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A GPS-less, outdoor, self-positioning method for wireless sensor networks ☆

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Abstract

One challenging issue in sensor networks is to determine where a given sensor node is physically located. This problem is especially crucial for very small sensor nodes. This paper presents a GPS-less, outdoor, self-positioning method for wireless sensor networks. In our method, a set of nodes, called reference points (RPs), are deployed in the sensor network with overlapping regions of coverage. The RP periodically broadcasts beacon frames which contain localization data. The sensor node collects the beacon frames from RPs and process the data in the frame; it can then easily localize itself. The analysis of positioning accuracy is given to show how well a sensor node can correctly localize itself. In the optimal transmitting power, the worst-case accuracy for all data points is within 28.87% of the separation-distance between two adjacent RPs and the average accuracy is within 15.51%. The simulation results also show the robustness of the proposed method. Finally, we have implemented our positioning method on a sensor network test bed and the actual measurement show that the method can achieve average accuracy within 17.9% of the separation-distance between two adjacent RPs in an outdoor environment.

Keywords: Location-sensing; Positioning

1. Introduction

The fast progress of micro-electro-mechanical systems (MEMS) technology and wireless communications has enabled us to deploy a large number of low-cost, low-power and networked sensors over wide areas. The sensor nodes can collect, store, and process the sensed data and communicate with neighboring nodes to provide observation of environmental systems. This makes monitoring and controlling the physical world more convenient and efficient. In such sensor network systems, we need sensor nodes to be able to locate themselves in various environments. The location data of sensor nodes are useful for the centralized server or the managing node to analyze their sensing information. Not only sensor nodes but also other objects in the network need to be located. For

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example, the forest fire detection system should detect exactly where the scene of a fire is. In location-aware applications, localization enables the intelligent context selection includes tour guide [1,2], points of interest, real-time traffic information and so on. In ad hoc networks, localization helps the transmitting node recognize where the communicating node is and thus reduces the power consumption. Simply put, localization is important for many sensor network applications.

For localization systems, global positioning system (GPS) [3] is a good solution in outdoor environments. However, it is not suitable to use GPS on all sensor nodes in sensor networks. This is because sensor nodes have size, cost, and power constraints. This paper focuses on the problem of GPS-less, outdoor, low-cost localization for wireless sensor networks.

A survey of location systems can be found in [4]. Generally speaking, the localization can be divided into three major classes: self-positioning, remote positioning, and indirect positioning. The basic operations of these classes are summarized below:

A. *Self-positioning system:* The positioning receiver receives the appropriate signal measurements from geographically distributed transmitters and then uses these measurements to localize itself. Global positioning system (GPS) [3] is a typical self-positioning system. Recently, several self-positioning systems [5,6] for sensor networks have been presented. In [5], they measure the received signal strength and apply a triangulation method to localize moving sensors and handle dynamically changing sensor topologies. In [6], some fixed reference nodes with overlapping regions of signal coverage are configured. These reference nodes transmit periodic beacon signals and then sensor nodes can localize themselves based on the received beacons. An ad hoc positioning system (APS) [7] is a distributed, hop by hop positioning system. The sensor node uses the distance vector and the location information of landmarks to estimate its own location. In [8], point-in-triangulation test (PIT) is proposed to narrow down the possible region which a node resides in. In [9], a ring-overlapping approach is proposed. Based on received signal strength, a sensor node can determine an intersection area where it resides and use the gravity of the intersection area as its position.
B. *Remote positioning system:* A set of nodes with special radio frequency (RF) functions are deployed in some fixed place and measure the direction or the time delay of a signal which is originating from, or reflecting off, the transmitter nodes. After that, a centralized location server collects these measurements to determine the transmitter node's location. Typical remote positioning systems are angle of arrival (AOA) [10,11], time of arrival (TOA) [11], time difference of arrival (TDOA) [10,11], and received signal strength indicator (RSSI) [11]. The AOA measures the direction of the transmitter's signals; the TOA measures the signal propagation time from transmitter to receiver; the TDOA measures the propagation time difference from a signal traveling from transmitter to two different receivers; and the RSSI measures the received signal strength (RSS) and uses RSS to estimate the distance between transmitter and receiver. Such solutions do not require any modification to the objects but they have low position accuracy and high network costs.
C. *Indirect positioning system:* The indirect position system combines self-positioning and remote positioning systems. First, the node measures signal data and transfers it to the remote positioning system. Next, the remote positioning system collects these measurements, processes position bias, and then determines the node's position. Typical indirect positioning systems are assisted GPS (AGPS) [12], differential GPS (DGPS) [13,14], and cell-based positioning [15] where AGPS and DGPS have the highest positioning accuracy.

The cell-based positioning system [15] simply utilizes the characteristic of cell overlapping in geometry. However, it determines the location in a centralized server. When a sensor node needs to localize itself, it sends location requests to the location server. The location server determines the sensor's location and then sends the location to the sensor node. Unfortunately, communications between the sensor and the location server require a lot of energy and thus are not suitable for wireless sensor networks. Based on the idea of cell overlapping, this paper presents a GPS-less, outdoor, self-positioning method for wireless sensor networks. In the proposed method, a set of nodes, called reference points (RPs), are deployed in the sensor

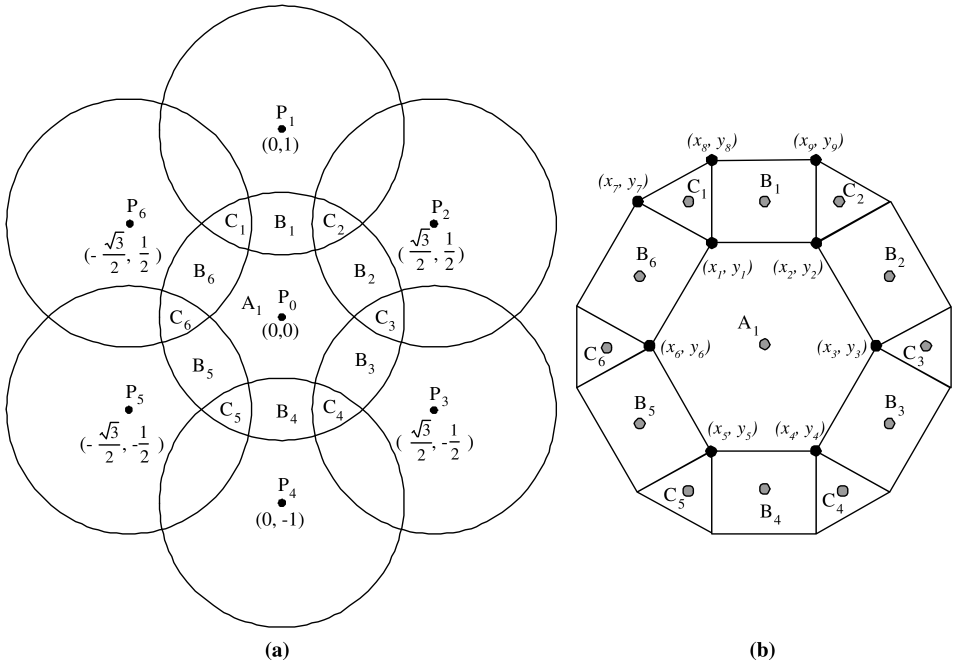

Fig. 1. The physical layout of reference points with a hexagonal structure.

network with overlapping regions of coverage. The RPs broadcast periodic beacon frames which contain localization data. The sensor node in the sensor network first receives the beacon frames from RPs, then processes the information in the frame, and finally the localization can be determined by itself. The proposed method has the following characteristics:

1. It is a distributed GPS-less self-positioning system. That is, the location can be determined by the sensor node itself without GPS or centralized server.
2. Sensor nodes only use simple connectivity metric and localization data in the beacon frame to calculate their locations. That is, sensor nodes require little computation to localize by themselves.

The remainder of this paper is organized as follows. In Section 2, we present the cell overlapping with an idealized radio model in detail. Section 3 gives the algorithm for the self-positioning system. The positioning accuracy analysis and simulation results are shown in Sections 4 and 5. A hardware implementation of the proposed method is given in Section 6. Finally, conclusions are given in Section 7.

2. Cell overlapping model

Consider that a set of RPs are deployed in the sensor network with overlapping regions of coverage. They are located at known positions and form a regular structure (e.g., hexagonal structure or meshed structure). As shown in Fig. 1(a), these RPs form a hexagonal structure. In our idealized radio model, we assume a perfect spherical radio propagation and identical transmission range for all reference points.[1] The area covered by the RP is called a *cell* and each cell is circle-shaped. The sensor node (SN) can receive radio signals from the RP if it is within the signal coverage of that RP. For example, as shown in Fig. 1(a), an SN in region A_1 can listen to signals from RP P_0; in region B_1, from RPs P_0 and P_1; and in region C_1, from RPs P_0, P_1 and P_6. The localization region is defined as the region in which every SN can listen a unique set of RPs' signals. As shown in Fig. 1(a), the coverage of RP P_0 has 13 localization regions, i.e., regions $A_1, B_1, \ldots, B_6$, $C_1, \ldots, C_5$ and C_6.

[1] This idealized model has been checked by experimental measurements for its validity in [6]. They concluded that the idealized radio model may be considered valid for outdoor unconstrained environments.

Table 1
The centroids of all regions in the hexagonal network structure

Region	Centroid	Region	Centroid
A_1	$(0,0)$	C_1	$\left(-\frac{\sqrt{3}}{6},\frac{1}{2}\right)$
B_1	$\left(0,\frac{1}{2}\right)$	C_2	$\left(\frac{\sqrt{3}}{6},\frac{1}{2}\right)$
B_2	$\left(\frac{\sqrt{3}}{4},\frac{1}{4}\right)$	C_3	$\left(\frac{\sqrt{3}}{3},0\right)$
B_3	$\left(\frac{\sqrt{3}}{4},-\frac{1}{4}\right)$	C_4	$\left(\frac{\sqrt{3}}{6},-\frac{1}{2}\right)$
B_4	$\left(0,-\frac{1}{2}\right)$	C_5	$\left(-\frac{\sqrt{3}}{6},-\frac{1}{2}\right)$
B_5	$\left(-\frac{\sqrt{3}}{4},-\frac{1}{4}\right)$	C_6	$\left(-\frac{\sqrt{3}}{3},0\right)$
B_6	$\left(-\frac{\sqrt{3}}{4},\frac{1}{4}\right)$	–	–

Consider a hexagonal structure as shown in Fig. 1(a). The localization regions in the coverage of a RP can be divided into three types according to the number of receiving signals as follows:

- *Type 1 region:* The region is covered by only one RP's signal, e.g., region A_1.
- *Type 2 region:* The region is covered by two RPs' signal coverage, e.g., regions B_1, B_2, B_3, B_4, B_5, and B_6.
- *Type 3 region:* The region is covered by three RPs' signal coverage, e.g., regions C_1, C_2, C_3, C_4, C_5, and C_6.

Note that the radio coverage of RP is represented as a circle. By using simple geometry, we can find all the intersections of the circles. For each localization region, we find the centroid (x_c, y_c) of the region by

$$(x_c,y_c)=\left(\frac{x_1+x_2+\cdots+x_n}{n},\frac{y_1+y_2+\cdots+y_n}{n}\right),$$

where $(x_1,y_1),(x_2,y_2),\ldots,(x_n,y_n)$ are the vertices of the region. If an SN can localize itself in the region, we use (x_c, y_c) to estimate the location of the SN. For example, as shown in Fig. 1(b), if an SN localizes itself in region B_1, the estimated location of SN is $\left(\frac{x_1+x_2+x_8+x_9}{4},\frac{y_1+y_2+y_8+y_9}{4}\right)$.

Given a set of RPs deployed in a hexagonal structure in which the distance between two neighboring RPs is one unit and the transmission range of RP is $r = 0.78$, we can find the centroids for all localization regions. The results are summarized in Table 1.

3. Self-positioning algorithm

As stated in the previous section, we can deploy RPs in a hexagonal structure and find the localization regions for each RP. The RP periodically broadcasts the beacon frame to notify all of the SNs staying in its signal coverage area. We assume that each RP knows all centroids of its localization regions. For example, RP P_0 knows the centroids of 13 localization regions. The centroids can be computed in the deployment stage. The beacon format contains the following data:

$$S=\{t_n,(t_{r_a},\{(x_{c_1},y_{c_1}),\ldots,(x_{c_a},y_{c_a})\}),\ \ldots,(t_{r_k},\{(x_{c_1},y_{c_1}),\ldots,(x_{c_k},y_{c_k})\})\},$$

where t_n represents the type of RP's structure, (e.g., $t_n = 1$ for hexagonal structure and $t_n = 2$ for meshed structure): t_{r_i} represents the type of localization region (e.g., $t_{r_i} \in \{1,2,3\}$ for hexagonal structure); and (x_{c_i}, y_{c_i}) represents the centroid of the region. Note that the type number of the region is equal to the number of signals that can be received in that region.

For example, as shown in Fig. 2, the beacon frames of RP 5 and RP 6 are

$$S_5=\{1,(1,\{M\}),(2,\{B,D,F,H,J,L\}),\ (3,\{A,C,E,G,I,K\})\},$$
$$S_6=\{1,(1,\{W\}),(2,\{J,N,P,R,T,V\}),\ (3,\{K,I,O,Q,S,U\})\},$$

where the symbols $A,B,\ldots,W$ represent the centroids of localization regions (e.g., $M=\left(\frac{\sqrt{3}}{2},\frac{1}{2}\right)$, $W = (0,0)$).

Then, the SN collects the beacon signals from the RPs and determines its location. The operations of SN are given as follows:

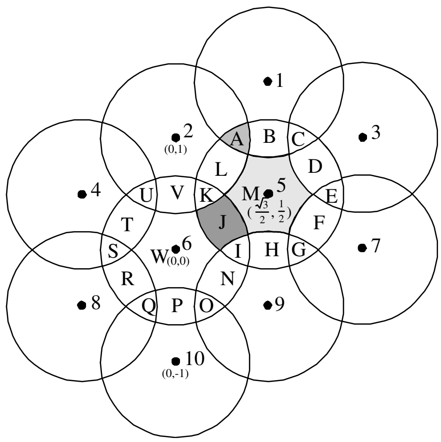

Fig. 2. An example of localization regions for hexagonal structure.

1. Collect and store the beacon signal that it receives.
2. Determine the number of RPs, denoted as m, that it can listen to. Then extract the centroid set with the type m from the beacon frames, denoted as S^m. Note that we can find m different centroid sets. For example, if an SN can receive beacons from RP 5 and RP 6, it extracts the centroid set with type 2 from the received beacon frames as follows:

$$S_5^2 = \{B, D, F, H, J, L\},$$
$$S_6^2 = \{J, N, P, R, T, V\}.$$

3. The SN finds a centroid by intersecting the centroid sets as its location, i.e., find $\bigcap_i S_i^m$. For example,

$$\begin{aligned} S_5^2 \bigcap S_6^2 &= \{B, D, F, H, J, L\} \cap \{J, N, P, R, T, V\} \\ &= \{J\} \\ &= \left\{ \left(\frac{\sqrt{3}}{4}, \frac{1}{4} \right) \right\}. \end{aligned}$$

4. Positioning accuracy analysis

Let the coordinate of the actual location of SN be (X, Y) where X and Y are random variables. In our proposed method, the SN localizes itself to the centroid of the localization region. Thus, the error distance D is

$$D = \sqrt{(X - x_c)^2 + (Y - y_c)^2},$$

where (x_c, y_c) is the centroid of the localization region (i.e., the estimated location of the sensor node). The *precision e(r)* can be defined as the probability that the SN can localize itself within distance r. That is,

$$e(r) = P\{D < r\}.$$

Assume that the SN falls equally likely to any point in the location region R. Then, the probability density function $f(x,y)$ of (X, Y) can be written as follows:

$$f(x,y) = \begin{cases} c & \text{if} (x,y) \in R, \\ 0 & \text{otherwise}, \end{cases}$$

where

$$\int_R \int f(x,y) \mathrm{d}x \, \mathrm{d}y = \int_R \int c \, \mathrm{d}x \, \mathrm{d}y = 1.$$

This gives

$$c = \frac{1}{\int_R \int \mathrm{d}x \, \mathrm{d}y} = \frac{1}{\text{area of } R}.$$

Therefore, the precision

$$e(r) = P\{D < r\} = \int_{C_r} \int f(x,y) \mathrm{d}x \, \mathrm{d}y = \frac{\text{area } C_r}{\text{area of } R},$$

where

$$C_r = \left\{ (x,y) | \sqrt{(x - x_c)^2 + (y - y_c)^2} < r \right\} \cap R.$$

4.1. The worst-case accuracy

Now, let us consider the shape of type 1 as shown in Fig. 3. The precision $e(r)$ is the area of C_r over the area of localization region R, if r is less then r_1. If r is greater than r_1, the precision $e(r)$ is 1. This means that SN can localize itself within distance r_1 with probability 1. In other words, if SN localizes itself in the type 1 region and the tolerance of error distance d is greater than r_1, the position of SN can be correctly determined. The radius r_1 is called the *critical radius*. Furthermore, let $r^* = \max\{r_1^{(1)}, r_1^{(2)}, r_1^{(3)}\}$ where $r_1^{(i)}$ is the critical radius for type i region. Thus, we can say that SN localizes itself correctly within distance r^*. Note that r^* is the *worst-case accuracy*.

For example, consider that a set of RPs are deployed in a hexagonal structure in which the distance between two neighboring RPs is one unit and the transmission range of RP is 0.78. We can compute the precision $e_i(r)$ for each type i. Fig. 4 shows the precision $e_i(r)$ for type $i = 1, 2, 3$. Note that $r^* = \max\{r_1^{(1)}, r_1^{(2)}, r_1^{(3)}\} = \max\{0.2685, 0.2993, 0.3088\} = 0.3088$. That is, for this hexagonal structure, SN localizes itself correctly within distance 0.3088.

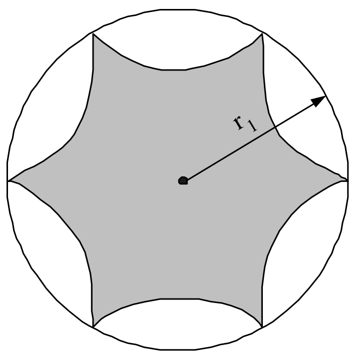

Fig. 3. The shape of type 1 in hexagonal structure.

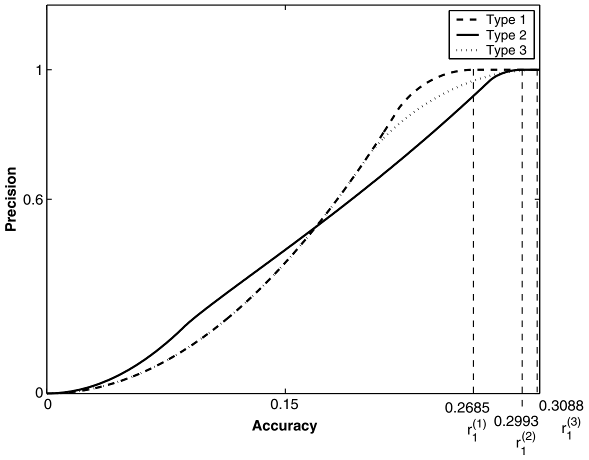

Fig. 4. The precision $e_i(r)$ of SN in the type 1, 2, and 3 areas.

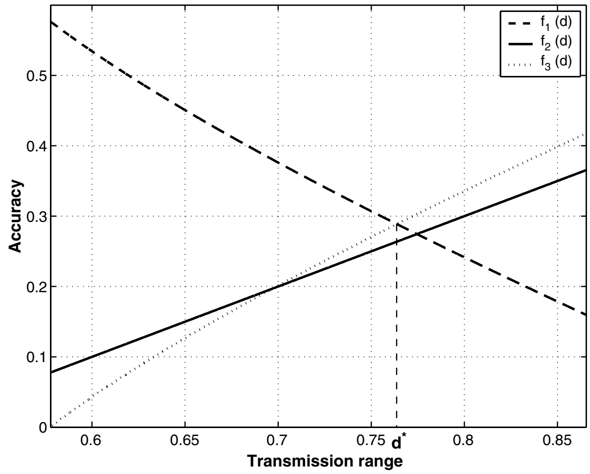

Fig. 5. The worst-case accuracy for hexagonal structure.

Note that critical radius $r_1^{(i)}$ is a function of RP's transmission range d. Let $f_i(d)$ be the critical radius for type i, $i = 1, 2, 3$. Then, the worst-case accuracy r^* can be rewritten as $r^*(d) = \max\{f_1(d), f_2(d), f_3(d)\}$. If the transmitting power of RP can be adjusted, then the transmission range of RP will vary. We assume that the radius d is bounded within $\left[\frac{1}{\sqrt{3}}, \frac{\sqrt{3}}{2}\right]$.[2] Let us consider how to arrange the transmission range of RP such that the worst-case accuracy is optimized. This problem is equivalent to finding a radius d such that $r^*(d) = \max\{f_1(d), f_2(d), f_3(d)\}$ is minimized. That is,

$$\begin{aligned} z &= \min_{\frac{1}{\sqrt{3}} \leqslant d \leqslant \frac{\sqrt{3}}{2}} r^*(d) \\ &= \min_{\frac{1}{\sqrt{3}} \leqslant d \leqslant \frac{\sqrt{3}}{2}} \max\{f_1(d), f_2(d), f_3(d)\}. \end{aligned} \tag{1}$$

Fig. 5 shows the functions $f_1(d)$, $f_2(d)$, and $f_3(d)$, for $\frac{1}{\sqrt{3}} \leqslant d \leqslant \frac{\sqrt{3}}{2}$. The function $f_1(d)$ is a decreasing function and the function $f_3(d)$ is an increasing function where $\frac{1}{\sqrt{3}} \leqslant d \leqslant \frac{\sqrt{3}}{2}$. Let d^* be the radius such that $f_1(d^*) = f_3(d^*)$. Thus,

$$\max\{f_1(d), f_2(d), f_3(d)\} = \begin{cases} f_1(d) & \text{if } \frac{1}{\sqrt{3}} \leqslant d \leqslant d^*, \\ f_3(d) & \text{if } d^* \leqslant d \leqslant \frac{\sqrt{3}}{2} \end{cases}$$

and the minimum of max $\{f_1(d), f_2(d), f_3(d)\}$ occurs at $f_1(d) = f_3(d)$. By using the numerical method, we find $d^* = 0.7638$ such that $f_1(d^*) \approx f_3(d^*) = 0.2887$.

4.2. The average-case accuracy

Given that the location (x, y) of SN falls in the type i area, the expected accuracy D_i is

$$E[D_i] = \int_{(x,y)\in R_i} \sqrt{(x - x_{c_i})^2 + (y - y_{c_i})^2} f(x, y) \mathrm{d}x \, \mathrm{d}y,$$

where R_i is the localization region of type i and (x_{c_i}, y_{c_i}) is the centroid of R_i. Thus, the expected accuracy of D for the network with hexagonal structure can be found by

$$E[D] = \sum_{i=1}^{3} p_i E[D_i],$$

where p_i is the probability that SN falls in the type i area. By this way, we can evaluate the average accuracy of the proposed method.

Note that the average accuracy $E[D]$ is also a function of RP's transmission range d. Let $g(d)$ be the average accuracy $E[D]$ for the RPs with hexagonal structure having transmission range d. Let us consider how to arrange the transmission range of RP such that the average accuracy is minimized. The problem is to find a radius d such that $z = \min_{\frac{1}{\sqrt{3}} \leqslant d \leqslant \frac{\sqrt{3}}{2}} g(d)$.

We can evaluate the average accuracy $E[D]$ by simulation. In our simulation, 10,000 sensor nodes were generated in the working area of 100×100 square units. The SNs are placed in the working

[2] This is because (1) if $d < \frac{1}{\sqrt{3}}$, then there are some areas not covered by RP's signal; (2) if $d > \frac{\sqrt{3}}{2}$, then the type 2 area will be separated into two sub-areas.

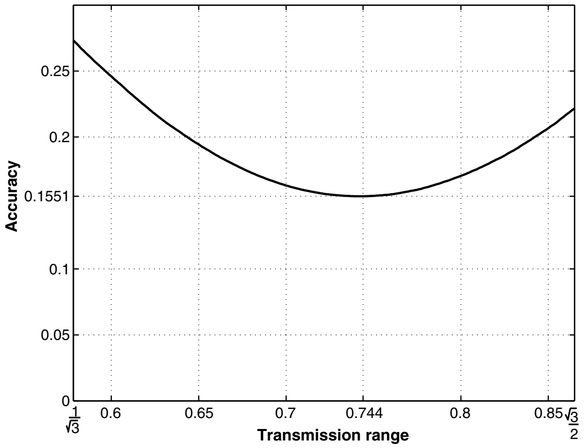

Fig. 6. The average accuracy for hexagonal structure.

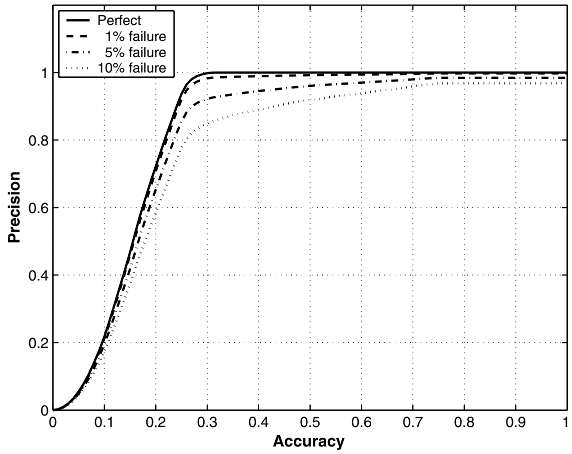

Fig. 7. The average accuracy for imperfect RPs in a hexagonal structure.

area with a uniform distribution. We assume that all RPs are deployed in a hexagonal structure with transmission range $\hat{d}$ and their locations are known in advance. By the proposed self-positioning method, each SN can localize itself at position (x_c, y_c). Thus, the positioning error can be found. By this way, we can evaluate the average accuracy $g(\hat{d})$. Furthermore, we find $g(d)$, for $\frac{1}{\sqrt{3}} \leqslant d \leqslant \frac{\sqrt{3}}{2}$, as shown in Fig. 6. Note that function $g(d)$ is a convex function. We find the minimum of $g(d)$ is 0.1551 where $d = 0.744$.

5. Positioning accuracy for imperfect RPs

In order to show the robustness of the proposed method, we assume that RPs are not perfect. Consider the example given in Section 3. Assume that an SN is in the region J (see Fig. 2) and RP 6 fails. The SN only receives the beacon frame $S_5 = \{1,(1,\{M\}),(2,\{B,D,F,H,J,L\}),(3,\{A,C,E,G,I,K\})\}$ from RP 5. As a result, the SN localized itself at $M = \left(\frac{\sqrt{3}}{2}, \frac{1}{2}\right)$. That is, the accuracy error becomes large.

We evaluate the average accuracy for imperfect RP by simulation. In our simulation, 10,000 sensor nodes were generated in the working area of 100×100 square units. Then, SNs are placed in the working area with a uniform distribution. We assume that all RPs are deployed in a hexagonal structure with transmission range 0.744 and their locations are known in advance. We consider three cases of imperfect RPs. That is, case 1 has a 1% of failure rate of RPs; case 2 has 5%; and case 3 has 10%. Fig. 7 shows the average accuracy of the proposed method with imperfect RPs. From Fig. 7, note that the proposed method with imperfect RPs having 1%, 5%, and 10% failure rates can locate SN to within 0.3088 unit distance for 98.68%, 92.74% and 85.6% of measurements, respectively. Because of the failure of RPs, some sensor nodes in the working area may not localize themselves. When the RPs failure rates are 1%, 5%, and 10%, the probabilities that the sensor nodes cannot localize themselves are 0.21%, 1.21%, and 2.36%, respectively. That is, the probability that the sensor node cannot localize itself is very small and the decease in positioning accuracy is very limited for the network with imperfect RPs having a 10% failure rate.

In the previous simulation, we assume the communication range is an ideal circle. In reality, the coverage of RP is irregular due to multipath propagation effects. Thus, we construct a simulation using the shadowing model [16] as its radio model. The shadowing model[3] can be represented by

$$\left[\frac{P_r(d)}{P_r(d_0)}\right]_{dB} = -10\beta \log\left(\frac{d}{d_0}\right) + X_{dB},$$

where $P_r(d)$ ($P_r(d_0)$) is the received signal power at distance d (d_0), β is the path loss exponent, and X_{dB} is a Gaussian random variable with $\mu = 0$ and standard deviation σ_{dB}. Note that the shadowing model extends the ideal circle model to a statistic model. For outdoor environments, we set

[3] This model does not include the effects of multipath fading. These effects can be significant when working with narrowband signals.

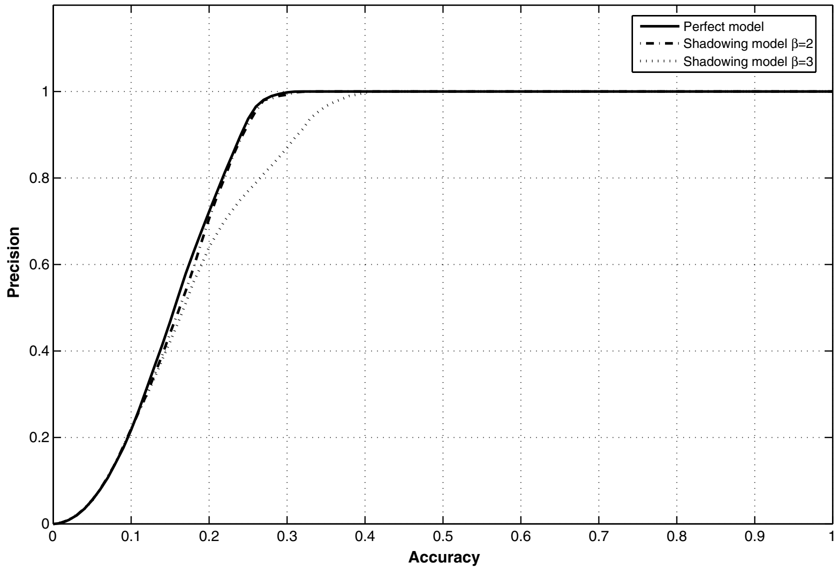

Fig. 8. The average accuracy for the shadowing propagation model.

$\sigma_{dB} = 11$ and $\beta = 2$ (free space) or $\beta = 3$ (shadowed urban area) in our simulation [17]. The SN can receive the beacon frame if the received signal power is greater than the value of $P_r(d)$ where d is 0.744 unit distance. A unit distance is equal to 20 m in the simulation. The working area was 100×100 square units and RPs were deployed with hexagonal structure. For randomly generating 100,000 SNs to be located in a working area, Fig. 8 shows the average accuracy of the proposed method. For outdoor, free space environment (i.e., $(\sigma_{dB}, \beta) = (11, 2)$), the accuracy curve is almost the same as the accuracy curve of perfect model. For outdoor, shadowed urban area (i.e., $(\sigma_{dB}, \beta) = (11, 3)$), the SN can localize itself to within 0.3 unit distance for 87% of measurements. Thus, the proposed method still worked well in the outdoor, shadowed urban area.

6. Hardware implementation

The proposed self-positioning method was implemented over a collection of MICA2 sensor nodes [18] to verify its feasibility and estimate its accuracy in a real-world environment. The resource constraints of MICA2 are listed in Table 2. We placed MICA2 sensor nodes as RPs on an outdoor skating rink in our campus. The topology is shown in Fig. 9(b) in which seven black dots represent seven RPs. The distance between two adjacent RPs is about 10 m. The transmission power of each RP was tuned such that its transmission range is about 8 m. Each RP broadcasts a beacon frame every 200 ms. The contents of beacon frames are listed in Table 3. A white dot with coordinate (x, y), where x and y are integers, in Fig. 9(b) represents a test point. Each time we placed a MICA2 sensor node on a test point (white dot) and then the sensor node collected beacon frames for 9600 ms. Let N_a be the total number of beacon frames collected at test point a and $N_a(i)$ be the number of beacon frames collected at test point a that were issued from RP i. The sensor node at test point a discards the beacon frames from RP i if $\frac{N_a(i)}{N_a}$ is less than 0.1. Based on the beacon frames it collected, the sensor node localized itself by the proposed positioning method. In our experiment, we measured 276 test points as shown in Fig. 9.

Table 2
The parameters and hardware information about MICA2 Mote

Component	Description
Processor	Atmel ATMega 128L
Program flash memory	128 KB
Configuration EEPROM (Data)	4 KB
Radio frequency	868–870 MHz
Radio transceiver	Chipcon CC1000
Battery	2 AA batteries

Fig. 10 shows the average accuracy for the experimental and simulation results. We use

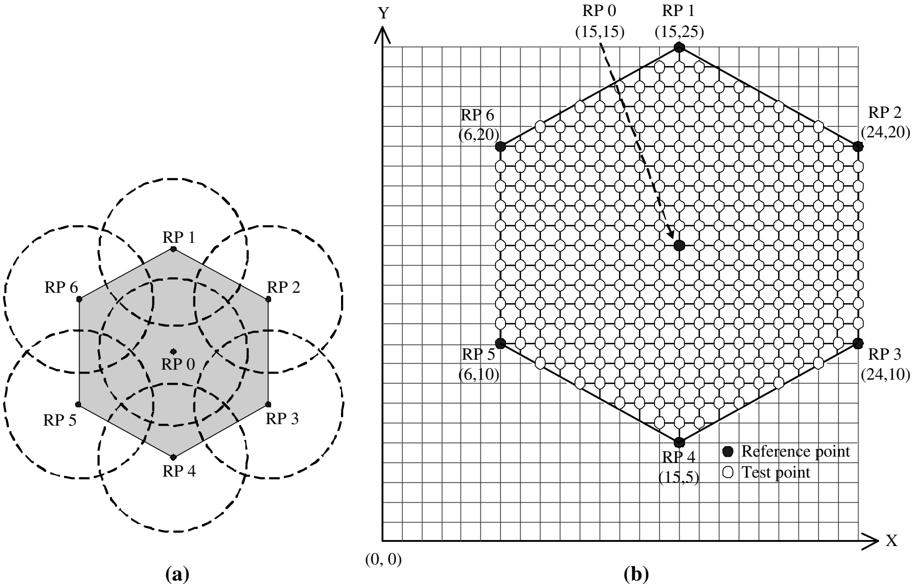

Fig. 9. The topology of RPs.

Table 3
The beacon content of RPs

RP	Beacon content
RP 0	{1, (1, {(15,15)}), (2,{(15,20),(19,18),(19,13),(15,10),(11,13),(11,18)}), (3,{(12,20),(18,20),(21,15),(18,10),(12,10),(9,15)})}
RP 1	{1, (1, {(15,25)}), (2,{(15,30),(19,28),(19,23),(15,20),(11,23),(11,28)}), (3,{(12,30),(18,30),(21,25),(18,20),(12,20),(9,25)})}
RP 2	{1, (1, {(24,20)}), (2,{(24,25),(28,23),(28,18),(24,15),(19,18),(19,23)}), (3,{(21,25),(27,25),(30,20),(27,15),(21,15),(18,20)})}
RP 3	{1, (1, {(24,10)}), (2,{(24,15),(28,13),(28,8),(24,5),(19,8),(19,13)}), (3,{(21,15),(27,15),(30,10),(27,5),(21,5),(18,10)})}
RP 4	{1, (1, {(15,5)}), (2,{(15,10),(19,8),(19,3),(15.0),(11,3),(11,8)}), (3,{(12,10),(18,10),(21,5),(18,0),(12,0),(9,5)})}
RP 5	{1, (1, {(6,10)}), (2,{(6,15),(11,13),(11,8),(6,5),(2,8),(2,13)}), (3,{(3,15),(9,15),(12,10),(9,5),(3,5),(0,10)})}
RP 6	{1, (1, {(6,20)}), (2,{(6,25),(11,23),(11,18),(6,15),(2,18),(2,23)}), (3,{(3,25),(9,25),(12,20),(9,15),(3,15),(0,20)})}

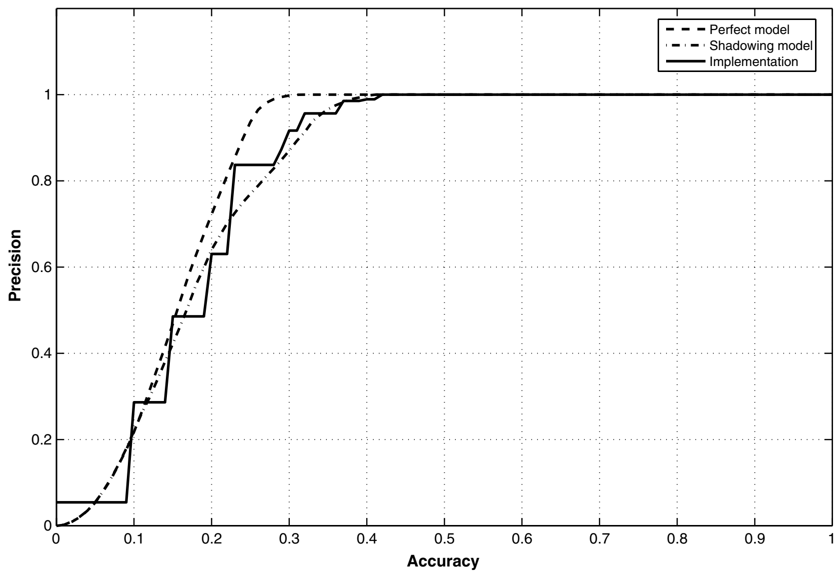

Fig. 10. The average accuracy for hexagonal structure in the experiment.

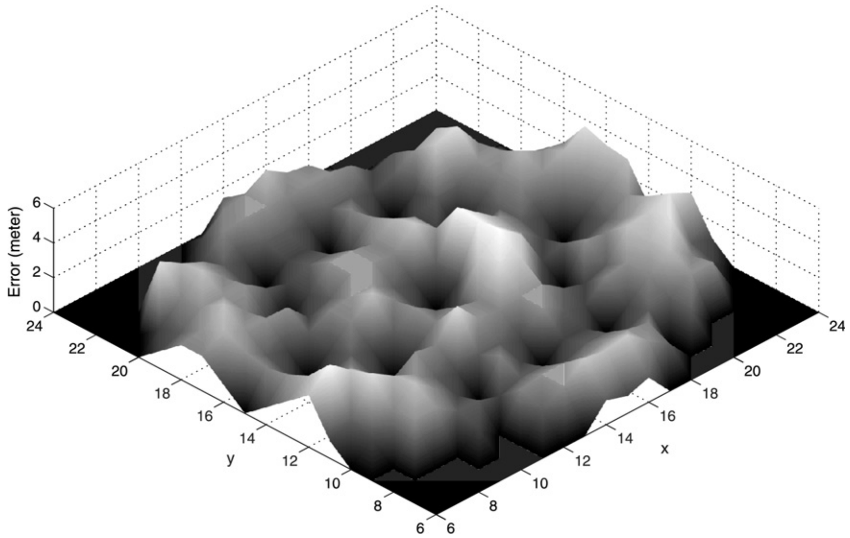

Fig. 11. The positioning error for all test points.

10 m as a unit distance in our experiment. From Fig. 10 we note that the SN can localize itself to within 0.3 unit distance (i.e. 3 m) for 91.67% of measurements in our outdoor experiments. The experimental results also agree with the simulation results using the shadowing model ($\beta = 3$, $\sigma_{dB} = 11$). In Fig. 11, the positioning error obtained from experiments is plotted as a function of the test points. The positioning error is lowest for the test points at the centroid of the regions and increases towards the edges of the regions. The average positioning error was 1.79 m and the standard deviation was 0.86 m. The minimum error was 0 m and the maximum error was 4.12 m across 276 test points.

7. Conclusions

In this paper, we proposed a GPS-less, outdoor, self-positioning method for wireless sensor networks. In our method, a set of RPs with overlapping regions of coverage are arranged in a hexagonal structure or meshed structure in the sensor network and broadcast the beacon frames. Sensor nodes only collect the beacon frames from RPs and use the localization data in the beacon frame to calculate their locations. Note that sensor nodes require little computation to localize by themselves. This kind of localization system, with its low cost and easy computation, is very suitable for sensor networks.

In the optimal transmitting power, the worst-case accuracy for all data points is within 28.87% of the separation-distance between two adjacent RPs and the average accuracy is within 15.51%. The simulation results also show the reliability and robustness of our proposed method. Regarding system robustness, the proposed method with imperfect RPs can locate SN to within 30.88% of the separation-distance between two adjacent RPs for 85.6% of measurements even though 10% of RPs failed. Finally, we have also implemented our positioning method on a sensor network test bed to verify its feasibility. The actual measurements show that it can achieve average accuracy within 17.9% of the separation-distance between two adjacent RPs in a outdoor environment.

Although the proposed positioning method is based on a regular structure, it might be extended to solve the positioning problem based on irregular structures, under the condition that each RP's position and coverage can be precisely determined and no two localization regions receive the same set of RP beacon frames. Furthermore, the analysis of the positioning accuracy and optimization of RP's coverage for irregular structures might be interesting for possible future work.

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