A New Distributed Localization Scheme for Wireless Sensor Networks

KUANG Xing-Hong[1, 2] SHAO Hui-He[1] FENG Rui[3]

Abstract Node localization in wireless sensor networks (WSN) is treated as a functional dual of target tracking from a novel perspective in the paper. Different from the traditional tracking problem in WSN, using the static location-ware node to estimate the moving target, the mobile node is used to help unknown nodes to accurately discover their positions. A new node localization scheme virtual beacons-energy ratios localization (VB-ERL) and its refinements for the WSN are presented. In the scheme, the mobile node moves in the surveillant field based on the Gauss-Markov mobility model and periodically broadcasts the information packets. Each static unknown node receives the virtual beacons and energy in its sensing range, and estimates its location by finding the intersection of a set of hyper-spheres. Simulation results show the proposed scheme is efficient.

Key words Wireless sensor networks (WSN), node localization, virtual beacon, energy radio

One of the critical issues in WSN research is to determine the physical positions of nodes. This is because: sensed data are meaningful to most applications only when they are labeled with geographical position information; position information is essential to many location-aware sensor network communication protocols, such as packet routing and sensing coverage. It has been a challenging task to design a practical algorithm for node localization given the constraints that are imposed on sensors, including limited power, low cost, etc.[1−2].

The existing localization algorithms can be classified into two categories: range-based and range-free. Range-based algorithms exploit range (distance or angle) information for localization. The range information can be acquired by different means such as received signal strength indicator (RSSI), time of arrival (TOA), time-difference of arrival (TDOA), or arrive of angle (AOA). The main range-based algorithms include maximum likelihood estimation[3], ad hoc positioning system (APS)[4], SDP-based localization algorithm[5], multidimensional scaling (MDS) algorithms[6−7], etc. They have higher location accuracy but require additional hardware on sensor nodes.

Range-free algorithms do not need absolute range information, the accuracy is less than the range-based but satisfy many applications′ requirements. Typical range-free algorithms including centroid, DV-Hop[8], amorphous[9], APIT[10], etc. The authors in [11] proposed a coarse-grained range-free algorithm to lower the uncertainty of nodes′ positions using radio connectivity constraints. In [12], the authors used geometry method to determine the sensor node′s location based on the cross point of the two chords in a circle. The range-free algorithms are more economical, cost-effective, and feasible for the large-scale WSN.

In the paper, node localization is investigated from a opposite perspective by taking it as a functional dual of target tracking. Different from the traditional tracking problems using one or more static location-aware sensors to track a moving target, each location-unaware sensor node discovers its position assisted by the moving targets.

We propose a new novel node localization scheme named VB-ERL for the WSN. In the scheme, the mobile node moves in the field based on Gauss-Markov mobility model[13], broadcasts the location packets, and acoustic energy at regular time intervals. So, the "virtual" beacons are used instead of deploying the actual stationary anchors. Each static unknown node passively receives these virtual beacons with no necessity to reply to the mobile node and estimates its location based on the received packets. In [14], a source localization method based on energy-ratio was proposed to track the target. We apply the method to the node localization. The absolute range measurements are needless, and the location estimation is solved by finding the intersection of a set of hyper-spheres. Here, each hypersphere specifies the likelihood of the unknown node based on the acoustic energy-ratio of a pair of virtual beacons. Each unknown node is estimated by minimizing the cost function using a nonlinear optimization algorithm. Several refinements, including virtual beacons optimum selection and weighted centroid method, are introduced for performance improvement. This design lets it avoid unnecessary range estimations as before. Hence, the accuracy can be increased. Simulations show the proposed scheme is efficient.

1 Proposed scheme

1.1 Node localization background

First, we assume: the whole WSN consists of static nodes and one mobile node; the mobile node knows its location in the localization instant; the mobile node can move by itself or other carriers such as robots or vehicles, and has sufficient energy for broadcasting messages[12].

Instead of deploying the actual anchors (proposed in many previous works), "virtual" beacons are used in the proposed scheme. During the localization process, the mobile node moves in the WSN while broadcasting virtual beacons packets (contains the current coordinates of the mobile node) periodically. Each unknown node receives the virtual beacons within its sensing range. At last, the unknown nodes estimate their locations using the proposed algorithm based on the received information.

Each virtual beacon acts as a stationary anchor in our localization. This method has an advantage that it can increase the localization accuracy by having the mobile node for a longer duration, thereby producing a large number of virtual beacons. At the same time, the proposed method eliminates the cost of stationary anchors by not having them deployed in the WSN actually.

Fig. 1 illustrates the localization scenario. The triangles denote the received virtual beacons; the curve denotes the mobility trajectory of the mobile node; and the circle denotes the sensing range of the static unknown node.

Received June 1, 2007; in revised form September 24, 2007
Supported by National High Technology Research and Development Program of China (863 Program) (2004AA412050)
1. Department of Automation, Shanghai Jiao Tong University, Shanghai 200240, P. R. China 2. College of Engineering Science & Technology, Shanghai Fisheries University, Shanghai 200090, P. R. China 3. Department of Electrical and Computer Engineering, Fudan University, Shanghai 200433, P. R. China
DOI: 10.3724/SP.J.1004.2008.00344

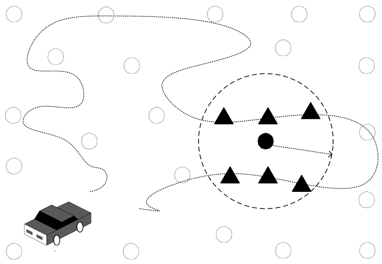

Fig. 1 Sensor node localization in WSN

1.2 Virtual beacons trajectory

In the robot localization, the robot can traverse the field along the predefined trajectory maps. However, there are substantial differences between the robot localization and the node localization for WSN because sometimes the mobile node has little or no control of its mobility. Here, the Gauss-Markov mobility model is adopted. Every unknown node expects to receive at least 4 noncollinear virtual beacons from the mobile node along the trajectory as long as the mobile time is appropriate.

The mobility model can be presented by[13]

$$v_k = \alpha v_{k-1} + (1-\alpha)\bar{v} + \sqrt{(1-\alpha^2)}v_{x_{k-1}} \tag{1}$$

$$d_k = \alpha d_{k-1} + (1-\alpha)\bar{d} + \sqrt{(1-\alpha^2)}d_{x_{k-1}} \tag{2}$$

where v_k and d_k are the new speed and direction of the mobile node at time interval k; $0\leq \alpha \leq 1$ is the tuning parameter used to vary the randomness; $\bar{v}$ and $\bar{d}$ are constants representing the mean value of speed and direction as $k \to \infty$; and $v_{x_{k-1}}$ and $d_{x_{k-1}}$are random variables from a Gaussian distribution.

At each time interval, the next location is calculated based on the current location, speed, and direction of movement. The position is given by

$$x_k = x_{k-1} + v_{k-1} \times \cos(d_{k-1}) \tag{3}$$

$$y_k = y_{k-1} + v_{k-1} \times \sin(d_{k-1}) \tag{4}$$

where (x_k, y_k) is the mobile node′s position at the kth time interval. The mobile node moves in the field based on such a mobility model and emits the signal periodically.

1.3 An acoustic model of the mobile node

When the sound is propagating through the air, it is known as the acoustic energy emitted omni-directionally from a sound source. It will attenuate at a rate that is inversely proportional to the distance. Experiment data confirms the energy decay model in [14]. The measured energy on the ith unknown node can be expressed as follows

$$z_i = A\Big/||\boldsymbol{X} - \boldsymbol{\zeta}_i||^{\beta} + n_i \tag{5}$$

where A is a scalar denoting the energy emitted by the mobile node; $\boldsymbol{X}$ is a vector denoting the coordinates of the unknown node; $\boldsymbol{\zeta}_i$ is a vector denoting the coordinates of the ith virtual beacon; and β (≈ 2) is an energy decay factor, and n_i is measurement noise, modeled as a Gaussian distribution with (μ, σ^2).

Every static unknown node estimates the location based on the received information using the localization mechanisms in the following.

1.4 Node localization mechanisms

In [14], energy-based collaborative source localization algorithm was proposed to track the moving target. The sensors in the sense field measured the information from the target, and the fusion center estimated the target location by minimizing the cost function based on the energy-ratio of the sensors. Here, we treat the node localization as a dual function of the target tracking, and use the method in the node localization application. The virtual beacons act as actual sensors, whereas the unknown nodes act as the moving target′s different locations.

Each unknown node estimates its location based on the received virtual beacons sets $[\boldsymbol{\zeta}_i(x_i, y_i); z_i]$ $i = 1, 2, \cdots, k$. Considering the additive noise term n in (5) by its mean value μ, each unknown node computes the energy ratio k_{ij} of the ith and the jth virtual beacons from its information set as follows[14]

$$k_{ij} = \left(\frac{z_i - \mu_i}{z_j - \mu_j}\right)^{-\frac{1}{\beta}} = \frac{||\boldsymbol{X} - \boldsymbol{\zeta}_i||}{||\boldsymbol{X} - \boldsymbol{\zeta}_j||} \tag{6}$$

where $\boldsymbol{X}$ denotes the unknown node location; and the other parameters are the same as before.

If $k_{ij} = 1$, the solution of (6) form a hyper-plane between $\boldsymbol{\zeta}_i$ and $\boldsymbol{\zeta}_j$. However, there is measurement noise existing between the virtual beacon and each unknown node, then $0 < k_{ij} \neq 1$. So, all the possible unknown node′s locations $\boldsymbol{X}$ that satisfy (6) reside on a d-dimensional hyper-sphere described by

$$||\boldsymbol{X} - \boldsymbol{O}_{ij}||^2 = R_{ij}^2 \tag{7}$$

where the center $\boldsymbol{O}_{ij}$ and the radius R_{ij} of this hyper-sphere associated with virtual beacon are given by

$$\boldsymbol{O}_{ij} = \frac{\boldsymbol{\zeta}_i - k_{ij}^2\boldsymbol{\zeta}_j}{1 - k_{ij}^2}, R_{ij} = \frac{k_{ij}||\boldsymbol{\zeta}_i - \boldsymbol{\zeta}_j||}{1 - k_{ij}^2} \tag{8}$$

Apparently, all the possible locations of the unknown node reside on the hyper-sphere. When $d = 3$, it is a sphere, when $d = 2$, such a hyper-sphere is a circle. Here, we only discuss localization in $2D$ plane, because it can be easily expanded to the $3D$ space.

We apply (6)$\sim$(8) which were proved in [14] to the node localization. Till now, we have obtained the hyper-sphere functions based on (7) using the ratio of energy readings at a pair of virtual beacons. So, the potential unknown nodes′ locations can be restricted to a hyper-sphere whose center and radius are functions of the energy ratio and the two virtual beacons′ locations. If more virtual beacons received by the unknown node are used, more hyper-spheres can be determined. The hyper-spheres must intersect at a small region that corresponds to the unknown node location[14]. As shown in (6), the absolute range measurement is not required but the energy-ratio is required for the unknown node localization. So, this method is robust.

Without noise taken into account, the node location is a unique point formed by the virtual beacons′ hyper-spheres. However, with noise taken into account, the unknown node location is solved as the position that is closest to all the hyper-spheres and hyper-planes formed by all energy ratios in the least square sense. Applying the cost function proposed in [14], the unknown node′s location is also solved by minimizing the following cost function

$$J = \sum_{l_1=1}^{L_1}(||\boldsymbol{X} - \boldsymbol{O}_{l_1}|| - R_{l_1})^2 + \sum_{l_2=1}^{L_2}(\boldsymbol{\Phi}_{l_2}^{\mathrm{T}}\boldsymbol{X} - \tau_{l_2})^2 \tag{9}$$

where $\boldsymbol{\Phi}_{ij} = \boldsymbol{\zeta}_i - \boldsymbol{\zeta}_j$, $\tau_{ij} = \frac{||\boldsymbol{\zeta}_i||^2 - ||\boldsymbol{\zeta}_j||^2}{2}$; $L_1 + L_2 = L$, where L is the pairs of energy ratios of the virtual beacons for a unknown node, L_1 and L_2 are the numbers of hyper-spheres and hyper-planes, respectively; l_1 and l_2 indicate the energy ratios computed between different pairs of virtual beacons energy readings.

As shown in (9), the function consists of a summation of several square items. It is a nonlinear least square optimization problem. We can solve it by a least-square analysis and apply the standard optimization algorithms, such as the Newton′s method, to minimize the cost function J.

1.5 Enhancements

In order to obtain the optimal estimation results, we propose several refinements to enhance the estimation performance.

1) Virtual beacons optimum selection. Filter the received information to obtain the optimum virtual beacons for localization:

a) Usually, if the mobile node is closer to the unknown node, the energy readings have higher SNRs. Therefore, the virtual beacons near the unknown node are chosen to compute the location because they are more reliable. Some beacons whose energy readings are approaching to the sense threshold of the unknown node are discarded.

b) Among the selected energy, when the two energy readings are almost the same (e. g., less than 0.01), we abort any one of them to reduce the computation burden, and then the cost function (9) can be replaced by

$$J = \arg\min \left(\sum_{l=1}^{L} (||\boldsymbol{X} - \boldsymbol{O}_l|| - R_l)^2 \right) \tag{10}$$

c) Suppose one unknown node receives N virtual beacons and their acoustic signals, $N(N-1)/2$ pairs of energy ratios will be computed based on (6). However, many of these relationships are actually redundant (e.g., given energy ratios k_{1i} and k_{1j}, the energy ratio k_{ij} is redundant, and the conclusion has been proved in [14]).

2) The initial estimation point is important for the optimization search algorithm. Here, we introduce the centroid technique which will obtain an initial point closer to the true location. Given locations of $m\,(m \geq 4)$ virtual beacons $(\boldsymbol{\zeta}_1, \cdots, \boldsymbol{\zeta}_m)$ and corresponding sensing data $(z_1, \cdots, z_m)$ from the mobile node, each unknown node′s location can be approximately estimated as a weighted centroid of its received virtual beacons′ locations. Each weight $(w_1, \cdots, w_m)$ disregarding the noise is characterized by

$$w_1 : \cdots : w_m = z_1 : \cdots : z_m = \frac{A}{||\boldsymbol{X} - \boldsymbol{\zeta}_1||^\beta} : \cdots : \frac{A}{||\boldsymbol{X} - \boldsymbol{\zeta}_m||^\beta} \tag{11}$$

The location estimate by weighed centroid $\boldsymbol{X}_C$ is given by: $\boldsymbol{X}_C = \sum_{i=1}^{m} (\boldsymbol{\zeta}_i \times (w_i \big/ \sum_{j=1}^{m} w_j))$. In our nonlinear least square optimization problem, $\boldsymbol{X}_C$ is used as the starting estimation point.

2 VB-ERL localization algorithm

According to the localization mechanism described above, the whole VB-ERL localization algorithm can be expressed in Table 1.

Table 1 Localization algorithm

Algorithm: VB-ERL localization algorithm
1 Obtain the optimum virtual beacons
1) The mobile node starts to move in the sensor field based on the Gauss-Markov mobility model, broadcasts the virtual beacons and acoustic signal periodically;
2) The unknown nodes receive the virtual beacons, and record the information $[\boldsymbol{\zeta}_i(x_i, y_i); z_i]$;
3) Each unknown node fuses the information when the received virtual beacons exceed the threshold or the mobile node stop broadcasting the packets;
4)Each unknown node uses the selected virtual beacons to take part in self-localization;
2 Compute the initial estimation point
Each unknown node computes the initial estimation point $X_C = \sum\limits_{i=1}^{m} (\boldsymbol{\zeta}_i \times (w_i \big/ \sum\limits_{j=1}^{m} w_j))$ for the optimization;
3 Self-localization
Each unknown node executes the optimization algorithm to minimize the cost function (10)

At last, the residual unknown nodes treat the nodes which have been localized as new actual anchors.

3 Simulation

3.1 Evaluation scenario

Our simulations were built using the Matlab simulator. The sensor field for simulation was a square of $100 \times 100\,\text{m}^2$ where 50 unknown sensor nodes were randomly deployed. Only one mobile node was used to transverse the field based on the Gauss-Markov mobility model. In the model, the initial value of $\bar{v}$ was $2\,\text{m/s}$, $\bar{d}$ was initially $90°$ but changed over time according to the edge proximity of the node, $v_{x_{k-1}}$ and $d_{x_{k-1}}$ were random variables from a Gaussian distribution, $\alpha = 0.75$. The initial broadcasting interval was 2 s. The initial moving time of the mobile node was 3 000 s. We assumed that each unknown node′s sensing rang was about 12 m and it could receive the RF beacons and acoustic energy within 10 m reliably. The source energy was set at $A = 5\,000$, and the background noise level was set at $\sigma_i = 1$ for all nodes in the field[14].

3.2 Evaluation metrics

Three performance metrics were considered for our node localization. 1) Computation overhead: The proposed scheme was running in a fully-distributed mode. Each node in WSN determined its location individual. It did rely on neighborhoods and it was insensitive to node density and network topology. The computation complexity was O(n), (n is the number of the unknown nodes). 2) Communication overhead: One major advantage of the proposed scheme is that no inter-sensor or sensor-to-mobile node communication was needed. 3) Average location error: It was the average distance between the estimated location and the actual location of all sensor nodes. The average location error can be calculated by $\bar{E} = \sum \sqrt{(x_e^{(i)} - x^{(i)})^2 + (y_e^{(i)} - y^{(i)})^2} \Big/ (\sum unknown - nodes)$. In the sub-section, we evaluate the important metric−the average location error from different aspects.

3.3 Simulation results

Fig. 2 shows the whole mobile node′s trajectory based on Gauss-Markov mobility model within the WSN field in one simulation. Along the trajectory, the mobile node periodically broadcasts virtual beacons packets. As shown in Fig. 2, the trajectory is easy to cover the whole field given appropriate mobile time to the mobile node. The unknown node is easy to obtain at least 4 noncollinear virtual beacons along the trajectory.

Fig. 3 clearly shows the virtual beacons received by a representative node in its sensing range along the trajectory. All the other unknown nodes are the same. The stars denote the virtual beacons broadcasted by the mobile node. The numbers beside the star denote the order of the virtual beacons received by the representative unknown node. The cross point denotes the unknown node.

As shown in Fig. 4, one representative unknown node estimates its location by finding the intersection of a set of hyper-spheres generated by the received pairs of virtual beacons-energy ratios. The dotted circles denote the likelihood of the unknown location based on the k_{ij}. With noise taken into account, about 31 hyper-spheres intersect at a small region that corresponds to the representative unknown node.

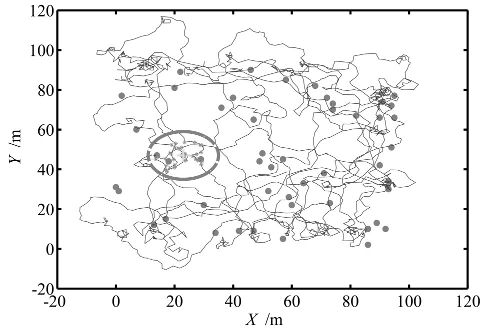

Fig. 2 The trajectory of the mobile nodes in the sensor field

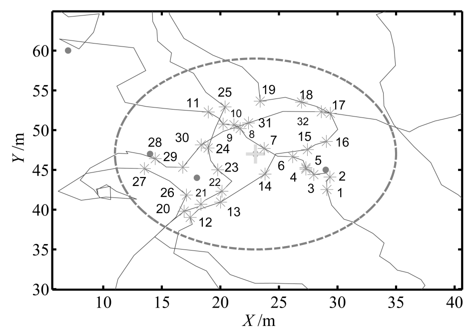

Fig. 3 The virtual beacons of one unknown node

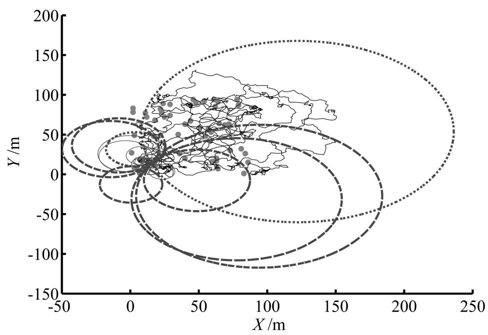

Fig. 4 Node localization using VB-ERL algorithm

Similarly, the others also obtain their locations based on their own hyper-spheres intersection regions. The whole final unknown nodes estimation results can be seen from Fig. 5, where small circles represent the original locations of sensor nodes, whereas small lines point to the estimated positions. The final residual unknown node is 0. The average localization error is about 0.423 m using the initial simulation parameters. So the localization accuracy is about 4%. The localization accuracy is high.

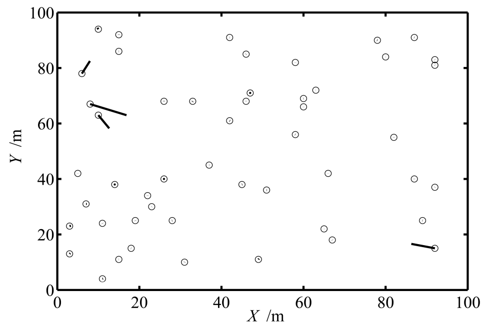

Fig. 5 Estimation results of the whole network

In the following subsections, we vary different parameters such as: the mobile node′s moving time, speed, and the beacon′s broadcasting interval, etc. to investigate how the VB-ERL scheme performs in terms of accuracy.

When moving time passing, more virtual beacons will be received and the localization accuracy will be improved. Also, there are more opportunities for some edges′ or corners′ unknown nodes covered by the virtual beacons along the trajectory, which leads to less residual unknown nodes left. As shown in Table 2, the localization accuracy improved with increasing of the moving time, and the residue unknown nodes are decreasing dramatically. The localization accuracy reaches 1% and the residual unknown node is zero when the moving time is about 5 000 s.

Table 2 Average error using different moving time

Total moving time (s)	1 000	2 000	3 000	5 000
Average error (/m)	1.024 74	0.430 4	0.121 1	0.095 9
Residue unknown nodes	6	4	1	0

Table 3 Average error using different speeds and intervals

Average speed (m/s)	0.5	1	2	4
beacons interval	4	2	1	0.5
Average error (/m)	0.603 0	0.594 2	0.523 3	0.539 2
Residue unknown nodes	0	1	0	0

Varying mobile node speed is similar to varying the time between the two beacons. Faster movement leads to less virtual beacons received by one unknown node in its sensing range. The increased speed makes the estimated locations less accurate. To maintain the localization accuracy with faster mobile node, it is necessary to lower the beacon interval correspondingly. We study the case that the mobile node sends a beacon at every fixed distance of movement (e. g. 1 beacon/2 m). Table 3 shows the impact of node speed and the beacons interval. The average estimation error is steady at 0.564 m with a little fluctuation. The residual unknown node is almost zero.

Apparently, in order to increase the localization accuracy we can prolong the moving time, decrease the interval of the beacons, etc. However, the computing costs will also be increasing. There is a tradeoff between the localization accuracy and the computing cost.

We also conducted extensive simulations comparing the proposed VB-ERL algorithm with the weighted centroid algorithm and the constraint algorithms[11] using different radio ranges. The weighted centroid algorithm takes the acoustic signal strength weighted mean of the received virtual beacons location as the estimate unknown location: $\boldsymbol{X}_{WC} = \sum_{i=1}^{k} w_i \boldsymbol{\zeta}_i / \sum_{i=1}^{k} w_i$. Table 4 shows the performance for the three localization schemes using 3 different radio ranges. The average localization accuracy for the centroid scheme is about 25%. The localization accuracy has little change with increasing of the radio range. The location accuracy of the constraint scheme decreases with larger radio ranges. Its average localization accuracy is about 19%. However, the location error of VB-ERL is improved slightly with the larger transmission range due to the more received virtual beacons. The accuracy for VB-ERL is about 1%∼6% of radio ranges.

Table 4 Average error using different radio range

Radio range	10	15	20
Weighted centroid	26%	25%	25%
Constraint	18%	19%	21%
VB-ERL	6%	2%	1%

The proposed VB-ERL performs the best among the three algorithms, and the localization accuracy is high. One of the important reasons is that the proposed VB-ERL does not require a direct range derived from signal strength but the energy ratio between the pairs of received energy. The simulation results validate the conclusion.

4 Conclusions

Node localization in WSN was treated as a functional dual to the target tracking problem. From the novel perspective, the paper proposed a VB-ERL localization scheme for WSN. Compared with other methods it has the following advantages: 1) The localization computation is fully distributed, there is no limitation to the network topology or scalability. It is applicable to large areas of WSN with arbitrary densities. 2) The virtual beacons eliminate the need to deploy the actual anchors, which leads to enhancement of the localization flexibility. 3) The unknown node listens passively to the mobile node, no inter-sensor or sensor-to-mobile node communication is needed, which reduces the energy consuming. 4) The localization accuracy is high.

Future work in our research is to set up a test-bed with Berkley nodes for the testing of the proposed scheme.

References

1 Akyildiz L F, Su W L, Sankarasubramaniam Y, Cayirci E. A survey on sensor networks. *IEEE Communications Magazine*, 2002, **40**(8): 102−114

2 Patwari N, Ash J N, Kyperountas S, Hero III A O, Moses R L, Correal N S. Locating the nodes: cooperative localization in wireless sensor networks. *IEEE Signal Processing Magazine*, 2005, **22**(4): 54−69

3 Patwari N, Hero III A O, Perkins M, Correal N S, Dea R J. Relative location estimation in wireless sensor networks. *IEEE Transactions on Signal Processing*, 2003, **51**(8): 2137−2148

4 Niculescu D, Nath B. Ad hoc positioning system (APS) using AOA. In: Proceedings of the 22nd Annual Joint Conference of the IEEE Computer and Communications Societies. San Francisco, USA: IEEE, 2003. 1734−1743

5 Biswas P, Ye Y. A Distributed Method for Solving Semidefinite Programs Arising from Ad Hoc Wireless Sensor Network Localization. Technical Report, Department of Computer Science, Stanford University, USA, 1993

6 Shang Y, Ruml W, Zhang Y, Fromherz M. Localization from mere connectivity. In: Proceedings of the 4th ACM International Symposium on Mobile Ad Hoc Networking and Computing. Annapolis, USA: ACM, 2003. 201−212

7 Shang Y, Ruml W. Improved MDS-based localization. In: Proceedings of the 23rd Annual Joint Conference of the IEEE Computer and Communications Societies. Hong Kong, China: IEEE, 2004. 2640−2651

8 Bulusu N, Heidemann J, Estrin D. GPS-less low cost outdoor localization for very small devices. *IEEE Personal Communications Magazine*, 2000, **7**(5): 28−34

9 Nagpal R. Organizing a Global Coordinate System from Local Information on an Amporphous Computer. Technical Report AI Memo 1666, MIT Artificial Intelligence Laboratory, 1999

10 He T, Huang C D, Blum B M, Stankovic J A, Abdelzaher T. Range-free localization schemes for large scale sensor networks. In: Proceedings of the 9th Annual Internationa1 Conference on Mobile Computing and Networking. San Diego, USA: ACM, 2003. 81−95

11 Galstyan A, Krishnamachari B, Lerman K, Pattem S. Distributed online localization in sensor networks using a moving target. In: Proceedings of the 3rd International Symposium on Information Processing in Sensor Networks. Barkeley, USA: ACM, 2004. 61−70

12 Su K F, Ou C H, Jiau H C. Localization with mobile anchor points in wireless sensor networks. *IEEE Transactions on Vehicular Technology*, 2005, **54**(3): 1187−1197

13 Camp T, Boleng J, Davies V. A survey of mobility models for ad Hoc network research. *Wireless Communications and Mobile Computing, Special Issue on Mobile Ad hoc Network: Research, Trends and Applications*, 2002, **2**(5): 483−502

14 Li D, Hu Y H. Energy-based collaborative source localization using acoustic microsensor array. *EURASIP Journal on Applied Signal Processing*, 2003, **2003**(4): 321−337

KUANG Xing-Hong Ph. D. candidate at Department of Automation, Shanghai Jiao Tong University. His research interest covers wireless sensor network, target localization and tracking. Corresponding author of this paper.
E-mail: kxhsyl@yahoo.com.cn

SHAO Hui-He Professor at Department of Automation, Shanghai Jiao Tong University. His research interest covers process control.
E-mail: hhshao@sjtu.edu.cn

FENG Rui Assistant professor at Department of Electrical and Computer Engineering, Fudan University. His research interest covers wireless sensor network.
E-mail: fengrui@fudan.edu.cn