Collaborative Sensing in Perceptive Mobile Networks: Opportunities and Challenges

Lei Xie, Shenghui Song, Yonina C. Eldar, and Khaled B. Letaief

Abstract

With the development of innovative applications that demand accurate environment information, for example, autonomous driving, sensing becomes an important requirement for future wireless networks. To this end, integrated sensing and communication (ISAC) provides a promising platform to exploit the synergy between sensing and communication, where perceptive mobile networks (PMNs) were proposed to add accurate sensing capability to existing wireless networks. The well-developed cellular networks offer exciting opportunities for sensing, including large coverage, strong computation, communication power, and, most importantly, networked sensing, where the perspectives from multiple sensing nodes can be collaboratively utilized for sensing the same target. However, PMNs also face big challenges, such as the inherent interference between sensing and communication, the complex sensing environment, and the tracking of high-speed targets by cellular networks. This article provides a comprehensive review on the design of PMNs, covering the popular network architectures, sensing protocols, standing research problems, and available solutions. Several future research directions that are critical for the development of PMNs are also discussed.

Introduction

After several generations of development, wireless communications has evolved from a system with only communication services to an intelligent network that not only moves data but also performs edge-computing and distributed learning/inference tasks [1]. The advancement of innovative applications, such as autonomous driving and environment monitoring further requires accurate sensing capabilities from future wireless networks. To this end, the recently proposed integrated sensing and communication (ISAC) paradigm offers a promising way to share the spectrum, hardware, and software between sensing and communication applications, especially after millimeter wave (mmWave) was adopted for 5G and beyond systems. Perceptive mobile networks (PMNs) are a special type of ISAC system that focuses on adding sensing capability to the cellular networks [2].

There are many favorable properties of cellular networks that can facilitate sensing. First, the well-developed mobile network with high-density base stations (BSs) can provide large sensing coverage. The high-density nodes are very important because mmWave experiences severe pathloss and is, thus, not suitable for long-range sensing tasks. Second, the large number of distributed and connected sensing nodes enables networked sensing, where multiple perspectives from different sensing nodes are exploited to sense the same target. Finally, the strong computation and communication power of PMNs create a good platform for large-scale environment estimation and mapping, which will not only benefit sensing but also enhance communication in terms of channel estimation, resource allocation, beam tracking, and more.

However, there are also challenges faced by the design of PMNs [2]. Since PMNs integrate sensing and communication in one system, interference management is one of the most important issues to tackle. In particular, there exist three types of interference. First, if the same node, for example, a BS, is utilized for transmitting sensing/communication signals and receiving radar echoes at the same time, there will be self-interference (SI) [3]. Second, given both communication and sensing users are served in the same frequency band, there will be interference between the two sub-systems. Finally, prior information about the environment is critical for sensing and normally obtained by environment training (estimation). In conventional radar systems, the transmitted signal in the environment training and target sensing periods is the same, thus, guaranteeing the same covariance structure for the echoes reflected by the environment, known as clutter. However, sensing and communication signals co-exist in PMNs and, due to the severe pathloss in the mmWave band, directional signals (beamforming) are utilized for both communication and sensing purposes. As a result, the transmitted signals may be different in the environment training and sensing periods, which will lead to different clutter covariance structures. This can be regarded as interference to environment estimation.

Besides interference management, the implementation of networked sensing and environment estimation algorithms also faces several obstacles. On the one hand, although networked sensing can take advantage of the multiple perspectives from several sensing nodes, the collaborative sensing algorithm must be computation and communica-

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	Sensing Transmitter	Sensing Receiver	Full-Duplex	Synchronization
Mono-static DFRC	BS	BS	Required	Not Required
PMN-RRU	RRU	RRU	Not Required	Required
PMN-TMT	BS	TMT	Not Required	Required

TABLE 1. Comparison of existing ISAC networks.

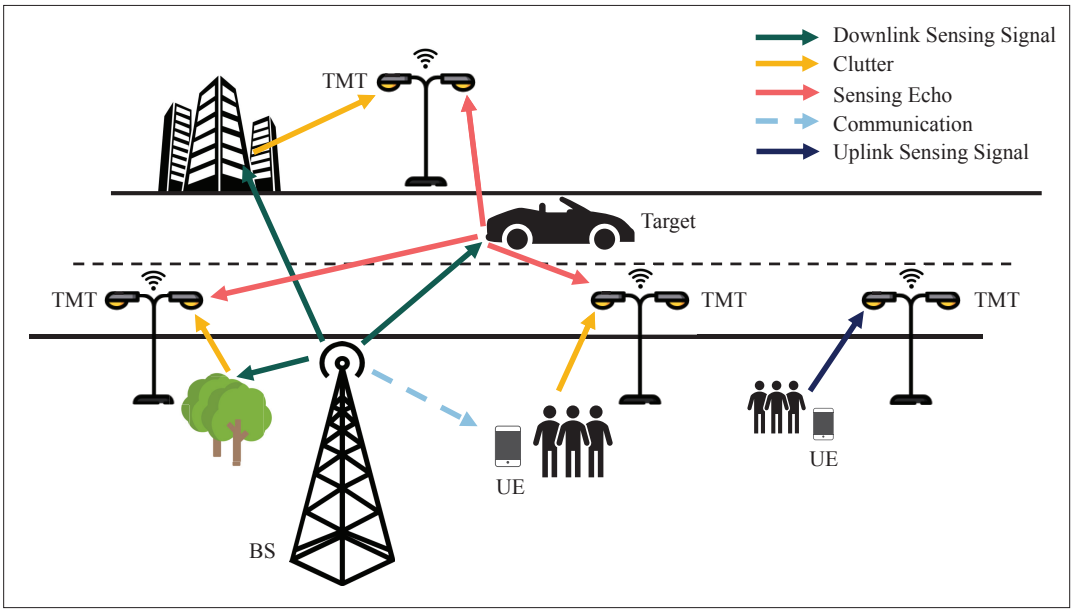

FIGURE 1. Illustration of the PMN-TMT architecture.

tion efficient due to strict latency requirements. On the other hand, the environment for networked sensing is much more complex than traditional radar systems because the communication users, the target and even the clutter patches in the environment may move, for example, in city streets of urban areas. This makes environment estimation very challenging, especially with distributed sensing nodes. Furthermore, the stringent latency constraint precludes estimation algorithms that require a large amount of training data and heavy computation.

This article aims to provide a comprehensive overview on the design of PMNs. For that purpose, we will first introduce and compare several existing network architectures and sensing protocols. In-depth discussions about the key research problems will then be given, revealing the key design opportunities and challenges in interference management, networked sensing and environment estimation. Future research directions that are critical for the development of PMNs and their service to other applications will also be covered. Different from the existing reviews about ISAC [3–6], this article mainly focuses on PMNs especially the benefits of networked sensing.

Network Architecture and Sensing Protocol

Network architecture and sensing protocol are the two most fundamental frameworks for integrating sensing into current cellular networks.

Network Architecture Design

There are three main network architectures proposed for PMNs in the literature. In traditional cellular networks, interconnected BSs will serve mobile user terminals (UEs). It is, thus, natural to select the BSs as the transmitter for the sensing signal and the receiver for the echo signal [7]. This is referred to as the mono-static dual-function radar and communication (DFRC) system, where the BSs are required to work in full-duplex mode for transmitting and receiving signals at the same time. Another architecture [2] integrates sensing into the cloud radio access network (C-RAN) where remote radio units (RRUs) are densely distributed. To address the full-duplex issue, some RRUs are selected as dedicated receivers in the downlink sensing time, such that the sensing transmitter and receiver are separated to be different RRUs. We will refer to this scheme as the PMN-RRU architecture.

A new PMN architecture was proposed in [8] where another layer of passive target monitoring terminals (TMTs) are added to the conventional cellular networks. TMTs are nodes designed for Internet of Things (IoT) applications with only passive sensing functionalities, such as radar and vision [9]. They are distributed in a target area and connected with the BSs through low latency links. Given that TMTs will serve as dedicated radar receivers, BSs only need to serve as the transmitter for sensing signals, thus saving the need for full-duplex operation. We will refer to this design as the PMN-TMT architecture.

Both PMN-RRU and PMN-TMT avoid the full-duplex operation at the cost of network synchronization. Compared with RRUs, TMTs are low cost IoT devices with only passive sensing functions that can also be utilized for other types of IoT services. TMTs work as passive radar detectors, but are different from traditional passive radar because they are connected with the BSs, which enables

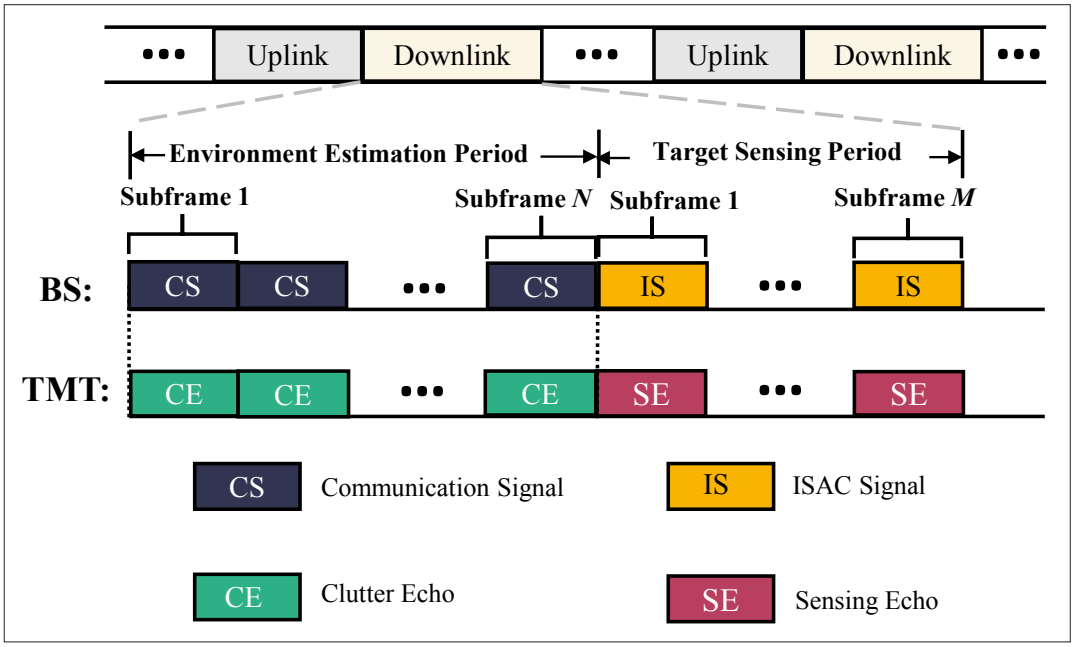

FIGURE 2. Frame structure for the two-stage sensing and communication protocol [11].

joint transceiver design. Table 1 compares the three architectures and Fig. 1 shows an example of the PMN-TMT scheme. Note that all three architectures may perform collaborative or networked sensing but with different sensing nodes, that is, BSs, RRUs, and TMTs, respectively. In the following, we will simply use TMTs as the sensing nodes and all discussions apply to the other two architectures.

Protocol Design

ISAC systems have inherent interference issues and proper protocols play the key role in interference management and resource allocation between sensing and communication [5]. In [4], the authors proposed a three-stage protocol to coordinate communication and sensing modules for a mono-static DFRC system. In Stage 1, the BS utilizes the omni-directional beam to search the sensing targets and scatterers, and receives the uplink pilot from the UEs. In Stage 2, the BS transmits the directional communication and sensing signals to the UEs and the sensing target, respectively, where the transmission directions are estimated in Stage 1. In Stage 3, the BS receives the radar echoes and the uplink signals from the UEs for target detection and tracking. A two-stage protocol was proposed in [10] to achieve joint target detection and channel estimation. In the initial stage, the BS sends omni-directional downlink pilots to search for the target, where the channel estimation is performed based on uplink pilots from the UEs. Based on the initial results about the target and communication scatterers obtained in the first stage, the BS sends directional downlink pilots in the second stage for refined target detection and channel estimation.

In PMNs, sensing nodes will receive both the target echo and the clutter. To handle target sensing in complex environment with the presence of the clutter, the authors of [11] proposed a two-stage sensing protocol where environment estimation (EE) and target sensing (TS) are performed in two consecutive periods as illustrated in Fig. 2. In particular, the downlink transmission time is divided into two periods, namely, the EE period and the TS period. In the EE period, the covariance matrix of clutter caused by communication signals is estimated, which is then utilized for sensing the target in the TS period. There are two interference management issues with this protocol:

- Interference between sensing and communication.
- Interference to environment estimation.

Key Research Problems: Opportunities and Challenges

The design of PMNs is still in its infancy. In the following, we identify several key research problems and discuss the design challenges, opportunities, and existing solutions.

Interference Management

There are three types of interference in PMNs:

- In the mono-static DFRC, the BS needs to transmit and receive signals at the same time, causing SI.
- As a special type of ISAC system, there is inherent interference between sensing and communication in PMNs.
- Due to the use of narrow beams in the mmWave band, both communication and sensing signals may change the environment statistics in the TS period, and this can be regarded as interference to environment estimation.

In the following, we discuss existing solutions for managing the above-mentioned interference.

Self Interference: Conventional pulse radar works in a half-duplex mode to avoid SI. In each pulse repetition period, antennas will utilize a long time to receive the potential echoes after transmitting the sensing signal. However, half-duplex mode will not work for PMNs because BSs need to transmit communication signals all the time. Among the three architectures mentioned above, the mono-static DFRC scheme requires the BS to work in full-duplex mode to transmit and receive signals

	Interference from Sensing to Communication	Interference from Communication to Sensing
AO	Allowed	Allowed
B-Syn	Not Allowed	Allowed
ZF	Not Allowed	Not Allowed

TABLE 2. Comparison of the beam patterns for AO, B-syn and ZF.

at the same time. Under such circumstances, the SI is mitigated by self-interference cancellation techniques, which unfortunately are not very mature [12]. On the other hand, the PMN-RRU and PMN-TMT architectures naturally avoid SI.

Interference between Sensing and Communication: There are several unique features of sensing and communication signals in PMNs:

- The sensing signals will interfere with the UEs and may degrade the communication performance.
- The communication signals reflected by the target can be utilized to probe the target as they are known by the BSs [7].
- The communication signals reflected by the environment will cause the clutter for sensing.

Depending on the design objective, different approaches have been proposed to manage the interference between sensing and communication.

There are works that consider both sensing and communication performance. Along this line, spectrum sharing between sensing and communication was investigated in [13] by dynamic spectrum access and mutual interference mitigation. In [8], the authors maximized the weighted average of sensing and communication performance by jointly designing the transmitter and receiver, where the sensing metric is selected as the signal-to-clutter-plus-noise ratio (SCNR) and the communication metric is the signal-to-interference-plus-noise ratio (SINR). An alternating optimization (AO) based framework is proposed to iteratively update the transmit and receive beamformers. There are also works that prioritize one side of the ISAC system. For example, the communication performance was maximized in [14] by treating radar signals as interference.

In terms of the transceiver design, besides the AO-based method that jointly optimizes the transmitter and receiver, linear transceivers have also been considered to reduce the computation complexity. For example, zero-forcing (ZF) and beam synthesis (B-syn) transmitter, and the minimum variance distortionless response (MVDR) receiver were investigated in [8]. These linear transceivers not only reduce the computation complexity but also provide interesting physical insights. For example, "leaking" energy from communication signals to the sensing target (ST)[1] is more efficient than forming a dedicated sensing signal, and the amount of energy leaked from one UE to the ST depends on their channel correlation, which is determined by their locations.

AO, B-syn, and ZF represent three different ways to tackle interference between sensing and communication. In particular, AO allows interference between sensing and communication and handles it by joint transceiver design, B-syn only allows interference from communication to sensing and utilizes communication signals as the sensing signal, while ZF eliminates all interference between sensing and communication by designing a dedicated sensing signal that will not interfere with the UEs. The interference pattern between sensing and communication with AO, B-syn, and ZE is illustrated in Table 2.

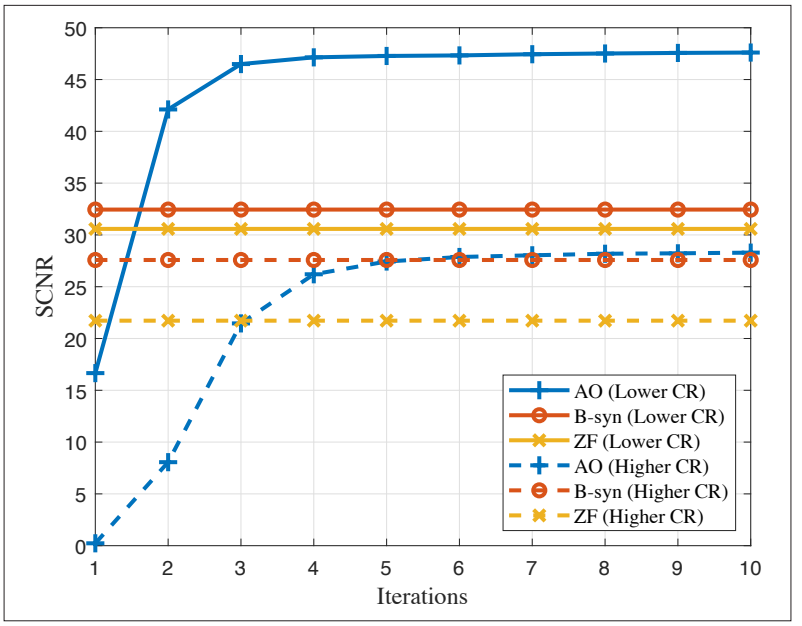

FIGURE 3. Comparison of SCNR between AO, B-syn, and ZF under different CR. The BS employs a ULA with N_t = 16 antennas. The receiver employs a hybrid beamforming structure with N_r = 16 antennas and N_{RF} = 4 RF chains. The signal-to-noise ratio and clutter-to-noise ratio are 17dB and 40dB, respectively.

Figure 3 compares the sensing performance of the three transmitters with high and low communication requirements (CR), respectively. It can be observed that, under both circumstances, the performance of AO is the best, and B-syn outperforms ZF. Note that different transceiver structures have different tolerance for interference, and the stronger the orthogonality constraint (ZF>B-syn->AO), the worse the sensing performance. Furthermore, when the CR is high, the gap between the three schemes is smaller. This is partially due to the less energy left for sensing when the CR is high. On the other hand, when the CR is low, high interference is acceptable to the UEs, thus it is not necessary to completely eliminate the interference from sensing to communication. However, high CR forces AO to avoid the interference from sensing to communication like what B-syn does. Therefore, the gap between AO and B-syn becomes smaller. When their performance is comparable, B-syn is preferred because its computational complexity is much lower than AO.

Interference to Environment Estimation: For the two-stage schemes proposed in [11], the signals transmitted in the EE and TS periods are different. In particular, in the EE period, the BS transmits the communication signals to serve the UEs, and the TMTs estimate the clutter covariance matrix based on the echoes triggered by the communication signals. However, in the TS period, the BS transmits the designed ISAC signal to serve the UEs and probe a target, simultaneously, while the TMTs utilize the sensing echo (SE) reflected by

[1] Here, leaking energy from communication signals means to revise the beamformer for the UEs so that part of the communication signals will also be sent toward the ST.

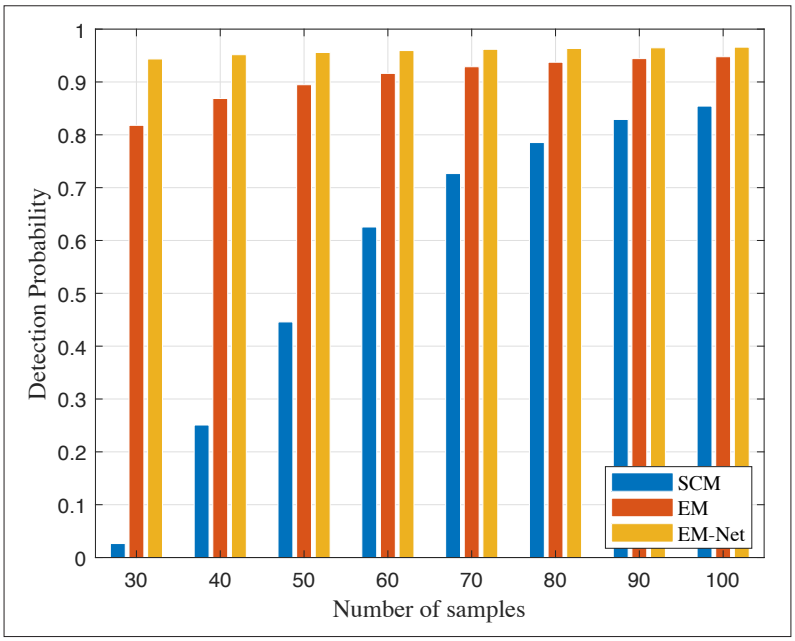

FIGURE 4. Detection performance versus the batch size for different environment estimation methods. The number of the antennas at one TMT and the number of TMTs are set as $N_R = 16$, and $L = 3$, respectively.

the target and clutter patches for target sensing. Therefore, the received clutter in the TS period may have different covariance matrix from that in the EE period. To tackle this issue, the sensing signal in the TS period must be designed to avoid generating any echoes from the clutter patches, such that the covariance matrix of the clutter received by TMTs will be the same as that in the EE period. For that purpose, the idea of B-syn can be adopted such that the sensing signal has no energy toward the clutter patches.

Networked Sensing

Networked sensing is one of the most exciting opportunities for PMNs, where the multiple perspectives from different TMTs can be collaboratively utilized to improve sensing performance. The biggest advantage of networked sensing comes from the macro-diversity of multiple TMTs. Note that, similar to wireless communications, the macro-diversity gain improves the reliability of target detection, because the chance that all the perspectives from different TMTs are blocked is very low. However, the impact of the multiple antennas at one TMT on sensing is different from that for wireless communications. The influence of both the number of TMTs and the number of antennas per TMT was analyzed in [11] with some interesting observations.

Contribution of One Multi-Antenna TMT: The contribution of a single multi-antenna TMT comes from several aspects. First, the distance between the ST and the TMT affects the receive SNR exponentially due to pathloss. Second, one TMT has its unique perspectives (AODs) toward the target and the clutter patches in the environment. The relation between those AODs dictates how easy it is for the TMT to separate the target from the clutter patches. Finally, the number of antennas at one TMT affects sensing in two aspects. On the one hand, the receive SNR at the TMT is directly proportional to the number of antennas, which is referred to as the antenna array gain. On the other hand, the number of antennas determines the array resolution, which indicates the TMT's ability to extract the target echo from the clutter. In particular, arrays with larger number of antennas can separate closer target and clutter patches.

However, multiple antennas no longer provide diversity gain for sensing. Note that multi-antenna receivers achieve diversity gain in wireless communications because the channel coefficients of different transmitter-receiver antenna pairs are not fully correlated or even independent. However, in sensing, only the line-of-sight (LoS) component is considered, and all non-LoS components are regarded as part of the clutter. As a result, the channel between the ST and the TMT becomes deterministic and no diversity can be achieved by the multiple antennas of one TMT.

Macro-Diversity and TMT Selection: Due to the different perspectives and independent reflection coefficients, the channels between the ST and different TMTs are normally independent. As a result, multiple TMTs will provide macro-diversity gain for sensing. But, this does not mean that we should include as many TMTs as possible, because the detection probability is not a monotonic increasing function of the number of TMTs. This phenomenon was analyzed and discussed in [11]. Assume there are already L TMTs participating in the networked sensing. A new TMT, that is, the $(L+1)$-th TMT, will change the distribution of the decision statistics under both the target-absence (TA) and target-presence (TP) hypotheses. Consider an extreme case where the new target-TMT link is blocked. Under such circumstances, the $(L+1)$-th TMT will only contribute noise under both hypotheses, and thus cause worse performance. As a result, it is unnecessary and even harmful to activate all TMTs to sense one target, making TMT selection a critical task. In [11], a sufficient condition for the contribution of one more TMT to be positive was derived, with which a TMT selection algorithm was proposed.

Data Fusion: The fusion of the target information collected by multiple TMTs is another challenge for PMNs, which can be achieved in two levels:

- Signal level fusion: The TMTs transmit their local data to the central processing unit (CPU). Then, the CPU performs collaborative sensing based on data from all TMTs.
- Information level fusion: Each TMT performs individual sensing based on its own data. The intermediate results, for example, the sensing parameters, are collected and fused at the CPU.

In general, the signal level fusion can achieve better performance than the information level fusion, at the cost of higher computation, communication, and hardware resources.

Environment Estimation

Another challenge for PMNs is EE. A compressed sensing-based method was proposed in [15] to achieve EE by utilizing the spatial parameters and Doppler shift of the clutter. Unfortunately, the computational cost of the compressed sensing-based method can be extremely high, due to the continuous and rapidly-changing environment parameters in the space and Doppler domains. This issue will be more serious when multiple distributed TMTs are involved in the networked sens-

ing where information sharing between different TMTs is necessary. Thus, a communication efficient EE algorithm is desired.

To reduce the number of required data samples for EE, the authors of [11] proposed the expectation-maximization (EM)-based covariance estimation algorithm. The low rank clutter in the mmWave band [13] makes it possible to estimate the clutter covariance by using partial samples of the received signal. However, the estimated covariance matrix may be ill-conditioned due to the limited data samples. To this end, the EM-Net algorithm was proposed by unfolding the EM detector with several learnable parameters, which achieves accurate estimation with less data samples than existing methods. Figure 4 shows that EM-Net outperforms both the EM approach and the conventional sample covariance matrix (SCM) based method, and the detection performance will improve as the batch size increases. The lower requirement on data samples reduces the hardware (memory) requirement, data processing time, and more importantly, communication workload, which significantly decreases the latency of the system.

Future Research Directions

In this section, we list several future research directions for the development of PMNs.

Target Tracking

A big challenge for networked sensing is to track a moving target. This is because, different from traditional radar, the coverage of one TMT is very limited. Thus, the sensing task needs to be smoothly handed over to another TMT when the target is moving. The situation is even worse for networked sensing where the handover is not from one TMT to another TMT, but from one group of TMTs to another group with possible overlapping between two groups. Note that handover is not a new problem, as it is also required for wireless communication services. However, the problem is not the same for sensing due to several reasons. First, the synchronization requirement for networked sensing makes the problem much more difficult. Second, the handover criteria are more complex. Specifically, besides the signal strength which is normally the criterion for handover in communication, angles (AOA/AOD) and moving direction of the target also matter a lot for sensing. Third, for a fast moving target, for example, an autonomous vehicle on the highway, the narrow sensing beams may have difficulty following the target so that "predictive" sensing beams may be required.

To this end, besides the Kalman filter (KF) based method, machine learning or data-driven approaches may play a more important role due to several reasons. On the one hand, the physical environment, for example, the roads, for a fast moving target is relatively fixed, making it easier to extract useful information from history data. On the other hand, the strong computation and communication power of PMNs make it possible to build a map of the environment, that is, Simultaneous Localization and Mapping (SLAM). Furthermore, graph neural networks (GNNs) have been shown effective to handle wireless network design problems, such as traffic prediction, resource allocation, and data detection, and the handover problem can also be formulated as a graph optimization problem.

Joint Networked and Individual Sensing

Networked sensing can be utilized to facilitate the design of many smart applications. For example, in autonomous driving, a key task for the vehicle is to understand the environment, including the road, other vehicles, pedestrians, and so on. Currently, this is mainly achieved by many sensors installed on the vehicle, such as vision, lidar, and radar. We will refer to this as individual sensing. Networked sensing by PMNs can help measure the position and velocity of a moving vehicle. Due to latency requirement, such results can not be directly utilized to control the vehicle. However, networked sensing may provide useful complement for individual sensing in autonomous driving applications.

There are several promising research directions. First, networked sensing is able to reduce the workload of individual sensing. For example, networked sensing can build up and keep updating a map about the static environment, saving the need for individual sensing to construct such a map. Second, networked sensing will be able to monitor the changing environment, for example, other moving vehicles, to provide assistant information for individual sensing. Finally, many long-term tasks such as routing and traffic management can be taken over by networked sensing.

Intelligent Reflecting Surfaces (IRS)-aided Sensing

Compared with the sub-6GHz band, mmWave experiences high pathloss which makes directional transmission by spatial beamforming inevitable. As a result, both mmWave sensing and communication rely heavily on the LoS link, which unfortunately can be easily blocked. Intelligent reflecting surfaces (IRSs) have been proposed to create an alternative link between the transmitter and receiver, and attracted much attention in the design of wireless communication. The ability of IRSs in creating semi-LoS links can be utilized to facilitate the design of PMNs in several aspects, including interference management, networked sensing, and velocity estimation. In particular, due to the complex environment, it is possible that the sensing target has the same AoA/AoD as some UEs with respect to one TMT. Under such circumstance, IRSs will be able to create another link and avoid the interference between sensing and communication users. The same idea can be utilized for networked sensing, when one TMT's perspective to the target is blocked. In fact, with proper phase-shift design, one IRS can help multiple TMTs.

The application of IRS in sensing is not limited to creating alternative paths. The additional perspective can also help improve velocity estimation. For example, with the conventional mono-static radar, only the radial projection of the true velocity can be estimated due to the nature of Doppler effect. As a result, if the target is moving on the direction perpendicular to the line connecting the target and one TMT, the velocity estimation will not be accurate. The additional path provided by the IRS can provide another perspective to observe the target, which is useful to recover the true velocity.

A big challenge for networked sensing is to track a moving target. This is because, different from traditional radar, the coverage of one TMT is very limited. Thus, the sensing task needs to be smoothly handed over to another TMT when the target is moving.

Networked sensing brings unprecedented opportunities to exploit the well-developed infrastructure of cellular networks for sensing purposes, but at the same time faces serious challenges in interference management and environment estimation.

Joint Active and Passive Sensing

The above discussions considered networked sensing in an active manner, that is, the BS actively transmits the sensing signal and TMTs perform the detection based on the echoes. The active mode works for any targets. However, if the PMNs want to locate the UEs, which also use the communication service, there is another mode of passive sensing. In particular, the UEs will transmit signals in the uplink period, which can also be used for radar detection. For targets with weak electromagnetic wave reflection characteristics, for example, pedestrians, the passive method can provide a good detection performance. The passive mode is also more power-efficient as there is no transmission overhead. However, it loses several advantages of active sensing, such as the well-designed waveform, flexible transmitting beam, and higher detection range. As a result, it may not be sufficient to only utilize the passive mode to achieve accurate sensing performance. A joint design between active and passive sensing in PMNs is an interesting direction to investigate, which is especially useful for sensing-aided communication.

Sensing-Aided Communication

By far, we have been focusing on the design of PMNs for sensing purposes by exploiting the well-developed communication network. On the other hand, sensing can also be utilized to assist communication especially in the mmWave band where highly directional signals are transmitted in a sparse channel.

Sensing-Aided Channel Estimation: The transmission of highly directional beams over a sparse channel creates challenging problems for channel estimation, because of the very large searching space in the angular domain plus the limited measurements. Among other solutions, the compressed sensing-based methods were widely studied to exploit the sparse structure, but they suffer from high computational complexity and are not robust to noise, hardware-led errors in array response, and the off-grid issues. To this end, the sensing results by PMNs can be of great assistance. In particular, the sparse channel is composed of several main scatterers whose locations can be obtained by sensing. As a result, sensing results can significantly reduce the searching space for channel estimation and improve the estimation performance with limited measurements.

Sensing-Aided Beam Tracking: Beam alignment is a fundamental issue in mmWave communication. The narrow mmWave beams are very sensitive to the change of environment, for example, the movement of the UEs. As a result, beam alignment becomes more difficult in highly mobile scenarios, as the state of a UE can change before beam training has been completed. Thus, under certain circumstance, "predictive" beams are required to maintain good communication performance. To this end, the powerful capability of sensing in location and velocity estimation will be able to help for tracking the moving UE and forming communication beams.

Clock Synchronization

Clock synchronization (CS) is an inherent challenge for networked sensing, due to the distributed nature of the network [10]. Both software and hardware based CS methods have been developed for wired and wireless networks. In general, hardware based solutions can provide better synchronization accuracy than software based methods but at the cost of additional hardware requirements.

PMNs face special challenges in CS. First, the network structure in PMNs is very complex, including the BSs, the sensing nodes (TMTs), and the UE (passive sensing), making CS very challenging. Second, the mobility of the target will lead to the handover issue between different sets of sensing nodes, causing additional difficulties for CS.

Conclusion

Networked sensing brings unprecedented opportunities to exploit the well-developed infrastructure of cellular networks for sensing purposes, but at the same time faces serious challenges in interference management and environment estimation. Joint processing among distributed nodes over the network also incurs difficulties in designing communication and computation-efficient algorithms. Existing network architectures, sensing protocols, and transceiver design could tackle some of the challenges while achieving favorable results, such as the macro-diversity from multiple sensing nodes, the array gain by multiple receive antennas, and the efficient environment estimation with data-driven methods. However, the development of ISAC/PMNs is in its infancy and there are still many obstacles to conquer before we can fully enjoy the synergy between sensing and communication to support more innovative applications.

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