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Intelligent Mobility Assisted Mobile Sensor Network Localization*

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Abstract— **The trajectories of mobile seeds have a great influence on localization accuracy and efficiency. This paper presents a novel information-driven intelligent mobility-assisted wireless sensor network localization algorithm. Without requiring any prior knowledge of the sensing field, seeds' or pseudo-seeds' (common sensors which have been positioned) trajectories are scheduled dynamically aiming at position estimates of neighboring non-positioned common sensors. With an information-theoretic utility measure as the objective function, mobile seeds or pseudo-seeds actively determine their motion directions for minimizing the uncertainty in position estimates of neighboring sensors. At the first level, seeds estimate the neighboring sensor nodes' positions with bearing measurements by means of extended Kalman filters and optimize their motion directions by maximizing the mutual information between the position estimates and the motions of seeds. Afterwards the seeds forward the position estimates to the corresponding sensor nodes, which then act as pseudo-seeds. By repeating this process at the following levels, all sensor nodes can obtain position estimates. Compared with heuristic mobility and random mobility-assisted mobile sensor network localization algorithms, the proposed algorithm requires fewer maneuvers of seed or pseudo-seeds for quick convergence to good position estimates. Extensive simulations show that this algorithm can provide more accurate position estimates with fewer maneuvers, especially in the case of limited seeds.**

I. INTRODUCTION

For information seeking, sensor networks have obvious advantages, such as complementary heterogeneous sensing, inherent robustness, greater coverage and relatively lower cost.

Data collected by sensors are useful only with labeling the location information. Although low-cost GPS can be commercially available, it cannot work indoors or in the presence of obstacles that limit line-of-sight to the satellites. GPS signals may be jammed and unavailable in some hostile scenarios such as battlefield surveillance. Numerous localization techniques have been proposed for wireless sensor networks [1].

Mobile seeds have been used for wireless sensor network localization to decrease the cost for seeds [2]. Mobility has been exploited by Monte Carlo Localization (MCL) which is specially proposed for mobile sensor network [3], [4]. Random motion of nodes is typically assumed.

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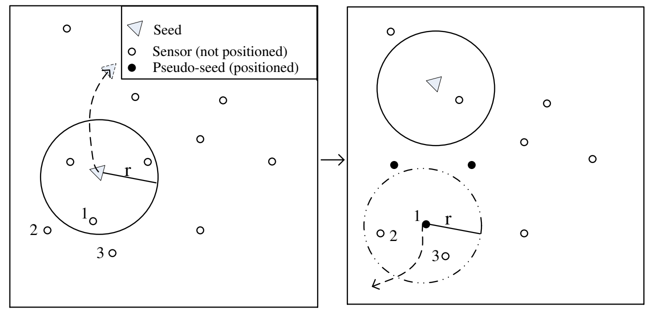


Fig. 1. Information-driven intelligent mobility assisted hierarchical mobile sensor network localization algorithm

Actually, mobile sensor nodes have controllable mobility in many application scenarios. By means of controllable mobility [5], mobile sensor networks are expected to perform active sensing or active perception.

Controllable mobility of mobile seeds has been researched for localization. In [6], mobile beacons' paths are set for increasing localization accuracy with the known sensing field. Dynamic mobility scheduling without any prior knowledge of the sensing field boundary has been started from scratch. Some heuristic movement strategies have been designed. In [7], a mobile beacon is guided close to a certain unknown sensor by depth-first traversal (DFT) of the network graph, or, to the unknown neighboring sensor with most neighbors [8], [9]. These dynamic path planning algorithms only consider coverage of mobile beacons without taking localization accuracy into account.

In this paper, a novel information-driven mobility scheduling algorithm for mobile sensor network localization is presented. Trajectories of seeds or pseudo-seeds (common sensors which have been positioned) are dynamically scheduled aiming at position estimates of neighboring non-positioned sensors. With an information-theoretic utility measure as the objective function, mobile seeds determine their next motion directions for minimizing uncertainty in position estimates of their neighboring nodes obtained with extended Kalman filters. With this controllable mobility, localization accuracy can be dramatically improved even with only a very limited number of seeds. Extensive simulations demonstrate efficiency of the proposed information-driven hierarchical localization algorithm.

II. INTELLIGENT MOBILITY ASSISTED MOBILE SENSOR NETWORK LOCALIZATION ALGORITHM

A. System environment and assumptions

Our research is motivated by the following scenario. In search-and-rescue in urban ruins, where only a few sensor nodes can acquire GPS signals or be manually configured with geographic locations. Initially, all sensor nodes and seeds are randomly scattered. All sensor nodes have data processing, storage and communication capabilities. They can acquire the bearing measurements with their neighbors within a certain range and are mounted with actuators. It is preferred that mobile sensor networks localize themselves as soon as possible before executing sensing tasks so as much as possible energy could be conserved for the next sensing tasks. The common sensor nodes which need to be positioned stay at rest.

B. Framework of the information-driven hierarchical localization algorithm

The proposed information-driven hierarchical localization algorithm is depicted in Figure 1.

At the beginning, seeds estimate the neighboring sensor nodes' positions with bearing measurements by means of extended Kalman filters, they optimize their motion directions by maximizing the mutual information between the bearing measurements and the position estimates. With the bearing measurements obtained by the active movements, the positions of the common sensor nodes can be estimated quickly by the seed's filter. As soon as the accurate estimates are acquired, seeds stop movement and estimation and forward the position estimates to the corresponding sensor nodes.

After acquiring the position estimates, the sensor nodes act as pseudo-seeds to aid their neighboring non-positioned common sensor nodes in acquiring position estimates. Since pseudo-seeds have no GPS receivers, their own position information has to be estimated during the maneuvers. Each pseudo-seed chooses its optimal motion direction to minimize the uncertainty of its neighboring nodes' position estimates and its own position estimate with an information-theoretic utility measure as the objective function. This measure is different from that of the seeds. After the pseudo-seeds acquire accurate position estimates of their neighboring non-positioned common sensors, the pseudo-seeds stop movement and estimation and forward the position estimates to the corresponding common sensor nodes. By repeating this process, all sensor nodes can obtain accurate position estimates.

The core of information-theoretic hierarchical localization algorithm lies in that seed estimates its neighboring sensor nodes' positions through bearing measurements obtained through active movements. Although the positions of sensor nodes can be estimated from a sequence of bearing measurements obtained by random maneuvers of seed or pseudo-seed with the Stanfield algorithm, the maximum likelihood or the Kalman filter [10], [11], clearly course maneuvers have an effect on estimation. This effect is analyzed with

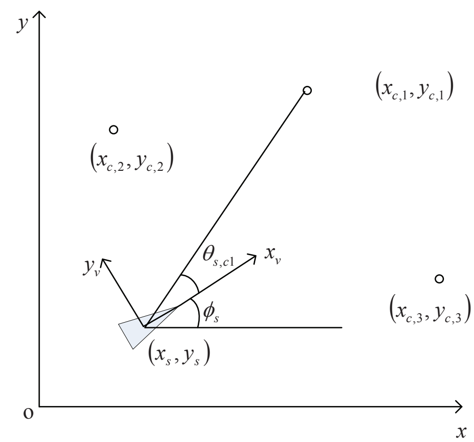


Fig. 2. Geometric relationship between a seed and its neighboring non-positioned common sensor nodes

the Cramer-Rao lower bound (CRLB) in [12]. Optimization of observer trajectories for bearings-only fixed-target localization is designed by maximizing the determinant of the Fisher Information Matrix (FIM) [13]. It has been shown that the active maneuvers can greatly enhance the estimator's performance (i.e., accuracy, stability, and convergence rate). Mutual information can be used to measure the value of a sensing action for its associated reduction in uncertainty [14].

In our research, mutual information which formally measures the utility of a observation obtained by a maneuver for its associated reduction in uncertainty of position estimates is used as the objective function.

1) System architecture: We define the state vectors $\mathbf{X}_s(k) = [x_s(k) \quad y_s(k) \quad \phi_s(k)]^T$ and $\mathbf{X}_{ps}(k) = [x_{ps}(k) \; y_{ps}(k) \; \phi_{ps}(k)]^T$ to be the coordinates of a seed and a pseudo-seed at time k, respectively. During localization, the non-positioned sensor nodes whose positions need to be estimated by the filter of seed or pseudo-seed stay still. The state vectors $\mathbf{x}_{c,i} = [x_{c,i} \;\; y_{c,i}]^T$, $i = 1, \cdots, N_c$, are the coordinates of common sensor nodes. N_c is the number of the common sensor nodes. The seed or pseudo-seed moves with a predefined velocity during localization. Their geometric relationship is shown in Figure 2. The control is exerted over the seed's motion or the pseudo-seed's motion through a predefined velocity and a controllable heading, $\mathbf{u}_s(k) = [V_s(k) \quad \psi_s(k)]^T$ and $\mathbf{u}_{ps}(k) = [V_{ps}(k) \quad \psi_{ps}(k)]^T$, respectively. The motion of seed and pseudo-seed can be described in terms of the following nonlinear discrete-time state transition equations

$$\mathbf{X}_s(k) = f_s(\mathbf{X}_s(k-1), \mathbf{u}_s(k), k) + \boldsymbol{w}_s(k), \tag{1}$$

$$\mathbf{X}_{ps}(k) = f_{ps}(\mathbf{X}_{ps}(k-1), \mathbf{u}_{ps}(k), k) + \boldsymbol{w}_{ps}(k). \tag{2}$$

where $\boldsymbol{w}_s(k)$ and $\boldsymbol{w}_{ps}(k)$ are the process noises due to modeling errors and uncertainty in control. The noises are modeled as uncorrelated white sequences with $E[\boldsymbol{w}_s(i) \cdot \boldsymbol{w}_s^T(j)] = \delta_{ij} \cdot \mathbf{Q}_s$, $E[\boldsymbol{w}_{ps}(i) \cdot \boldsymbol{w}_{ps}^T(j)] = \delta_{ij} \cdot \mathbf{Q}_{ps}$.

Seed or pseudo-seed measures the bearings of their neighboring non-positioned common sensor nodes. Measurement equations are given by the non-linear measurement models,

$$z_{s,ci}(k) = \mathbf{h}_s(\mathbf{X}_s(k), \mathbf{x}_{c,i}) + v_s(k) \tag{3}$$

$$z_{ps,ci}(k) = \mathbf{h}_{ps}(\mathbf{X}_{ps}(k), \mathbf{x}_{c,i}) + v_{ps}(k), \tag{4}$$

or more precisely,

$$\theta_{s,ci}(k) = arctan(\frac{y_{c,i} - y_s(k)}{x_{c,i} - x_s(k)}) - \phi_s(k) + v_s(k), \tag{5}$$

$$\theta_{ps,ci}(k) = arctan(\frac{y_{c,i} - y_{ps}(k)}{x_{c,i} - x_{ps}(k)}) - \phi_{ps}(k) + v_{ps}(k), \tag{6}$$

where the random vectors $v_s(k)$ and $v_{ps}(k)$ describe the noise in the observation process due to modeling errors and uncertainty in observation. The observation noises are modeled as uncorrelated white sequences with $E[v_s(i) \cdot v_s^T(j)] = \delta_{ij}\mathbf{R}_s$, $E[v_{ps}(i) \cdot v_{ps}^T(j)] = \delta_{ij}\mathbf{R}_{ps}$.

The filter of a seed only estimates the positions of its neighboring common sensor nodes. However, the filter of a pseudo-seed needs to estimate both the positions of its neighboring non-positioned common sensor nodes and its own position. Their information-theoretic utility measures are different.

2) Localization via seeds: With the known positions of seeds, the position estimates of neighboring non-positioned common sensor nodes are irrelative with each other. Assume that $\widehat{\mathbf{x}}_{c,i}(k|k), i = 1, \cdots, N_c$ is the position estimate of the ith non-positioned common sensor node at time k, given all measurements up to time k, and its corresponding estimated error covariance $\mathbf{P}_{c,i}(k|k)$. N_c filters estimate the positions of the N_c common sensor nodes with their corresponding bearing measurements individually. Information filter is used for position estimation.

Each information filter of the seed maintains the information state vector $\widehat{\mathbf{y}}_{c,i}(k|k)$ and information matrix $\mathbf{Y}_{c,i}(k|k)$ for one neighboring non-positioned common sensor node,

$$\widehat{\mathbf{y}}_{c,i}(k|k) \triangleq \mathbf{P}_{c,i}^{-1}(k|k)\widehat{\mathbf{x}}_{c,i}(k|k), \tag{7}$$

$$\mathbf{Y}_{c,i}(k|k) \triangleq \mathbf{P}_{c,i}^{-1}(k|k). \tag{8}$$

The information state and information matrix contribution from an observation $z_{s,ci}(k)$ are $\mathbf{i}_{c,i}(k)$ and $\mathbf{I}_{c,i}(k)$

$$\mathbf{i}_{c,i}(k) \triangleq \mathbf{H}_{c,i}^{s\,T}(k)\mathbf{R}_s^{-1}z_{s,ci}(k), \tag{9}$$

$$\mathbf{I}_{c,i}(k) \triangleq \mathbf{H}_{c,i}^{s\,T}(k)\mathbf{R}_s^{-1}\mathbf{H}_{c,i}^{s}(k), \tag{10}$$

where $\mathbf{H}_{c,i}^{s}(k)$ is the Jacobian of $\mathbf{h}_s$ evaluated at $\mathbf{X}_{c,i} = \widehat{\mathbf{X}}_{c,i}(k|k-1)$.

The information state and information matrix update equations are:

$$\widehat{\mathbf{y}}_{c,i}(k|k) = \widehat{\mathbf{y}}_{c,i}(k|k-1) + \mathbf{i}_{c,i}(k), \tag{11}$$

$$\widehat{\mathbf{Y}}_{c,i}(k|k) = \widehat{\mathbf{Y}}_{c,i}(k|k-1) + \mathbf{I}_{c,i}(k). \tag{12}$$

Although, the simplicity of the update stage of the information filter generally comes at the cost of increased complexity in the prediction stage, the non-positioned common sensor nodes stay at rest and have no dynamics during the localization process. Thus, the prediction is also simple

$$\widehat{\mathbf{y}}_{c,i}(k|k-1) = \widehat{\mathbf{y}}_{c,i}(k-1|k-1), \tag{13}$$

$$\mathbf{Y}_{c,i}(k|k-1) = \mathbf{Y}_{c,i}(k-1|k-1). \tag{14}$$

The mutual information $\mathscr{I}_{c,i}(k)$ formally measures the information gain for one common sensor node's position estimate from a sensing action $\mathbf{u}_s(k)$. For Gaussian errors,

$$\mathscr{I}_{c,i}(k) = \frac{1}{2}log\frac{|\mathbf{Y}_{c,i}(k|k-1) + \mathbf{I}_{c,i}(k)|}{|\mathbf{Y}_{c,i}(k|k-1)|}. \tag{15}$$

The mutual information gain for the position estimates of all of its neighboring non-positioned common sensor nodes $i = 1, \cdots, N_c$ from the seed's observation is the sum of the mutual information gain for each neighboring common sensor node. That is,

$$\mathscr{I}_s(k) = \sum_{i=1}^{N_c} \mathscr{I}_{c,i}(k). \tag{16}$$

In our case, the seed's velocity is constant during the localization process. It is preferred that the seed's movement direction maximizes its mutual information defined as above. The seed actively moves for minimizing the uncertainty in position estimates of its neighboring non-positioned common sensor nodes by solving

$$\psi_s^*(k) = \arg\max \mathscr{I}_s(k). \tag{17}$$

Here, the set of available actions represents the possible movement direction changes exerted on the seed. The control vector parameterization is used to determine a direct numerical solution for the movement direction of seed with zero-look-ahead [15].

With the mutual information as control objective, the seed moves along the trajectory that maximizes the reduction of estimate uncertainty. After several active movements, the information filter of the seed can obtain accurate enough position estimates of its neighboring non-positioned common sensor nodes. As soon as the accurate position estimates are obtained after several purposeful maneuvers, the seed will stop movement and forward the position estimates to the corresponding common sensor nodes. After receiving the position estimates, the common sensor nodes can act as pseudo-seeds.

3) Localization via pseudo-seeds: Although the pseudo-seed has acquired accurate enough position estimate, its position error accumulates with its movements. Its own position information $\mathbf{X}_{ps}(k)$ must be estimated along with the position information of the neighboring non-positioned common sensor nodes $\mathbf{x}_{c,i}, i = 1, \cdots, N_c$. Assuming each sensor node is mounted with a compass, the pseudo-seed's heading does not need to be estimated. The augmented state vector at time k of extended Kalman filter of the pseudo-seed is $\mathbf{X}(k) = [\mathbf{X}_{ps}^T(k)\ \mathbf{X}_c^T]^T$, where $\mathbf{X}_c = [\mathbf{x}_{c,1}^T\ \cdots \mathbf{x}_{c,N_c}^T]^T$. The neighboring non-positioned common sensor nodes stay at rest.

The non-linear discrete-time state transition equation is:

$$\mathbf{X}(k) = f(\mathbf{X}(k-1), \mathbf{u}_{ps}(k), k) + \boldsymbol{w}(k). \tag{18}$$

The position estimates of the pseudo-seed and its neighboring non-positioned common seeds are relative. Extended Kalman filter is implemented to generate estimate $\widehat{\mathbf{X}}(k|k)$ at time k given all measurements up to time k, $\mathbf{Z}_{ps}^k = [\mathbf{Z}_{ps}(1), \cdots, \mathbf{Z}_{ps}(k)]$, together with its corresponding estimated error covariance $\mathbf{P}(k|k)$. The observation at time k is:

$$\mathbf{Z}_{ps}(k) = [z_{ps,c1}(k)\ \cdots z_{ps,cN_c}]^T. \tag{19}$$

Since the position estimates of the neighboring non-positioned common sensor nodes and the pseudo-seed are relative, the mutual information gain between the posterior states and measurements is different from that of the seed's filter. Under Gaussian multivariate assumption, the mutual information gain is calculated by

$$\mathscr{I}_{ps}(k) = \frac{1}{2}(log|\mathbf{P}(k|k-1)| - log|\mathbf{P}(k|k)|). \tag{20}$$

During the localization process, the pseudo-seed's velocity is constant. We optimize the pseudo-seed's movement direction by maximizing the above mutual information,

$$\psi_{ps}^*(k) = \arg\max \mathscr{I}_{ps}(k). \tag{21}$$

The pseudo-seed moves along the trajectory that maximizes the reduction of the whole estimate uncertainty. After several active movements, the pseudo-seed could obtain the position estimates of its neighboring non-positioned common sensor nodes. Then, the pseudo-seed stops movement and forwards the position estimates to the corresponding non-positioned common sensor nodes. The accuracy of the position estimates of the neighboring non-positioned common sensor nodes can not surpass the accuracy of position estimates of the pseudo-seed. Due to the process noise of pseudo-seeds and the bearing observation noise, the estimated errors of non-positioned common sensor nodes accumulate with increasing levels.

III. Experimental results

A. Simulation environment

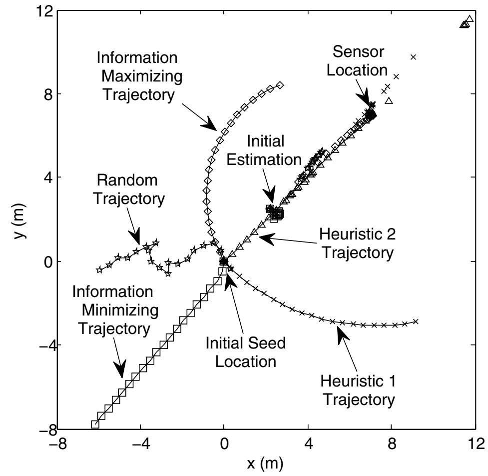
We evaluate the performance of the proposed information-driven intelligent mobility assisted hierarchical mobile sensor network localization through MATLAB simulation. Sensor nodes are randomly scattered in a $100m \times 100m$ rectangular region. Every sensor node has a fixed sensing and transmission range $R = 10m$. Each seed and sensor node has fixed velocities V_s and V_{ps} respectively when they move. Each pseudo-seed's process noise covariance is $\mathbf{Q}_{ps} = \begin{bmatrix} q_x^2 & 0 & 0 \\ 0 & q_y^2 & 0 \\ 0 & 0 & q_\phi^2 \end{bmatrix}$, where $q_x = q_y = 0.1m$ and $q_\phi = 1.5^0$. The bearing observation noise covariance is $R_s = R_{ps} = \sigma_\theta^2$ and $\sigma_\theta = 2.5^0$. The state covariance is initialized by $\mathbf{P}_{c,i}(0|0) = \begin{bmatrix} R^2 & 0 \\ 0 & R^2 \end{bmatrix}$. The position estimates of the non-positioned common sensor nodes are initialized with random positions in the sensing/transmission sectors of seed or pseudo-seed.

B. Error convergence analysis of information-driven mobility vs. random, heuristic mobility for one common sensor node with one seed

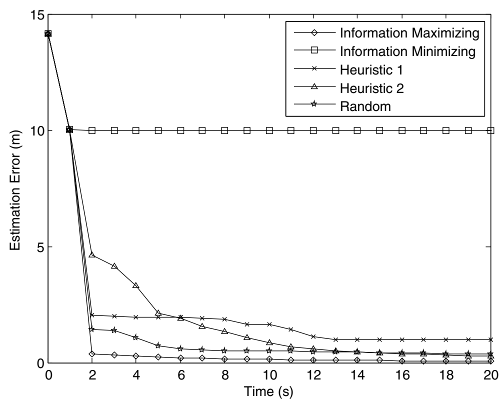
Seed uses extended Kalman filter to estimate its neighboring non-positioned common sensor node's position with bearing measurements. A series of bearing measurements can be obtained by random or purposeful maneuvers. Different maneuvers obtain different bearing measurements with different information values for position estimates. We first simulate a simple case that there is one seed and one non-positioned common sensor node in the sensing/transmission region of the seed. We compare the convergence of estimated error of one non-positioned common sensor node with one mobile seed in the five cases: seed mobility is driven by information maximizing, information minimizing, heuristic (moves straight forward to the position estimate or moves perpendicularly to the direction pointing to the position estimate) and random.

Figure 3 shows the different trajectories of the seed and estimated error convergence driven by different mobility. At $t = 0s$, the seed observes and obtains the first bearing measurement of the common sensor node. The initial position estimate at $t = 0s$ is a random position in the sensing section of the seed. Assume that the initial position estimate is the same in the five cases. At the first step, the seed does not move. An extended Kalman filter is used to estimate the position of the common sensor node with the first bearing measurement. Because the seed does not move, the seed obtains the same bearing measurement in the five cases. Thus, the estimated errors at $t = 1s$ are the same in the five cases. Then, the seed performs a maneuver with the velocity $V_s = 0.5m/s$. Driven by the different mobility, the seed moves to different directions and obtains different measurements at new positions in the five cases. With the different bearing measurements, the extended Kalman filter can get different position estimates at $t = 2s$. It can be seen in Figure 3 that the most informative bearing measurement is obtained by the first maneuver with the information-driven mobility (information-maximizing).

Table I shows average estimates error and maneuver number when reaching convergence with information-driven mobility versus random, information-minimizing, and heuris-



(a) Trajectories driven by different mobility and corresponding position estimates



(b) Comparison of error convergence of one common sensor node driven by different mobility

Fig. 3. Estimated error of one common sensor node acquired by information-driven mobility vs. random, heuristic mobility. Heuristic 1: seed moves perpendicularly to the direction pointing to the position estimate; Heuristic 2: seed moves straight forward to the position estimate.

tic mobility. It can be seen that the position estimates error becomes convergent to $0.24m$ after only 5 maneuvers with information-driven mobility. The extended Kalman filter only runs fewer than 5 times for the position estimates. Although the position estimates can become convergent with random and heuristic mobility, the most accurate position estimates can be acquired with the fewest number of maneuvers by means of information-driven mobility. The energy consumption on movements for localization and computation complexity decrease greatly.

C. Analysis of error accumulation of the proposed hierarchical localization algorithm

The proposed algorithm is a hierarchical localization approach. It is necessary to address the error accumulation problem. The process noise of pseudo-seeds and the bearing observation noise cause accumulation of estimates errors of common sensor nodes. These increase as localization levels increase. We compare the estimates errors at different levels by varying the magnitude of process noise of pseudo-seeds and the bearing observation noise respectively.

TABLE I
ERROR AND MANEUVER NUMBER WHEN REACHING CONVERGENCE WITH INFORMATION-DRIVEN MOBILITY VS. RANDOM, INFORMATION-MINIMIZING, AND HEURISTIC MOBILITY.

	Error (m)	Maneuvers Num
Information-maximizing driven	0.24	5
Random	0.42	15
Heuristic 1	0.98	15
Heuristic 2	0.42	16
Information minimizing	10	3

TABLE II
THE INFLUENCE OF PROCESS NOISE OF PSEUDO-SEED ON POSITION ESTIMATES ERRORS (BEARING OBSERVATION NOISE IS σ_θ). (UNIT: m)

Process noise	Level 1	2	3	4	5
$\mathbf{Q}_{ps}$	0.44	0.81	1.09	1.33	1.58
$4\times\mathbf{Q}_{ps}$	0.44	1.00	1.42	1.76	2.05
$9\times\mathbf{Q}_{ps}$	0.44	1.23	1.67	1.99	2.27

TABLE III
THE INFLUENCE OF BEARING OBSERVATION NOISE ON POSITION ESTIMATES ERRORS (PROCESS NOISE COVARIANCE IS $\mathbf{Q}_{ps}$). (UNIT: m)

Observation noise	Level 1	2	3	4	5
σ_θ	0.44	0.81	1.09	1.33	1.58
$2\times\sigma_\theta$	0.71	1.31	1.74	2.14	2.43
$3\times\sigma_\theta$	1.02	1.81	2.53	2.88	3.22

Tables II and III show that estimates errors increase with the localization levels. Error accumulation results from the process noise of pseudo-seeds and the bearing observation noise. With the increase of the magnitude of process noise of pseudo-seeds and the bearing observation noise, the estimates errors accumulate dramatically.

D. Performance evaluation of the proposed localization algorithm in a large-scale sensor network

We evaluate the performance of the proposed hierarchical localization algorithm in a large-scale sensor network. The environment is $100m\times100m$. There are 300 common sensor nodes. They are randomly scattered in the environment. There are one, two or four seeds in the network respectively. We compare the average estimates errors of common sensor nodes, the total maneuvers done by seeds and pseudo-seeds and the total time for localization with different mobility: information-driven and random. We run the simulation 10 times and obtain the results shown in Table IV.

Table IV shows that the large-scale wireless sensor network localization with information-driven mobility with only one seed needs about $67.84s$, and about 969 maneuvers done by seeds and pseudo-seeds. The final average estimates error of common sensor nodes with information-driven mobility is about $1.48m$. With random mobility, localization needs about $125.7s$, and about 1880 maneuvers done by seeds and pseudo-seeds. The final average estimates error with random mobility is about $1.74m$. For the similar estimate accuracy,

TABLE IV

PERFORMANCE EVALUATION OF THE PROPOSED ALGORITHM IN A LARGE-SCALE SENSOR NETWORK

Seeds	Convergence Time (s)		Maneuvers Num		Estimates error (m)	
	Information	Random	Information	Random	Information	Random
1	67.84	125.7	969	1880	1.48	1.74
2	54.51	97.77	743	1290	1.23	1.47
4	46.27	63.21	654	1207	1.08	1.31

the information-driven mobility localization algorithm needs do about half of the number of maneuvers with random mobility.

It is also shown that with the increasing number of seeds, the localization accuracy improves, the convergence time decreases, and the number of maneuvers for convergence decrease. The information-driven hierarchical localization algorithm can acquire accurate position estimates very fast even with low seed density.

E. Analysis and comparison with other seed-controllable-mobility-assisted localization algorithms

Compared with other seed-controllable-mobility-assisted localization algorithms, the proposed localization algorithm is distinctive in that:

First, seeds and pseudo-seeds run extended Kalman filters with bearing measurements to estimate positions of non-positioned neighboring common sensor nodes. Uncertainty can be processed reasonably with extended Kalman filters.

Second, controllable mobility driven by an information measure is found to be very helpful for localization. The mutual information between the position estimates of neighboring non-positioned common sensors and the motion directions of seeds or pseudo-seeds is measured to optimize the motion of seeds or pseudo-seeds. With the most informative bearing measurements obtained by the purposeful movements, the uncertainty in position estimates of neighboring sensors can be quickly reduced.

IV. CONCLUSIONS

In this paper, we present an information-driven intelligent mobility assisted hierarchical localization algorithm for mobile sensor networks. We utilize an information-theoretic utility measure for seeds and pseudo-seeds, for the purpose of localizing their neighboring common sensor nodes. With this measure as the objective function, the seeds and pseudo-seeds actively choose their movement directions to minimize the uncertainty in position estimates of their neighboring common sensor nodes.

The simulation experiments show that with bearing measurements acquired through active movements of seeds or pseudo-seeds, accurate position estimates of neighboring common sensor nodes can be obtained with fewer maneuvers than with random mobility.

In this paper, with the use of the information-theoretic utility measure, seeds and pseudo-seeds only have to do a limited number of maneuvers to acquire position estimates of all sensor nodes. We have conducted the theoretical analysis and computer simulations. However, there are still some issues for its practical applications in real environments, such as data association and time synchronization, which are big problems of wireless sensor network system.

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