This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/LWC.2017.2750685, IEEE Wireless Communications Letters

Distributed Cooperative Localization for Mobile Wireless Sensor Networks

Soheil Salari, *Member, IEEE*, Il-Min Kim, *Senior Member, IEEE*, and Francois Chan, *Senior Member, IEEE*

***Abstract*—In this letter, we consider a mobile wireless sensor network (WSN), in which all nodes have some knowledge about their movements. Exploiting the sensor mobility information in the localization process, we develop novel cooperative second order cone programming (SOCP)-based localization algorithms for both time-of-arrival (TOA) and received signal strength (RSS) measurement models. We show that the developed algorithms can also be implemented in a distributed manner, and hence, are suitable for large-scale WSNs. The proposed mobility-aided localization framework significantly improves the localization accuracy and addresses some typical positioning problems.**

***Index Terms*—Cooperative localization, distributed implementation, mobile wireless sensor network.**

I. INTRODUCTION

In wireless sensor networks (WSNs), determining the locations of the sensors, often called localization, is a crucial component for many applications, such as environmental monitoring, search and rescue, target tracking, and others [1]. The constraints on the cost, size, energy consumption, and deployment environment of the sensors often limit or even prohibit the applicability of traditional localization methods in WSNs [2]. In such cases, the (noisy) ranging information between the sensors and a-priori known locations of a few nodes (called the anchors) can be utilized for positioning purposes [3]. The required ranging information can be usually obtained by measuring the physical parameters of the radio signal exchanged between neighboring nodes (i.e., the nodes which are in the communication range of each other). Among different measurement techniques, the received signal strength (RSS) [4] and the time of arrival (TOA) [5] methods are most popular ones, respectively, due to their simplicity and accuracy.

Although localization of sensor networks has been the focus of numerous studies, most existing literature concentrates on the simple scenario where all the sensor and the anchor nodes are *stationary*. However, in some practical scenarios, such as underwater sensor networks, track movements of small objects, and Vehicular Ad Hoc Networks (VANets), all the sensor and the anchor nodes are *non-stationary*. Few recent works have addressed the mobile anchor assisted localization problem; we refer the reader to see [6] and the references therein. More recently, [7] studied the problem of maximum likelihood (ML) localization for the case where mobile sensor nodes exploit their movement knowledge in the localization process. The described scheme in [7] is *non-cooperative* [4] in the sense that each sensor can communicate with mobile anchor nodes exclusively, i.e., no cooperation among sensor is allowed. With the non-cooperative approach, however, the sensors cannot localize themselves if they cannot directly connect to a sufficient number of anchor nodes, which might be difficult due to the limited communication range and/or lack of accessible anchor nodes. For example, in a 2-dimensional case, each sensor needs to connect to at least 3 anchor nodes. Otherwise, the sensor cannot localize itself. In order to address this issue, the *cooperative* localization [4] was also studied, in which each sensor node can communicate with any node within its communication range. To the best of our knowledge, however, the cooperative scheme has never been studied for completely mobile WSNs.

In this letter, for the first time in the literature, we investigate the *mobility-aided* localization problem for the *non-stationary cooperative* WSNs. Incorporating the movement knowledge of the nodes in the process of localization not only reduces the density of the required expensive anchor nodes but also significantly improves the localization accuracy. In particular, exploiting the attractive features of second order cone programming (SOCP) technique, we develop a novel and effective ML-based cooperative localization algorithm and its distributed version, which are applicable to both TOA and RSS measurement models. Our distributed implementation strategy divides the complex ML problem into a set of smaller subproblems that can be solved locally at the sensor nodes. Thus, the proposed approach is suitable for large-scale WSNs.

II. MEASUREMENT MODEL

We consider a WSN with m_s regular sensor nodes and m_a mobile anchor nodes in which all the sensor and the mobile anchor nodes can move independently. The locations of the mobile anchors are known. However, the sensor nodes need to estimate their locations. Similarly to [7], it is assumed that each mobile sensor node measures its own velocity vector including the magnitude and the direction. The measured velocity vectors will be used in the localization process. Although we focus on the two-dimensional scenario, the extension to higher dimensions is straightforward.

We denote by $\mathbf{s}_i^{(n)}$ the vector that contains the actual coordinates of the i-th node at time instant n, for $i = 1, ..., m_s + m_a$ and $n = 1, ..., N$, where N is the total number of observation time instants. Without loss of generality, we assume that $\mathbf{s}_1^{(n)}, ..., \mathbf{s}_{m_s}^{(n)}$ are the sensor node locations while $\mathbf{s}_{m_s+1}^{(n)}, ..., \mathbf{s}_{m_s+m_a}^{(n)}$ correspond to the mobile anchor node locations. Furthermore, we denote the true velocity vector of the i-th sensor between time instants $(n-1)$ and n by $\mathbf{v}_i^{(n)}$, where $i = 1, ..., m_s$ and $n = 2, ..., N$. It is assumed that $\mathbf{v}_i^{(n)}$ remains fixed between consecutive time instants $(n-1)$ and n, for $n = 2, ..., N$. In addition, we will use the following sensor movement model to incorporate the velocity measurements in the localization process [7]:

$$\mathbf{s}_i^{(n)} = \mathbf{s}_i^{(n-1)} + T_s\big(\mathbf{v}_i^{(n)} + \mathbf{e}_i^{(n)}\big), i = 1, ..., m_s; n = 2, ..., N, \tag{1}$$

where T_s is the length of the sampling interval. In (1), $\mathbf{e}_i^{(n)}$ represents the velocity measurement error which is modeled as a zero-mean white Gaussian process with covariance $\sigma_e^2 \mathbf{I}_2$.

S. Salari and I.-M. Kim are with the Faculty of Engineering and Applied Science, Queen's University, Kingston, Canada, (e-mails: salari.sohei@gmail.com; ilmin.kim@queensu.ca).
F. Chan is with the Department of Electrical and Computer Engineering, Royal Military College of Canada, Kingston, Canada, (email:chan-f@rmc.ca).

2162-2337 (c) 2017 IEEE. Personal use is permitted, but republication/redistribution requires IEEE permission. See http://www.ieee.org/publications_standards/publications/rights/index.html for more information.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/LWC.2017.2750685, IEEE Wireless Communications Letters

The Euclidean distance between the i-th and the j-th nodes at time instant n, $\|\mathbf{s}_i^{(n)} - \mathbf{s}_j^{(n)}\|$, can be measured only when they are in the communication range, R, of each other, i.e., $\|\mathbf{s}_i^{(n)} - \mathbf{s}_j^{(n)}\| \leq R$. Here, we assume that the set of links, denoted by $\mathcal{A}$, does not include the anchor-anchor links, i.e., $\mathcal{A} = \Big\{(i,j,n)\Big|\ \|\mathbf{s}_i^{(n)} - \mathbf{s}_j^{(n)}\| \leq R\Big\}$, where $1 \leq i \leq m_s$, $1 \leq j \leq m_s + m_a$, $i \neq j$, and $1 \leq n \leq N$. In practice, the ranging information is measured based on one or more physical parameters of the radio signal exchanged between nodes that are in the communication range of each other. In this letter, we consider the common TOA- and RSS-based measurement models. As we will see, the major difference between these measurement models is the different assumption of the ranging errors.

Distance Measurement Model: Under the TOA-based model [5], the distance between the i-th and the j-th nodes at time instant n, $d_{ij}^{(n)}$, can be written as

$$d_{ij}^{(n)} = \|\mathbf{s}_i^{(n)} - \mathbf{s}_j^{(n)}\| + \lambda_{ij}^{(n)}, \qquad \forall(i,j,n) \in \mathcal{A}, \tag{2}$$

where the TOA range measurement error, $\lambda_{ij}^{(n)}$, is modeled as a zero-mean white Gaussian process with variance σ_λ^2.

Signal Strength Measurement Model: Let $P_{ij}^{(n)}$ denote the RSS of the signal transmitted by the j-th node and received by the i-th sensor at time instant n. According to [8], $P_{ij}^{(n)}$, $\forall(i,j,n) \in \mathcal{A}$, can be expressed as

$$10\log_{10} P_{ij}^{(n)} = 10\log_{10}\Big(\frac{d_0^\alpha P_T}{P_0}\Big) - 10\log_{10}\|\mathbf{s}_i^{(n)} - \mathbf{s}_j^{(n)}\|^\alpha + z_{ij}^{(n)}, \tag{3}$$

where P_0 denotes the path loss value at a reference distance d_0, α stands for the path loss constant, P_T is the transmitted power, and $z_{ij}^{(n)}$ is a zero-mean white Gaussian process with variance σ_z^2. Notice that the RSS ranging error is modeled, mainly due to shadowing, as a log-normal disturbance. Defining $P \triangleq {d_0}^\alpha P_T/P_0$, (3) can be concisely rewritten as

$$\ln P_{ij}^{(n)} = \ln\Big(\frac{P}{\|\mathbf{s}_i^{(n)} - \mathbf{s}_j^{(n)}\|^\alpha}\Big) + w_{ij}^{(n)}, \ \forall(i,j,n) \in \mathcal{A}, \tag{4}$$

where $w_{ij}^{(n)} \triangleq 0.1\ln(10) z_{ij}^{(n)}$ is a zero-mean white Gaussian process with variance $\sigma_w^2 = (0.1\ln(10))^2\sigma_z^2$.

III. Velocity-Aided Cooperative Localization

In this section, we first show that the ML estimators for both TOA- and RSS-based scenarios have the same formulation. Then, we propose a novel and effective cooperative algorithm and its distributed version for localization of mobile WSNs.

A. ML Localization

The set of all available velocity measurements is denoted by $\mathcal{V} = \big\{\mathbf{v}_i^{(n)} \ \big|\ i = 1, ..., m_s \text{ and } n = 2, ..., N\big\}$, where $\mathbf{v}_i^{(n)} = \frac{1}{T_s}\big(\mathbf{s}_i^{(n)} - \mathbf{s}_i^{(n-1)}\big) - \mathbf{e}_i^{(n)}$. In the following lemma, we derive the ML estimator of $\mathcal{S} = \big\{\mathbf{s}_i^{(n)} \ \big|\ i = 1, ..., m_s \text{ and } n = 1, ..., N\big\}$ for both considered ranging measurement models.

Lemma 1. For the TOA-based measurement model, the ML localizer is formulated as

$$\min_{\mathcal{S}} \Big[\sum_{(i,j,n)\in\mathcal{A}} \frac{1}{\sigma_\lambda^2}\Big(\|\mathbf{s}_i^{(n)} - \mathbf{s}_j^{(n)}\| - d_{ij}^{(n)}\Big)^2 + \sum_{(i,n)\in\mathcal{V}} \frac{1}{\sigma_e^2}\Big\|\frac{1}{T_s}\big(\mathbf{s}_i^{(n)} - \mathbf{s}_i^{(n-1)}\big) - \mathbf{v}_i^{(n)}\Big\|^2\Big]. \tag{5}$$

For the RSS-based scenario, the ML localizer is given by

$$\min_{\mathcal{S}} \Big[\sum_{(i,j,n)\in\mathcal{A}} \frac{1}{\sigma_w^2}\Big(\ln P_{ij}^{(n)} - \ln\Big(\frac{P}{\|\mathbf{s}_i^{(n)} - \mathbf{s}_j^{(n)}\|^\alpha}\Big)\Big)^2 + \sum_{(i,n)\in\mathcal{V}} \frac{1}{\sigma_e^2}\Big\|\frac{1}{T_s}\big(\mathbf{s}_i^{(n)} - \mathbf{s}_i^{(n-1)}\big) - \mathbf{v}_i^{(n)}\Big\|^2\Big]. \tag{6}$$

Proof. See Appendix A. □

Interestingly, it turns out that the ML localizer (6) of the RSS model can be (accurately) approximated by that of the TOA model in (5). Let us define $\rho_{ij}^{(n)} \triangleq (P_{ij}^{(n)}/P)^{-1/\alpha}$. Then, the first order Taylor series approximation of the logarithmic terms in (6) can be written as

$$\ln\Big(\frac{\|\mathbf{s}_i^{(n)} - \mathbf{s}_j^{(n)}\|}{\rho_{ij}^{(n)}}\Big) \approx \frac{\|\mathbf{s}_i^{(n)} - \mathbf{s}_j^{(n)}\|}{\rho_{ij}^{(n)}} - 1. \tag{7}$$

Notice that the approximation (7) is accurate for all $\Big|\frac{\|\mathbf{s}_i^{(n)} - \mathbf{s}_j^{(n)}\|}{\rho_{ij}^{(n)}} - 1\Big| < 1$ values. In view of (7), the first term of (6) can be reexpressed as

$$\sum_{(i,j,n)\in\mathcal{A}} \frac{1}{\big(\sigma_w\rho_{ij}^{(n)}\big)^2}\Big(\|\mathbf{s}_i^{(n)} - \mathbf{s}_j^{(n)}\| - \rho_{ij}^{(n)}\Big)^2, \tag{8}$$

which means that (6) is (accurately) approximated by (5).

Remark 1: It is interesting to see that a common ML estimator can be derived for both considered measurement models. The universal form of (5) is very useful in practice because it is independent of the measurement models adopted.

Remark 2: The first term in (5) reflects the likelihood of the ranging measurements, while the second one is the likelihood of velocity measurements. Inaccurate velocity measurements and/or inaccurate range measurements result in performance loss. In fact, for small $\sigma_e^2/\sigma_\lambda^2$ values, the second term will be dominant in (5) and the first one will be almost ignored. On the other hand, for large $\sigma_e^2/\sigma_\lambda^2$ values, problem (5) heavily relies on the first term and the second term is almost ignored.

Remark 3: The existing standard ML localizer is the special case of (5). Specifically, if we set the nodes velocities to zero, (5) reduces to the standard ML formulation.

Remark 4: The universal ML-based cooperative localizer (5) is non-convex and in general NP-hard. Applying semi-definite programming (SDP) relaxation technique is a common approach in the context of localization [7]. However, the SDP-based methods are not suitable for problem (5) because they are firstly very expensive for large-scale networks; and secondly, they require centralized computation due to their complex structures [9]. In this letter, we employ the SOCP relaxation technique due to its simpler structure, shorter computation time, and most importantly its potential for development of *distributed* implementation.

B. Algorithm Development

This subsection describes the procedure of converting (5) into a centralized convex SOCP problem. We begin by reformulating (5) as the following constrained problem:

$$\begin{aligned} \min_{\mathcal{S},\mathcal{B}} \quad & \sum_{(i,j,n)\in\mathcal{A}} \frac{1}{\sigma_\lambda^2}\Big(b_{ij}^{(n)} - d_{ij}^{(n)}\Big)^2 + \\ & \sum_{(i,n)\in\mathcal{V}} \frac{1}{\sigma_e^2}\Big\|\frac{1}{T_s}\big(\mathbf{s}_i^{(n)} - \mathbf{s}_i^{(n-1)}\big) - \mathbf{v}_i^{(n)}\Big\|^2 \\ \text{s.t.} \quad & b_{ij}^{(n)} = \|\mathbf{s}_i^{(n)} - \mathbf{s}_j^{(n)}\|, \qquad \forall(i,j,n) \in \mathcal{A}, \end{aligned} \tag{9}$$

2162-2337 (c) 2017 IEEE. Personal use is permitted, but republication/redistribution requires IEEE permission. See http://www.ieee.org/publications_standards/publications/rights/index.html for more information.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/LWC.2017.2750685, IEEE Wireless Communications Letters

where $\mathcal{B} \triangleq \{b_{ij}^{(n)} \mid (i,j,n) \in \mathcal{A}\}$. Equation (9) clearly shows that our localizer keeps the former sensor/anchor positions and their previous measurements. Let $\mathcal{C} \triangleq \{c_{ij}^{(n)} \mid (i,j,n) \in \mathcal{A}\}$ and $\mathcal{X} \triangleq \{x_i^{(n)} \mid (i,n) \in \mathcal{V}\}$. Then, (9) can be equivalently rewritten as

$$\begin{aligned}
\min_{\mathcal{S},\mathcal{C},\mathcal{X},\mathcal{B}} \quad & \sum_{(i,j,n)\in\mathcal{A}} \left(c_{ij}^{(n)}\right)^2 + \sum_{(i,n)\in\mathcal{V}} \left(x_i^{(n)}\right)^2 \\
\text{s.t.} \quad & x_i^{(n)} \geq \frac{1}{\sigma_e}\left\|\frac{1}{T_s}\left(\mathbf{s}_i^{(n)} - \mathbf{s}_i^{(n-1)}\right) - \mathbf{v}_i^{(n)}\right\|, \forall (i,n) \in \mathcal{V} \\
& c_{ij}^{(n)} \geq \frac{1}{\sigma_\lambda}\left|b_{ij}^{(n)} - d_{ij}^{(n)}\right|, \qquad \forall (i,j,n) \in \mathcal{A} \\
& b_{ij}^{(n)} = \|\mathbf{s}_i^{(n)} - \mathbf{s}_j^{(n)}\|, \qquad \forall (i,j,n) \in \mathcal{A}. \qquad (10)
\end{aligned}$$

Defining $\mathbf{z} \triangleq \{c_{ij}^{(n)} \mid (i,j,n) \in \mathcal{A},\ x_i^{(n)} \mid (i,n) \in \mathcal{V}\}$ and applying the SOCP relaxation, we then obtain the following standard SOCP program

$$\begin{aligned}
\min_{\mathcal{S},\mathbf{z},\mathcal{B},y} \quad & y \\
\text{s.t.} \quad & y \geq \|\mathbf{z}\|^2 \\
& x_i^{(n)} \geq \frac{1}{\sigma_e}\left\|\frac{1}{T_s}\left(\mathbf{s}_i^{(n)} - \mathbf{s}_i^{(n-1)}\right) - \mathbf{v}_i^{(n)}\right\|, \forall (i,n) \in \mathcal{V} \\
& c_{ij}^{(n)} \geq \frac{1}{\sigma_\lambda}\left|b_{ij}^{(n)} - d_{ij}^{(n)}\right|, \qquad \forall (i,j,n) \in \mathcal{A} \\
& b_{ij}^{(n)} \geq \|\mathbf{s}_i^{(n)} - \mathbf{s}_j^{(n)}\|, \qquad \forall (i,j,n) \in \mathcal{A}, \qquad (11)
\end{aligned}$$

which can be efficiently solved using off-the-shelf solvers, such as CVX. Unfortunately, the centralized implementation of (11) requires transmission of all range measurements among nodes (local maps) to a fusion center (FC) that is responsible for network localization. This results in large power consumption, high network traffic, and wide communication bandwidth, as well as high computational cost at the FC. To address these critical issues, in the next subsection, we implement (11) in a fully distributed manner.

C. Distributed Implementation of SOCP Algorithm

In this subsection, we develop the distributed implementation of the proposed SOCP algorithm. To this end, we first relax the constrained optimization problem (9) as

$$\begin{aligned}
\min_{\mathcal{S},\mathcal{B}} \quad & \sum_{(i,j,n)\in\mathcal{A}} \frac{1}{\sigma_\lambda^2}\left(b_{ij}^{(n)} - d_{ij}^{(n)}\right)^2 + \\
& \sum_{(i,n)\in\mathcal{V}} \frac{1}{\sigma_e^2}\left\|\frac{1}{T_s}\left(\mathbf{s}_i^{(n)} - \mathbf{s}_i^{(n-1)}\right) - \mathbf{v}_i^{(n)}\right\|^2 \\
\text{s.t.} \quad & b_{ij}^{(n)} \geq \|\mathbf{s}_i^{(n)} - \mathbf{s}_j^{(n)}\|, \qquad \forall (i,j,n) \in \mathcal{A}. \qquad (12)
\end{aligned}$$

Next, we use the logarithmic barrier function $f(\alpha) = -\frac{1}{\eta}\log(-\alpha)$ ($\eta \gg 1$) to replace the inequality constraint in (12) by a penalizing term in the objective function which is easier to handle. Then, (12) can be approximated as

$$\begin{aligned}
\min_{\mathcal{S},\mathcal{B}} & \sum_{(i,j,n)\in\mathcal{A}} \frac{1}{\sigma_\lambda^2}\left(b_{ij}^{(n)} - d_{ij}^{(n)}\right)^2 + \sum_{(i,j,n)\in\mathcal{A}} f\left(\|\mathbf{s}_i^{(n)} - \mathbf{s}_j^{(n)}\|^2 - (b_{ij}^{(n)})^2\right) \\
& + \sum_{(i,n)\in\mathcal{V}} \frac{1}{\sigma_e^2}\left\|\frac{1}{T_s}\left(\mathbf{s}_i^{(n)} - \mathbf{s}_i^{(n-1)}\right) - \mathbf{v}_i^{(n)}\right\|^2. \qquad (13)
\end{aligned}$$

It is seen that for each specific $i \in \{1, ..., m_s\}$, (13) depends only on the location and ranging information of the set of the i-th relay's neighboring nodes as well as the i-th relay velocity measurements. This attractive feature enables us to decompose (13) into m_s separate subproblems. Let $\mathcal{N}_i \triangleq \{(j,n) \mid (i,j,n) \in \mathcal{A}\}$, i.e., $(j,n) \in \mathcal{N}_i$ means that the j-th sensor/anchor node is within the communication range of the i-th sensor at time instant n. Also, suppose that $\mathcal{B}_i \triangleq \{b_{ij}^{(n)} \mid (j,n) \in \mathcal{N}_i\}$, $\mathcal{C}_i \triangleq \{c_{ij}^{(n)} \mid (j,n) \in \mathcal{N}_i\}$, $\mathcal{X}_i \triangleq \{x_i^{(n)},\ n = 2, ..., N\}$, and $\mathbf{z}_i \triangleq \{c_{ij}^{(n)} \mid (j,n) \in \mathcal{N}_i,\ x_i^{(n)}, n = 2, ..., N\}$. Then, adopting a similar approach to the one employed in the previous subsection, we can show that the i-th sensor node needs to solve the following subproblem

$$\begin{aligned}
\min_{\mathcal{S}_i,\mathcal{C}_i,\mathcal{B}_i,\mathcal{X}_i,y_i} \quad & y_i \\
\text{s.t.} \quad & y_i \geq \|\mathbf{z}_i\|^2 \\
& x_i^{(n)} \geq \frac{1}{\sigma_e}\left\|\frac{1}{T_s}\left(\mathbf{s}_i^{(n)} - \mathbf{s}_i^{(n-1)}\right) - \mathbf{v}_i^{(n)}\right\|, 2 \leq n \leq N \\
& c_{ij}^{(n)} \geq \frac{1}{\sigma_\lambda}\left|b_{ij}^{(n)} - d_{ij}^{(n)}\right|, \ \forall (j,n) \in \mathcal{N}_i \\
& b_{ij}^{(n)} \geq \|\mathbf{s}_i^{(n)} - \mathbf{s}_j^{(n)}\|, \forall (j,n) \in \mathcal{N}_i, \qquad (14)
\end{aligned}$$

where $i = 1, ..., m_s$ and $\mathcal{S}_i = \left[\mathbf{s}_i^{(1)} \ \dots \ \mathbf{s}_i^{(N)}\right]$ represents the optimization variable matrix that includes the location of the i-th sensor at different time instants. In this scenario, each sensor independently solves its local subproblem using *only* its own observations. This step is followed by a communication step where neighbor nodes exchange their estimated locations, which were approximated by solving (14). The computational complexity of any SOCP problem is a function of both number and size of its constraints. Considering the fact that $\mathcal{N}_i$ is a very small subset of $\mathcal{A}$, we conclude that the computational cost of (14) is much lower than that of (11).

IV. Simulation Results

All presented simulation results have been averaged over 1000 independent realizations. Specifically, at the beginning of each realization, all the sensor and the anchor nodes are randomly placed inside a square region of length 10 m and the initial locations of sensor nodes are unknown. Then all of them start to move randomly. In each realization, the random movement of all nodes was repeated for N times. Note that the entire process (including the random initial placements of all nodes and next N subsequent random movements) is repeated for 1000 times. For simplicity, the initial estimates of the sensors' locations are also randomly generated.

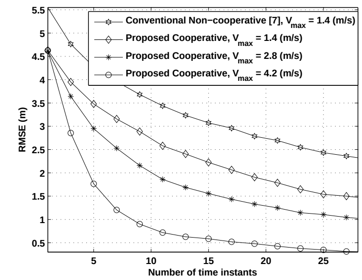

Fig. 1. The RMSE of location estimates against the number of time instants, when $\sigma_\lambda^2 = 0.1\ \mathrm{m}^2$, $\sigma_e^2 = 0.1\ (\mathrm{m/s})^2$, $R = 3$ m, $m_\mathrm{s} = 10$, and $m_\mathrm{a} = 3$.

Fig. 1 presents the root mean square error (RMSE) curves of the proposed cooperative TOA-based algorithm against the number of time instants. Fig. 1 also shows the performance of the (non-cooperative) TOA-based scheme proposed in [7]. Here, we only change the maximum velocity, V_{max}, and keep all other parameters fixed. It is seen that increasing the velocity of movement significantly improves the localization accuracy.

2162-2337 (c) 2017 IEEE. Personal use is permitted, but republication/redistribution requires IEEE permission. See http://www.ieee.org/publications_standards/publications/rights/index.html for more information.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/LWC.2017.2750685, IEEE Wireless Communications Letters

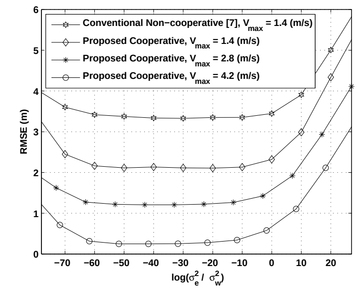

Fig. 2. The RMSE of location estimates against $\log(\sigma_e^2/\sigma_w^2)$ ratio, when $R = 3$ m, $N = 25$, $m_{\rm s} = 10$, and $m_{\rm a} = 3$.

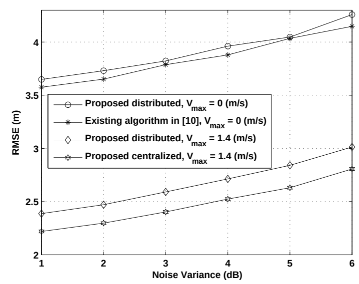

Fig. 3. The RMSE curves of different RSS-based localizers against variance of noise, when $R = 4$ m, $m_{\rm s} = 10$, and $m_{\rm a} = 4$.

This is because increasing V_{max} increases the average number of seen sensor/anchor nodes; which in turns reduces the convergence time from 0.93 seconds ($V_{max} = 1.4$ (m/s)) to 0.34 seconds ($V_{max} = 7$ (m/s)), when $R = 3$ m, $m_{\rm s} = 100$, and $m_{\rm a} = 20$. Fig. 2 illustrates the RMSE curves of the proposed cooperative RSS-based algorithm versus $\log(\sigma_e^2/\sigma_w^2)$ ratio. Also, it illustrates the performance of the (noncooperative) RSS-based method proposed in [7]. Fig. 2 again shows that increasing V_{max} improves the positioning accuracy. Furthermore, the behavior of plotted curves in Fig. 2 reveals that both inaccurate velocity measurements (low $\log(\sigma_e^2/\sigma_w^2)$ values) and inaccurate range measurements (large $\log(\sigma_e^2/\sigma_w^2)$ values) result in performance loss. Our simulations confirm that the proposed cooperative method outperforms the non-cooperative scheme proposed in [7] in the sense of accuracy, complexity, and computation time. All of these observations are consistent with our discussions in Remark 2, which were obtained from the analysis. Fig. 3 compares the performance of our centralized and distributed RSS-based localizers. Also, it shows the performance of the state-of-the-art RSS-based algorithm proposed in [10] for static WSNs. It can be seen that the proposed distributed scheme performs close to the centralized scheme. Also, it is clear that incorporating mobility information in the localization process significantly improves the accuracy in comparison to algorithm proposed in [10].

V. Conclusions

In this letter, we have proposed a novel and effective cooperative algorithm and its distributed version for localization of mobile WSNs, based on attractive features of SOCP relaxation technique. Compared with the existing methods, the accuracy of the proposed scheme is substantially improved, since in addition to TOA or RSS measurements, it also incorporates the mobility information of the sensors in the localization process. Simulation results confirmed that the proposed distributed framework could be effectively used in large-scale WSNs. Designing intelligent movement of the mobile anchors will be the focus of our further work.

Appendix A
Proof of Lemma 1

Under the TOA-based scenario, the set of all available distance measurements can be given by $\mathcal{D} = \big\{d_{ij}^{(n)} = \big\|\mathbf{s}_i^{(n)} - \mathbf{s}_j^{(n)}\big\| + \lambda_{ij}^{(n)} \mid (i,j,n) \in \mathcal{A}\big\}$. Given the measurements $\mathcal{V}$ and $\mathcal{D}$, the ML estimate of $\mathcal{S}$ can be obtained by maximizing the conditional probability distribution function $f\big(\mathcal{D}, \mathcal{V} \mid \mathcal{S}\big)$. Since the velocity and distance measurement errors are independent, we have $f\left(\mathcal{D}, \mathcal{V} \mid \mathcal{S}\right) = f\left(\mathcal{D} \mid \mathcal{S}\right) f\left(\mathcal{V} \mid \mathcal{S}\right)$, or, equivalently,

$$f(\mathcal{D},\mathcal{V}\,|\,\mathcal{S}) = \prod_{(i,j,n)\in\mathcal{A}} \frac{1}{\sqrt{2\pi\sigma_\lambda^2}} \exp\Big(-\frac{\big(\big\|\mathbf{s}_i^{(n)} - \mathbf{s}_j^{(n)}\big\| - d_{ij}^{(n)}\big)^2}{2\sigma_\lambda^2}\Big) \times \prod_{(i,n)\in\mathcal{V}} \frac{1}{\sqrt{2\pi\sigma_e^2}} \exp\Big(-\frac{\big\|\frac{1}{T_s}\big(\mathbf{s}_i^{(n)} - \mathbf{s}_i^{(n-1)}\big) - \mathbf{v}_i^{(n)}\big\|^2}{2\sigma_e^2}\Big). \quad \text{(A.1)}$$

Taking the logarithm of (A.1) leads to (5).

Under the RSS-based case, the set of all available distance measurements can be presented as $\mathcal{P} = \big\{P_{ij}^{(n)} \mid (i,j,n) \in \mathcal{A}\big\}$, where $\ln P_{ij}^{(n)} = \ln\big(\frac{P}{\|\mathbf{s}_i^{(n)} - \mathbf{s}_j^{(n)}\|^\alpha}\big) + w_{ij}^{(n)}$. Similarly, the ML estimate of $\mathcal{S}$ is obtained by maximizing $f\left(\mathcal{P}, \mathcal{V} \mid \mathcal{S}\right) = f\left(\mathcal{P} \mid \mathcal{S}\right) f\left(\mathcal{V} \mid \mathcal{S}\right)$ or, equivalently, minimizing

$$f(\mathcal{D},\mathcal{V}\,|\,\mathcal{S}) = \prod_{(i,j,n)\in\mathcal{A}} \frac{1}{\sqrt{2\pi\sigma_w^2}} \exp\Big(\frac{\big[\ln P_{ij}^{(n)} - \ln\big(\frac{P}{\|\mathbf{s}_i^{(n)} - \mathbf{s}_j^{(n)}\|^\alpha}\big)\big]^2}{2\sigma_w^2}\Big) \times \prod_{(i,n)\in\mathcal{V}} \frac{1}{\sqrt{2\pi\sigma_e^2}} \exp\Big(-\frac{\big\|\frac{1}{T_s}\big(\mathbf{s}_i^{(n)} - \mathbf{s}_i^{(n-1)}\big) - \mathbf{v}_i^{(n)}\big\|^2}{2\sigma_e^2}\Big). \quad \text{(A.2)}$$

Taking the logarithm of (A.2) results in (6).

References

[1] A. E. Assaf, S. Zaidi, S. Affes, and N. Kandil, "Low-cost localization for multihop heterogeneous wireless sensor networks," *IEEE Trans. Wireless Commun.*, vol. 15, no. 1, pp. 472–484, Jan. 2016.

[2] S. Srirangarajan, A. Tewfik, and Z.-Q. Luo, "Distributed sensor network localization using SOCP relaxation," *IEEE Trans. Wireless Commun.*, vol. 7, no. 12, pp. 4886 –4895, Dec. 2008.

[3] P. M. Ghari, R. Shahbazian, and S. A. Ghorashi, "Wireless sensor network localization in harsh environments using SDP relaxation," *IEEE Commun. Lett.*, vol. 20, no. 1, pp. 137–140, Jan. 2016.

[4] S. Tomic, M. Beko, and R. Dinis, "RSS-based localization in wireless sensor networks using convex relaxation: Noncooperative and cooperative schemes," *IEEE Trans Veh. Tech.*, vol. 64, no. 5, pp. 2037–2050, May 2015.

[5] G. Naddafzadeh-Shirazi, M. B. Shenouda, and L. Lampe, "Second order cone programming for sensor network localization with anchor position uncertainty," *IEEE Trans. Wireless Commun.*, vol. 13, no. 2, pp. 749–763, Feb. 2014.

[6] G. Han, J. Jiang, C. Zhang, T. Q. Duong, M. Guizani, and G. K. Karagiannidis, "A survey on mobile anchor node assisted localization in wireless sensor networks," *IEEE Commun. Surveys Tutorials*, vol. 18, no. 3, pp. 2220–2243, third quarter 2016.

[7] S. Salari, S. Shahbazpanahi, and K. Ozdemir, "Mobility-aided wireless sensor network localization via semidefinite programming," *IEEE Trans. Wireless Commun.*, vol. 12, no. 12, pp. 5966–5978, Dec. 2013.

[8] T. Rappaport, *Wireless communications: Principles and practice*. Prentice Hall PTR, 2002.

[9] Q. Shi, C. He, H. Chen, and L. Jiang, "Distributed wireless sensor network localization via sequential greedy optimization algorithm," *IEEE Trans. Signal Process.*, vol. 58, no. 6, pp. 3328–3340, June 2010.

[10] S. Tomic, M. Beko, and R. Dinis, "Distributed RSSt lh7 b-based localization in wireless sensor networks based on second-order cone programming," *MDPI Sensors*, vol. 14, no. 10, pp. 18 410–18 432, Oct. 2014.

2162-2337 (c) 2017 IEEE. Personal use is permitted, but republication/redistribution requires IEEE permission. See http://www.ieee.org/publications_standards/publications/rights/index.html for more information.