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Weighted Centroid Localization Algorithm Based on Least Square for Wireless Sensor Networks

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Abstract: Localization algorithm is an important and challenging topic in today's wireless sensor networks (WSNs). In order to improve the localization accuracy, a weighted centroid localization algorithm based on least square to predict the location of any sensor in WSNs is proposed in this paper. The proposed algorithm proposes a Least-Square-based weight model which can reasonably weigh the proportion of each anchor node in the unknown node. In the weight model, we utilize least square method to compute the weight. Then, we increase the weight of anchor nodes closer to the unknown node, introduce the parameter k into the proposed likelihood model, and we determine the optimal value of the parameter k through our real experiments. Simulation and experimental results show that the proposed weighted centroid algorithm is better than Weighted Centroid Localization (WCL) and Anchor-optimized Modified Weighted Centroid Localization based on RSSI (AMWCL-RSSI) in terms of the localization accuracy. *Copyright © 2014 IFSA Publishing, S. L.*

Keywords: Localization, RSS, Wireless sensor networks, Least square, Weight.

1. Introduction

Recent advancements in the wireless communications and hardware technology field have facilitated the development of wireless sensor networks (WSNs) for a wide variety of real-world applications, including environmental monitoring, disaster relief, site security, medical diagnostics, battlefield surveillance, home automation, assisted living, and so on [1-6].

A recent outdoor application for WSNs is the localization of moving targets. This application is motivated primarily by the low cost of this solution and the lack of effective positioning and tracking systems working inside buildings. Indeed, the global positioning system solves many localization problems outdoor, where the devices can receive the signals coming from satellites. Moreover, wireless nodes show some advantages in terms of system miniaturization, scalability, quick and easy network development, cost, and lower energy consumption.

Most of the proposed localization algorithms rely on received-signal-strength (RSS) measurements. In fact, RSS can be used to estimate the distance between an unknown node (called a target node) and a number of anchor nodes with known coordinates.

The location of the target node is then determined by multilateration [7-9].

Unfortunately, due to the degrading effects of reflections, shadowing, and fading of radio waves, some studies have shown the large variability of RSS [10-12]. As a result, localization methods using RSS are affected by large errors and lack of accuracy. However, RSS-based techniques remain an appealing approach [13]. This is mainly due to the fact that RSS measurements can be obtained with minimal effort and do not require extra circuitry, with remarkable savings in cost and energy consumption of a sensor node. In fact, most of WSN transceiver chips have a built-in RSS indicator (RSSI), which provides RSS measurement without any extra cost.

There exist several algorithms that can be used to determine the position of a target through RSS measurements. Some of them are geometric methods, such as lateration or a minimum–maximum method, whereas some others are based on statistical approaches, such as maximum likelihood.

Alippi *et al*. have tested an RSS-based outdoor localization methodology exploiting a minimum least square (LS) algorithm, after modeling a propagation channel [14]. The deployment of anchors has a density of one node over 25 m^2 on an area of 500 m^2. The average distance error obtained is about 3 m.

In [15], an extensive indoor RSS measurement campaign is carried out in order to tune the parameters of the assumed channel model. Then, the collected RSS data have been used offline as inputs for two localization methods, i.e., the min–max and Bayesian filtering algorithms. A distance error of the order of 5 and 2 m is achieved for the two algorithms, respectively.

Centroid localization (CL) and weighted centroid localization [16-22], have attracted a lot of interest because of their simplicity and robustness to changes in wireless propagation properties such as path loss. This characteristic makes them suitable candidates for systems requiring coarse grained, but reliable and cost-effective techniques. Strictly speaking, weighted centroid localization is not an entirely range-free technique because it requires additional information aside from simple connectivity.

Recently many proposed approaches on weighted centroid localization focused more on error control and management. Weighted centroid localization (WCL) is firstly proposed in [23]. In order to avoid the creation of RSS maps, complicate probability models, or high-computational-effort algorithms, Reichenbach and Timmermann proposes approximated indoor localization based on a weighted centroid approach combined with RSS measurements in an IEEE 802.15.4 sensor network [24]. The weights are defined as inversely proportional to the RSS values measured between the target and each anchor node. The solution is tested in a square room with a side length of 3 m, using four anchor nodes displaced at the corners and one target node located in 13 different positions. The obtained relative localization error varies between 7.8 % and 26 %. In [25], Hongyu *et al*. proposes an anchor_optimized modified weighted centroid localization algorithm based on RSSI (AMWCL-RSSI). Other schemes are to discuss inexact position problems [26], or analyze the performance of weighted centroid localization algorithm [27], or enhance its performance for specific scenarios [28-29].

The aim of this paper is to improve the localization accuracy of weighted centroid localization, and we propose a weighted centroid localization algorithm based on least square for WSNs. We compare our proposed scheme with some existing solutions via simulations and experiments.

The rest of this paper is organized as follows. Section 2 presents proposed localization algorithm, followed by Performance evaluation in Section 3. We conclude the paper in Section 4.

2. Proposed Localization Algorithm

2.1. Overview of Localization System

The aim of the RSS-based localization is to seek a mapping between the measurements to a physical location. One of the most important mapping functions is the probabilistic model finding the weight $p(i)$ [30, 31]. Then, the location can be regarded as a regression problem [30] as $(x, y) = \sum_{i=1}^{n} (I_i \cdot p(i))$, where n is the number of anchor nodes, I_i represents the coordinate of the ith anchor node and (x, y) represents the estimated result. This paper adopts a novel approach to compute the weight.

2.2. RSS Model

RSS model can be expressed as

$$RSS = PL0 - 10\beta \log_{10}(d / d_0) + N_\alpha , \qquad (1)$$

where d is the real distance, $PL0$ is the received signal strength at reference distance d_0 ($d_0 = 1$ m), β is the path loss exponent, and N_α is a zero-mean Gaussian noise with standard deviation α .

2.3. Weighted Centroid Localization Algorithm Based on Least Square (WCLLS)

In this section, we will introduce the proposed weighted centroid Localization Algorithm for location estimation. Let d_i denote the Euclidean distance between the coordinator of anchor i and the coordinate $(\hat{x}, \hat{y})$ for a specific unknown node. We assume that each unknown node can hear at least n anchor nodes. The variables $D = (\tilde{d}_1, \tilde{d}_2, \tilde{d}_3, \cdots, \tilde{d}_n)$ represent the set of measured distances to anchor nodes $1, 2, 3, \cdots, n$ from the unknown node. The coordinate (x, y) is an estimated position of an unknown node. The coordinate $(\hat{x}, \hat{y})$ is the position of each anchor node. According to [30] and [31], the estimated position (x, y) can be expressed by

$$(x, y) = \sum_{i=1}^{n} \left(I_i \cdot p(i) \right), \tag{2}$$

where I_i represents the i[th] anchor node location, and $I_i = (x_i, y_i)$.

$$\sum_{i=1}^{n} p(i) = 1, \quad i = 1, 2, \cdots, n \tag{3}$$

With the geometric relationships, the measured distances $\tilde{d}_i$ can be expressed by

$$\tilde{d}_i = \sqrt{(x - x_i)^2 + (y - y_i)^2} \tag{4}$$

$$\begin{cases} (x_1 - x_2) \cdot x + (y_1 - y_2) \cdot y = \frac{1}{2}[(x_1^2 + y_1^2) - (x_2^2 + y_2^2) - (\tilde{d}_1^{\,2} - \tilde{d}_2^{\,2})] \\ (x_1 - x_3) \cdot x + (y_1 - y_3) \cdot y = \frac{1}{2}[(x_1^2 + y_1^2) - (x_3^2 + y_3^2) - (\tilde{d}_1^{\,2} - \tilde{d}_3^{\,2})] \\ \vdots \\ (x_1 - x_i) \cdot x + (y_1 - y_i) \cdot y = \frac{1}{2}[(x_1^2 + y_1^2) - (x_i^2 + y_i^2) - (\tilde{d}_1^{\,2} - \tilde{d}_i^{\,2})] \\ \vdots \\ (x_1 - x_n) \cdot x + (y_1 - y_n) \cdot y = \frac{1}{2}[(x_1^2 + y_1^2) - (x_n^2 + y_n^2) - (\tilde{d}_1^{\,2} - \tilde{d}_n^{\,2})] \end{cases} \quad (i = 2, \cdots, n) \tag{5}$$

With (2) and (5), we can get

$$\begin{cases} \sum_{j=1}^{n} [(x_1 - x_2) \cdot x_j + (y_1 - y_2) \cdot y_j] p(j) = \frac{1}{2}[(x_1^2 + y_1^2) - (x_2^2 + y_2^2) - (\tilde{d}_1^{\,2} - \tilde{d}_2^{\,2})] \\ \sum_{j=1}^{n} [(x_1 - x_3) \cdot x_j + (y_1 - y_3) \cdot y_j] p(j) = \frac{1}{2}[(x_1^2 + y_1^2) - (x_3^2 + y_3^2) - (\tilde{d}_1^{\,2} - \tilde{d}_3^{\,2})] \\ \vdots \\ \sum_{j=1}^{n} [(x_1 - x_i) \cdot x_j + (y_1 - y_i) \cdot y_j] p(j) = \frac{1}{2}[(x_1^2 + y_1^2) - (x_i^2 + y_i^2) - (\tilde{d}_1^{\,2} - \tilde{d}_i^{\,2})] \\ \vdots \\ \sum_{j=1}^{n} [(x_1 - x_n) \cdot x_j + (y_1 - y_n) \cdot y_j] p(j) = \frac{1}{2}[(x_1^2 + y_1^2) - (x_n^2 + y_n^2) - (\tilde{d}_1^{\,2} - \tilde{d}_n^{\,2})] \end{cases} \quad (i = 2, \cdots, n; j = 1, 2 \cdots, n) \tag{6}$$

According to (3) and (6), we can get

$$Q = \begin{bmatrix} (x_1 - x_2) \cdot x_1 + (y_1 - y_2) \cdot y_1 & (x_1 - x_2) \cdot x_2 + (y_1 - y_2) \cdot y_2 & \cdots & (x_1 - x_2) \cdot x_j + (y_1 - y_2) \cdot y_j & \cdots & (x_1 - x_2) \cdot x_n + (y_1 - y_2) \cdot y_n \\ (x_1 - x_3) \cdot x_1 + (y_1 - y_3) \cdot y_1 & (x_1 - x_3) \cdot x_2 + (y_1 - y_3) \cdot y_2 & \cdots & (x_1 - x_3) \cdot x_j + (y_1 - y_3) \cdot y_j & \cdots & (x_1 - x_3) \cdot x_n + (y_1 - y_3) \cdot y_n \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ (x_1 - x_i) \cdot x_1 + (y_1 - y_i) \cdot y_1 & (x_1 - x_i) \cdot x_2 + (y_1 - y_i) \cdot y_2 & \cdots & (x_1 - x_i) \cdot x_j + (y_1 - y_i) \cdot y_j & \cdots & (x_1 - x_i) \cdot x_n + (y_1 - y_i) \cdot y_n \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ (x_1 - x_n) \cdot x_1 + (y_1 - y_n) \cdot y_1 & (x_1 - x_n) \cdot x_2 + (y_1 - y_n) \cdot y_2 & \cdots & (x_1 - x_n) \cdot x_j + (y_1 - y_n) \cdot y_j & \cdots & (x_1 - x_n) \cdot x_n + (y_1 - y_n) \cdot y_n \\ 1 & 1 & \cdots & 1 & \cdots & 1 \end{bmatrix} \tag{7}$$

$$, \ p=\begin{bmatrix} p(1) \\ p(2) \\ \vdots \\ p(j) \\ \vdots \\ p(n) \end{bmatrix}, \ S=\begin{bmatrix} \frac{1}{2}[(x_1^2+y_1^2)-(x_2^2+y_2^2)-(\tilde{d}_1^{\,2}-\tilde{d}_2^{\,2})] \\ \frac{1}{2}[(x_1^2+y_1^2)-(x_3^2+y_3^2)-(\tilde{d}_1^{\,2}-\tilde{d}_3^{\,2})] \\ \vdots \\ \frac{1}{2}[(x_1^2+y_1^2)-(x_i^2+y_i^2)-(\tilde{d}_1^{\,2}-\tilde{d}_i^{\,2})] \\ \vdots \\ \frac{1}{2}[(x_1^2+y_1^2)-(x_n^2+y_n^2)-(\tilde{d}_1^{\,2}-\tilde{d}_n^{\,2})] \\ 1 \end{bmatrix}, \ (i=2,\cdots,n;\ j=1,2\cdots,n)$$

$$Qp = S$$

By using least square method, $p(i)$ can be expressed as:

$$p=\left(Q^TQ\right)^{-1}Q^TS \tag{8}$$

$p(i)$ is as the weight of anchor node i ($i=1,2,\cdots,n$), but $p(i)$ can't fully reflect the binding on the estimated position of the unknown node due to the interference of external environment. To this problem, we propose a novel weight model. In the novel weight model, we increase the weight of anchor node closer to the unknown node. Because the closer anchor node gets to the unknown node, the greater weight anchor node has [23]. Meantime, we introduce the parameter k into the weight model. The reasonable parameter k can further weigh the proportion of each anchor node in the unknown node.

$p(i)\cdot(\frac{n}{k})^{p(i)}$ is the improved weight model, and $p(i)\cdot(\frac{n}{k})^{p(i)} > p(i)$ (n is the number of anchor nodes, k is a parameter, and $0<k<n$). Here, we consider the impact of the number of anchor nodes to localization accuracy in $p(i)\cdot(\frac{n}{k})^{p(i)}$.

After $p(i)\cdot(\frac{n}{k})^{p(i)}$ normalization, the weight can be expressed as:

$$w(i)=p(i)\cdot(\frac{n}{k})^{p(i)} / \sum_{j=1}^{n}(p(j)\cdot(\frac{n}{k})^{p(j)}), \ 0<k<n \tag{9}$$

$$(x,y)=\sum_{i=1}^{n}I_i w(i) \tag{10}$$

2.4. The Optimal Value of the Parameter k

In this section, we obtain the optimal value of the parameter k through the real experiment. A wireless node is based on a MSP430 microprocessor and equipped with an IEEE 802.15.4 compliant Chipcon CC2500 radio module. The antenna is a 2.4 GHz planar inverted-F antenna. In our experiments, anchor nodes are randomly distributed in a 50 m x 50 m region. The position of an unknown node is randomly deployed in this region. Here, we choose the number of anchor nodes $n=4,5,6$ respectively for our experiment, and all nodes are able to communicate with each other.

Fig. 1, Fig. 2 and Fig. 3 show the average localization error when k chooses a different value.

From Fig. 1, when the number of anchor nodes $n=4$ and the parameter $k=4$, WCLLS has a significant change in the localization accuracy. Clearly, it can be seen that when the number of anchor nodes $n=4$, k should be closer to 4, but not equal to 4.

From Fig. 2, when the number of anchor nodes $n=5$ and the parameter $k=5$, WCLLS has a significant change in the localization accuracy. Clearly, it can be seen that when the number of anchor nodes $n=5$, k should be closer to 5, but not equal to 5.

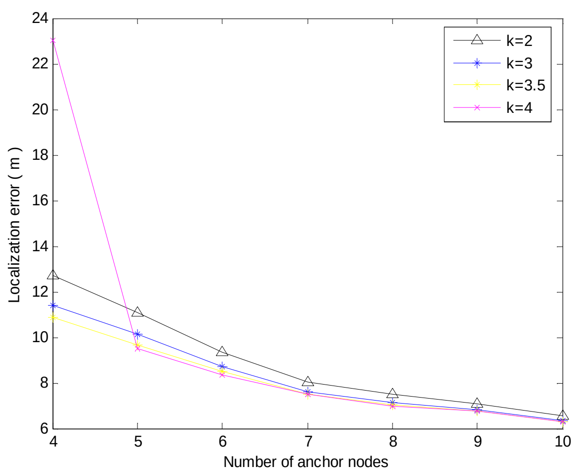

Fig. 1. Localization error versus the number of anchor nodes.

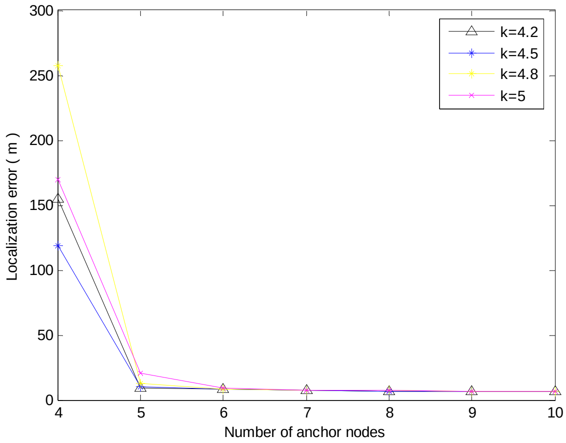

Fig. 2. Localization error versus the number of anchor nodes.

From Fig. 3, when the number of anchor nodes $n=6$ and the parameter $k=6$, WCLLS has a significant change in the localization accuracy. Clearly, it can be seen that when the number of anchor nodes $n=6$, k should be closer to 6, but not equal to 6.

From the analysis above, it can be seen that k should be closer to n, but not equal to n, and $k<n$. Hence, we assume $k=n-b$ as the value of the parameter k, where $k<n$, $0<b<n$. Next, we determine the value of the parameter b through MATLAB simulation.

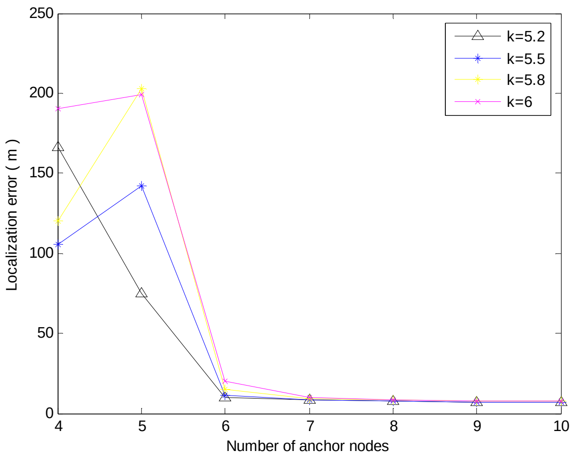

Fig. 3. Localization error versus the number of anchor nodes.

We assume that an unknown node and 8 anchor nodes are randomly deployed in a $50\text{m} \times 50\text{m}$ region, and the unknown node is randomly placed in 10000 different positions. We set $PL0=-60dB$ and choose $\beta = 2, 2.5, 3, 3.5, 4, 4.5$, the zero-mean Gaussian noise N_α has a standard deviation of $3dB$. The simulation results are as shown in Table 1. From Table 1, we can choose $n-0.1$ as the optimal value of the parameter k.

Table 1. The parameter b.

Path loss exponent	b
2	0.09
2.5	0.11
3	0.12
3.5	0.098
4	0.10
4.5	0.085

Therefore, the weight model $w(i)$ in Eq. (9) can be expressed as follows:

$$w(i) = p(i)\cdot\left(\frac{n}{n-0.1}\right)^{p(i)} / \sum_{j=1}^{n}(p(j)\cdot\left(\frac{n}{n-0.1}\right)^{p(j)}) \quad (11)$$

2.5. Process of Localization Algorithm

The algorithm process of the proposed localization algorithm is as follows:

Step 1: Beacon nodes periodically transmit information of themselves which include node ID and position information of themselves;

Step 2: After unknown node receives signals, it records RSS values which come from beacon nodes;

Step 3: Compute the measured distance $\tilde{d}_i$;

Step 4: Compute the weight $p(i)$ and the improved weight $p(i)\cdot(\frac{n}{k})^{p(i)}$;

Step 5: Compute the weight $w(i) = p(i)\cdot\left(\frac{n}{n-0.1}\right)^{p(i)} / \sum_{j=1}^{n}(p(j)\cdot\left(\frac{n}{n-0.1}\right)^{p(j)})$ through Eq. (11);

Step 6: Compute the estimated position $(x,y)=\sum_{i=1}^{n} I_i w(i)$.

3. Performance Evaluation

In this section, we analyze the performance of the studied localization schemes through simulations and experiments. We compare the proposed weighted centroid localization algorithm with WCL [23] and AMWCL-RSSI [25]. We set the degree $g=1$ in all experiments.

3.1. Localization Error Versus the Number of Anchor Nodes

In this experiment we evaluate the effect that the number of anchors has on the location accuracy.

Fig. 3 depicts the effect on localization error when varying the number of anchors. All nodes are deployed in an 100m x 100m area. Anchor nodes are randomly deployed at the edge of the selected area, 1000 sensor nodes are randomly placed in the region. We assume that $PL0 = -60dB$ and the zero-mean Gaussian noise N_α has a standard deviation of $3dB$. We set $\beta = 2$.

From Fig. 4, it can be observed that WCLLS outperforms AMWCL-RSSI and WCL in localization accuracy. The explanation is that WCLLS increases the weights of anchors closer to the unknown node. It is also shown that the increase of the number of anchor nodes can reduce the localization error of WCLLS. When the number of anchor nodes is 8, the average localization error of WCLLS is approximately 0.6 m which is significantly lower than the average localization error of AMWCL-RSSI and WCL.

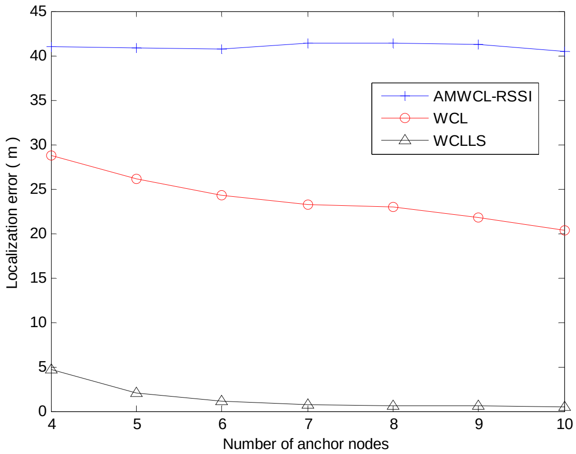

Fig. 4. Localization Error versus the Number of Anchor Nodes.

3.2. Localization Error Versus the Path Loss Exponent

In this experiment we evaluate the effect that the pass loss exponent has on the location accuracy. Fig. 5 depicts the effect on localization error when varying the pass loss exponent. All nodes are deployed in a 100m x 100m area. Four anchors are respectively placed in four corners, 1000 sensor nodes are randomly placed in the region. We assume that $PL0 = -60dB$ and the zero-mean Gaussian noise N_α has a standard deviation of $3dB$.

From Fig. 5, it can be observed that as the pass loss exponent increases, the error in location estimation increases for WCLLS. When $\beta > 2.1$, the average localization error of WCLLS is greater than the average localization error of WCL. So, we can see that the pass loss exponent has an important impart on the localization error of WCLLS. Clearly, it is shown that when β is about 2, WCLLS can obtain relative comparison small localization error. When the pass loss exponent $\beta = 2$, the average localization error of WCLLS is about 0.54 m.

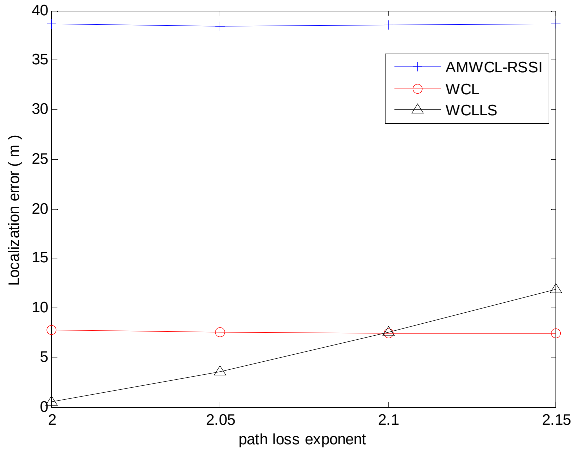

Fig. 5. Localization Error versus the Path Loss Exponent.

3.3. Localization Error Versus the Standard Deviation

In this experiment we evaluate the effect that the standard deviation has on the location accuracy. Fig. 5 depicts the effect on localization error when varying the standard deviation. All nodes are deployed in an 100m x 100m area. Four anchors are respectively placed in four corners, 1000 sensor nodes are randomly placed in the region. We assume that $PL0 = -60dB$ and $\beta = 2$.

From Fig. 6, it can be observed that as the standard deviation increases, the error in location estimation increases for WCLLS. Obviously, the standard deviation has an impact on the localization error of WCLLS. Additionally, WCLLS obviously outperforms WCL and AMWCL-RSSI in localization error.

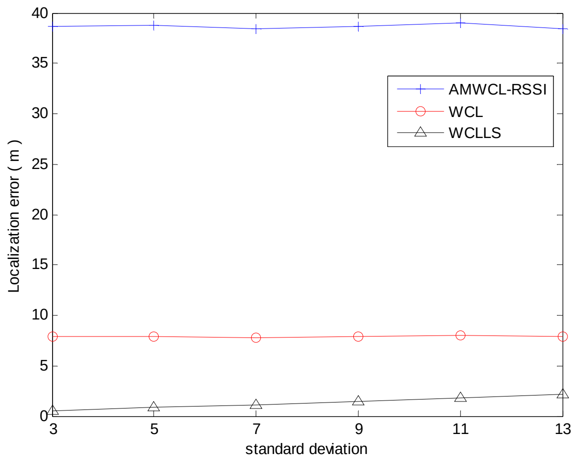

Fig. 6. Localization Error versus the Standard Deviation.

3.4. Localization Error Versus Network Size

In this simulation, we evaluate the effect the size of the network has on the location error. We simulated three network sizes: $50\text{m} \times 50\text{m}$, $100\text{m} \times 100\text{m}$ and $200\text{m} \times 200\text{m}$. Four anchors are respectively placed in four corners, 1000 sensor nodes are randomly placed in the region. We assume that $PL0 = -60dB$ and $\beta = 2$, and the zero-mean Gaussian noise N_α has a standard deviation of $3dB$.

From Table 2, it can be observed that as the network size increases, the localization error increases for all three localization algorithms. The explanation is that the error of the RSS measurement increases as the network size increases. It also can be observed that WCLLS outperforms AMWCL-RSSI and WCL in localization accuracy. From Table 2, we can clearly know that the average localization errors of WCLLS in three network sizes are respectively about 0.2 m, 0.53 m and 1 m.

Table 2. Localization error.

Localization algorithm (m)	50 m×50 m	100 m×100 m	200 m×200 m
AMWCL-RSSI	19.3	39	78
WCL	4	7.8	15
WCLLS	0.2	0.53	1

3.5. Experiments

In this section, we analyze the performance of the studied localization schemes through experiments. We compare the proposed algorithm with WCL and AMWCL-RSSI. In this experiment, the proposed algorithm is tested in a 200 m × 200 m region of our University's campus lawn, 10 anchors are randomly placed in the region and an unknown node is placed in 50 different positions. Fig. 7, a wireless node is based on a MSP430 microprocessor and equipped with a compliant Chipcon CC2500 wireless module. We obtain the measured distance by (1).

Fig. 7. Sensor node.

Table 3 shows the localization error of three localization algorithms in real experiment. In Table 3, the localization error of WCLLS is 1.2 m which is lower than that of AMWCL-RSSI and WCL. Clearly, WCLLS outperforms WCL and AMWCL-RSSI in the localization accuracy.

Table 3. Localization error.

Localization algorithms	Localization error (meters)
AMWCL-RSSI	82.3
WCL	40.1
WCLLS	1.2

4. Conclusions

Many weighted centroid localization schemes have been widely used for WSNs. However, these schemes do not help, since the localization errors are high in practical deployments. To solve these problems, in this paper we have researched and analyzed many weighted centroid localization algorithms and RSS-based localization algorithms, and we have proposed a localization scheme, called Weighted Centroid Localization Algorithm Based on Least Square. WCLLS presents a Least-Square-based weight model which can reasonably weigh the proportion of each anchor node in the unknown node. In the proposed weight model, firstly, we utilize least square method to compute the weight. Secondly, the proposed weight model increases the weight of anchor node closer to the unknown node to estimate the location. Thirdly, the parameter is introduced into the proposed weight model, and we get the optimal value of through our real experiments. We have analyzed the performance of WCLLS through the network size, the number of anchor nodes, the standard deviation and the path loss exponent. All the experimental results demonstrate that WCLLS is superior to WCL and AMWCL-RSSI in the localization accuracy. From the experimental results, we can see that WCLLS is also suitable for an outdoor environment. More importantly, WCLLS has a lower localization error.

Acknowledgements

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