Mobility Assisted Wireless Sensor Network Cooperative Localization via SOCP

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Abstract. Cooperative sensor localization plays an essential role in the Global Positioning System (GPS) limited indoor networks. While most of the earlier work is of static nodes localization, the localization of mobile nodes is still a challenging task for wireless sensor networks. This paper proposes an effective cooperative localization scheme in the mobile wireless sensor network, which exploits distance between nodes as well as their mobility information. We first use multidimensional scaling (MDS) to perform initial location estimation. Then second-order cone programming (SOCP) is applied to obtain the location estimation. To make full use of the mobility of nodes, we further utilize Kalman filter (KF) to reduce the localization error and improve the robustness of the localization system. The proposed mobility assisted localization scheme significantly improves the localization accuracy of mobile nodes.

Keywords: Cooperative localization · Wireless sensor network · Multidimensional scaling · Second order cone programming · Kalman filter

1 Introduction

In many sensor network applications, the availability of accurate information on the location of the node is essential, such as target tracking and detection, cooperative sensing and energy-efficient routing. Cooperative localization is a relatively new concept, trying to overcome the limitations of traditional settings, in addition to the measurement between nodes and anchor nodes, distance measurement among nodes is also considered. Many studies have shown

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that accurate inter-node distance measurement can be achieved using techniques such as sound signals or Ultra Wide Band (UWB) technology. This provides a broad application space for cooperative localization.

MDS is a widely used cooperative localization algorithm [2,11]. It can accurately restore the topological relationships among nodes under precise distance measurement between nodes. Authors in [3] proposed a cooperative localization method which not only utilized the initial results of the fingerprint-based algorithm but also used MDS to refine the location estimates for multiple users simultaneously. Another approach is to relax the original non-convex localization problem to obtain a convex optimization problem, which can be efficiently solved using existing algorithms. The two main convex relaxation techniques which utilized widely are SOCP [4,5], and semidefinite programming (SDP) [6,7]. Compared to SDP relaxation, SOCP relaxation is weaker, but its structure is simpler and potential to be solved faster.

At present, most studies about cooperative localization focus on the localization of static nodes. However, in practical applications, the localization of mobile nodes deserves more attention. Recently, authors in [1] studied the problem of maximum likelihood (ML) localization via SDP in the case where mobile sensor nodes utilize their movement information in the localization. In [9], the authors used RSS measurements for distance estimation and formulated the localization problem as an SDP. The inertial measurement unit (IMU) data is used to improve the localization performance further. However, SDP is not suitable for mobile nodes due to its high complexity. Extend Kalman filter (EKF) is widely used in the mobile nodes tracking algorithms is proposed in [8]. Authors in [10] utilized pair-wise range measurements and relative velocity measurements between communicating nodes to obtain the relative positions by EKF. However, EKF is a sub-optimal method compared to KF because it uses a Jacobian matrix to apply KF to nonlinear systems. Although this method expands the application space of KF, the consequences will be severely divergent in a strongly nonlinear scenario. Moreover, EKF has high computational complexity due to the calculation of the Jacobian matrix, which is not appropriate for real-time localization systems.

In this paper, we propose a novel cooperative localization scheme based on node's mobility in the indoor environment, combines the advantages of MDS and SOCP to improve the accuracy and robustness of the mobile localization system. To better take advantage of the node's mobility information, we apply KF to fuse the location estimation of SOCP-based and velocity-based. Simulation results are presented to confirm that mobility information and KF can effectively improve the localization accuracy.

2 System Model

We consider a 2-dimensional mobile wireless sensor network, there are N_s mobile nodes with unknown position and N_a anchor nodes with known position. Each mobile node move independently from their position at time instant t to a new time instant $t+1$, for $t=1,2,...,N$, where N is the total number of observation time instants. In addition, we assume that each mobile node could obtain its velocity which is assumed to be constant between two successive time instants. Let a_k be the position of the k-th anchor node and ${x_i}^{(t)}$ be the position of the i-th mobile node at time instant t. Let $\mathcal{W}$ be defined as $\mathcal{W}=\{(\mathrm{i},\mathrm{t}),1\leq \mathrm{i}\leq N_s, 2\leq t\leq N\}$. The velocity between time instants $t-1$ and t is denoted by ${v_i}^{(t)}$

$$ {v_i}^{(t)} = ({x_i}^{(t)} - {x_i}^{(t-1)})/\Delta T + {w_i}^{(t)}, \forall (i,t) \in \mathcal{W} \tag{1} $$

where ΔT is the sampling length and ${w_i}^{(t)}$ is the measurement noise which follows a zero-mean Gaussian distribution $N(0,{\sigma_e}^2)$. Let us define $\mathcal{A}$ as $\mathcal{A}=\{(i,j,t)|\left\|{x_i}^{(t)}-{x_j}^{(t)}\right\| \leq R\}$, where R is the communication range, $i=1,2,...,N_s$, $j=1,2,...,N_s+N_a$, $t=1,2,...,N$. The distance measurement between the i-th mobile node and the j-th node at time instant t is denoted by ${\delta_{ij}}^{(t)}$

$$ {\delta_{ij}}^{(t)} = \left\| {x_i}^{(t)} - {x_j}^{(t)} \right\| + {n_{ij}}^{(t)}, \forall (i,j,t) \in \mathcal{A} \tag{2} $$

where ${n_{ij}}^{(t)}$ is the measurement noise which follows a zero-mean Gaussian distribution $N(0,{\sigma_\lambda}^2)$.

The localization problem can be described as that given the distance measurement between nodes and the instantaneous velocity vector of each node, estimating the location of all mobile nodes in the network.

3 Cooperative Localization

The proposed algorithm utilizes the velocity and distance measurement to locate multiple mobile nodes simultaneously. Figure 1 illustrates the overall system architecture.

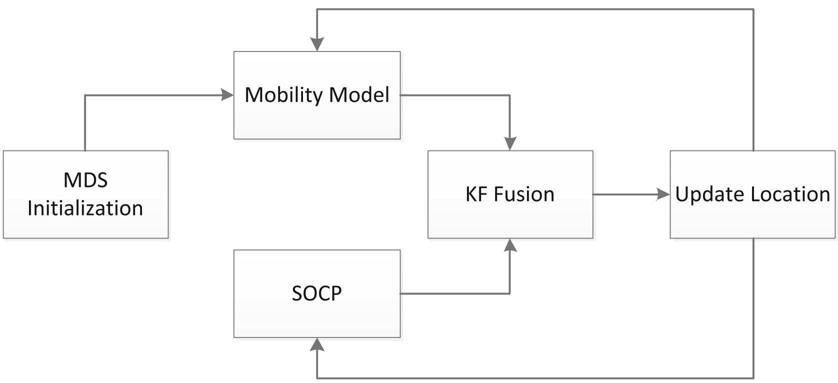

Fig. 1. System architecture.

The localization system uses MDS to perform initialization. Then according to distance and velocity measurement, we derive the localization problem as a non-convex optimization problem and utilize the SOCP relaxation method to estimate the position of nodes. In addition to this, we apply a mobility model based on velocity information and precious estimation to obtain the other location estimation. The KF fusion algorithm is used to enhance the location estimation further.

3.1 MDS-Based Initialization

Firstly, according to the distance between nodes at the initial time, we build the distance matrix D:

$$\mathrm{D} = \begin{bmatrix} \delta_{12}^2 & \delta_{12}^2 & \cdots & \delta_{1\mathrm{n}}^2 \\ \delta_{21}^2 & \delta_{22}^2 & \cdots & \delta_{2n}^2 \\ \vdots & \vdots & \ddots & \vdots \\ \delta_{\mathrm{n}1}^2 & \delta_{n2}^2 & \cdots & \delta_{nn}^2 \end{bmatrix} \tag{3}$$

where δ_{ij} is the distance measurement at time instant 0.

Let us define the true location of the nodes as $X^{(0)} = [{x_1}^{(0)}, {x_2}^{(0)}, \ldots, {x_n}^{(0)}]$, and the corresponding estimated location is $\widehat{X}^{(0)} = [\widehat{x}_1^{(0)}, \widehat{x}_2^{(0)}, \ldots, \widehat{x}_n^{(0)}]$. It can be shown that [11]

$$B \triangleq (X^{(0)})^T X^{(0)} = -\frac{1}{2} JDJ \tag{4}$$

where $J = I - \frac{ee^T}{n}$, I is the $n \times n$ identity and e is the n-dimensional vector of all ones, $n = N_s + N_a$. B is symmetric and positive definite, and we can perform eigenvalue decomposition of B

$$B = Q\Lambda Q^T \tag{5}$$

Then we sort the eigenvalues of matrix B in descending order and select the first two largest eigenvalues to form the matrix $\Lambda^{'}$, the corresponding eigenvector matrix is $Q^{'}$, the relative coordinates of n nodes are approximated by

$$\overline{X}^{(0)} = Q' \Lambda'^{1/2} \tag{6}$$

Finally utilizes the Procrustes analysis [12] to convert the relative location to absolute location $\widehat{X}^{(0)}$.

3.2 SOCP-Based Localization

Let $\mathcal{D} = \{{\delta_{ij}}^{(t)} | (i, j, t) \in \mathcal{A}\}$ be the set of all available distance measurement and $\mathcal{V} = \{{v_i}^{(t)} | (i, t) \in \mathcal{W}\}$ be the set of velocity measurement. Given $\mathcal{D}$, $\mathcal{V}$, and the location of mobile nodes estimated from last time instant $\widehat{X}^{(t-1)}$, the location estimation $\mathcal{X} = \{x_i{}^{(t)}|(i,t) \in \mathcal{W}\}$ at time instant t can be obtained by maximizing the conditional probability distribution function [1]

$$\begin{array}{l} f(\mathcal{D}, \mathcal{V}, \widehat{X}^{(t-1)}|\mathcal{X}) = f(\mathcal{D}|\mathcal{X})f(\mathcal{V}, \widehat{X}^{(t-1)}|\mathcal{X}) \\ = \prod\limits_{(i,j,t)\in\mathcal{A}} \frac{1}{\sqrt{2\pi\sigma_\lambda{}^2}} \exp - \frac{(\delta_{ij}{}^{(t)} - \left\|x_i{}^t - x_j{}^{(t)}\right\|)^2}{2\sigma_\lambda^2} \times \\ \prod\limits_{(i,t)\in\mathcal{W}} \frac{1}{\sqrt{2\pi\sigma_e{}^2}} \exp(-\frac{\left\|v_i{}^{(t)} - (x_i{}^{(t)} - \widehat{x}_i{}^{(t-1)})/\Delta T\right\|^2}{2\sigma_e{}^2}) \end{array} \tag{7}$$

By taking the logarithm to the above equation, the localization problem can be written as

$$\min_{\mathcal{X}} \sum_{(i,j,t)\in\mathcal{A}} \frac{\left(\delta_{ij}{}^{(t)} - \left\|x_i{}^{(t)} - x_j{}^{(t)}\right\|\right)^2}{\sigma_\lambda{}^2} + \sum_{(i,t)\in\mathcal{W}} \frac{\left\|v_i{}^{(t)} - (x_i{}^{(t)} - \widehat{x_i}{}^{(t-1)})/\Delta T\right\|^2}{\sigma_e{}^2} \tag{8}$$

(8) is non-convex, to obtain SOCP relaxation of (8), we first define $\mathcal{M} = \{m_{ij}{}^{(t)}|(i,j,t) \in \mathcal{A}\}$, $\mathcal{S} = \{s_i{}^{(t)}|(i,t) \in \mathcal{W}\}$, (8) can be written as the following equivalent form

$$\begin{array}{ll} \min\limits_{\mathcal{X},\mathcal{M},\mathcal{S}} & \sum\limits_{(i,j,t)\in\mathcal{A}} \left(m_{ij}{}^{(t)}\right)^2 + \sum\limits_{(i,t)\in\mathcal{W}} \left(s_i{}^{(t)}\right)^2 \\ s.t. & \\ & \frac{1}{\sigma_\lambda} \left|\delta_{ij}{}^{(t)} - \left\|x_i{}^{(t)} - x_j{}^{(t)}\right\|\right| \le m_{ij}{}^{(t)}, (i,j,t) \in \mathcal{A} \\ & \frac{1}{\sigma_e} \left\|v_i{}^{(t)} - (x_i{}^{(t)} - \widehat{x}_i{}^{(t-1)})/\Delta T\right\| \le s_i{}^{(t)}, (i,t) \in \mathcal{W} \end{array} \tag{9}$$

Next we define u $\triangleq \{m_{ij}{}^{(t)}|(i,j,t) \in A, s_i{}^{(t)}|(i,t) \in W\}$ and $\mathcal{Q} = \{q_{ij}{}^{(t)}|(i,j,t) \in \mathcal{A}\}$. Then we can obtain the following SOCP problem

$$\begin{array}{ll} \min\limits_{\mathcal{X},\mathcal{Q},u,v} \mathrm{v} & \\ s.t & \\ & \left\|u\right\|^2 \le v \\ & \left\|x_i{}^{(t)} - x_j{}^{(t)}\right\| \le q_{ij}{}^{(t)}, (i,j,t) \in \mathcal{A} \\ & \frac{1}{\sigma_\lambda} \left|q_{ij}{}^{(t)} - \delta_{ij}{}^{(t)}\right| \le m_{ij}{}^{(t)}, (i,j,t) \in \mathcal{A} \\ & \frac{1}{\sigma_e} \left\|v_i{}^{(t)} - (x_i{}^{(t)} - \widehat{x}_i{}^{(t-1)})/\Delta T\right\| \le s_i{}^{(t)}, (i,t) \in \mathcal{W} \end{array} \tag{10}$$

3.3 Fusion Algorithm

Given the position of the mobile node at the last time instant and velocity information, we can easily get the current node's position in each time instant by the following mobility model

$$\begin{array}{l} \mathrm{x}_i{}^{(t)} = x_i{}^{(t-1)} + \Delta t \bullet v_i{}^{(t)} \cos\theta_i{}^{(t)} \\ y_i{}^{(t)} = y_i{}^{(t-1)} + \Delta t \bullet v_i{}^{(t)} \sin\theta_i{}^{(t)} \end{array} \tag{11}$$

The proposed localization system applies KF to fuse the position estimation provided by velocity-based and SOCP-based algorithm. At each time instant t, the state of the nodes is represented by $\widehat{X}^{(t)} = [\widehat{x}_1^{(t)}, \widehat{x}_2^{(t)}, \ldots, \widehat{x}_n^{(t)}]^T$.

The KF estimates a posteriori state $\widehat{X}^{(t|t)}$, given the above algorithm location estimates $z^{(t)}$, and $z^{(t)} = X'$, where X' is the location estimated by SOCP.

According to the dynamical system model and measurement model, the state equation and measurement equation of the localization system are formulated as follows [13]

$$\widehat{X}^{(t)} = F\widehat{X}^{(t-1)} + v^{(t)} + w^{(t-1)} \tag{12}$$

$$z^{(t)} = H\widehat{X}^{(t)} + r^{(t)} \tag{13}$$

where $F = I_{2N}$, $H = I_{2N}$, w and r are the process noise and measurement noise, which covariance matrix are Q and R. The KF equations can be derived as Prediction equations

$$\widehat{X}^{(t|t-1)} = F\widehat{X}^{(t-1|t-1)} + u^{(t)} \tag{14}$$

$$P^{(t|t-1)} = FP^{(t-1|t-1)}F^T + Q^{(t-1)} \tag{15}$$

Update equations

$$K^{(t)} = P^{(t|t-1)}H^T(HP^{(t|t-1)}H^T + R^{(t)})^{-1} \tag{16}$$

$$\widehat{X}^{(t|t)} = \widehat{X}^{(t|t-1)} + K^{(t)}(z^{(t)} - HX^{(t|t-1)}) \tag{17}$$

$$P^{(t|t)} = P^{(t|t-1)} - K^{(t)}HP^{(t|t-1)} \tag{18}$$

4 Simulation Results

We assume that there are ten mobile nodes and five anchor nodes in a $50\,\mathrm{m} \times 50\,\mathrm{m}$ area. The nodes follow the Markov mobility model at each time instant, each node randomly selects a velocity and a direction, where velocity is uniformly distributed between 0 and ν_{max}. Upon reaching the boundary, the node keeps the velocity while moving in the opposite direction. The distance, velocity, and direction errors are 5% respectively. The performance of different algorithms is compared using RMSE and CDF through MATLAB simulations, where all expectations are calculated empirically over 1000 independent runs.

We first studied the positioning performance of static nodes using the MDS algorithm and SOCP relaxation. Figure 2 is the RMSE curves of MDS and SOCP algorithm over ranging error under the static scenario, both of which increase with the increase of ranging error. Combining the CDF of Fig. 3, we can see that the MDS has higher localization accuracy than the SOCP. This is because SOCP relaxes the objective function and only obtains suboptimal location estimation. Moreover, in the static scenario, the objective function only contains the distance information between the nodes, without the help of the velocity vector. The positioning scene diagram in Fig. 4 further validates this result.

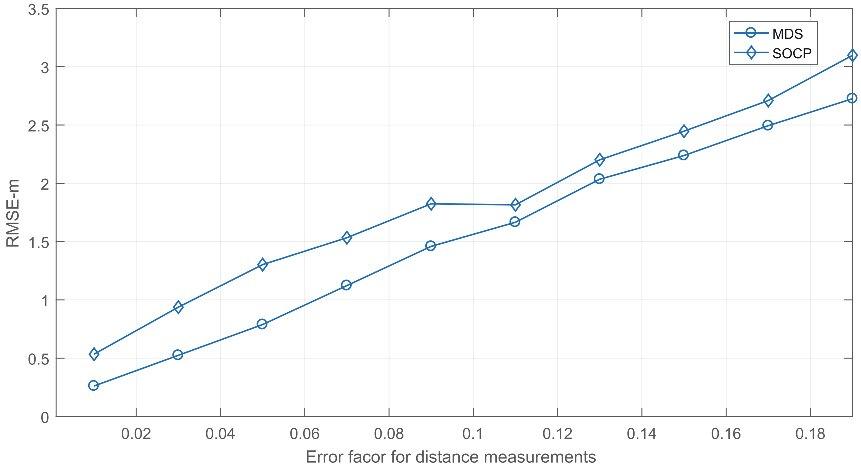

Fig. 2. The RMSE curves of MDS and SOCP against distance measurement error when nodes are static.

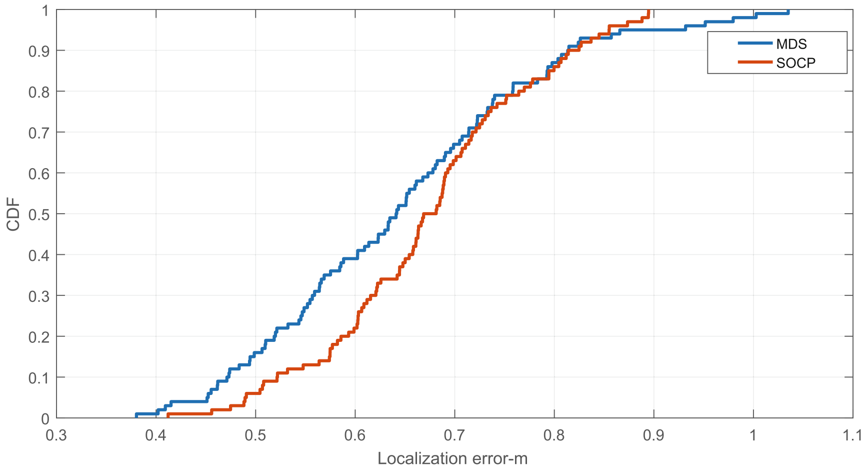

Fig. 3. The CDFs of MDS and SOCP against distance measurement error when nodes are static.

Figures 5 and 6 respectively show the comparison of the RMSE and CDF between the four algorithms when nodes are moving. Figure 5 shows that the MDS-based localization algorithm has the largest localization error compared to the other three algorithms. The RMSE of velocity-based location estimation shows an upward trend with time. Although the localization error of the velocity-based at the beginning is less than that based on the SOCP relaxation algorithm, the performance of the SOCP relaxation algorithm quickly increases over time and exceeds the velocity-based algorithm. This is due to that it relies on the

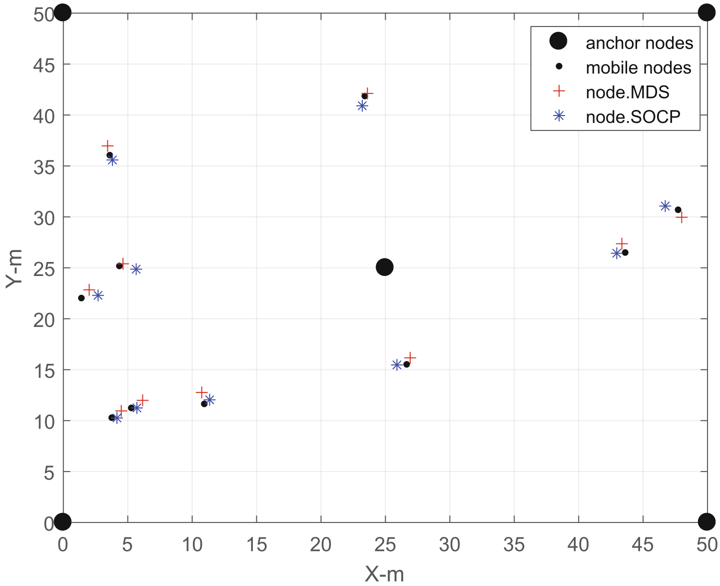

Fig. 4. Location of static nodes estimated by the MDS and SOCP.

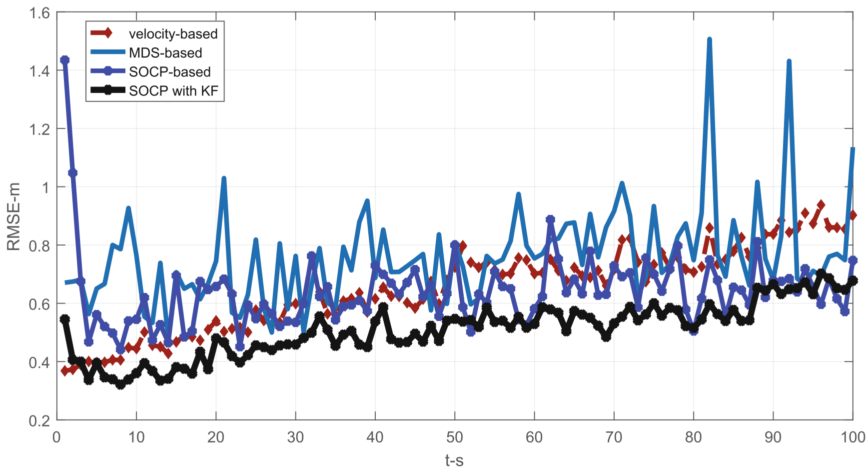

Fig. 5. The RMSE curves of the four algorithms when nodes are moving.

location estimation at the last moment, and the error will accumulate over time. After the SOCP-based relaxation algorithm has incorporated the mobile information, the localization error is significantly lower than that of the MDS. The CDF of Fig. 6 further validates this result. The Kalman filter is applied to fuse the velocity-based location estimation with the location estimation of the SOCP relaxation algorithm, which improves the localization accuracy and robustness

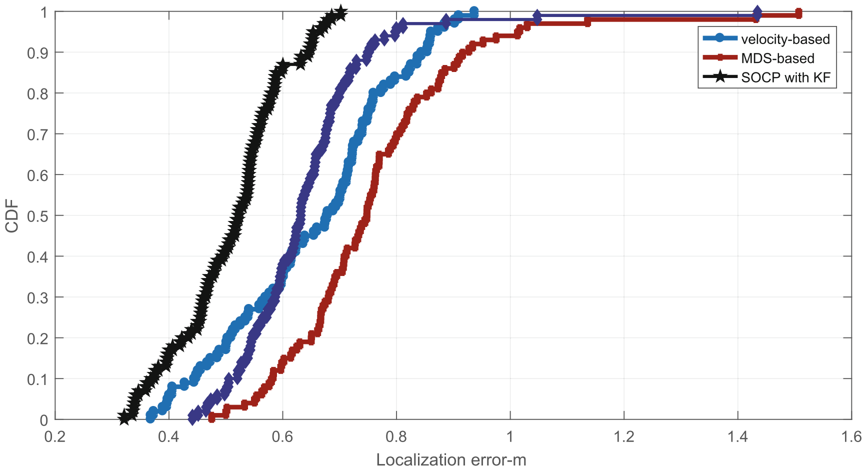

Fig. 6. The CDFs of the four algorithms when nodes are moving.

of the entire localization system. As can be observed in Fig. 6, the localization error after fusion is within 0.8 m, which is better than other algorithms.

5 Conclusion and Future Work

In this paper, we proposed a new cooperative localization scheme of exploiting the distance and mobility information of nodes in the process of localization under mobile wireless network. We utilized the node's mobility to enhance the SOCP-based relaxation localization algorithm and further applied KF to improve the positioning accuracy and robustness of the localization system. The simulation results confirm the effectiveness of the localization scheme. Cooperative localization in heterogeneous networks and NLOS environment will be the focus of our further work.

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