Perceptive Mobile Network: A Cellular Network with Radio Vision via Joint Communication and Radar Sensing

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Abstract

Joint communication and radar/radio sensing (JCAS, aka, dual-function radar-communications) enables the integration of communication and radio sensing into one system, sharing a single transmitted signal. The perceptive mobile network is a natural evolution of JCAS from simple point-to-point links to a mobile/cellular network with integrated radio sensing capability. In this article, we present a system architecture that unifies three types of sensing, investigate the required modifications to existing mobile networks, and exemplify the signals applicable to sensing. We then provide a review for stimulating research problems and potential solutions, including mutual information, joint design and optimization for waveform and antenna grouping, clutter suppression, sensing parameter estimation and pattern recognition, and networked sensing under the cellular topology.

Keywords

Joint communication and radio/radar sensing, mobile networks, dual-function radar-communications, perceptive mobile networks.

Introduction

Wireless communications and radio sensing (C&S) share many commonalities in terms of hardware, signal processing, and network architecture. This motivates integrating these two systems using joint communications and radio sensing (JCAS, aka radar-communications) techniques [1, 2, 3, 4]. The preliminary JCAS concept can be traced back to the 1970s. Although there is no much development in the following years, it has re-gained interest in the early 2010s, due to the drive for more efficient radio spectral usage and growing emerging demands for radio sensing [2]. Instead of having two separate C&S systems, JCAS can integrate them into one by sharing a majority of hardware and signal processing algorithms. Radar sensing here refers to information retrieval from the received radio signals for both transmitters and dumb objects in the surrounding environment. Such information includes both conventional *sensing parameters* such as location and speed, and feature signals of objects and events. In such integrated systems, the same transmitted signal is used for both communications and sensing. Integrating C&S into one system can achieve immediate benefits of reduced cost, size, and improved spectral efficiency.

Applying JCAS to large-scale mobile/cellular networks can potentially evolve the communication-only network to a *perceptive mobile network (PMN)* with integrated communication and radio sensing capabilities [5, 6, 7]. The PMN is expected to serve as a ubiquitous radio-sensing network, while providing uncompromised communication services. The potential sensing applications of PMN is illustrated in Fig. 1.

Some key features of a PMN network can be summarized as follows:

- A single transmitted signal is optimized and used for both communications and sensing;
- Both uplink and downlink signals can be used for C&S;
- A majority of the hardware and signal processing modules in the transceiver are shared by C&S; and
- Sensing can be implemented in a single node, either in a base station (BS) or a user equipment (UE), as well as across networked nodes.

There exist major differences between PMNs and existing systems and technologies that combine radar and mobile communications. In Table 1, we compare JCAS with other two types of systems: the

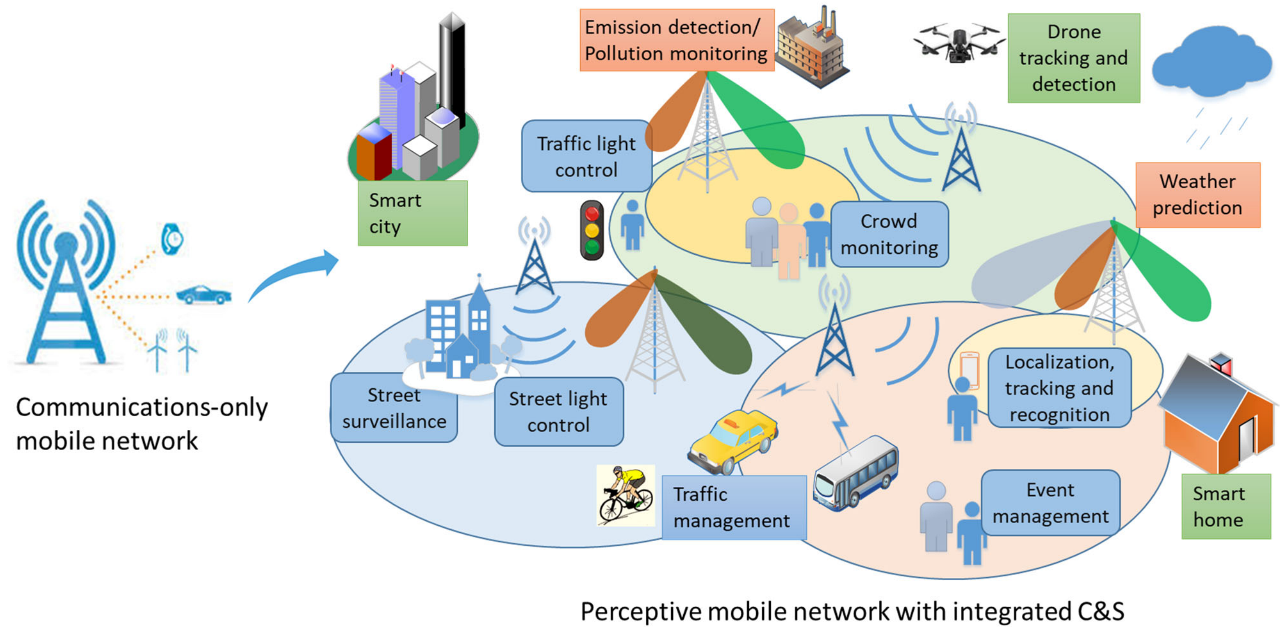

Figure 1 Illustration of the evolution of PMN and its sensing applications.

coexisting mobile communication and radar systems [6], where the two separated systems share the same resource blocks such as frequency channels in a cooperative way; and the integrated system with separately transmitted signals where C&S are integrated on one platform but their signals use separate or even orthogonal resources.

This article aims to provide a review of PMNs, leveraging recent findings as well as our own research experiences. We first present a system architecture for the PMNs, together with the required modifications on network and hardware of current mobile networks, and the available mobile signals for sensing. We then highlight the potential and some applications for PMNs. Finally, we review open research challenges and opportunities for integrating radio sensing into mobile networks, by considering specific network architecture and components, practically sophisticated communication signal format, and complicated signal propagation environment.

System Architecture

In this section, we describe the system architecture of PMN, summarizing and extending the results in our work of [5]. PMN can be evolved from a general mobile network. More advanced network infrastructure, such as denser cells, larger signal bandwidth, and larger antenna arrays, can lead to better sensing performance. We describe the PMNs by referring to emerging 5G networks, and most of the results in this article also apply to other mobile networks such as LTE.

We present the architecture by referring to distributed antenna systems, in particular, cloud-radio-access network (CRAN) as shown in Fig. 2, as well as a general standalone BS. The CRAN allows a more flexible and diverse configuration of radar sensing, reflecting the mono-static, bi-static, and multi-static settings in conventional radar systems. In this architecture, cooperative remote radio units (RRUs) are densely distributed and synchronized in clock. Signal processing for C&S based on collected signals from these RRUs is done centrally in CRAN central, which includes the baseband unit pool for C&S processing. All RRUs' clocks are synchronized, via, e.g., GPS. A typical communication scenario is as follows: several RRUs work cooperatively to provide connections to UE, using multiuser MIMO techniques over the same subcarriers. While it is not necessary, we assume that cooperative RRUs are within the signal coverage area of each other for increasing flexibility in sensing. This assumption is reasonable when dense RRUs are deployed and used to support surrounding UEs via coordinated

Table 1 Comparison between communication and radar sensing co-existing and integration schemes.

Schemes	Advantages	*Disadvantages*
Co-existing Systems sharing the same resource	• Independent individual system design and optimization • Relatively independent operation • High spectral efficiency	• Potentially large mutual interference and complicated interference mitigation techniques required • Highest overall cost
Integrated System but Using Separately Transmitted Signals (time, frequency, code, or polarization division duplex)	• Mutual interference can be removed at the cost of spectrum efficiency • Flexible individual waveform design and optimization, and resource allocation • Potential for joint design and optimization, and mutual information sharing	• Lower spectrum efficiency due to partitioning of resources and the requirement of guarding interval or equivalent • Lower order of system integration, more complex transmitter hardware.
Integrated JCAS System Using a Single Transmitted Signal	• Highest spectral efficiency (almost doubled) • Simultaneous operation without mutual interference • Fully shared transmitter and largely shared receiver, in terms of hardware and signal processing. Smallest size, weight, and cost • Joint design and optimization, and mutually beneficial processing by information sharing	• Require full-duplex operation or equivalent setup • Limited sensing range of individual nodes due to limited transmission power (in mobile networks), but can be mitigated by network-wide sensing • Potential performance loss with conflicting requirements for comm. and sensing

multipoint techniques. Technically, it is also feasible at the cost of increased transmission power even if only for supporting sensing, as the downlink signals do not cause interference to RRUs.

We focus on BS-side sensing in this article, although UE-side sensing is also possible. The BS has the advantages of flexible cooperation, a large antenna array, powerful computation capability, and known and fixed locations.

Three Types of Sensing

In PMNs, the same transmitted signal from RRUs or mobile stations is used for both C&S. We define *uplink and downlink sensing*, consistent with uplink and downlink communications, as shown in Fig. 2. In uplink sensing, the sensing signal is from UEs. Uplink sensing estimates relative, instead of absolute, time delay parameters because the estimate includes both propagation delay and the unknown timing offset between UE transmitters and RRU receivers. In downlink sensing, the sensing signals are from BSs. For CRAN, downlink sensing is further classified as *Downlink Active Sensing* and *Downlink Passive Sensing*, for the cases when an RRU collects the echoes from its own and other RRUs' transmitted signals, respectively; for a standalone BS, only downlink active sensing exists. Note that in CRAN, the signals from RRUs are processed centrally, and hence sensing can be done jointly over RRUs whose signals reach each other, even when their transmitted signals are different [5]. A brief comparison of these three types of sensing is provided in Table 2, and more details can be seen from [5].

The three types of sensing can be unified and implemented together. An RRU may implement downlink active and passive sensing during downlink signal transmission, and then operate on communication and uplink sensing modes during the uplink stage.

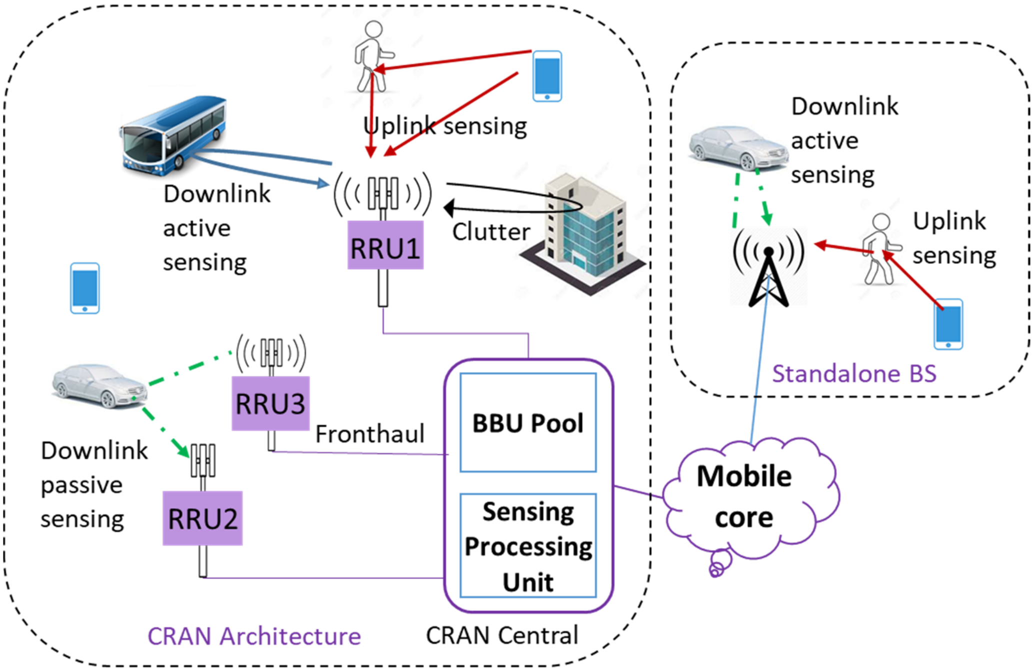

Figure 2 System architecture demonstrating a PMN network based on either a standalone BS or a CRAN architecture. In the CRAN, RRU2 represents a receiving only node, and RRU3 represents a transmitting only node working as a special UE in uplink communication.

Table 2 Comparison among Three Types of Sensing.

<table>
<tr><th></th><th>Signals Used for Sensing</th><th colspan="2">Advantages</th><th>Disadvantages</th></tr>
<tr><td>Downlink Active Sensing</td><td>Reflects from a RRU/BS's own transmitted downlink communication signal</td><td rowspan="2">• All data symbols in the received signals can be used and are centrally known.
• RRUs are synchronized.
• Privacy is less an issue because sensed results not directly linked to any UEs.</td><td>• Sense surrounding environment of the RRU/BS.</td><td rowspan="2">Generally requires full-duplex operation. Devices can be specially deployed to resolve this problem.</td></tr>
<tr><td>Downlink Passive Sensing</td><td>Received downlink communication signals from other RRUs</td><td>• Sense environment between RRUs.</td></tr>
<tr><td>Uplink Sensing</td><td>Uplink communication signals from UE transmitters</td><td colspan="2">• Sense UEs and environment between UEs and RRU.
• Require minimum modification to communication infrastructure.</td><td>• Timing and distance measurement is relative.
• Transmitted information signals are not directly known.
• Rapid channel variation due to moving UEs.</td></tr>
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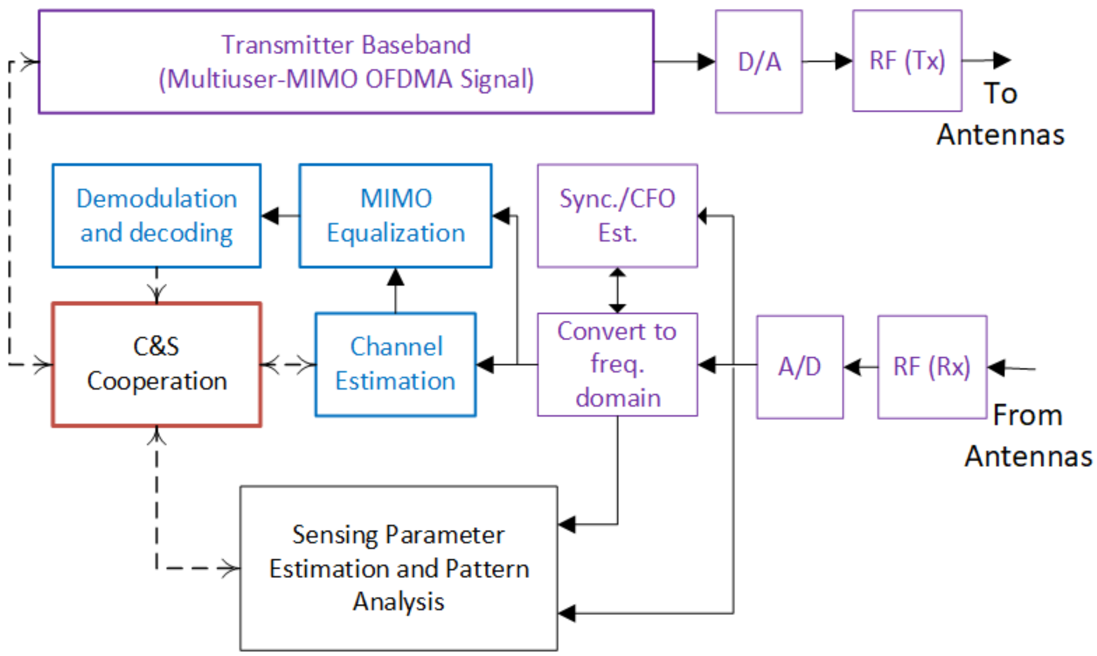


Figure 3 Block diagram of a typical transmitter and receiver in PMN. Blocks in purples, in blue and in black, are for those shared by C&S, specific to communications, and specific to sensing, respectively.

Required Network and Hardware Modifications

At a transceiver level, many modules, including the whole transmitter and part of the receiver, can be shared by C&S, as shown in Fig. 3. The module of sensing parameter estimation and pattern analysis is added for sensing, and the C&S Cooperation module shares information between C&S, which can be used for improving the performance of C&S. Despite the sharing of a majority of system components, some modifications are necessary to evolve current mobile networks to PMNs, and they are quite different for uplink and downlink sensing.

Uplink sensing can be implemented with almost no change in hardware or system architectures of current mobile systems, but other improvements in, e.g., signal and scheduling, will be beneficial. Here, one main problem is that the phase clock between UEs and BSs is not synchronized, hence timing and ranging ambiguity needs to be solved. It is also possible to deploy RRUs or dedicated UEs as uplink transmitting devices only for uplink sensing, like RRU3 in Fig. 2.

Downlink sensing requires changes to hardware; the extent of changes depends on the network duplexing mode. Basically, downlink sensing requires a transceiver to work on the full-duplex mode, where receiver and transmitter can operate at the same time using the same frequency channel. Without modifying the current hardware, transmitted signal leakage can easily overwhelm the reflected echoes for downlink sensing. Before full duplex technologies become mature, some feasible near-term solutions for downlink sensing are as follows:

- Using two sets of spatially well-separated antennas for transmitting and receiving; and
- Deploying RRUs that only work on the receiving mode, like RRU2 in Fig. 2.

For these near-term solutions, a time division duplexing (TDD) system generally requires less hardware modification than frequency division duplexing (FDD) for downlink sensing. This is because, for FDD, a receiver needs to be enabled to process downlink signals that are in a different frequency band, while for TDD, only the controlling switch needs to be adjusted.

Signals Available for Sensing

For downlink sensing, all the data symbols in the transmitted signals are known to the RRUs, and hence in principle, any type of signals can be used

Table 3 Signals available to PMN with reference to 5G NR

Signal Properties / Performance Criteria	Types of Signals			Impact on Sensing
	Reference Signals (DMRS and SRS)	SSB (SS and PBCH)	Data Payload in PDSCH and PUSCH	
Occurrence of Signal in Time domain	Irregular and variable length.	Short (4 OFDM symbols), Less frequent (every ~20 ms)	UE-specific, irregular and long.	Regular and frequent signals in time domain can lead to better Doppler estimation and higher SNR in general.
Occurrence of Signal in Freq Domain	Allocation-dependent. Can be on a regular comb structure.	Sparse; use a small number of ~20 RBs.	Allocation-dependent.	Signals occupying more resource blocks (RB) can lead to better delay estimation. Signals with irregular subcarrier indexes are preferred to avoid estimation ambiguity.
Knowledge of Signal Values	Known	Known	Unknown	Unknown signals may introduce symbol detection errors and degrade sensing performance.
Correlation and Orthogonality	Typically orthogonal over time, frequency and spatial domains for different UEs.	Orthogonal over smaller spatial layers.	Non-orthogonal. Statistically independent.	Orthogonality leads to improved sensing performance, via both increased SNR and improved degree-of-freedom, e.g., leading to increased virtual array aperture.
Flexibility in Signal Structure and precoding	Flexible. On demand when possible.	Typically fixed.	Flexible.	Flexible signal design enables signal optimization via, e.g., precoder and scheduling, by jointly considering the requirements of C & S.

for sensing. However, different signals could have different statistical properties and lead to different sensing performance. For uplink sensing, data symbols are not directly known, and received signals for each user can be scattered in frequency, time and spatial domains depending on resource allocation. Referring to 5G New Radio (NR, 3GPP TS 38.211 Release 15) [8], here we briefly discuss three typical types of signals, not exclusively, that can be used for sensing. These signals can be directly used for sensing, and they can also be further optimized by jointly considering the C&S requirements, as will be detailed later. The properties of the signals, together with their impact on sensing, are summarized in Table 3 and elaborated below.

Standard Signals for Channel Estimation: The first option will be the deterministic signals, provided specifically for channel estimation, including demodulation reference signals (DMRS) for both uplink and downlink, sounding reference signals (SRS) for uplink, and channel state information – reference signals (CSI-RS) for downlink. Most of them are comb-type pilot signals, shifted across OFDM symbols, and are orthogonal between different ports to support multiuser-MIMO. Among them, DMRS is user-specific and always transmitted with data payload, and therefore is random and irregular over time. SRS and CSI-RS can be either periodic or aperiodic. These signals are flexible and may be optimized during resource scheduling for joint C&S.

Deterministic Non- Channel Estimation Signals: The BS may also exploit deterministic non- channel estimation signals for sensing such as the synchronization signal and broadcast blocks (SSB). Such signals typically have regular patterns and are periodic and fixed at an interval of several to tens of milliseconds. But they only occupy a limited number of subcarriers, which leads to limited identification of multipath delay values.

Data Payload Signals: In addition to the above two types of signals, which are both known to RRUs directly, we can also exploit the data payload signals for sensing. In the downlink, these data payload signals are centrally known. In the uplink, it is possible to use a decision-directed approach, that is, re-modulate the demodulated and decoded data signals. These approaches increase the number and occurring frequency of available sensing signals at a given period, and hence improve the sensing performance at increased complexity.

Key Research Problems

As a new platform and network, PMN is still in its very early stage of research and development. There are many challenges to be overcome to make it practical, which also implies excellent research opportunities. Here we review a few critical research problems, explore existing and potential solutions, and highlight future research directions as summarized in Table 4. Since the major challenge in PMN is how to achieve radio sensing without compromising the performance of existing communications, we mainly focus on the issues of realizing radio sensing, leveraging the existing cellular communication infrastructure.

Performance Bounds: Mutual Information and CRLB

Mutual information (MI) is a tool that has been widely used for characterizing the performance of both communication and radar systems [10]. For communications, the MI is well known and is defined between the received and transmitted signals, conditional on the known (estimated) channels. For radar, MI is defined between the received signals and the propagation channel, conditional on the known (estimated) transmitted signals. Maximizing the radar MI ensures that the received signals contain the most channel information, which could be particularly meaningful for sensing applications that do not require estimating sensing parameters. It is interesting to investigate whether and how we can establish an information-theory foundation for sensing using communication signals, like for communications.

MI for JCAS systems has been studied and reported in a limited number of publications. For example, in [10], considering a JCAS MIMO setup, the expressions for radar MI and communication channel capacity are derived. These results can be used as a good basis for studying the MI for PMNs, with the consideration of their specific problems, such as the two described below.

Firstly, uplink and downlink sensing require different treatments. In downlink sensing, the symbols are known to the receiver, and the channels for C&S are correlated but are different. For uplink sensing, the symbols are unknown to the receiver, and the channels are the same. Hence, the optimization formulations and results can be quite different for uplink and downlink sensing. For example, the MI formulation for uplink sensing needs to take into consideration of signal estimation errors, which makes communication and sensing more entangled.

Secondly, formulations of MI need to be adapted to the actual signal format in cellular networks, which is quite complicated, involving, e.g., training sequence and different resource usage by each user and hence each link. These observations indicate that the optimal solution for one function is generally not optimal for the other, and some tradeoff needs to be made, particularly when the requirements for C&S are very different, for example, when the directions of C&S deviate significantly. Considering that UEs are typically uniformly distributed in mobile networks, sensing-motivated user scheduling may be applied to alleviate this problem.

Although sensing MI measures the sensing information contained in the received signals, it does not evaluate how accurate the sensing parameter estimation can be. The parameter estimation performance in radar is typically characterized by the Cramer-Rao lower bounds (CRLBs). Because of the significant differences between communication and radar signals, most

Table 4 Highlights of open key research problems in PMN.

MI and Performance Bounds

$$I(\mathbf{H}_s;\mathbf{Y}_s|\mathbf{X})$$
$$I(\mathbf{X};\mathbf{Y}_c|\mathbf{H}_c)$$

- PMN-specific MI formulation
- Sensing performance bounds for mainstream communication signals

Joint Optimization

$$\arg\max_{\mathbf{P}} \lambda(\mathbf{P}), \quad \text{subject to Constraints}$$

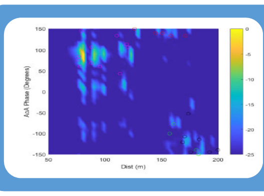
- Waveform optimization adapt to pratical siganl formats and varying C&S requirements
- Antenna placement and virtual array design

Clutter Suppression

$$\hat{\mathbf{H}}_n(i) = \alpha\hat{\mathbf{H}}_n(i-1) + (1-\alpha)\hat{\mathbf{H}}_n(i),$$

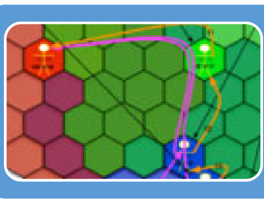
- Adaptive recursive averaging algorithms
- Transplant of background subtraction technologies in image processing

Sensing Parameter Estimation



- Sensing algorithms capable of handling non-continuous samples
- Off-grid compressive sensing with discontinuous samples

Networked Sensing



- Fundamental theories and performance bounds for cellular sensing networks
- Distributed sensing with node grouping and cooperation

CRLB results for radar are not applicable to PMN signals. CRLBs for channel estimation and signals' angles-of-arrival in communications are also well known. However, there almost no CRLB results on delay and Doppler estimates reported for broadband communication signals, although there is one for passive sensing using narrowband signals [11]. The nonlinear nature of the estimation makes the derivation and usage of closed-form CRLB expressions challenging. Overcoming the challenge would provide us with important insights on PMN sensing performance bounds and waveform design.

Joint Design and Optimization

When integrating the two functions, which share the same transmitted signal and many common signal processing modules, into one system, there exist various joint design and optimization problems yet to be investigated. In PMNs, communication is the primary function, and sensing is the secondary. Hence communication should have a high priority during system design and optimization. We will mainly discuss waveform design and antenna grouping here.

Waveform optimization: Earlier work has investigated the impact of the waveform and basic signal parameters on the performance of a general JCAS system. For example, in [1], the linkage between the resolution capabilities for radar sensing and the signal parameters for both single carrier and multicarrier communication systems was demonstrated both analytically and numerically. These results serve useful references for waveform optimization in PMNs. However, the latter is more challenging because its communication signals are very complicated and time-varying, depending on, e.g., numerology and channel aggregation (in 5G), user and resource allocation, and adopted precoding matrices. Waveform optimization here is generally realized via designing precoding matrices for signals to be transmitted. To support sensing at directions that are very different to those for communications, some signal energy may be wasted, and additional multipath signals may be generated. This can cause reduced signal power for communications, but will not cause interference even for multiuser-MIMO signals because MIMO-precoding can be carefully designed to remove potential multiuser interference.

A general waveform optimization problem can be formulated as optimizing the transmitted signals by maximizing an objective function under some constraints. The objective function and the constraints can use various metrics and their combinations, such as the capacity and signal-to-interference-and-noise ratio (SINR), for communications, and the MI, CRLB, and the radar ambiguity function, for sensing. Both of them can be constructed either for communications or sensing individually, or as a weighted joint function. There could be two practical methods for waveform optimization in PMN. One method is to optimize the precoding matrices to change the statistical property of the transmitted signals. Recent work in [6,7] provides an example for this method with constraints on SINR for multiuser MIMO downlink communications. In [12], the weighting vector for subcarriers in OFDM systems is optimized by considering a multi-objective function involving communication capacity and CRLBs for the estimates of sensing parameters. However, the precoding matrix needs to be redesigned once the communications setup changes, therefore incurring higher complexity. Another method is to add the sensing waveform to the underlying communications waveform, while considering a coherent combination of the two waveforms for destination nodes. This could be particularly useful for millimetre wave systems where directional beamforming is used. One example is available from [3], where a multibeam approach is proposed to flexibly generate C&S subbeams using analogue antenna arrays. Such a method provides suboptimal but simple generation of the waveform fulfilling both C&S purposes.

MIMO and Antenna Grouping: C&S have seemingly conflicting requirements for antenna placement, grouping, and signal formats in MIMO systems. In a MIMO communication system, the transmitted signals are often generated from random information bits, and their correlation matrix largely depends on the precoding matrix [5], while MIMO-radar sensing signals are typically orthogonal [13]. When using an array, radar sensing focuses on optimizing antenna placement and virtual subarrays to increase antenna aperture and then resolution [14], but communication emphasizes beamforming gain for spatial diversity and a low signal correlation between antennas for spatial multiplexing. Such different requirements demand a tradeoff for joint design. We can also explore the following commonalities between MIMO communication and radar: Similar to the diversity and multiplexing tradeoff in communications, there are processing gain and resolution tradeoffs in sensing, related to the independent spatial streams [13]. In communications, we can apply resource allocation and precoding matrices to achieve higher capacity. In MIMO radar, we can form either overlapped or non-overlapped subarrays among all the antennas, and design transmitted waveform to achieve lower error bounds for sensing parameter estimation [14]. Considering the benefits of antenna grouping in both C&S, using hybrid antenna arrays will be a low-cost balanced option. This is particularly true for millimeter wave (mmWave) systems where propagation loss is high, and beamforming gain is essential for achieving sufficiently high signal-to-noise ratio.

Clutter Suppression

We will mainly treat multipath signals as useless clutter if they remain mostly unchanged and have near-zero Doppler frequencies over a period of time of interest. Mobile signals propagate in a complex environment, and a lot of clutter is present in the received signal. The clutter can significantly increase the number of sensing parameters to be estimated and make sensing algorithms fail if it is not reduced from the input to the algorithms.

Clutter suppression in the PMN can be potentially tackled by referring to work on clutter suppression for traditional radar such as the one in [9]. These techniques are typically applied to the Delay-Doppler domain after sensing parameter estimation. Nevertheless, they need to exploit

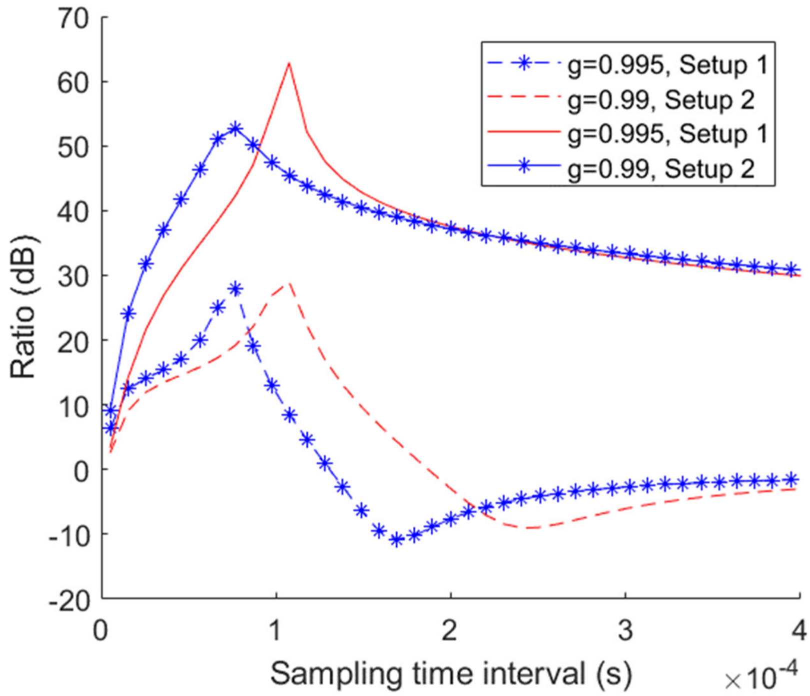


Figure 4 Signal suppression effect with different forgetting factors and sampling intervals. Setup 1: speed ranges [0, 5] and [25, 30] m/s. Setup 2: Speed ranges [10, 15] and [25, 30] m/s. Signal bandwidth is 100MHz, and the total recursion operation period is 100ms. The y-axis denotes the output power ratio between the two groups of signals with different speed ranges in each setup after applying the recursive operation.

different features of desired and unwanted echoes, such as a low correlation between them. These different features may not always be available in mobile networks, because desired multipath and echoes can come from the same classes of reflectors.

Alternative approaches exploit the correlation in time, frequency, and space domains, and use recursive averaging or differential operation to construct or remove clutter signals [5]. These approaches could be more viable for PMNs. They have similarities to background subtraction in image processing. However, there are some major differences in background subtraction between radio sensing and image processing. Firstly, in image processing, the image difference corresponds to pixel variation. But in radio sensing, both Doppler shifts and the variation of sensing parameters cause differences in two channel matrices. Secondly, background and foreground contents overlap with each other in an image, but in radio sensing, clutter and desired multipath signals are additive. Nevertheless, the large number of background subtraction methods developed for image processing can be revised and applied to radio sensing in PMNs. In [5], we proposed a simple recursive operation that can construct the clutter. Beyond clutter suppression, we can actually use this recursion to flexibly divide signals with widely separated Doppler frequencies into different sets by using different forgetting factors. In Fig. 4, we show the averaged power ratio between two groups of multipath signals that correspond to varying ranges of moving speeds, after applying the recursive method. The figure indicates that significant power suppression can be achieved between multipath signals with different ranges of Doppler shifts that correspond to different moving speeds. The sampling interval also has an important impact on the ratio, as it decides whether signals at different time are added constructively or destructively.

Although we have demonstrated the feasibility of clutter suppression in PMNs, there are still a lot of problems to be solved to make these methods practical. For example, signals need to be adequately segmented, as the actual variation of signals due to Doppler frequency or changed parameters are continuous. Apart from correlation processing in time, the background suppression principle may also be applied in the frequency and spatial domains.

Sensing and Pattern Recognition

Radar sensing is evolving from traditional radar with significantly expanded scope, involving sophisticated source signals, complicated propagation environment, advanced detection algorithms, and diverse applications such as object, activity, and event recognition.

In PMNs, the tasks of sensing can include both explicit estimation of sensing parameters for locating objects and estimating their moving speeds, and high-level application-oriented pattern recognition such as object and behaviour recognition and classification. Application-oriented pattern recognition can be combined or independently implemented with sensing parameter estimation, and more detailed examples can be referred to WiFi sensing [4]. Here we focus on sensing parameter estimation.

The extraction of sensing parameters from complicated mobile signals in complex propagation environments is very challenging. On the one hand, mobile signals are very complicated because of multiuser access, diverse and fragmented resource allocation, and spatial multiplexing. On the other hand, a modern mobile network connects diverse devices that occupy staggered resources interleaved and discontinued over time, frequency, and space. Existing techniques for passive sensing and radar may not work efficiently in this scenario, as typical radar systems are optimized for sensing a limited number of objects in open spaces using narrow beamforming [1,9]. Existing channel estimation and localization algorithms are not directly applicable either. In particular, channel estimation in communications only requires estimation of composite channels at quantized discrete grids, and localization focuses predominantly on the line-of-sight path. For sensing, detailed channel composition needs to be obtained.

In general, PMNs require sensing algorithms capable of estimating continuous parameter values, operating on non-consecutive measurements, and having low-to-medium complexity suitable for real-time implementation. Existing algorithms have respective shortcomings for sensing parameter estimation in PMNs, as compared in Table 5. Considering that the observed received signals could be discontinuous in time, frequency and space, compressive sensing (CS) is an excellent tool for sensing parameter estimation here. In [5], we demonstrated the feasibility by presenting two schemes, direct sensing that uses block CS and can directly work on the received signals, and indirect sensing that uses signal stripping to separate signals from different users and remove their data symbols. Both schemes are shown to work for multiuser-MIMO OFDMA signals, which are typical in modern mobile networks.

One important problem for CS-based sensing is how to select the dimension of CS algorithms underlying the sensing algorithms. Higher-dimension CS is more likely to resolve repeated parameters, but they have higher computational complexity. If on-grid models are used, the number of available observations in the dimension also limits the accuracy and resolution.

Networked Sensing under Cellular Topology

Integrating sensing into mobile communication networks provides excellent opportunities for radio sensing under a cellular structure. However, research on sensing under a cellular topology is still very limited. The cellular structure for communication is designed to greatly increase the frequency reuse factor and hence improve spectrum efficiency and communication capacity. A mobile sensing network intuitively also increases frequency reuse factor, and therefore the overall “sensing” capacity. There are few known performance bounds for such cellular sensing networks yet, except for a limited number of slightly related works, such as performance analysis for coexisting radar and mobile communication systems [2]. This may be investigated using the well-known stochastic geometry models of wireless networks. Although research exists on distributed radar and multi-static radar, sensing algorithms that consider and

Table 5 Comparison of Available Algorithms for Sensing Parameter Estimation.

Methods	Properties	Suitability and Main Limitation
Periodogram such as 2D DFT	Simple, but low resolution.	Generally require a full set of measurements in time or frequency domain, which may not be satisfied in uplink sensing.
Subspace methods such as ESPRIT	High resolution. High complexity. High dimension Tensor-based ESPRIT algorithms also available.	Require at least a large segment of consecutive samples, which may not be satisfied in uplink sensing.
Compressive sensing (On-grid model)	Flexible. Do not require consecutive samples. Algorithms can be selected to adapt to complexity and performance requirements.	Work well even for estimating a small amount of off-grid parameter values. Performance can degrade significantly when there are many unknown parameters, particularly in block CS algorithms.
Compressive Sensing (Off-grid) such as atomic norm	Flexible and do not require consecutive samples. Capable of estimating continuous values.	Limitation in real-time operation due to very high complexity, e.g., atomic norm requires semidefinite programming. Still require sufficient separation between parameter values.

exploit the cellular structure, such as co-cell interference, node cooperation, and sensing-handoff over base-stations, are yet to be developed. The challenge lies in the way to address competition and cooperation between different base-stations under the cellular topology, for both performance characterization and algorithm development of networked sensing.

One example is the development of distributed and cooperative sensing techniques by scheduling and grouping UEs and enabling cooperation between RRUs. On the one hand, existing research has shown that distributed radar techniques can improve location resolution and moving target detection by providing large spatial diversity and broad angular observation [13, 15]. Such diversity can be maximized by optimizing both waveform design and placement of radar nodes [15]. In the PMN, we can group multiple UEs' sensing results to improve uplink sensing. On the other hand, distributed radar can enable high-resolution localization, exploiting coherent phase difference of carrier signals from different distributed nodes [13]. This requires phase synchronization among radar nodes, and can only be potentially achieved in downlink sensing.

Conclusions

We have shown that by slightly modifying current cellular networks, they may become more perceptive. In this context, radio sensing may be integrated without sacrificing communication capability. Referring to the 5G NR standard, we show that uplink and downlink sensing can be realized with different degrees of modifications and enhancement to current hardware infrastructure, using existing communication signal format. There are many research opportunities for developing ground-breaking technologies and theorems for the integration of radio sensing into wide-area cellular communication networks. The PMN can potentially provide a ubiquitous radio sensing platform, and enable various smart applications for cities and transportation.

Although the system architecture presented here is specific to the mobile network, many of the results are also applicable to other networks such as point-to-point links and WiFi networks. However, there exist some major differences between the mobile network and other networks, which can have different impacts on sensing. These should be taken into consideration, as shown for WiFi in Table 6.

Table 6 Differences of WiFi networks with respect to mobile networks, and their implications on sensing, if JCAS is applied to WiFi, compared to PMN.

Aspects	WiFi networks (with respect to Mobile networks)	Different Implications on Sensing in WiFi-JCAS (with respect to PMN)
Signal Format and Transmission	Simpler and flexible packet structure, while PMN has rigid timing and channel structure.	Waveform optimization has more flexibility. Available sensing signals are more random in time.
Multiuser Access	Relatively simpler, while PMN has complicated resource allocation and mixed multiuser access methods	Sensing parameter estimation can be simpler with more optional algorithms.
Deployment Environment	Mostly indoor, and Low-speed movement.	Richer multipath but more stable clutter. Less challenging in sensing due to a simpler environment.
Network infrastructure and Scale	Smaller network. Less powerful infrastructure such as smaller antenna array.	Low potential for networked sensing. Lower sensing resolution.

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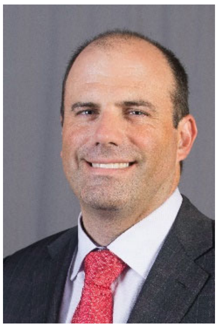

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