ON OPTIMAL MOBILE RSSI-SENSOR POSITIONING FOR MULTI TARGET TRACKING

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ABSTRACT

This paper presents an analysis on optimal mobile sensor configuration for multiple-target-tracking (MTT) with Received-Signal-Strength-Indicator (RSSI) based measurements. The analysis is based on the underlying assumption that the complexity of this inherently high-dimensional problem is reduced by employing a multi-agent distributed tracking system. The assumed system assigns a single target of interest (TOI) to each agent and treats the remaining targets as interference sources. The measurement interference due to these sources is effectively compensated for by exchanging TOI information between agents, and fusing this information during the estimation process. Proper sensor placement within such an environment represents a unique challenge and optimal solutions are fundamentally different from a conventional MTT scenario. The main results of this paper include formulation and subsequent simplification of the optimality criterion along with a suboptimal solution yielding competitive performance and superior efficiency. Simulation results are presented demonstrating the performance of the proposed solution and comparisons are made to existing techniques.

Index Terms**—** RSSI-based target tracking, multiple target tracking, mobile sensors, sensor positioning

1. INTRODUCTION

With recent advances in technology, the concept of a network of mobile autonomous units (agents), each fitted with specialized sensing devices, cooperatively acting to track and follow some target, has become a physically achievable reality [1]. There are numerous benefits of employment of a mobilized suite of sensors to track a target. The most important of them is the fact that the sensors can be positioned so as to extract the maximum possible information at each time instant regarding the target state. Determination of an optimal trajectory for the sensors can be an ambiguous task. In general, it will depend on the used optimality criteria, the actual target track estimation methodology, and the specific characteristics of the underlying target environment. A wide variety of solutions have been developed to handle sensor management, many with the common theme of "information-driven" mobility as in [2, 3, 4, 5], whereby the sensor motion is carried out with the specific intent of optimizing the projected quality of measurements or the "information gain," at the new sensor locations. Others place an emphasis on a more balanced approach, paying specific attention to energy efficiency [6] or sensor coverage [7].

The current literature is relatively sparse in considering sensor positioning for an MTT environment. The work in [8] is a notable exception and provides a thorough investigation of the problem for a scenario involving sensors that provide range-only measurements corrupted by Gaussian noise. There, closed-form expressions are found for optimal sensor configurations with an arbitrary number of sensors or targets. While [8] can possibly be applied to RSSI sensor systems, it cannot be done so directly. In that case, one must first produce range estimates for each sensor-target pair from the measurements and act as if these estimates are themselves measurements adequately modeled as corrupted by Gaussian noise.

There is a fundamental difference between that work and what we present here. In this paper, sensor positioning is considered as a *joint task with estimation*. To be more precise, the optimality criterion for sensor positioning is based directly on the RSSI measurements. This is a significantly more challenging task as each measurement is affected by all the present targets. We believe that this approach has a significant benefit over that of [8] since the effect of sensor positions on performance is more accurately represented.

While the initial approach and model basis taken here for sensor trajectory-planning are based on [9], our approach differentiates considerably due to the presence of interference sources. Our main motivation in handling interference lies in the desire to develop a feasible divide-and-conquer based method for MTT that is clarified in the next section.

It is our aim in this paper to address the investigation of optimal sensor positioning for a single TOI, based directly on RSSI measurements, and with the presence of an arbitrary number of interfering sources. The main contributions of the paper include the derivation of a structured form for the positioning objective function and the sub-optimal solutions that

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perform reasonably well and are considered of high value due to their superior computational simplicity.

2. PROBLEM FORMULATION

The basis of the tracking environment under consideration was first introduced in [10]. There, a simple case involving a given agent estimating a single TOI with a single source of interference was considered. A complete MTT scenario can be realized by considering multiple interference sources[1] as will be done here. Each agent estimates its own TOI and broadcasts Gaussian parameters regarding its estimate. This information is then used by other agents to compensate for measurement interference when estimating their own TOI.

Let us proceed by assuming that for a given agent, there exists a single TOI moving in a 2D plane whose location is described by the vector, $\mathbf{x}_t = [x_{t,1},\ x_{t,2}]^\top$ at time t. Note that for the remainder of the paper we drop the t subscript, all quantities are assumed to be dynamically varying over time. Furthermore, assume there exists a total of L interfering sources, with the location of the lth interferer described by the vector $\mathbf{q}_l = [q_{l,1}, q_{l,2}]^\top$, at time t. The true location of each interferer is unknown, but it is assumed to be described probabilistically by the agent in charge of the interferer. Namely, we assume $\mathbf{q}_l \sim \mathcal{N}\left(\hat{\mathbf{q}}_l, \sigma_l^2 \mathbf{I}_2\right)$,[2] where $\mathcal{N}\left(\hat{\mathbf{q}}, \mathbf{C}\right)$ denotes a bivariate Gaussian random variable with mean $\hat{\mathbf{q}}$ and covariance matrix $\mathbf{C}$, and where $\mathbf{I}_2$ is the 2×2 identity matrix. An agent tracks its TOI using a total of K mobile sensors. The measurement of the kth sensor, y_k, is given by

$$\begin{aligned} y_k &= y_k^{(\mathbf{x})} + \sum_{l=1}^{L} y_k^{(\mathbf{q}_l)} + v_k \\ &= \left(\frac{\Phi}{\|\mathbf{s}_k - \mathbf{x}\|^\alpha + \epsilon}\right) + \sum_{l=1}^{L}\left(\frac{\Phi}{\|\mathbf{s}_k - \mathbf{q}_l\|^\alpha + \epsilon}\right) + v_k, \end{aligned} \quad (1)$$

where Φ represents the transmitted power, $\mathbf{s}_k = [s_{k,1}, s_{k,2}]^\top$ is the position vector of the kth sensor, α is the path-loss coefficient, ϵ is a saturation parameter, $y_k^{(\mathbf{x})}$ and $y_k^{(\mathbf{q}_l)}$ are the respective measurement contributions from the TOI and interfering target, respectively, and v_k represents the uncorrelated sensor noise. Based on the results in [10], we can approximate the measurement likelihood as,

$$\begin{aligned} & f\left(y_{1:K} \mid \mathbf{x}, \mathbf{s}_{1:K}, \hat{\mathbf{q}}_{1:L}, \sigma_{1:L}^2\right) \\ & \approx \prod_{k=1}^{K} \mathcal{N}\left(y_k \mid y_k^{(\mathbf{x})} + \sum_{l=1}^{L} y_k^{(\mathbf{q}_l)}, \sigma_k^2\left(\mathbf{s}_k\right)\right), \end{aligned} \quad (2)$$

where

$$\sigma_k^2\left(\mathbf{s}_k\right) = \sigma_v^2 + \sum_{l=1}^{L}\left(\frac{\Phi\alpha\sigma_l\|\mathbf{s}_k - \hat{\mathbf{q}}_l\|^{\alpha-1}}{\left(\|\mathbf{s}_k - \hat{\mathbf{q}}_l\|^\alpha + \epsilon\right)^2}\right)^2. \quad (3)$$

[1] Each interferer is the TOI of some other agent.

[2] One can easily extend this derivation to a general covariance matrix.

We point out the explicit dependence of the likelihood and individual variance terms (σ_k^2) on all the sensor locations. In fact, σ_k^2 also depends on the external information ($\hat{\mathbf{q}}_{1:L}, \sigma_{1:L}^2$) as well, but this is left implicit here.

We use as optimality objective the maximization of the determinant of the Fisher information matrix (FIM).[3] This is termed D-optimality in the literature in contrast to A-optimality, which uses the minimum trace of the inverse of the FIM. Defining $\mathbf{r}$ as the 2×1 vector of partial derivatives of the log-likelihood w.r.t. $\mathbf{x}$, i.e.,

$$\mathbf{r} = \frac{\partial \log f\left(y_{1:K} \mid \mathbf{x}, \mathbf{s}_{1:K}, \hat{\mathbf{q}}_{1:L}, \sigma_{1:L}^2\right)}{\partial \mathbf{x}}, \quad (4)$$

we express the optimization problem as

$$\begin{aligned} \mathbf{s}_{1:K} &= \underset{\mathbf{s}_{1:K}}{\operatorname{argmax}} \left\{\det\left(\mathbb{E}\left[\mathbf{r}\mathbf{r}^\top\right]\right) \triangleq O\right\} \\ & \text{subject to} \quad \|\mathbf{s}_k - \mathbf{x}\| \geq \rho \quad \forall\, k. \end{aligned} \quad (5)$$

Note that the constraint indicates that each sensor must maintain a minimum separation of ρ from the target location. Also note that the symbol $\mathbb{E}$ denotes expectation over the K measurements. It can easily be shown that

$$r_i = \sum_{k=1}^{K} \frac{1}{\sigma_k^2\left(\mathbf{s}_k\right)}\left(y_k - y_k^{(\mathbf{x})} - \sum_{l=1}^{L} y_k^{(\mathbf{q}_l)}\right)\left(\frac{\partial y_k^{(\mathbf{x})}}{\partial x_i}\right). \quad (6)$$

The derivative term is evaluated using (1) and is given by

$$\left(\frac{\partial y_k^{(\mathbf{x})}}{\partial x_i}\right) = \frac{\Phi\alpha\left(s_{k,i} - x_i\right)\|\mathbf{s}_k - \mathbf{x}\|^{\alpha-2}}{\left(\|\mathbf{s}_k - \mathbf{x}\|^\alpha + \epsilon\right)^2}. \quad (7)$$

By making the following definitions:

$$c_k = \frac{\Phi^2\alpha^2\|\mathbf{s}_k - \mathbf{x}\|^{2(\alpha-2)}}{\sigma_k^2\left(\mathbf{s}_k\right)\left(\|\mathbf{s}_k - \mathbf{x}\|^\alpha + \epsilon\right)^4}, \quad (8)$$

$$d_{k,i} = \left(s_{k,i} - x_i\right), \quad (9)$$

one can show that

$$\det\left(\mathbb{E}\left[\mathbf{r}\mathbf{r}^\top\right]\right) = \frac{1}{2}\sum_{k=1}^{K}\sum_{p=1}^{K} c_k c_p \|\mathbf{d}_k \otimes \mathbf{d}_p\|^2, \quad (10)$$

where the symbol $\otimes$ denotes the outer product between two vectors.

It is fairly easy to prove that the optimal sensor deployment without interference consists of the sensors uniformly distributed around a circle of radius ρ centered at $\mathbf{x}$ (subsequently referred to as the "ρ-circle"). Although not proven explicitly here, we assume that the optimal solution satisfies $\|\mathbf{s}_k^\star - \mathbf{x}\| = \rho$. Therefore, for the remainder of the paper we consider for the kth sensor,

$$\mathbf{s}_k = \mathbf{x} + \rho\left[\cos\left(\theta_k\right) \quad \sin\left(\theta_k\right)\right]^\top. \quad (11)$$

[3] Interferers are regarded as nuisance parameters for the FIM.

The complexity of the problem grows remarkably by the addition of interference.[4] The $\sigma_k^2(\mathbf{s}_k)$ term in the denominator of c_k renders the combined form of (10) intractable to a closed-form solution. Additionally, it can be seen that the interference creates "competing constraints" in the objective. The minimization of the $\mathbf{s}_k$ terms can push the $\|\mathbf{d}_k \otimes \mathbf{d}_p\|^2$ terms away from their optimal values. At this point, one could proceed by using a numerical technique such as Genetic Algorithm [11] or Particle Swarm Optimization [12] to approach the problem. However, it is highly desirable to formulate a solution that is as computationally inexpensive as possible since sensor positioning is a real time task. As such, we formulate a fast approach that achieves positioning close to the optimal one. The solution is based on a divide-and-conquer approach.

3. PROPOSED SOLUTION

It is clear that the c_k terms in (10) represent a dominating factor in optimization of the objective. Indeed, if the outer product term were absent from this expression, the problem would consist solely of optimizing each sensor location w.r.t. the interference sources by minimizing $\sigma_k^2(\mathbf{s}_k)$ for all k. The outer product can in a way be seen to *force a compromise* between optimality of each sensor w.r.t. the net interference configuration and *orthogonality* of the net sensor configuration. Let us for the moment neglect this compromise and focus on the expression for $\sigma_k^2(\mathbf{s}_k)$ given in (3) for the kth sensor. It can easily be shown that for $L=1$, $\sigma_k^2(\mathbf{s}_k)$ is minimum when the sensor is positioned on the farthest point from the predicted location of the interfering target on the circle with radius ρ centered at the predicted location of TOI.

Based on the previous reasoning, we propose our first solution based on optimizing a weighted combination of the sensor-interferer distances,

$$\tilde{\theta}_k = \underset{\theta_k}{\operatorname{argmax}} \sum_{l=1}^{L} g_l \|\mathbf{s}_k - \hat{\mathbf{q}}_l\|^2 \quad \text{subject to} \quad \mathbf{s}_k = \mathbf{x} + \rho\left[\cos\theta_k \quad \sin\theta_k\right]^\top, \qquad (12)$$

where g_l are weighting coefficients chosen to affect the solution's optimality w.r.t. minimizing the expression (3). For what follows, we write the interference locations in polar coordinates as

$$\hat{\mathbf{q}}_l = \mathbf{x} + \hat{\phi}_l\left[\cos\hat{\lambda}_l \quad \sin\hat{\lambda}_l\right]^\top. \qquad (13)$$

It can be shown that the solution to (12) is given by

$$\tilde{\theta}_k = \operatorname{atan2}\left(\sum_{l=1}^{L} g_l\hat{\phi}_l\sin\hat{\lambda}_l, \sum_{l=1}^{L} g_l\hat{\phi}_l\cos\hat{\lambda}_l\right). \qquad (14)$$

[4] Even one interferer eliminates the possibility of a closed-form solution.

We can then select a solution to minimize (3) as

$$\theta_k = \frac{n\pi}{2} + \tilde{\theta}_k, \quad n = \underset{n\in\mathcal{N}}{\operatorname{argmin}}\, \sigma_k\left(\rho\begin{bmatrix}\cos\left(\frac{n\pi}{2}+\theta_k\right)\\ \cos\left(\frac{n\pi}{2}+\theta_k\right)\end{bmatrix}\right). \qquad (15)$$

The reason this configuration can work reasonably well is intuitive. The objective in (12) ensures the sensor is not positioned too close on the ρ-circle to any given interferer. The weighting coefficients can be chosen in a number of different ways. One way is to simply assign maximum weight to the term involving the interference source closest to the target location. While this solution can perform well if there is a single dominating interferer, it can deteriorate rapidly when this assumption does not hold.

The second method we propose is based on a piecewise-linear approximation to (3). In what follows, we will assume the parameter values $\alpha = 2$ and $\epsilon = 0$ for the measurement model in (1). While the results can be extended to cover more general values, the derivation is considerably lengthier and would not contribute to the main idea here. The form for (3) then becomes:

$$\sigma_k^2(\mathbf{s}_k) = \sigma_v^2 + \sum_{l=1}^{L}\left(\frac{\Phi^2\alpha^2\sigma_l^2}{\|\mathbf{s}_k - \hat{\mathbf{q}}_l\|^6}\right). \qquad (16)$$

We propose to approximate each term of the sum in (16) as follows:

$$\sigma_{k,l}^2(\mathbf{s}_k) \triangleq \left(\frac{\Phi^2\alpha^2\sigma_l^2}{\|\mathbf{s}_k - \hat{\mathbf{q}}_l\|^6}\right) \approx m_{k,l}^\star(\theta_k)\left(\theta_k - \hat{\lambda}_l\right) + b_{k,l}^\star(\theta_k). \qquad (17)$$

With the functions $m_{k,l}^\star(\theta_k)$ and $b_{k,l}^\star(\theta_k)$ defined as,

$$b_{k,l}^\star(\theta_k) = b_{k,l}\mathbb{1}\left[\theta_{k,l}^- \leq \theta_k < \theta_{k,l}^+\right] \qquad (18)$$

$$m_{k,l}^\star(\theta_k) = m_{k,l}\left(\mathbb{1}\left[\theta_{k,l}^- \leq \theta_k < \hat{\lambda}_l\right] - \mathbb{1}\left[\hat{\lambda}_l \leq \theta_k < \theta_{k,l}^+\right]\right), \qquad (19)$$

where $\mathbb{1}[x]$ denotes the indicator function for the argument and the slope constant $m_{k,l}$ is the scaled magnitude[5] of the derivative $\frac{\partial}{\partial\theta_k}\sigma_{k,l}^2(\mathbf{s}_k)$ evaluated at half-max[6], noted as $\theta_{k,l}^H$,

$$\theta_{k,l}^H = \hat{\lambda}_l + \arccos\left(\frac{\left(1-2^{\frac{1}{3}}\right)\left(\rho^2+\hat{\lambda}_l^2\right) + 2^{\frac{2}{3}}\rho\hat{\lambda}_l}{2\rho\hat{\lambda}_l}\right),$$

$$m_{k,l} = c\left|-\frac{6\Phi^2\alpha^2\sigma_l^2\rho\hat{\phi}_l\sin\left(\theta_{k,l}^H - \hat{\lambda}_l\right)}{\left(\rho^2+\hat{\phi}_l^2 - 2\rho\hat{\phi}_l\cos\left(\theta_{k,l}^H-\hat{\lambda}_l\right)\right)^4}\right|, \qquad (20)$$

[5] The approximation tends to underestimate $\sigma_{k,l}^2(\mathbf{s}_k)$ when $c=1$. Setting $c = \frac{1}{\sqrt{2}}$ yields a substantial improvement.

[6] The notion half-max is defined as the value for θ_k where $\sigma_{k,l}^2(\mathbf{s}_k)$ is half of its maximum.

Step 1: For each segment $\Psi_i \in \Psi$ form $\left\{\Psi_i^{(m)}\right\}_{m=1:M}$
where, $\Psi_i^{(m)} = \Psi_i^{(-)} + \max\left(\frac{m\pi}{K}, \frac{m\left(\Psi_i^{(+)} - \Psi_i^{(-)}\right)}{M}\right)$.
Step 2: Augment Ψ to $\Psi^{(a)}$ with all $\left\{\Psi_i^{(m)}\right\}_{m=1:M}$
Step 3: Choose θ_1 as $\mathrm{argmin}_{\Psi^{(a)}}\ \sigma_1^2(\mathbf{s}_1)$. Set $k = 2$.
Step 4: Form all K-tuples $\hat{\theta}_\tau = \{\theta_{1:k-1}, \tau\}$ with $\tau \in \Psi^{(a)}$.
Step 5: Compute $O^{(\tau)}$ for the k sensor arrangement $\hat{\theta}_\tau$.
Step 6: Set $\theta_{1:k} = \mathrm{argmax}_{\hat{\theta}_\tau}\ O^{(\tau)}$. If $k < K$ go to Step 4.

Table 1. Fast-Piecewise Algorithm Summary

and the remaining terms are defined as,

$$b_{k,l} = \frac{\Phi^2\alpha^2\sigma_l^2}{\left(\rho^2 + \hat{\lambda}_l^{\,2} - 2\rho\hat{\lambda}_l\right)^3}, \quad \theta_{k,l}^{\pm} = \hat{\lambda}_l \pm \frac{b_{k,l}}{m_{k,l}} \tag{21}$$

with all the points of θ_k understood to be w.r.t. modulo 2π.

An approximation to the minimum of (3) is then easily found by minimizing over each distinct segment of the piecewise function. Namely, the set of all points $\left(\theta_{k,l}^{-}, \hat{\lambda}_l, \theta_{k,l}^{+}\right)$ are arranged into a sorted array Ψ. The ith non-overlapping line segment formed by two adjacent points of this array is labeled Ψ_i, written as $\left[\Psi_i^{(-)}, \Psi_i^{(+)}\right]$. The critical point of each segment, denoted as $\Psi_i^{(\star)}$ is given by,

$$\Psi_i^{(\star)} = \begin{cases} \Psi_i^{(-)} & \text{if } \sum_{l=1}^{L} m_{k,l}^{\star}\left(\Psi_i^{(-)}\right) > 0 \\ \Psi_i^{(+)} & \text{if } \sum_{l=1}^{L} m_{k,l}^{\star}\left(\Psi_i^{(-)}\right) < 0 \\ \frac{1}{2}\left(\Psi_i^{(+)} + \Psi_i^{(-)}\right) & \text{if } \sum_{l=1}^{L} m_{k,l}^{\star}\left(\Psi_i^{(-)}\right) = 0. \end{cases} \tag{22}$$

The optimal point is then simply $\mathrm{argmin}_i\ \sigma_k^2\left(\Psi_i^{(\star)}\right)$.

While the piecewise algorithm's final result is to provide an approximation to the global minimum value for $\sigma_k^2(\mathbf{s}_k)$, we can also use the points in Ψ to maximize (10) over a discrete set of K-tuples as opposed to maximization over $\mathbb{R}^K$. Various algorithms can be formulated that make best use of Ψ in optimizing (10). Here we present one possibility, labeled as Fast-Piecewise, and outlined in Table 1. Notice in step 1 the notation $\{\Psi_i^m\}_{m=1:M}$ which refers to a set of M points derived from the i-th segment Ψ_i; here $\Psi_i^{(m)}$ is the m-th point from that set.

4. ALGORITHM PERFORMANCE

We compared the performance in an example scenario between Fast-Piecewise, Genetic Algorithm (GA), and the Quasi-Newton method, with two separate runs, the first consisting of two interferers and the second with six. In both cases, $\hat{\phi}_l = 2$ for all l except the first, for which $\hat{\phi}_1 = 1.5$. The values for $\hat{\lambda}_l$ were fixed at $0, \frac{\pi}{2}, \frac{\pi}{8}, \frac{3\pi}{2}$, and π for the second through the sixth interferers, respectively. The value for $\hat{\lambda}_1$ was varied uniformly over 0 to 2π for 50 different values, with each marking a separate trial of the given run (and producing different objective values). The remaining parameter values were fixed at $M = K$, $\alpha = 2$, $\epsilon = 0$, $\Phi = 10$, $\sigma_v^2 = 0.01$, and $\sigma_l^2 = 0.01$ for all l. The objective function O at each different position of $\hat{\lambda}_1$ is plotted in Fig. 1. It is seen that Fast-Piecewise performed equally well to the alternative techniques, yet it has been found to be roughly *60 times faster*.

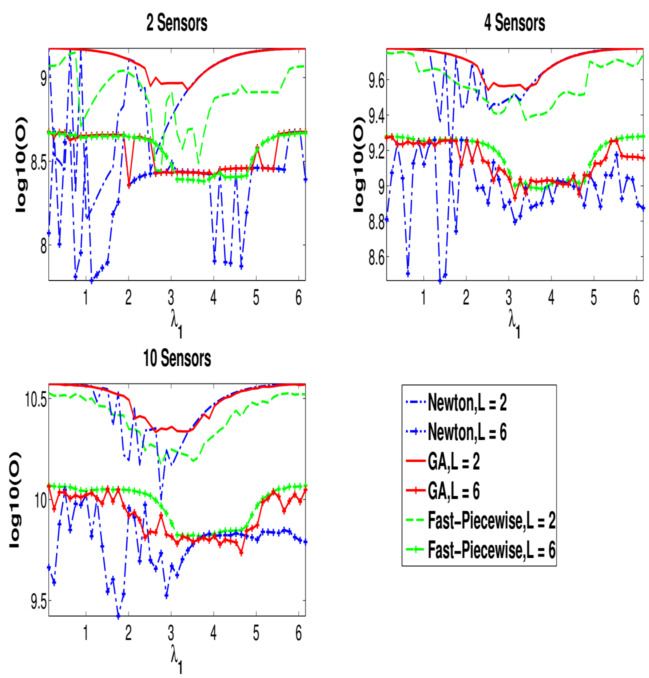

Fig. 1. Comparison of proposed solution to numerical/evolutionary techniques.

5. CONCLUSION

In this paper, an analysis regarding optimal sensor positioning within a particular MTT environment was conducted. The location of a single TOI is estimated using a group of RSS sensors whose measurements are corrupted by other targets existing within the environment. This scenario was motivated to employ a multi-agent distributed tracking system to solve the full MTT problem. Each agent tracks a single target and exchanges estimates with other agents to cope with the aforementioned measurement interference. Optimality criteria for the problem were derived and a suboptimal solution based on a piecewise linear approximation to the objective function was found. This solution was compared to other well-known numerical techniques and was found to yield comparable accuracy with vastly superior computational efficiency.

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