A Scalable Localization Scheme using Particle Swarm Approach for Sensor Networks

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***Abstract*—This paper proposes a scalable grid-based localization scheme for establishing relative coordinate system of sensor networks. A distributed selection algorithm is proposed to select a small number of nodes from the set of sensor nodes as virtual grid nodes. The virtual grid nodes are then used to establish grid coordinate system by using particle swarm optimization. The grid coordinate system forms the backbone of node localization. The other nodes, which are not selected as grid nodes, can then compute (distributed) their locations based on the grid coordinate system efficiently. The precision of node localization is highly dependent on the number of grid nodes and can be adaptively adjusted according to target applications. Furthermore, the proposed localization scheme has high scalability and can work without any assistance of GPS. The simulation results show that about sixty percent of non-grid nodes could be correctly positioned in terms of grid coordinates, and nearly all of the non-grid nodes could be correctly be located in one of nine grids surrounding their real positions.**

Keywords*—*wireless sensor networks; localization; grid coordinate system.

I. Introduction

In recent years, wireless sensor networks have become an active research topic because of its wide variety of applications, such as battlefield surveillance, smart environments, healthcare, disaster relief [1], [2]. Wireless sensor networks also draw a lot of research challenges, such as sensing coverage controls, energy-efficient communication protocols, and data aggregations. The problem of localization aims to compute the coordinates of nodes in the network. Geographic information can be obtained by installing a Global Positioning System (GPS) receiver on each node in the network. Feasible solutions, however, are to equip only a few nodes with GPS, called *anchor nodes*, and the other nodes, using the estimated distances between anchor nodes and them to infer their position. Extensive studies have shown that the more estimated distances used to compute the coordinates of nodes, the higher accuracy of the established coordinate system, because measurement errors in the estimation of distances can be more effectively eliminated. However, the computational complexity of establishing the coordinate system increases exponentially with the number of distances used in calculating the coordinates of nodes. Although location information is crucial in wireless sensor networks, it is not necessary for all nodes in the network to know their precise position. In fact, requirements of location accuracy is highly application dependent in wireless sensor networks. For example, for many location-based routing protocols [3]–[6], grid-based coordinate system provides sufficient geographic information. Another example is that, in many event-based applications, we are interested in the region where an event takes places rather than the precise location of the node issuing the event. In this case, region-based coordinates are accurate enough for supporting target applications.

In this paper, we propose a scalable grid-based localization scheme for establishing relative coordinate system of sensor networks. The basic idea of the localization scheme is to establish a grid-based coordinate system by using a small number of virtual grid nodes selected from a given set of sensor nodes (In the following, those nodes that are not selected as grid nodes will be referred to as non-grid nodes). The grid coordinate system acts as the backbone of localization for the non-grid nodes. That is, the non-grid nodes can compute their positions via information exchange with their adjacent grid nodes. The overall precision of node localization is highly dependent on the number of grid nodes. The more the number of grid nodes, the higher the accuracy of localization. In such way, the localization scheme can be adaptively adjusted to balance the tradeoff between computation complexity and precision of the established coordinate system according to target applications. In summary, the proposed localization scheme has the following features:

1) **Adaptive**: The precision of the grid-based localization technique can be adjusted adaptively according to the requirements of target applications so that all nodes in the network could be positioned efficiently.
2) **Self-configurable**: The grid-based localization technique establishes the local grid coordinate system without the existence of anchor nodes (the sensor nodes that know their global coordinates). The grid coordinates, however, can also be transformed into the global coordinates if there are at least three grid nodes knowing their global position.
3) **Scalable**: The grid-based localization scheme works in large-scale sensor networks, e.g., more than 500 nodes.

The rest of this paper is organized as follows. Section II introduces the related works. In Section III, the proposed localization scheme is presented. The simulation results are given in Section IV. Finally, we draw the conclusion of this paper and the future work in Section V.

II. Related Works

DV-Hop approach assumes that the network comprises a small number of anchor nodes [7]. The other non-anchor nodes calculate their locations based on the averaged one-hop distance to every anchor nodes in the network. Leng et al. [14] addressed the problem of sensor localization in wireless networks in a multipath environment and proposed a distributed and cooperative algorithm based on belief propagation, which allows sensors to cooperatively self-localize with respect to a single anchor node in the network, using range and direction of arrival measurements. The research study [8] investigated neighborhood collaboration based distributed cooperative localization of all sensors in a particular network with the convex hull constraint. Three iterative self-positioning algorithms were present for independent implementation at all individual sensors of the considered network. Gu et al. [9] addressed the localization with incompletely paired mutual distances and proposed a Partially Paired Locality Correlation Analysis (PPLCA) algorithm. Sugihara and Gupta [10] described a novel SDP-based formulation for analyzing node localizability and providing a deterministic upper bound of localization error. The SDP-based formulation gives a sufficient condition for unique node localizability for any frameworks. A compressive sensing (CS) based approach for node localization in wireless sensor networks was presented by Zhang et al. [15]. Low et al. [16] proposed a localization system in which localization information is obtained through a probability based algorithm that requires the solving of a nonlinear optimization problem. The authors used the particle swarm approach to solve the nonlinear optimization problem.

III. The Proposed Grid-based Localization Algorithm

Given a set of sensor nodes S deployed in an interested region F, the coordinate system is established in two steps. First, a small number of nodes are selected as grid nodes to establish the grid coordinate system by using the proposed distributed selection algorithm. The grid nodes compute their grid coordinates themselves by exchanging information between each other and minimizing an error objective function. In this paper, a Particle Swarm Optimization technique is proposed to minimize the error objective function and to establish the grid coordinate system. The grid coordinate system then serves as the backbone of the coordinate system, whereby the other nodes in the network can compute their own position according to the grid coordinate system.

A. Grid Coordinate System Establishment

1) Distributed Grid Node Selection Algorithm: To create the grid coordinate system, all the nodes in the network need to estimate the distances between themselves and their communication neighbors. There are several technologies that can be used for this purpose, such as Received Signal Strength (RSS) and Time-of-Arrival (ToA) [17]. Generally, RSS is easier to implement, while ToA may have higher accuracy. Let $\tilde{d}_{i,j}$ be the estimated distance between two adjacent nodes s_i and s_j. Let w be the grid width of the grid coordinate system. We assume, without loss of generality, sensor nodes are deployed in a $L \times L$ square region, where L is multiple of w. To improve computation efficiency as well as localization accuracy, if the estimated distance between two adjacent nodes is smaller than the grid width w, only one of them is selected as a grid node for establishing the grid coordinate system. Thus we need to find the maximum set of nodes so that the distance measurement between any two nodes in the set is larger than or equal to the grid width w. Let $G = (V, E)$ be a graph. Each node $s_i \in S$ is represented by a vertex $v_i \in V$. There is an edge $e \in E$ between two vertices v_i and v_j if and only if $\tilde{d}_{i,j} < w$. An independent set of graph G is a subset $V' \subseteq V$ vertices such that each edge in E is incident on at most one vertex in V'. A maximal independent set is an independent set V' such that for all vertices $v \in V - V'$, the set $V \cup \{v\}$ is not independent. The selection of maximum set of grid nodes for creating the grid coordinate system is equivalent to one of finding the maximum independent set of the graph G, which is a NP-complete problem.

In this paper, we propose a distributed grid node selection algorithm, similar to the one proposed by Luby [18]. Let N_i be the set of nodes that are within the transmission range of node s_i. Let $NG_i = \{v_j \| \forall v_j \in V \text{ and } \tilde{d}_{i,j} < w\}$ be the set of nodes that their distances to s_i is smaller than the grid width. The distributed grid node selection algorithm proceeds in rounds. In each round, every node sends to all its neighbors a message containing its identity. When a node s_i collects all such messages from its neighbors, it becomes a grid node (winner) if either of the following two conditions is satisfied:

1) NG_i is nonempty (there exists at least one communication neighbor s_j such that $\tilde{d}_{i,j} < w$). Moreover, s_i has the smallest Node ID when comparing its Node ID with the received Node IDs of the nodes in NG_i.
2) NG_i is empty

Subsequently, grid nodes (winners) send to all their neighbors a message specifying their winner state. A sensor that receives such a message from one of its neighbors becomes a non-grid node, loser. Winners and losers of a round do not participate in subsequent rounds. The expected number of rounds is $O(logn)$ where n is the number of initial participants. An analysis of the expected number of rounds and a proof of termination of a similar algorithm can be found in Luby [18].

2) Particle Swarm Optimization (PSO) Algorithm: Let S' be the set of grid nodes obtained by using the proposed distributed grid node selection algorithm. In order to establish the grid coordinate system, it is crucial to obtain the distance measurement between two grid nodes in S'. If two grid nodes are adjacent, ToA or RSS can be employed to estimate their distances. However, the distance estimation becomes nontrivial when the two grid nodes are not within the transmission range of each other. In this paper, we employ a simple and effective scheme to estimate the distance between two remote grid nodes, called multi-hop distance estimation model [15]. The model utilizes the correlation of the Euclidean distance and the corresponding shortest path length between two nodes in the network for a given node distribution. Based on this model, a node s_i can estimate the Euclidean distance to another node s_j by sending a control packet that includes a *route length field*

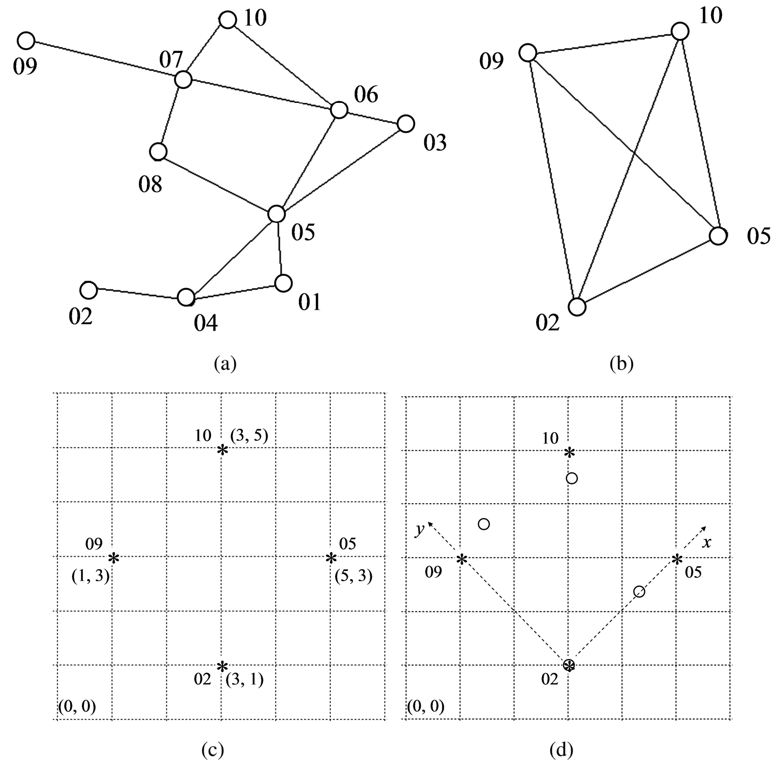

Fig. 1. Grid coordinate system establishment. (a) The constructed graph G(V, E) (b) The set of grid nodes for establishing the grid coordinate system. (c) The local grid coordinate system. (d) The transformed grid coordinate system.

with initial value of zero. When an intermediate node receives the control packet, it adds the one-hop distance between itself and the previous node, obtained by using ToA or RSS, to the route length field. Upon receiving the control packet, node s_j sends it back to node s_i. After node s_i receives the return control packet from s_j, it can read the route length field and estimates the distance between s_i and s_j according to the multi-hop distance estimation model. Here, we also use $\tilde{d}_{i,j}$ to denote the estimated distance, obtained by using the multi-hop estimation model, between two remote grid nodes s_i and s_j. (If two nodes are adjacent, $\tilde{d}_{i,j}$ denotes the estimated distance obtained by using ToA or RSS). We assume, without loss of generality, the grid node with the lowest identify number, say s_1, will perform the calculation for creating the grid coordinate system. Once a grid node s_i has obtained a set K_i of distances to all other grid nodes, i.e., $K_i = \{\tilde{d}_{i,j} \| \forall s_j \in S' \text{ and } j \neq i\}$, it sends K_i to s_1. Thus s_1 has the distance information between any two grid nodes in the network. Our objective is to calculate the grid coordinate system that minimizes the sum of the errors of the distances between any two grid nodes. Let (g_{x_i}, g_{y_i}) be the grid coordinate of node $s \in S'$. Then, the distance between two grid nodes s_i and s_j in the established grid coordinate system is

$$D_{ij} = \sqrt{(g_{x_i} - g_{x_j})^2 + (g_{y_i} - g_{y_j})^2} \quad (1)$$

Without loss of generality, assuming that $|S'| = M$ and $S' = \{s_i \| i = 1, 2, ..., M\}$. The error function is defined as.

$$\epsilon(X) = \sum_{i=1}^{M} \sum_{j=1}^{M} (D_{i,j} - \tilde{d}_{i,j})^2 \quad (2)$$

Where $X = \{(g_{x_i}, g_{y_i}) \| i = 1, 2, ..., M\}$. A PSO algorithm is applied to minimize the error function and give each node the grid coordinate. PSO is an optimization technique developed by Kennedy and Eberhart in 1995, inspired by social behavior of organisms such as bird flocking and fish schooling [11]–[13]. PSO is a population-based search method where individuals, called particles, change their position with time. Particles change their position by flying around in a multidimensional problem space. During flight, each particle keeps track of its coordinate that has the best solution encountered by itself so far and modifies its position based on its own history and the history of all other particles to make use of the best position. Therefore, PSO combines local search methods with global search methods. Here, each particle represents a solution set of grid coordinates of nodes in S'. Each particle evaluates how good the solution is according to the value, called fitness, of the error objective function in (2). One of the advantages of the proposed grid-based localization approach is that the PSO algorithm can be calculated efficiently because the number of grid nodes used to create the backbone of grid coordinate system is usually small (e.g., 5 to 15 grid nodes). Specifically, the number of grid nodes can be adjusted adaptively by setting the grid width according to the requirements of target applications. Furthermore, the grid-based coordinate system digitizes the solution space of the PSO algorithm. Let $K = (L/w)^2$ be the number of grid points in the established grid coordinate system. The upper bound of position vectors needed to be checked is

$$C_M^K \cdot M! = \prod_{i=1}^{M} (K - i + 1) \quad (3)$$

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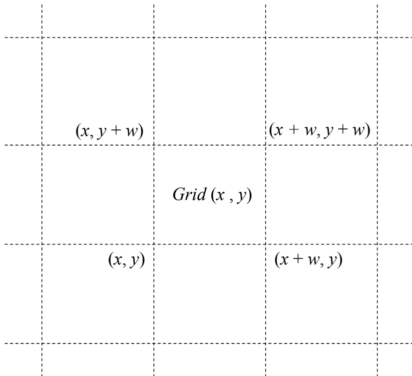


Fig. 2. Grid(x, y).

Fig. 1(a)-(d) illustrate an example of the grid coordinate system establishment in the network consisting of ten nodes. Fig. 1(a) is the constructed graph $G(V,E)$, where $V = \{01, 02, ..., 10\}$ and $E = \{(01,04),(01,05),(02,04),(03,05),(03,06),(04,05),(05,06),(05,08),(06,07),(06,10),(07,08),(07,09),(07,10)\}$. Fig. 1(b) shows the set of grid nodes $S' = \{02, 05, 09, 10\}$ for establishing the grid coordinate system.
$\epsilon = (d_{02,05} - \tilde{d}_{02,05})^2 + (d_{02,09} - \tilde{d}_{02,09})^2 + (d_{02,10} - \tilde{d}_{02,10})^2 + (d_{05,09} - \tilde{d}_{05,09})^2 + (d_{05,10} - \tilde{d}_{05,10})^2 + (d_{09,10} - \tilde{d}_{09,10})^2$
Fig. 1(c) shows the established local grid coordinate system. Note that the coordinate system is relative coordinate system and it can be arbitrary rotated or translated as long as the relative distances between nodes remain unchanged. To facilitate the comparison between the real positions of grid nodes and the established grid coordinates, the coordinate system in Fig. 1(c) is transformed to obtain Fig. 1(d). The node with lowest ID is set to be the origin $(0,0)$, the node with the second lowest ID is set to be on positive X-axis with coordinate $(x,0)$ where $x > 0$, and the node with the third lowest ID is set to be on positive Y-axis. In 1(d), the small circles ("o") denote the real coordinates of the nodes and the squares ("*") represent the grid coordinates after coordinate transformation.

B. The Non-grid Nodes

Let $Grid(x,y)$ denote the grid shown in Fig. 2. Then, $(x + w/2, y + w/2)$ is the center coordinate of $Grid(x,y)$. $Grid(x,y)$ is said to be within the $R + \epsilon$ range of the grid node s_i if $\sqrt{(x + w/2 - g_{x_i})^2 + (w + w/2 - g_{y_i})^2} \leq R + \epsilon$. After the grid coordinate system is established, the non-grid nodes compute their locations, i.e., the grid they are located in, by sending a request message to the nearby grid nodes (within the transmission range R) on demand. Let G_i be the set of grid nodes that receive the request message from non-grid node s_i. Upon receiving the request, every grid node $s_j \in G_i$ responses a message containing its identity number, the grid coordinate (g_{x_i}, g_{y_i}), and the set H_j of grid coordinates that are within the $R + \epsilon$ range of grid node s_j. (ϵ is a tunable parameter used to tolerate possible measurement errors in estimation of distance.) Let $H = \cap_{s_j \in G_i} H_j$ be the intersection set of grid coordinates. With the received information from nearby grid nodes, s_i calculates its own location (p,q) by calculating the following formula.

$$(p,q) = \arg \min_{(x,y) \in H} \{f(x,y)\}$$

where

$$f(x,y) = \sum_{s_k \in G_i} (\sqrt{(x + w/2 - g_{x_k})^2 + (y + w/2 - g_{y_k})^2} - \tilde{d}_{i,k})^2 \quad (4)$$

The proposed localization scheme for the non-grid nodes is a digitized triangulation approach. The advantage of this scheme is that every non-grid node can be positioned efficiently because the total number of grids needed to be evaluated in (4) is bounded by $(\frac{(R+\epsilon)^2 \cdot \pi}{w^2})$. Since R and w are usually constant in most wireless sensor networks, the computation complexity of the localization approach for non-grid nodes is $O(1)$. For example, let $R = 40, w = 15$ and $\epsilon = 5$ in a wireless sensor networks. Then, each regular node only requires evaluating at most 28 grids to determine the best grid in which they reside. Fig. 3 shows an example to illustrate this scheme more clearly. Assume $G_i = \{A, B, C\}, R + \epsilon = 3, w = 1, \tilde{d}_{i,A} = 1, \tilde{d}_{i,B} = 2$, and $\tilde{d}_{i,C} = 3$. $H = \{(1,1),(2,1),(3,1),(1,2),(2,2),(3,2),(2,3)$. $f(2,2) \simeq 3.3$.

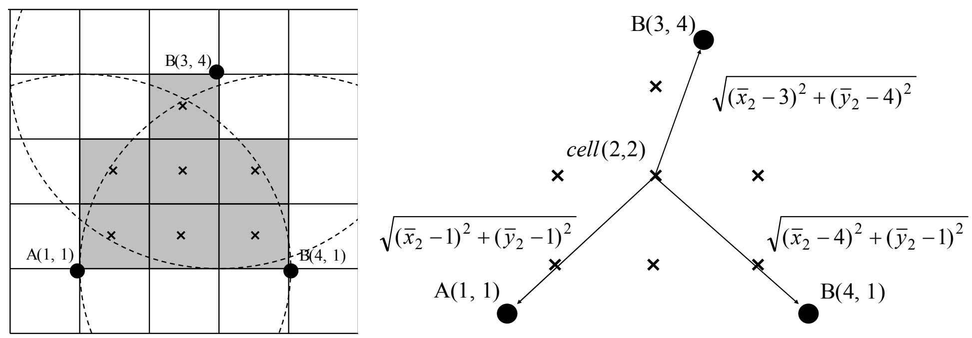
IV. SIMULATION

In this section, we evaluate the performance of the proposed localization technique via extensive simulations. Particularly, we study the impact of several parameters of interest, such as the number of grid nodes, grid width, and node density (grid nodes plus non-grid nodes). The proposed grid-based localization method was implemented in Matlab. Measurement error in the estimation of distances between adjacent nodes were modeled as zero-mean additive white Gaussian noise, which was also adopted in [17]. In the following evaluations, the sensor nodes are randomly deployed in a 100×100 square area, i.e., $L = 100$.

A. Grid Nodes

1) Grid Width versus Number of Grid Nodes: Extensive simulations have shown that the more distance measurements used to locate nodes, the higher accuracy of the established grid coordinate system, since the errors in the estimation of distances could be smoothed out more effectively. However, since the coordinate of every grid node is restricted by grid coordinate (see the error function in (2)), this would bring additional errors slightly, depending on the grid width and the total number of grid nodes used in the establishment of grid coordinate system. To evaluate the accuracy of the established grid coordinate system, the grid coordinate system is transformed by setting the node with lowest ID to be the origin $(0,0)$, the node with the second lowest ID to be on positive X-axis with coordinate $(x,0)$ where $x > 0$, and the node with the third lowest ID to be on positive Y-axis. The average error of the grid coordinate system is evaluated as follows.

$$\psi = \frac{\sqrt{\sum_{i=1}^{M} (x_i - g_{x_i})^2 + (y_i - g_{y_i})^2}}{M} \quad (5)$$



(a) (b)

Fig. 3. Location computation of non-grid nodes. (a) The intersection set. (b) The distances between grid cell (2,2) and grid nodes.

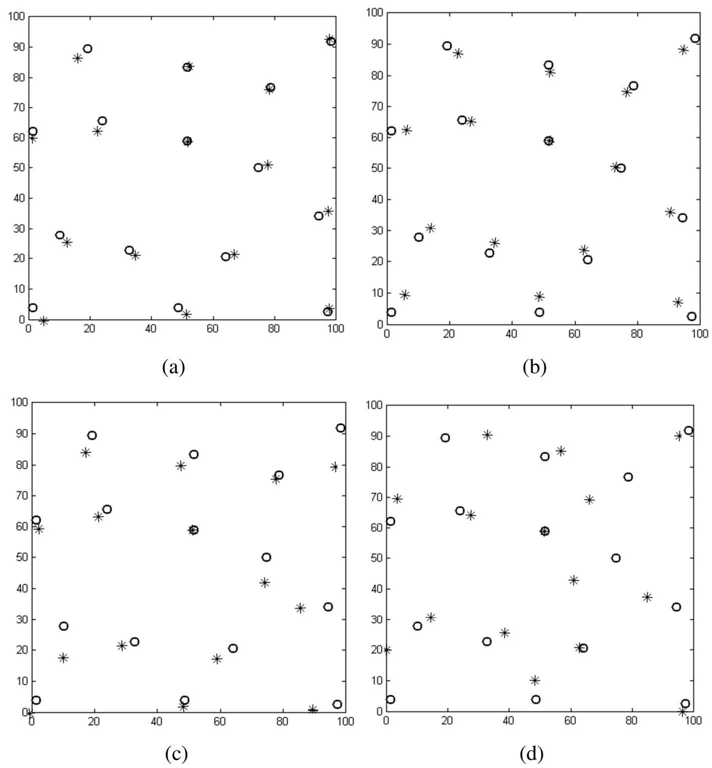


Fig. 5. The established grid coordinate system with $M = 15$. (a) $\psi = 1.7804, w = 5$. (b) $\psi = 4.0752, w = 10$. (c) $\psi = 4.8085, w = 15$. (d) $\psi = 8.4885, w = 20$.

where (x_i, y_i) is the real coordinate of grid node s_i and (g_{x_i}, g_{y_i}) is the calculated grid coordinate after coordinate transformation, and M is the total number of grid nodes. Here, ψ represents the average of distance between the real coordinates of grid nodes and the grid coordinates. Fig. 4 shows the average error of the grid coordinate system where the X-axis represents grid width w and the Y-axis denotes the average error ψ. As demonstrated in Fig. 4, ψ increases (approximately) linearly with grid width w and the average error is no more than $w/2$ when $M \leq 20$ and $1 \leq w \leq 20$. (Note that $M \leq (100/w)^2$ in a 100×100 area.) Additionally, ψ increases about $k \cdot (M_2 - M_1) \cdot w$ (e.g., in our simulations, $k \simeq 1/50$) as M increases from M_1 to M_2. For example, ψ increases about 3 units when M changes from 10 to 20 and $w = 15$.

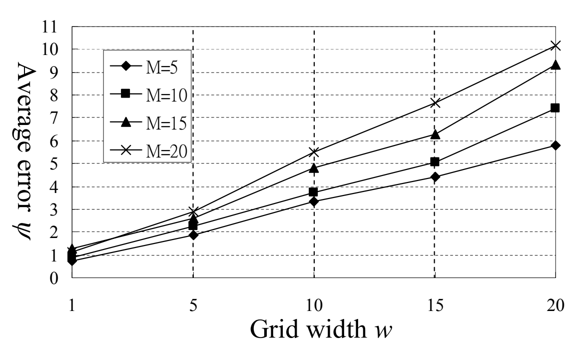


Fig. 4. Average grid coordinate error versus grid width.

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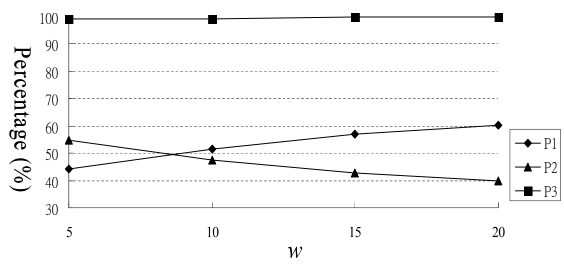

Fig. 6. The localization accuracy of non-grid nodes versus grid width.

2) Grid Coordinate System: Fig. 5(a)-(d) depicts the established grid coordinate system with $M = 15$. The small circles ("o") denote the real coordinates of the nodes and the squares ("$*$") represent the calculated grid coordinates after coordinate transformation. As shown in Fig. 5, the real coordinates are very close to the estimated coordinates when $w = 5$ and 10. As w increases, the differences between them become slightly obvious, but the simulation results in Fig. 4 demonstrate that the average error is no more than 10 units. This simulation also verifies that our proposed grid-based localization indeed establishes the local grid coordinate system.

B. Non-grid Nodes

We simulate networks containing 100 randomly distributed sensor nodes. Fifteen nodes are selected to serve as grid nodes, i.e., $M = 15$, and the non-grid nodes communicate with the nearby grid nodes to obtain necessary information. Then, they determine which grid they belong to using (4). We set $R = 40$ units so that each non-grid node has an average of about five neighboring grid nodes. The non-grid nodes that their real positions are near grid boundary in the grid coordinate system may be located incorrectly due to errors of the estimated distances between non-grid nodes and grid nodes. Let (x_i, y_i) be the real grid coordinate in which node s_i is located and $(\tilde{x}_i, \tilde{y}_i)$ be the estimated grid coordinate, respectively. Let P_1 represent the percentage of non-grid nodes that locate themselves correctly, i.e., $(\tilde{x}_i, \tilde{y}_i) = (x_i, y_i)$. Let P_2 denote the percentage of non-grid nodes that locate themselves *partially correct*. The localization result of a node s_i is said to be partially correct if $(\tilde{x}_i, \tilde{y}_i)$ equals to one of eight grids surrounding the real grid (x_i, y_i). Let $P_3 = P_1 + P_2$. Fig. 6 demonstrates that P_1 increases slightly with grid width w. About sixty percent of non-grid nodes locate themselves at correct grid as $w \leq 20$. Significantly, although some of non-grid nodes (near 40%) locate themselves incorrectly, almost all of them are located correctly in one of eight grids surrounding their real positions.

V. CONCLUSION

In this paper, we propose a scalable grid-based localization technique to balance the tradeoff between computation complexity and precision of localization. The simulation results show that a small number of nodes, e.g., five to fifteen, are usually enough for create the coordinate system with acceptable localization accuracy for many applications. The average error of the grid coordinate system is no more than half the grid width. About sixty percent of non-grid nodes could compute in which grids they are located correctly. Significantly, although some of non-grid nodes (near 40%) locate themselves incorrectly, almost all of them are located correctly in one of eight grids surrounding their real positions.

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