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Performance analysis and path planning for UAVs swarms based on RSS measurements

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A B S T R A C T

In the localization estimation system, it is well known that the sensor-emitter geometry can seriously impact the accuracy of the location estimate. In this paper, we analyze the optimal deployment for received signal strength (RSS) localization with the measurement noise is set to be distance dependent. First, the Cramer–Rao low bound (CRLB) with distance-dependent noise in RSS localization is calculated and chosen to be the optimality criterion. The optimal deployment is analyzed via angle and distance criterion, respectively. Then, the analytic solutions to the optimal deployment are derived in both static and movable target scenarios. Finally, we extend our work to the path planning problem with constraints and interior penalty method is applied to settle the constrained nonlinear optimization problem. The simulation results show that the path optimization verifies the accuracy of the analytical findings.

1. Introduction

Passive emitter localization has significant applications in both civilian (wireless communication networks, search and rescue, etc.) and military (surveillance, localization and tracking in electronic warfare) areas. The objective of passive emitter localization is to determine the location of a target by processing the emitter signals received by static or movable receiver platforms, and it has drawn considerable attentions over the past decades in wireless sensor networks (WSN) [1–6]. Compared with other different passive localization methods such as time of arrival (TOA) [1], time difference of arrival (TDOA) [2] and angle of arrival (AOA) [3], energy-based localization like received signal strength (RSS) [4] or received signal strength difference (RSSD) [5] enables low complexity and cost in software and hardware implementations. Recent progress has made it practical to realize the energy-based localization in WSNs [6].

Maximum likelihood (ML) estimator [7], semi-definite programming (SDP) [8] and weighted least squares (WLS) [9,10] approaches are the common solutions for target localization using RSS measurements. It is well known that the localization performance is highly related to the relative receiver-target geometry for any particular localization algorithm [11–16]. Therefore, the selection of optimal deployments can further improve the location accuracy. The optimal receiver-target geometry characterized by the CRLB in RSS localization has been studied in [11,12]. However, the connection between the variance lower-bound and the target-receiver geometry is not explicitly explored. Bishop et al. [13,14] provided a rigorous characterization of the relative receiver-target geometry for RSS localization based on the Fisher information matrix (FIM) with assuming that the measurement noise was independent of actual sensor-emitter distance. In this paper, a more realistic distance-dependent noise model is applied and A-optimality criterion is used to evaluate optimal deployment in RSS localization, which aims to minimize the trace of the Cramer–Rao low bound (CRLB). The optimal sensor placement is investigated by angle and distance criterion and deriving corresponding upper bounds under different cases, and necessary conditions for achieving these bounds are acquired. We also provide the optimal RSS localization in movable target scenario, the extended Kalman filter (EKF) framework is applied and the prediction error covariance in EKF is considered when deriving the optimal receiver deployment.

Unmanned aerial vehicle (UAV) swarms provide unique platforms for RSS localization [15]. Their characteristics of flexible movement enable them to rapidly change the deployments so as to achieve higher location accuracy. H. Duan et al. [16] mainly studied the formation control algorithm in the swarm. D. Xing [17] solved the search-attack mission planning problem using UAV swarms based on the ant colony algorithm. We applied the UAV swarms in the localization mission. Usually the UAVs localization can be applied in two ways: one is the target searching with predefined deployment of UAV to get a better performance in the whole surveillance area, the other is the path planning for optimal deployment to get high accuracy when the target is locked. Gen-

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erally, it is rather difficult to meet the location task requirements by pre-programmed paths or the man-in-the-loop control method. Therefore, the sensor management method of online UAV path optimization is a current hot spot research issue [18]. Refs. [19–23] separately showed the UAVs path optimization under different detection methods, and their kernels are to establish the optimal control criteria for target detection. The determinant of Fisher information matrix (FIM) was adopted as control objective function to control the UAVs movement [19–21]. X. Wang et al. [22] took the Renyi information divergence as the criterion to control UAVs speed within each time step. Position error covariance matrix was applied to generate guidance points for the UAVs localization guidance law in [23].

In this paper, UAVs trajectories are optimized by generating a sequence of waypoints based on CRLB. The CRLB of RSS localization is not only taken as a performance estimator but also used for optimizing sensor trajectories. The target position is solved by combining the ML and EKF algorithm. Meanwhile, due to the platform constraints, the problem becomes a constrained UAV path planning problem for optimal target localization. The interior penalty function method [24] is adopted to convert the nonlinear optimization to simple unconstrained optimization so as to get the flight path of each UAV for the next time step.

The remainder of the paper is structured as follows. Section 2 states the problem description of RSS localization. In Section 3, optimal deployment based on the CRLB with distance-dependent noise is presented in both static and movable scenarios. Section 4 presents the UAV path optimization model and path planning problem is addressed. Finally, simulations and conclusions are shown in Section 5 and Section 6, respectively.

2. Problem description

Consider a swarm of M UAVs equipped with passive receivers performing target localization and tracking missions shown in Fig. 1. The state vector of each UAV is $\boldsymbol{\chi}_i(k) = (\mathbf{x}_i(k)^T, \dot{\mathbf{x}}_i(k)^T)^T$, $i = 1, 2, \ldots, M$, $\mathbf{x}_i(k) = (x_i(k), y_i(k))^T$ denotes the position and $\dot{\mathbf{x}}_i(k) = (\dot{x}_i(k), \dot{y}_i(k))^T$ the velocity. Let $\mathbf{x}_t = (x_t, y_t) \in \mathbb{R}^2$ be the location of an unknown target, r_i is the distance from target to i-th receiver, $r_i = \|x_t - x_i\|$. The angles subtended at the target by the receiver pairs (e.g. i, j) is given by $\varphi_{ij} = \varphi_{ji} \in [0, \pi)$.

The basic RSS path-loss model is given by [25]

$$\widehat{p}_i = p_i + n_i = p_s - 10\gamma_i \log_{10} d_i + n_i, \quad i = 1, 2, \ldots, M \tag{1}$$

where p_i is the averaged signal strength in dB received by i-th receiver, p_s is the unknown target transmit power in dB, γ_i is the known path-loss factor, n_i is the average shadow fading and is assumed to be the additive Gaussian white noise with variance σ_i^2, i.e. $n_i \sim \mathcal{N}(0, \sigma_i^2)$. In order to model the variance of the noise more realistically, the RSS measurements with distance-dependent noises is studied. The Gaussian noise σ_i is dependent of r_i, which can be expressed as

$$\sigma_i^2 = \sigma_0^2 r_i^\alpha \tag{2}$$

where $\alpha \geq 0$ is the path-loss exponent and σ_0^2 is the variance at one meter.

For M receivers, we get

$$\widehat{\mathbf{p}} = \mathbf{p} + \mathbf{n} = [p_1, \ldots, p_M]^T + [n_1, \ldots, n_M]^T, \quad i = 1, 2, \ldots, M. \tag{3}$$

Assumed that the measurement errors from different receiver are mutually independent, with the covariance $\mathbf{R}_p = \mathrm{diag}(\sigma_1^2, \ldots, \sigma_n^2)$. Then the measurement model in vector form can be described by $\widehat{\mathbf{p}} \sim \mathcal{N}(\mathbf{p}, \mathbf{R}_p)$.

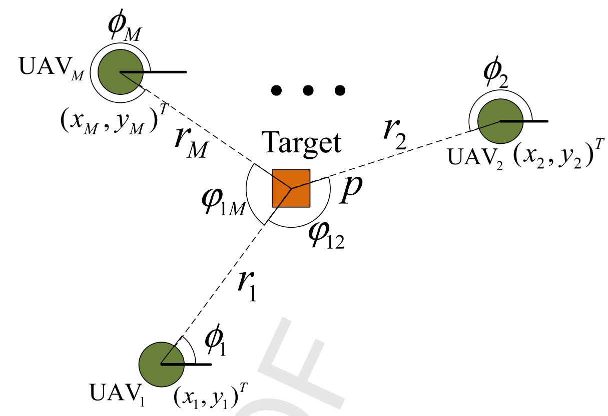

Fig. 1. RSS based localization with M UAVs.

The purpose of RSS localization and tracking is to estimate the true target location $\mathbf{x}_t$ given by $\widehat{\mathbf{p}}(\mathbf{x}_t)$ and $\boldsymbol{\chi}_i(k)$, $i = 1, 2, \ldots, M$. In this paper, we mainly focus on the performance analysis of optimal receiver-target geometries in RSS localization in order to improve the target localization and tracking accuracy. Theoretical results based on CRLB are studied, which can provide guidance in the receiver deployment problem. Indeed, the CRLB itself plays a significant role in determining waypoints and control laws for optimal RSS localization and tracking. Combining the analytic solutions, it can help to understand and improve the path planning performance, when sensor platform motion and communication constraints are considered.

3. Optimal deployment analysis without constraints

In this section, theoretic analysis of optimal deployment is given for RSS localization performance without considering receiver constraints. Analytic solutions are derived in the static as well as the movable target scenario.

3.1. Static target scenario

The relative receiver-target geometry is closely related to the location accuracy, which can be reflected by CRLB. Therefore, the performance of the measurements based on the CRLB can be used as optimization criterion for the optimal deployment.

Considering an unbiased estimate $\widehat{x}_t$ the CRLB states that:

$$E\left[(\widehat{x}_t - x_t)(\widehat{x}_t - x_t)^T\right] \geq \mathbf{J}^{-1} \tag{4}$$

where $\mathbf{J}$ is the Fisher information matrix. Let $\widehat{\mathbf{p}}$ be the set of measurements from M receivers, the (i, j)-th element of $\mathbf{J}$ is given by:

$$\mathbf{J}_{(i,j)} = E\left[\frac{\partial}{\partial x_i} \ln\big(f(\widehat{\mathbf{p}}; \mathbf{x}_t)\big) \frac{\partial}{\partial x_j} \ln\big(f(\widehat{\mathbf{p}}; \mathbf{x}_t)\big)\right] \tag{5}$$

where $f(\widehat{\mathbf{p}}; \mathbf{x}_t)$ is the probability density function (PDF) of $\widehat{\mathbf{p}}$ given by:

$$f(\widehat{\mathbf{p}}; \mathbf{x}_t) = \frac{1}{(2\pi)^{M/2}\sqrt{\det(\mathbf{R}_p)}} \times \exp\left[-\frac{1}{2}\big(\widehat{\mathbf{p}} - \mathbf{p}(\mathbf{x}_t)\big)^T \mathbf{R}_p^{-1}\big(\widehat{\mathbf{p}} - \mathbf{p}(\mathbf{x}_t)\big)\right]. \tag{6}$$

Substitute it to (4) and the FIM for RSS localization with distance-dependent noise is given by

$$\mathbf{J}_{(i,j)} = \underbrace{\frac{1}{\sigma^2(\mathbf{x}_t)} \frac{\partial \mathbf{p}(\mathbf{x}_t)}{\partial x_i} \frac{\partial \mathbf{p}(\mathbf{x}_t)}{\partial x_j}}_{\mathbf{J}_{1,(i,j)}} + \underbrace{\frac{1}{2} \frac{1}{\sigma^2(\mathbf{x}_t)} \frac{\partial \sigma(\mathbf{x}_t)}{\partial x_i} \frac{\partial \sigma(\mathbf{x}_t)}{\partial x_j}}_{\mathbf{J}_{2,(i,j)}}. \tag{7}$$

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