access points were recorded. Access point visibility was marked in binary, 1 for those which were visible during that acquisition timestep and 0 otherwise. This simplifies the data acquisition and training at the cost of sacrificing estimation accuracy. A test sample was done which used the actual signal strength of the access point and the difference between binary vs raw was only 3% (80% vs 77% model accuracy). As the results were only marginally different, it was deemed insignificant enough and the binary method was used on subsequent occasions.

To build the model, the data collected was trained using 2-fold cross validation/holdout method and a simple linear kernel was used. The resultant model is then used to classify a completely independent set to validate the model. To ensure independence of the model, the data for the validation was taken a few days after the initial data acquisition.

4.3 Hidden Markov Model

The system uses a standard Hidden Markov Model to improve on the estimates provided by the SVM. The floor location is the state and is not directly visible. Instead, emissions are observed from the model through the SVM floor estimates.

Hidden Markov Models rely on having three distinct parts available to make a prediction, a transition matrix, an observation matrix and the prior state probabilities. The transition matrix defines how the system moves between states and the observation matrix defines the probability of observing an emission, given states. From the hidden Markov model update equation, we can calculate the probability of being in a certain state given an observation.

$$P(x_t \mid y_{1:t-1}) = \frac{P(y_t \mid x_t)P(x_t \mid y_{1:t-1})}{\sum\limits_{x_t \in X} P(y_t \mid x_t)P(x_t \mid y_{1:t-1})} \tag{1}$$

Given $Y_t = \{p, q, r\}$ observations and $X_t = \{a, b, c\}$ states, the probabilities of being in any given floor are calculated as follows:

$$P(x_1 = a \mid y_1 = p); P(x_1 = b \mid y_1 = p); P(x_1 = b \mid y_1 = p) \tag{2}$$

$$P(x_1 = a \mid y_1 = p) = \frac{P(y_1 = p \mid x_1 = a)P(x_1 = a)}{\sum\limits_{j \in \{a,b,c\}} P(y_1 = p \mid x_1 = j)P(x_1 = j)} \tag{3}$$

$P(y_1 = p \mid x_1 = a)$ can be obtained from the emission matrix and $P(x_1 = a)$ can be obtained by calculating

$$P(x_1 = a) = \sum_{k \in \{a,b,c\}} P(x_1 = a \mid x_0 = k)P(x_0 = k) \tag{4}$$

where $P(x_1 = a \mid x_0 = k)$ is obtained from the transition matrix and $P(x_0 = k)$ is the prior probability.

This calculation is done every time the WiFi obtains a reading and an SVM prediction is made.

Transition Matrix

The transition matrix is a good way of expressing movement within a building as there are two main modes of travel. Intra and inter-floor travel. Thus, two transition matrices are sufficient to describe movement within the building. This is guaranteed in the aged-care context as the residents cannot physically use escalators or stairs while using their walkers and as such are restricted to moving between floors by only using an elevator.

The system relies on using different transition matrices depending on whether inter (travel between floors) or intra (travel within the floor) has been detected. This is done through an elevator event which is marked by the sudden disappearance of access points. These occur when the elevator doors close and the amount of available access points significantly drops.

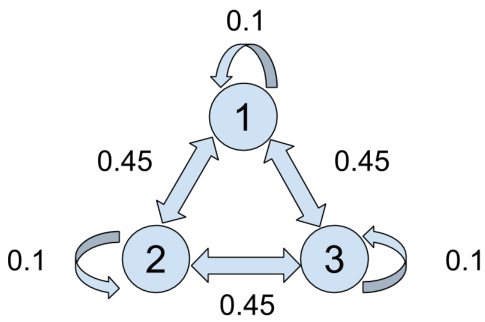

Figure 2: HMM Graphical Model - Inter-Floor

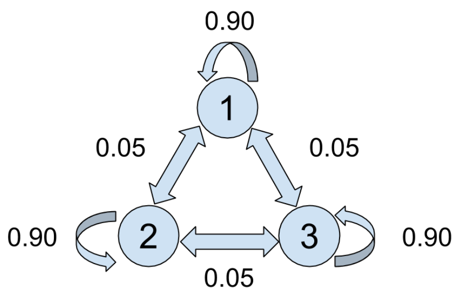

Figure 3: HMM Graphical Model - Intra-Floor

If inter-floor travel has been detected, i.e. an elevator has been used. The HMM applies the model on Figure 3 as its transition matrix. These values have been estimated through heuristics as there is a very low chance that once one has entered an elevator that one would exit on the same floor. Travel between any of the other two floors have been given equal probability of happening but this estimate will be improved on in future work. Currently, the applied heuristics are done as a proof-of-concept of the system and whether it will be applicable to the aged-care walkers.

If intra-floor travel has been detected, i.e. an elevator has not been used and user is walking on the same floor, The HMM applies the model on Figure 2 as its transition matrix. These values here have also been estimated through heuristics. As long as the user has not used an elevator, there is a very low chance that they will have moved floors.

Observation Matrix

The observation matrix was created after calculating the confusion matrix of the SVM classification. The confusion matrix directly models the observation matrix as it is a measure of the likelihood of observing emissions (estimated floor) given a state (true floor). This is defined by the expression $P(y_t = p \mid x_t = a)$ .Which is a measure of the probability of the SVM observing/estimating a floor given that it is in a particular floor.

Table 1: Observation Matrix

$y_t \setminus y_t$	p	q
a	$P(y_t = p \mid x_t = a)$	$P(y_t = q \mid x_t = a)$
b	$P(y_t = p \mid x_t = a)$	$P(y_t = q \mid x_t = b)$
c	$P(y_t = p \mid x_t = a)$	$P(y_t = q \mid x_t = b)$

Figure 1 shows an example observation matrix for a 2-floor scenario. A 3-floor observation matrix was used but has not been displayed here due to column width constraints.

5 Results

Results from the testing show a marked improvement between the lone SVM floor estimates and the HMM improved floor estimates. Table 2 demonstrates the difference in accuracy between the two methods. This was calculated by taking 2 different sample readings.

The first sample contains data from only one floor in the building which demonstrates intra-floor travel. The second dataset demonstrates inter-floor travel and is divided into two halves. The first half contains data walking towards the elevator on the second floor which is then separated by an elevator event. The second half then contains data walking out from the elevator on the third floor walking towards a different area of the building. Both samples contain 20 readings. To provide a more detailed description, Tables 6 and 7 show a sub-sample of the 20 readings.

As can be seen in Table 2, The HMM enhanced model performs better on both inter and intra-floor travel. Further analysis into the values and probabilities calculated are further expanded on Subsection 5.2

Table 2: SVM vs HMM Overall Accuracy

	Intra-Floor	Inter-Floor
SVM Floor Prediction	0.75	0.7
SVM-HMM Floor Prediction	0.9	0.95

Table 3: Confusion Matrix

		Predicted Floor		
		1	2	3
Actual Floor	1	0.79	0.20	0.01
	2	0.21	0.67	0.12
	3	0.1	0.13	0.86

5.1 SVM

Table 3 shows the confusion matrix obtained from validating the SVM model. The resultant matrix was also used to represent the observation matrix in the HMM. Upon inspecting the table, it is clear to see that Floor 2 is the hardest floor to correctly classify as it appears to look very similar to both floors 1 and 3 in the SVM. This result is understandable as the floor exists between the other two floors and thus access point RSSI on this floor will be very similar to RSSI obtained in the other 2 floors. The poor result from the SVM floor prediction is the main justification as to why Floor 2 was chosen for both the inter-floor and intra-floor testing.

5.2 HMM

Tables 5 and 4 details the transition matrices used to model inter and intra-floor travel. They've been included here as reference to the graphical models from Figures 3 and 2.

Table 4: Intra-Floor Transition Matrix

		Previous Floor		
		1	2	3
Current Floor	1	0.90	0.05	0.05
	2	0.05	0.90	0.05
	3	0.05	0.05	0.90

Table 6 shows a sub-sample sequence of the readings used to compare the difference between the SVM and the HMM enhanced floor predictions. The readings were taken on Floor 2 and measurement samples were taken. The second row of the table shows the output of the SVM floor prediction and the third row of the table shows the HMM enhanced floor predictions. This sub-sample occurs at the very start of the test and equal probabilities of being in each floor are given as prior since it is initially unknown what floor we being on.

Table 5: Inter-Floor Transition Matrix

		Previous Floor		
		1	2	3
Current Floor	1	0.10	0.45	0.45
	2	0.45	0.10	0.45
	3	0.45	0.45	0.10

The last three rows show the probabilities calculated for the HMM model. They show the probabilities of being at that state for that respective sample. The floor with the highest probability is the output of the HMM model. Between samples 4 and 5, it is quite visible to see the change in floor predictions for the HMM model as two consecutive wrong floors were predicted by the SVM. As the readings become more stable, the probabilities of being in the second floor tends towards 1.

Table 6: Intra-Floor Localisation Test Sequence

Actual	2	2	2	2	2	2
SVM	2	2	1	1	2	2
HMM	2	2	2	1	2	2
Floor 1	0.196	0.090	0.364	0.693	0.382	0.165
Floor 2	0.675	0.867	0.603	0.288	0.591	0.814
Floor 3	0.127	0.042	0.031	0.018	0.025	0.020

Table 7 shows a sub-sample sequence of the other set of readings used to compare the difference between the SVM and the HMM enhanced floor predictions. As per Table 6, the top three rows show the actual floor and the outputs of the SVM and HMM models. This sub-sample captures the moments with a detected elevator event. The elevator event happens between samples 3 and 4 and the floor change is visible on the 'Actual Floor' column of the table.

The readings were taken on Floor 2 and measurement samples were taken. The second row of the table shows the output of the SVM floor prediction and the third row of the table shows the HMM enhanced floor predictions. It is clear to see that the HMM predictions are more stable than the SVM output and it better tolerates rapid switching of floor estimates, especially towards elevator events.

6 Conclusion

This paper demonstrated how information about transitions between floors can be employed within a probabilistic framework to accurately predict the floor

Table 7: Inter-Floor Localisation Test Sequence

Actual	2	2	2	3	3	3
SVM	2	1	2	3	2	3
HMM	2	2	1	3	3	3
Floor 1	0.023	0.227	0.558	0.011	0.067	0.001
Floor 2	0.961	0.747	0.420	0.031	0.294	0.065
Floor 3	0.014	0.025	0.020	0.956	0.638	0.932

level of a person or a robot moving in a multi-floor indoor environment. An application scenario where RSSI measurements of infrastructure wireless access points were used to both to detect the floor transitions and to estimate the floor level location was employed to demonstrate the improvements brought about by the proposed system, when compared to the classical SVM based classification techniques. Our experiments demonstrated that by augmenting the SVM with an HMM, accurate floor level estimates could be obtained under diverse conditions even when operating in an environment sparsely populated with WiFi access points.

In future work, we plan to extend the proposed system by fusing inertial and RSSI measurements to operate in a variety of environments with different ways of transitioning between floors.

7 Acknowledgements

This work was supported by IRT Research Foundation, Australia. We thank the management, the staff and the residents of IRT Peakhurst care facility, Australia for their involvement in the design development, implementation and evaluation of the technology.

We also acknowledge Prof. Gamini Dissanayake, Prof. Dikai Liu, A/Prof. Jaime Valls Miro and Prof. Lynn Chenoweth for their guidance and Mr. Stefan Lie, Ms. Zoe Green and Mr. James Poon for their assistance during the project.

References

[Chen *et al.*, 2008] Q. Chen, D. Lee, and W. Lee. Rule-based wifi localization methods. In *Embedded and Ubiquitous Computing, 2008. EUC '08. IEEE/IFIP International Conference on*, volume 1, pages 252–258, Dec 2008.

[Chen *et al.*, 2013] L. Chen, B. Li, K. Zhao, C. Rizos, and Z. Zheng. An improved algorithm to generate a wi-fi fingerprint database for indoor positioning. *Sensors*, 13(8):11085–11096, 2013.

[Faulkner *et al.*, 2010] W.T. Faulkner, R. Alwood, D.W.A. Taylor, and J. Bohlin. Altitude accuracy while tracking pedestrians using a boot-mounted imu. In *Position Location and Navigation Symposium (PLANS), 2010 IEEE/ION*, pages 90–96, May 2010.

[Feliz, 2009] R. et.al. Feliz. Pedestrian tracking using inertial sensors. *Journal of Physical Agents*, 3:35–43, January 2009.

[Ferris *et al.*, 2006] B. Ferris, D. Hahnel, and D. Fox. Gaussian processes for signal strength-based location estimation. In *In: Proceedings of Robotics: Science and Systems*, 2006.

[Hernandez *et al.*, 2012] N. Hernandez, J.M. Alonso, M. Magro, and M. Ocana. Hierarchical wifi localization system. In *Proceedings of the 2012 Intelligent Vehicles Symposium Workshops*, Nov 2012.

[Hernandez *et al.*, 2014] N. Hernandez, M. Ocana, J.M. Alonso, and K. Euntai. Wifi-based indoor localization and tracking of a moving device. In *Ubiquitous Positioning Indoor Navigation and Location Based Service (UPINLBS), 2014*, pages 281–289, Nov 2014.

[Huang *et al.*, 2011] J. Huang, D. Millman, M. Quigley, D. Stavens, S. Thrun, and A. Aggarwal. Efficient, generalized indoor wifi graphslam. *Conference: Robotics and Automation (ICRA), 2011 IEEE International Conference*, June 2011.

[Iocchi *et al.*, 2007] L. Iocchi, S. Pellegrini, and G.D. Tipaldi. Building multi-level planar maps integrating lrf, stereo vision and imu sensors. In *Safety, Security and Rescue Robotics, 2007. SSRR 2007. IEEE International Workshop on*, pages 1–6, Sept 2007.

[Li *et al.*, 2014] P. Li, H. Meng, and X. Wang. A feature selection method based on the sparse multi-class svm for fingerprinting localization. *Proceeding of the Vehicular Technology Conference*, 2014.

[Liu *et al.*, 2014] Yang Liu, M. Dashti, M.A. Abd Rahman, and Jie Zhang. Indoor localization using smartphone inertial sensors. In *Positioning, Navigation and Communication (WPNC), 2014 11th Workshop on*, pages 1–6, March 2014.

[Navarro *et al.*, 2010] E. Navarro, B. Peuker, and M. Quan. Wi-fi localization using rssi fingerprinting. 2010.

[Ocana *et al.*, 2005] M. Ocana, L.M. Bergasa, M.A. Sotelo, J. Nuevo, and R. Flores. Indoor robot localization system using wifi signal measure and minimizing calibration effort. In *Industrial Electronics, 2005. ISIE 2005. Proceedings of the IEEE International Symposium on*, volume 4, pages 1545–1550, June 2005.

[Serrano and Rodero, 2004] J. M. Matellan V. Serrano, O. Canas and L. Rodero. Robot localization using wifi signal without intensity map. *WAF04*, March 2004.

[Xia, 2015] H. et.al. Xia. Using multiple barometers to detect the floor location of smart phoens with built-in barometric sensors for indoor positioning. *Sensors*, 15(4):7857–7877, 2015.