Optimal Sensor Placement for Target Localization in IoT Systems: A Cramér-Rao Bound Perspective

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Abstract

Wireless sensor network (WSN) constitutes the backbone of the Internet of Things (IoT), where target localization is an essential function that enables various IoT applications. Apart from the observations and signal-to-noise ratio, the localization performance of a WSN is affected by the relative geometry between the sensors and the target. Placing the sensors at better positions can reduce the noise sensitivity to the target location estimate, making most IoT operations more effective. This article provides a comprehensive overview of the models, technologies, implementations and challenges of optimal sensor placement for IoT. Specifically, we first illustrate the influence of sensor placement on the target localization performance using the Cramér-Rao lower bound (CRLB) theory that defines the asymptotic performance of a location estimator. Then, several CRLB-based metrics to characterize the positioning accuracy are introduced and elaborated. Next, based on the desired performance criterion, major techniques for solving the optimal sensor placement problem are discussed, including the analytical, numerical and data-driven approaches. Finally, we demonstrate some practical implementations of IoT systems with sensor optimal placements for localization, followed by a summary of challenges for future research and conclusions.

I. Introduction

The Internet of Things (IoT) envisages the coordination and mobility of a huge number of devices with sensing, computation, and communication capabilities to embrace the proliferation of advanced applications such as smart city, industry 4.0, and many others. According to the public data from Statista, Grand View Research and Market Research Future, the IoT market is projected to increase at around 16% compounded average growth rate through 2030, driven by 5G, WSN, and location-based services. The IoT market size will reach \$1.3 trillion and thus IoT technique is a hot topic nowadays. Underlying this game-changing technology, wireless sensor networks (WSNs) form the fundamental framework that constitutes the backbone of IoT where the IoT devices can be the sensor nodes, whose basic purpose is to support the key functionalities of communication and detection leveraged by the deployment of a large number of perceptive sensors. In this article, we focus on the localization aspect, and refer to a target as an object of interest.

Accurate target localization is vital to facilitate the IoT service in applications including search and rescue, manufacturing, community safety, beacon detection, precision agriculture, and others [1], [2]. The localization accuracy is limited by the inevitable measurement noise due to the various environmental factors and sensor hardware electronics. Methodologies to mitigate the noise sensitivity on the localization performance are highly sought as a main subject for research. Among them, sensor placement is a novel approach to achieve this purpose, by exploiting the fact that the performance of localization is affected by the sensor-target geometry. From the estimation perspective, such a placement would improve localization performance through a well-conditioned Fisher information matrix (FIM) or Cramér-Rao lower bound (CRLB) in minimizing the geometric dilution of precision compared to a random or ad-hoc deployment.

While the proliferation of WSN has recently increased the interest in optimal sensor placement for localization, this research topic has some history from the literature. Back in the 1980s, researchers found that a certain orientation of the bearing angle sensor with respect to the target can achieve better estimation performance [1], [3]. Since then, many studies on optimal sensor placement have appeared for other measurements, e.g., time-of-arrival (TOA) [4], received-signal-strength (RSS) [3], and angle-of-arrival (AOA) [5]. These works primarily focused on the optimal sensor placement on the 2-dimensional (2D) plane with applications mostly on long-range localization by radar systems. Subsequently, many researchers extended the scope of the topic to the undersea sonar system, and in recent years, the related research has been further extended to cover the 3-dimensional (3D) space, leading to many

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insightful results serving as design guidance and performance benchmarks for many applications. Nowadays, the rapid developments of WSN have resulted in advanced sensing agents such as robots and unmanned aerial vehicles (UAV), together with emerging applications such as unmanned logistics and intelligent warehouses. These advances bring additional challenges and opportunities that have collectively foster the research on optimal sensor placement to a new stage.

Motivated by the pressing need for IoT development and the research to surmount the related challenges, it would be imperative to academicians and practitioners to have an overview of this critical topic that highlights the research efforts, the latest results, and the state-of-the-art methodologies. To this end, we hope the article will encourage the research and development of optimal sensor placement for WSN technology in IoT applications.

The rest of this article is organized as follows. We first present in Section II the basics for the sensor placement problems. The corresponding design principles and their performance are illustrated in Section III. Section IV gives the implementation details and some use case examples. Section V introduces some research frontiers related to sensor placement, followed by the conclusions in Section VI.

II. Fundamentals for Sensor Placement

We shall introduce the basics of the sensor placement problem, which will serve as a preliminary for the discussions followed. Specifically, we shall present the measurement model for various RF sensors, the CRLB that relates the estimation accuracy with the sensor positions, the metrics that define the localization performance for optimization, and some typical constraints for sensor placement considerations.

A. Measurement Model

The applications based on the location of a target are diverse, common ones are mobile user localization, IoT-assisted manufacturing, bush fire detection, and underwater object localization. Fig. 1 depicts a deployment of multiple sensors to form a WSN aimed at target localization for achieving these applications. The common localization measurements are TOA, RSS, AOA, or Doppler frequency shift [6], [7]. Apart from these basic measurements, improved and hybrid versions could also be constructed, e.g., time-difference-of-arrival (TDOA), frequency-difference-of-arrival (FDOA), TOA-RSS, etc. [6]. The goal is to extract the target location as accurately as possible from the collected set of measurements.

Due to the imperfections, disturbances, or interferences from the ambient environment and sensor itself, the measurements are deficient, resulting in a limitation of the localization accuracy. To characterize the estimation performance, we model a measurement as the perfect (true) value added with corrupting noise. The true value is a function of the location of the target to be found, and the positions of the sensors. The additive noise is specified statistically by the probability density function (PDF). The localization accuracy is defined by both the sensor positions and the PDF.

B. CRLB

The FIM [8] is often used to statistically describe the underlying information available from the measurement for estimation. In general, the larger and better conditioned the FIM, the more information we can gain from the measurement to achieve better estimation of the unknowns of interest. It is derived from the measurement model, determined mathematically by the negative of the expectation of the second order derivative of the log-likelihood function with respect to the unknown vector, please refer to [8] for the details about the evaluation of FIM. Consequently, the mathematical expression of the FIM will be different when using RSS, TOA, AOA, or hybrid measurements, which will lead to different sensor placement results.

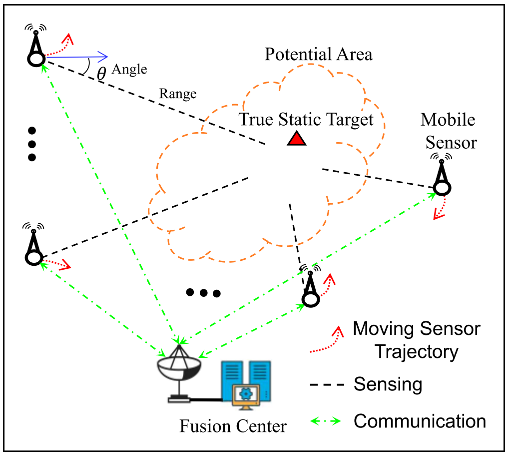

FIG. 1. System model for locating the static target represented by the triangle using a WSN system composed of several mobile sensors denoted by circles. Sensors can acquire angle, range and some other kinds of measurements and the fusion center collects them to locate the target.

The inverse of FIM is the CRLB [9], which defines the lower bound on the covariance matrix of an unbiased estimator. The CRLB for localization turns out to be a function of both the actual target location and the sensor positions. It is therefore logical to use the CRLB to derive metrics for optimal sensor placement to minimize the localization error. The CRLB can be very complex in some cases, depending on the number of targets, the number of sensors, the measurement types, and the noise PDFs. For the multiple-target scenario, the CRLB of all targets can be decomposed into multiple single-target sub-CRLBs. However, the cross-coupling of the sub-CRLBs could make the analysis cumbersome [4] for sensor placement. As a result, most of the studies in the literature focus on the localization of a single target, having one measurement type and independent and identically distributed (IID) noise from different sensors. Furthermore, the noise PDF is reasonably assumed to be Gaussian to simplify the CRLB evaluation.

However, the CRLB will become inefficient or not tight-enough in some other localization scenarios, e.g., the low signal-to-noise ratio cases, or estimation under strong nonlinearity. Thus, other alternative bounds including the Ziv-Zaka bound or unscented CRLB may be more appropriate. Most previous studies of optimal sensor placement used CRLB for its simpler analytical expression, and sensor placement optimization using a different performance bound is a frontier topic in this research area.

C. CRLB Based Performance Metrics

In target localization, the research community was originally concentrated on developing estimation

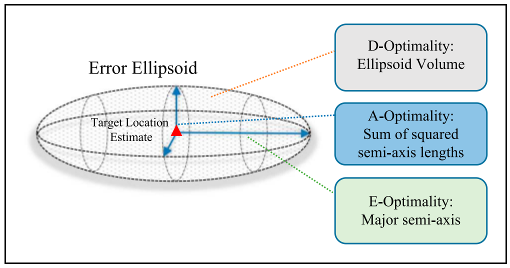

FIG. 2. The error ellipsoid visualizes the covariance of parameter estimates, while the CRLB governs its theoretical limits. Differences between A-, D- and E-optimality criteria.

algorithms to determine the target position, rather than on the sensor placement. To have a reference against the performance of an estimator, the CRLB is a reasonable choice as the benchmark. As the researchers realize that the benchmark is related to the sensor positions, it is then natural to derive different metrics from the CRLB to further optimize the performance with better sensor placements. There are three widely used metrics for this purpose, viz., A-, D- and E-optimality criteria, which aim at minimizing the trace, determinant and largest eigenvalue of the CRLB, respectively.

In the Gaussian noise case, the uncertainty region of the estimation can be described by an ellipsoid [8], and these metrics reflect the diverse characteristics of this ellipsoid. As shown in Fig. 2, the trace of the CRLB (A-optimality) denotes the sum of the squared semi-axis lengths of the ellipsoid, the determinant of the CRLB (D-optimality) indicates the volume of the estimation uncertainty, and the largest eigenvalue of CRLB (E-optimality) reflects the elongation of the ellipsoid. Each metric has its own focus and limitations [8], and optimizing different metrics may lead to different sensor geometries. Consequently, it is essential to select an appropriate metric according to the practical requirement objective. For example, the mean square error of localization is connected with the A-criterion, the size of the location uncertainty region with the D-criterion, and the sensitivity of localization feasibility (regularity of FIM or CRLB) with the E-criterion.

D. Sensor Placement Constraints

In practical scenarios, it is very likely that the deployment of sensors will encounter additional limitations or restrictions, which may lead to geometric constraints. First, there are sensor position constraints. As a case in point, when obstacles such as mountains are present, sensor placement should guarantee observability of the target by a sensor, especially for the line of sight measurements, such as AOA observations by visual cameras. Second, sensors with different functionalities also need to be described by their unique constraints. For example, some sensors deal with multiple targets simultaneously, while others can only focus on one target at a time. Consequently, these advanced sensors will form different groups, each of which localizes one target. In such a scenario, the optimal locations of the sensors shared among groups should be confined by an appropriate constraint [4].

In a nutshell, considering practical circumstances is vital to reach a practical deployment of sensors to account for physical limitations. However, it will lead to constraints in the sensor placement problem and increase the difficulty of finding the global optimal solution.

III. Design Approaches to Sensor Placement

As stated in the previous section, an appealing objective function for the sensor placement problem is derived from the CRLB. Such a problem is typically non-convex and rather complicated, especially in the situation of 3D or multi-target localization. In recent years, many researchers have proposed methods for reaching effective solutions under different problem settings and assumptions. In this section, we will provide a brief overview of these solution methods. Then we discuss their practical deployment briefly and present the performance results in a representative simulation setting. The solution methods can be categorized as analytical, numerical-based or data-driven approaches.

A. Analytical Approach

Under IID Gaussian measurement noise, most CRLB-based performance metrics can be rewritten in terms of trigonometric functions, i.e. $\sin(\cdot)$ and $\cos(\cdot)$, of the angles defining the relative geometry between the target and sensors. The general idea of reaching an analytical solution is to simplify the objective function using an algebraic method and then find the conditions on the angles that minimize the objective function for reaching the optimal sensor placement. By using inequality scaling and trigonometric function transformation, these optimality conditions could yield a closed-form solution or at least a set of explicit requirements to define the geometry.

Such an approach entails careful algebraic manipulations to derive the final results. As an example, the resistor network method was explicitly developed in [10] to obtain the optimal sensor-target geometries quickly. Also, a step-by-step deployment strategy was proposed for a particular scenario of the multi-target case with equal variance measurement noise [4]. In [3], a method by the frame theory was developed to quickly find the optimal sensor placement for target localization in both 2D and 3D cases. The methodology of finding optimal sensor placement for elliptic localizations was extended to optimal transmitter or scatter placements as well [11].

The advantage of the analytical method lies in the simplicity of the derived solution or the set of requirements, and the ability to evaluate the optimal performance quickly. However, a major drawback of the analytical method is its limited applicability, as it is usually applicable under IID Gaussian noise and without additional constraints to the sensor positions.

B. Numerical-Based Optimization Approach

In light of the development of nonconvex optimization techniques, many optimization frameworks such as majorization-minimization, block coordinate descent, and alternating direction method of multipliers (ADMM) have been proposed and achieved success in many applications. These optimization techniques can also be applied to sensor placement problems. They are, however, iterative in nature and can reach a numerical solution only. In particular, [12] developed a unified iterative algorithm based on the ADMM framework, which can solve the sensor placement problem for TOA, TDOA and RSS localization with A-, D- or E-optimality. In [4], an ADMM

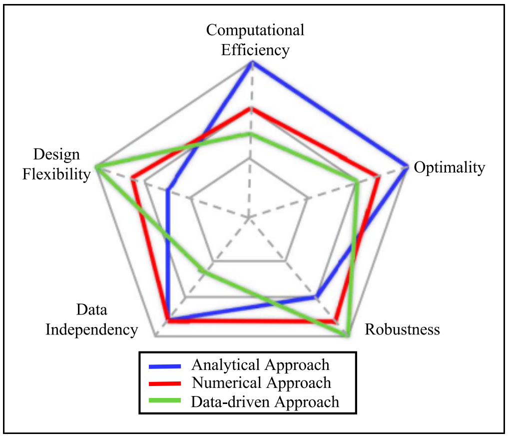

FIG. 3. Comparison among analytical, numerical and data-driven approaches with five characteristics at three levels, bad, medium and good from inner to outer.

Step 1:	Estimate the target position using the measurements from randomly placed sensors.
Step 2:	Calculate the optimal sensor-target geometry with the current target estimate.
Step 3:	Move the sensors to the optimal positions obtained in Step 2, and collect new measurements.
Step 4:	Update the target position estimate using the new measurements, from the latest sensor placement.
Step 5:	Go back to Step 2 for the next time instant, until a steady target location estimate is settled.

TABLE I. Steps for practical applications of the optimal sensor placement method.

based optimization method was proposed as an effective numerical solution for the sensor placement issue.

Compared to other methodologies, especially the analytical approach, the numerical-based optimization approach enjoys flexibility and generality since it can be applied to many scenarios under different conditions and various constraints, as long as the optimization problem can be formulated to the expected structural form of a numerical optimization method. However, its main drawback is the possible issue of sub-optimality, which is easily understood given the nonconvex nature of the sensor placement problem where a poor initialization would lead to the stuck at a local minimum.

C. Data-Driven Approach

Apart from the two widely applied methods discussed above, data-driven method such as by frame theory or artificial intelligence (AI) is an alternative to solve the sensor placement problem. FT was developed to derive the optimal results, but the measurement model should be constructed in a vector form [3] in order to apply this method. Furthermore, the neural network, Gaussian mixture models, and support vector machine, which are data-driven methods, have also been successfully applied to the optimal sensor placement problem [13]. With the measurement type, sensor and target number, and sensor characteristics as the input, the NN method can yield the desired optimal deployment and estimation bound. As long as the neural network has been trained with adequate data, it can provide a (sub-) optimal geometry fast when the input conditions (e.g., sensor number and measurement noise variance) vary. However, once some localization conditions change to a large extent or the constraints are different, it is required to restart the training process and it may undermine the real-time efficiency, especially in a dynamic sensing environment.

The characteristics of these three mainstream approaches for solving the optimal sensor placement problem are summarized in Fig. 3. The values of the different features in Fig. 3 were concluded according to a systematical review of the previous publications. More specifically, we consider five relevant features and set three levels for each feature of each methodology. After considering the positive aspects of each approach, it is possible to combine different approaches judiciously to form a hybrid method that complements each other. As demonstrated in [4], the analytical approach can provide an excellent initial point for the numerical-based iterative optimization algorithm, which will mitigate the sub-optimality issue and improve computational efficiency.

IV. Practical Implementation and Performance Analysis

Regardless of the approach to solve the optimization problem, the sensor placement problem inherently requires the position of the target, which is yet to be found. Indeed, if the target position is known, there is no need for optimal sensor placement to locate the target.

In practical applications, therefore, it is crucial to work out how to apply the optimal sensor placement. Commonly, in a real-world WSN, the pre-allocated sensors can hardly reach the optimal estimation performance of the target location. The sensors are typically portable and being housed or integrated with mobile IoT agents such as an intelligent robot, UAV, or autonomous underwater vehicle (AUV). In such settings, for the target sensing mission, the WSN formed by the IoT agents will first estimate the target position using the measurements with an arbitrary sensor placement. Secondly, the optimal sensor placement problem is solved using the initial target position estimate, and the sensor positions are adjusted accordingly with the sensor placement solution. Thirdly, the target estimate is updated, which will provide feedback to re-calculate the optimal sensor geometry. By iterating these steps, the target estimate will improve and eventually reach the most accurate estimate [5]. Usually, due to the inaccuracy of the initial target position estimate, several iterations are needed to settle to a stable result. The detailed procedure is summarized in Table I.

A. Performance

In this subsection, the estimation accuracy differences of the optimal and non-optimal placements are intuitively shown through some typical examples using the multiple same quality sensors with AOA-TOA-RSS measurement modules. Refer to [7], when the

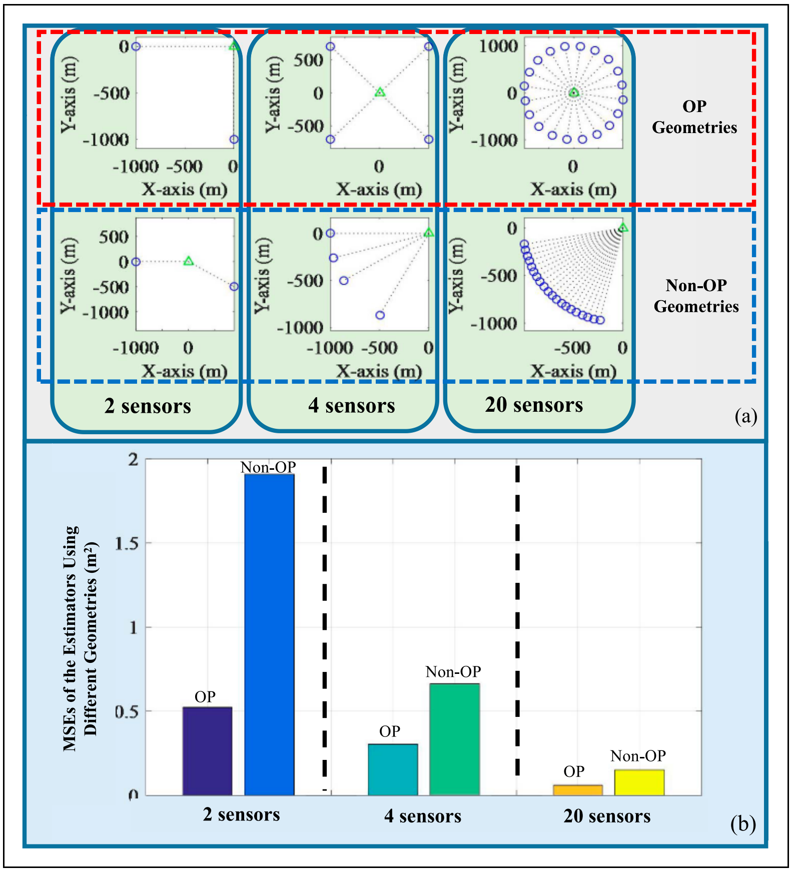

FIG. 4. Estimation performance differences by using optimal (OP) and random Non-OP placements using AOA-TOA-RSS hybrid sensors under Gaussian measurement noise. The optimal geometries are calculated by optimizing the trace of CRLB. (a) Geometries with different sensor numbers, (b) MSEs. Green "△" denotes the true target location, a blue "○" indicates a sensor, "OP" and "Non-OP" are the abbreviations of optimal and random sensor placements, respectively.

true target locates at $(0, 0)$ m, the optimal geometries can be calculated based on the A-optimality criterion. Then, the noisy measurements are simulated and the target position is estimated by the maximum likelihood estimator (MLE) [7] to obtain the MSE. The estimation MSEs for randomly created geometries are evaluated for comparison, as shown in Fig. 4(a). The measurement noise variances are set to 1 deg, 1 m and 1 W, respectively. As expected, the optimal geometries always offer the best accuracy in different test cases in Fig. 4(a) with the results shown in Fig. 4(b).

In another experiment, a practical sensor network consisting of multiple UAVs for acquiring measurements and a ground station for processing estimation is utilized for target localization, which is shown in Fig. 5. Each UAV carries a camera sensor and a high-speed data&image wireless communication module. Besides, we use a visual-based real-time target identification algorithm combined with a UAV compass module to locate the target. The system has a real-time communication network and the angular measurement data can be delivered to the ground station with the communication signal simultaneously. Diverse angular measurement groups acquired from different sensor positions lead to different estimation accuracies. Different target positions in a local coordinate system are estimated based on the GPS positions of the UAVs and measurements with the targets. The GPS calibrated target position is used as the ground truth. The averaged estimation root-mean-squared errors of the sensors at groups 1, 2 and 3, are 3.6445 m, 0.7263 m and 0.6034 m, respectively. With the sensor placement of group 1, the estimated target position has a large error since the sensors and target are lying in a straight line. Group 3 provides the optimal localization accuracy compared with group 2, due to the optimized sensor placement [10].

V. New Frontiers in Advanced Sensor Placement

From a practical perspective, sensor placement is an important factor for consideration when building up a WSN. However, due to the rapid development of the WSN technology, the vanilla sensor placement might not fulfill the requirements and achieve sub-optimal performance. For example, when the sensor in a WSN evolves to possess more functionalities, researchers/engineers should develop advanced sensor placement techniques to adapt to the new paradigm and exploit this potential brought by the WSN evolution. In this section, we will discuss several new frontiers regarding advanced sensor placements.

A. UAV-Assisted Sensor Placement

Due to their superior maneuverability, substantial concealment and high autonomy, UAVs have been widely used for target localization/tracking in many scenarios [2], [5] in diverse environments. In particular, a swarm of UAVs installed with sensors can form a dynamic ad-hoc IoT system. Thus, sensors become mobile to guarantee the calculated optimal placement in real-time and be reachable. In a practical dynamic environment, even including a mobile target, a closed-loop solution including target estimation, sensor placement optimization, sensor movement, and new measurement updates, can be applied. With these repeated dynamic steps, the localization accuracy can be improved. In light of the high mobility of UAVs, leveraging this feature to form an adaptive sensor geometry is crucial for UAV-assisted sensor placement.

B. Robotics and Sensor Placement

Apart from the scenarios of a UAV swarm, optimal sensor placement is also required in many robotic systems [14], especially the service robots, for not only target but also robot self-localization. This technique is also known as simultaneous localization and mapping (SLAM), which is the basis of all practical functions of robots [14]. Sensor fusion is applied to create awareness of the robot's position, which will form an integrated decision by fusing all the information collected through different sensor modalities such as the communication module, camera, lidar, and inertial measurement unit. Within the setting of SLAM, it is noted that the estimation accuracy is largely determined by the relative position of the robot and the sensors. For example, when the positions of the robot and multiple sensors are lying on a line, it would be hard to infer the distance between the robot and an anchor by a monocular camera only. To avoid degenerate situations, users need to steer the robot moving in an "S"-shape trajectory to complete its self-calibration. Compared to the conventional "S" shape maneuvering, an optimized moving path can provide a more accurate calibration result and lower running time, where a matched sensor geometry is needed.

In addition, some studies leverage the scene features to facilitate the robot's self-localization. Correspondingly, these features can also be considered when designing the sensor placement, which could alleviate the deployment of densely populated sensors and also allow an optimized selection among all the ambient sensors. Furthermore, it will be interesting from a theoretical and practical perspective to combine the techniques from robotics such as SLAM and path planning with the sensor placement techniques to reach an overall optimized performance.

C. Hybrid Sensor Placement

With the rapid developments of WSN devices, hybrid sensors have become popular recently and demonstrated the momentum as being mainstream in future IoT applications [6]. A hybrid sensor is a particular kind of sensor that acquires multi-type measurements on a single hardware or a platform integrating different sensing modules. Currently, the popular hybrid measurement types are AOA-TOA, TDOA-FDOA, AOA-RSS, TOA-RSS, and TOA-AOA-RSS [7]. Since multiple types of measurements can be obtained and each sensor has its own measurement model, the optimal placement of the hybrid sensors is more complex. For example, an optimal placement for AOA measurement may not be necessarily optimal for the RSS observation. Therefore, to address the mismatch issue of optimality, we need to impose some constraints to ensure that all the sensor geometries can be finally fused to form a final one. Nevertheless, previous studies have found some interesting results. For example, when the measurement noise variances of all sensors are identical, the optimal positioning of TOA-AOA-RSS sensors can be the same as the AOA-only scenario, allowing for the ADMM optimization algorithm to be used for the hybrid sensor placement problems as well [12]. In general, the optimal placement of hybrid sensors is still an under-explored research area, and theoretical guidance and algorithm developments are needed.

VI. Wrap Up and Open Challenges

This article presented a comprehensive overview of optimal sensor placement to support a plethora of WSN applications. Starting from the basics of estimation theory, the paper presents, at first, the connection between sensor placement and localization performance by exploiting the probabilistic measurement models with the CRLB. Then the CRLB-based performance metrics and some sensor-geometry-dependent placement constraints were introduced. Regarding the solutions to optimal sensor placement, three major design approaches were elaborated, for which the practical implementations and performance implications were also concisely illustrated. Furthermore, some new frontiers in advanced sensor placements have been discussed. To conclude, sensor placement strategy is an effective solution for localization improvement in diverse WSN systems.

Based on the above content, some challenges and opportunities in the optimal sensor placement problems have been identified below for future work:

- Leveraging the sensor mobility, the joint optimization of sensor placement and path planning can further improve the overall system performance, which also requires reconsideration of the modeling, solution and even performance criteria and evaluations.

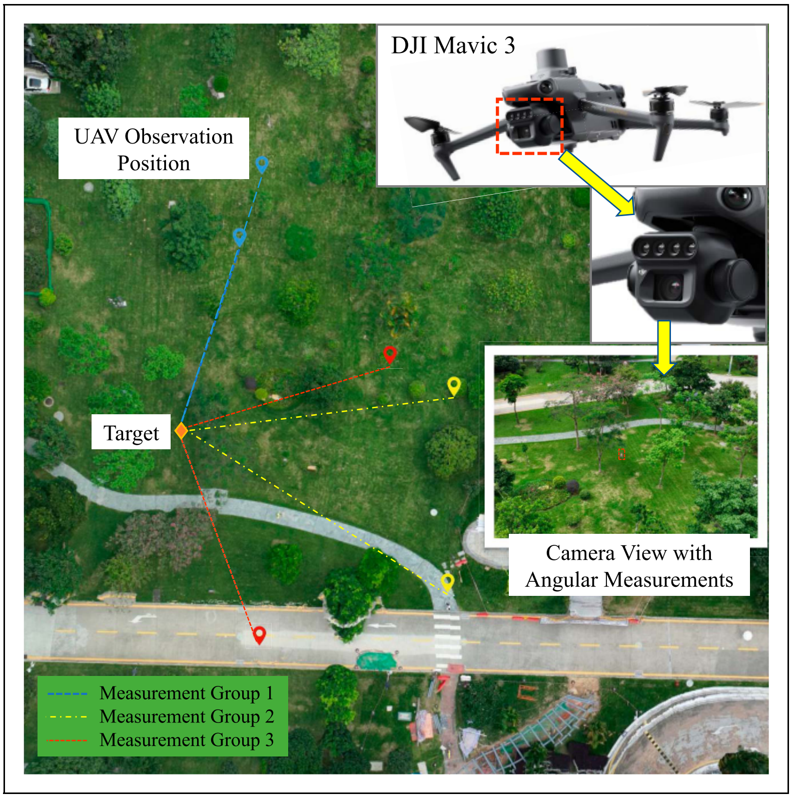

FIG. 5. A practical WSN with UAVs carried with visual sensors for acquiring AOA measurements to locate a target with optimized sensor placement.

- For non-IID, non-Gaussian noise or low signal-to-noise ratio (SNR) scenarios, the optimal sensor placement problem has not been well investigated, where the modeling of noise and selecting an appropriate bound [15] for the optimization criterion may need careful consideration.
- The perspective for the multi-target simultaneous localization is another challenging topic considering the requirement of data association and non-convexity of optimization.
- In the presence of unknown noise statistics and sensor positions, colored noise, or irregular arrays, it would be desirable to have a robust design, implying that a different performance metric (CRLB may be inappropriate) and different optimization objective are needed that may involve a harder max-min formulation.
- For many scenarios, sensor placement constraints are present. As these constraints are scenario-dependent and not general, the development of a unified solution is challenging.

These challenges appear in many sensor placement problems, and addressing them will make outstanding contributions to optimal sensor placement from both theoretical perspective and practical applicabilities. Finally, we hope this article serves the readers with an understanding of recent advances in this important topic and encourages research toward further integration of sensor placement in diverse IoT applications.

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