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Dynamic Node Localization Algorithm based on Cooperated Prediction for Wireless Sensor Networks

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Abstract. *The node localization is one of the key technologies in Wireless Sensor Networks (WSN). In this paper, we propose a dynamic node localization algorithm based on cooperated prediction. The model between Received Signal Strength Indicator (RSSI) and distance is constructed based on the radio path loss model. The proposed localization algorithm can be used into three cases to locate the unknown nodes according to the different numbers of anchor nodes. It solves the problem that the unknown nodes cannot be located when the number of anchor nodes is less than three. The unknown node can be located by using trilateration when it can communicate with three or more anchor nodes. The unknown nodes can be located by utilizing the historical localization coordinates of unknown nodes when the number of anchor nodes is two. When the number of anchor nodes is only one, the unknown nodes judge its coordinate by utilizing the historical localization coordinates and predictable incline angle. In order to be more consistent with the actual situation, the model of irregularity degree is applied to the algorithm. Simulation results show that, compared with the traditional RSSI localization algorithm, localization success rate of the proposed algorithm is increased by about 30%.*
Keywords: Wireless sensor networks; Dynamic node localization; RSSI; Cooperated localization; Prediction localization

1. **Introduction.** Wireless sensor networks (WSN) consist of many cheap micro sensor nodes which are deployed in the monitoring area [1]. These nodes form a multi-hop and self-organized network through wireless communication. The purpose is to perceive, collect, and process the object information in the sensing area and send the information to the observers [2, 3]. In the past two decades, wireless communication and sensor technology have been actively developed [4]. At present, Sensor networks have been widely applied such as in habitat monitoring, agriculture research, fire detection and trace control [5].

The node localization is one of the key technologies in wireless sensor networks [6]. The localization method based on Received Signal Strength Indicator (RSSI) [7] has been more widely adopted because of its low-complexity, low-density of anchor nodes, and applicability to the large-scale WSN. In [8], optimal power allocation for the anchor nodes in a sense of minimizing the energy consumption considering estimation errors is investigated and the average energy of the received beacon is introduced as a new decision metric. Reference [9] proposes a mobile node localization algorithm using RSSI. A measurement error observer (MEO) is newly developed to decrease the localization error. It is combined with an interacting multiple-model filter and takes the flexible dynamic model of the mobile node into consideration. Reference [10] proposes an improved RSSI-based localization algorithm through uncertain data mapping. Starting from an advanced RSSI measurement, the distributions of the RSSI data tuples are determined and expressed in terms of interval data. Then, a data tuple pattern matching strategy is applied to the RSSI data vector during the localization procedure. Reference [11] proposes a differential RSSI-3D localization algorithm. The algorithm is mainly divided into two steps: differential RSSI ranging algorithm to measure the distance between nodes; spherical shell localization method to compute the node coordinates. Reference [12] combines Monte Carlo localization algorithm with RSSI. RSSI measurement is applied to the observation model in the Monte Carlo method. Reference [13] proposes path planning scheme, which ensures that the trail of the mobile anchor node minimizes the localization error and guarantees that all of the sensor nodes can determine their locations. Reference [14] proposes an optimization localization in wireless sensor network based on multiobjective firefly algorithm (MFA). The localization model has made up two objective functions including the space distance constraint and the geometric topology constraint. There are other algorithms like flower pollination algorithm [15]. Although domestic and foreign scholars have proposed many kinds of improved methods for node localization, they did not apply for wireless sensor networks where all the anchor nodes and unknown nodes move randomly.

2. The ranging algorithm based on RSSI.

2.1. The basic principle of RSSI ranging algorithm. RSSI-based ranging algorithm uses the principle that attenuation of signal intensity changes with the distance to estimate the distance between nodes.

Within the wireless transmission process, Long-Distance Path Loss Model [16] is the theoretical model commonly. The path loss can be defined as

$$PL(d_{ij}) = PL(d_0) + 10k\lg(d_{ij}/d_0) + X_\sigma \tag{1}$$

where $PL(d_{ij})$ is the path loss, d_{ij} is the distance between nodes i and j. d_0 is the reference distance, typically $d_0 = 1m$. $PL(d_0)$ is the path loss at the reference distance. k is the path loss exponent which changes with the environment. Usually we need to conduct numerous field of experimental measurements, the path loss exponent is closely related to the environment where the nodes are. In different environments, the measured value can be different. X_σ is a zero mean Gaussian random variable, typically $\sigma = 4 \sim 6$.

The RSSI by receiver is defined as

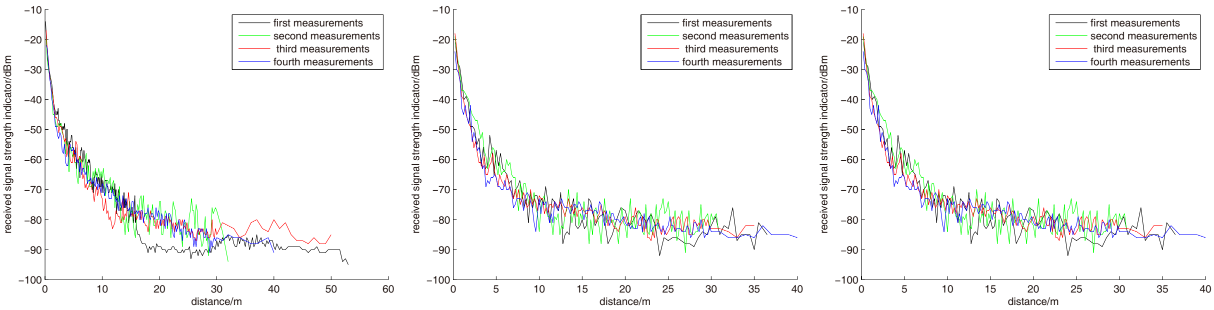
$$P(d_{ij}) = P_T + G - PL(d_{ij}) = P_T + G - PL(d_0) - 10k\lg(d_{ij}/d_0) - X_\sigma \tag{2}$$

where P_T is transmitting power, G denotes the antenna gain, $P(d_{ij})$ is the RSSI by the i^{th} receive node with respect to the j^{th} transmit node. Then, the distance between nodes i and j is

$$d_{ij} = d_0 \cdot 10^{\frac{P_T+G-PL(d_0)-X_\sigma-P(d_{ij})}{10k}} \tag{3}$$

When the unknown node can communicate with three or more anchor nodes, it can calculate its coordinates by using trilateration.

2.2. RSSI ranging experiment. To realize the localization algorithm based on RSSI, we conduct a lot of measurement experiments to obtain the actual relationship between RSSI and distance in the square, grassland, and woods respectively. We use the WLT2408Z and WAT2408Z of Xiao Wang Technology which are used as the two nodes. We totally conduct four experiments in different environments which are listed in Figure 1.



(A) (B) (C)

FIGURE 1. Raw data in different environments. (a) Raw data in the square; (b) Raw data in the grassland; (c) Raw data in the woods.

Table 1 shows the value of the path loss exponent and $PL(d_0)$ obtained by the least square fitting of a large number of data in different environments.

TABLE 1. The path loss exponent k and path loss $PL(d_0)$

	square	grassland	woods
k	3.38	3.32	3.17
$PL(d_0)$	−34.6	−38.3	−38.8

3. **Dynamic node localization algorithm based on cooperated prediction.** In WSN, the anchor nodes carrying the global position system (GPS) can obtain their positions and broadcast their localization information including their ID and coordinates in the certain time intervals. According to equation (3), the unknown nodes calculate their distances to the anchor nodes after receiving RSSI. Because all the nodes move at any time, the number of anchor nodes which can communicate with the unknown node is different at different time.

Signal transmission irregularity is a ubiquitous phenomenon in WSN. The signal transmission irregularity is affected by emission signal of non-isotropic characteristics, signal path loss of continuous change, and the anisotropy factors of hardware equipment. So the transmission radius and packet loss in different signal propagation direction are different. The irregular signal transmission model, DOI model, is proposed in [17], which also defines an upper bound and a lower bound on the radio propagation range. In order to make the algorithm be more suitable in the actual situation, the DOI model is applied to the algorithm, which is shown as:

$$P(d_{ij}) = P_T + G - PL(d_{ij}) = P_T + G - PL(d_0) - 10k\lg(d_{ij}/d_0) \times K_i \tag{4}$$

where K_i is different path loss in different transmission directions.

Besides the above factors, the signal transmission distance and the environment complexity have effect on the path loss of the signal transmission. Therefore we add the transmission radius and the environment factor into consideration and add the correction factor η to correct the path loss of the signal in all directions.

$$K_i = \begin{cases} 1, & i = 0 \\ \eta = 1 + DOI \times k^R & \\ K_{i-1} \pm \eta \times Rand \times DOI, & i = 1, 2, \ldots, 359 \\ |K_0 - K_{359}| \le \eta \times DOI & \end{cases} \tag{5}$$

where *Rand* follows Weibull distribution.

In DOI model, the actual received signal strength is in an irregular circular ring, the upper bound and lower bound of the signal can be replaced by a maximum distance and the minimum distance. Based on the large amount of data measured in the field, we can obtain the maximum distance by (6) and the minimum distance by (7).

$$d_{ij\_\min} = d_0 \cdot 10^{\frac{P_T+G-PL(d_0)-P(d_{ij})}{10k_{\min}K_i}} \tag{6}$$

$$d_{ij\_\max} = d_0 \cdot 10^{\frac{P_T+G-PL(d_0)-P(d_{ij})}{10k_{\max}K_i}} \tag{7}$$

We respectively measure the data in the cement ground square, asphalt pavement square, the square of the soil surface, and the ceramic tile face square when measuring the square data. We select the newly trimmed grassland, grassland with 5cm-high grass, grassland with 10cm-high grass, and grassland with 15cm-high grass to measure the data. When we measure the woods data, we select some different densities of the woods. From these experiments, we get the range of path loss exponent in different environments in the case of $PL(d_0) = -34.6$ dBm, which are shown in Table 2.

Table 2. The range of the path loss exponent in different environments

	square	grassland	woods
Maximum value	3.6	3.71	3.55
Minimum value	3.36	3.46	3

Table 3 shows the measurement values of $PL(d_0)$ when $d_0 = 1m$.

Table 3. The measurement values of $PL(d_0)$ in different environments

	square	grassland	woods
Experiment 1	-33	-34	-33
Experiment 2	-35	-37	-46
Experiment 3	-35.5	-39	-40
Experiment 4	-35	-43	-36

The localization algorithm can be used into three cases to locate the unknown nodes according to the different numbers of anchor nodes.

3.1. **The unknown node can communicate with three or more anchor nodes.** At time k, if the unknown node X can communicate with three or more anchor nodes, the unknown node will choose three anchor nodes whose RSSI are at the top three and calculate the maximum and minimum distance to the anchor nodes according to the equation (6) and (7). The unknown node will calculate their own coordinates by trilateration and save them. The specific process is as follows: Supposing the unknown node X separately obtains $RSSI_A$, $RSSI_B$, $RSSI_C$ from anchor nodes $A\,(x_A, y_A)$, $B\,(x_B, y_B)$, $C\,(x_C, y_C)$ and utilizes the distance transforming model to get the maximum and minimum distances d_A and d_a, d_B and d_b, d_C and d_c. So there forms three circular ring whose centers are anchor nodes A, B, C separately. The center of overlapping area of the three circular rings is the position of the unknown node as shown in Figure 2. The position of unknown node can be described as:

$$\begin{cases} d_a \le \sqrt{(x-x_A)^2+(y-y_A)^2} \le d_A \\ d_b \le \sqrt{(x-x_B)^2+(y-y_B)^2} \le d_B \\ d_c \le \sqrt{(x-x_C)^2+(y-y_C)^2} \le d_C \end{cases} \tag{8}$$

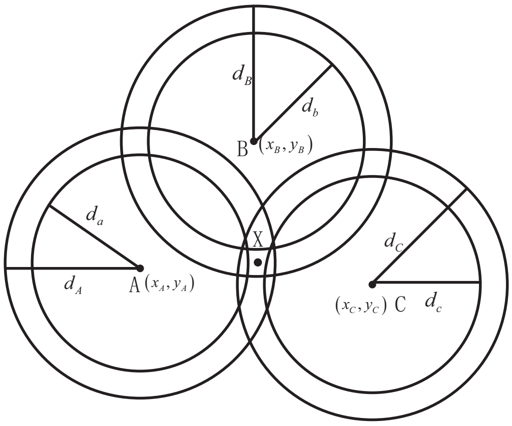


FIGURE 2. Using three anchor nodes to locate the unknown node

Anchor nodes and unknown nodes move according to their preseted speed and angle. At time $k+1$, the unknown nodes can re-judge the number of anchor nodes which can communicate with, then repeat localization operation.

3.2. **The unknown node can communicate with two anchor nodes.** At time k, if the unknown node X can only communicate with the anchor node A and B, which is listed in Figure 3, X can't locate itself by trilateration. Supposing the moving speed of unknown node is v and it has been located successfully at time $k-1$. The coordinate at time $k-1$ is (x_{k-1}, y_{k-1}). At time k, the maximum distances between the unknown node X and the anchor nodes A and B are d_A and d_B, the minimum distances between the unknown node X and the anchor nodes A and B are d_a and d_b. So there form two circular rings whose centers are anchor nodes A, B separately. The centers of two overlapping area are $X_1\,(x_1, y_1)$ and $X_2\,(x_2, y_2)$ respectively. At time $k-1$, the distances between the unknown node X and X_1, X_2 are d_1 and d_2. At time k, we can locate X by comparing speed and d_1, d_2. if $|d_1 - v| < |d_2 - v|$, the X coordinate equals X_1 coordinate; if $|d_2 - v| < |d_1 - v|$, the X coordinate equals X_2 coordinate.

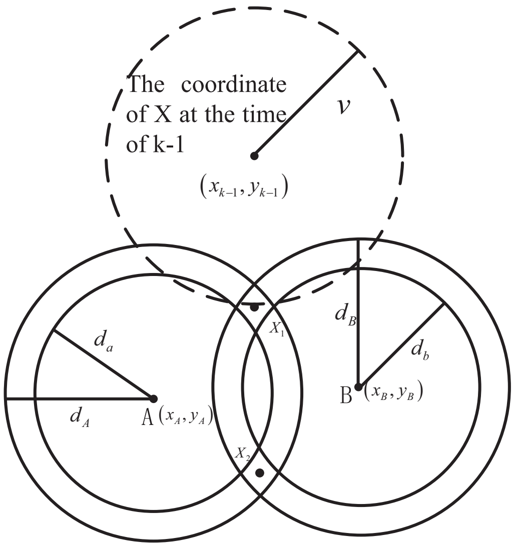


FIGURE 3. Using 2 anchor nodes to locate the unknown node

3.3. **The unknown node can communicate with only one anchor node.** In this situation, the algorithm uses grey model (GM) to predict the moving direction of the unknown nodes. At time k, the unknown node X can communicate with only one anchor node A, the speed of the unknown node is v. It has been located successfully from $(k-n)^{\text{th}}$ moment to $(k-1)^{\text{th}}$ moment. $\theta_i = (\theta_{k-n}, \theta_{k-n+1}, \cdots, \theta_{k-1})$ is the first n moments coordinate incline angle set. Where $\theta_i = arc\tan(y_i/x_i)$. A set of value difference of adjacent angle $\Delta\theta_i = (\Delta\theta_1, \Delta\theta_2, \cdots, \Delta\theta_{n-1})$ can be obtained by two adjacent elements subtraction. The $n-1$ angle differences can be obtained to predict n^{th} angle difference so as to calculate the incline angle of the unknown node at time k. here take the angle difference sequence as the original sequence, we can get θ_k by GM.

There are two circles. The first one's centre is the X coordinate at time $k-1$. Its radius is speed v. The second is a circular ring. Its centre is anchor node A at time k. Its radius ranges from d_A to d_a. The overlapping areas are two curves. Their centers are X_1 and X_2. The X coordinate is one of them at time k. The incline angle of the Line L is the incline angle of the unknown node (θ_k). The unknown node X can be located by judging the distances between X_1, X_2 and line L. The coordinate of the unknown node is the one who is closer to line L among X_1 and X_2. As shown in Figure 4, the X coordinate equals X_2 coordinate at time k.

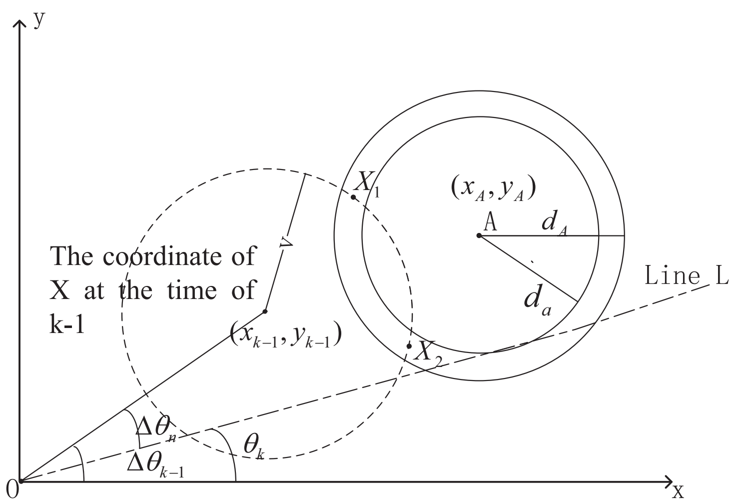


FIGURE 4. Using one anchor node to locate the unknown node

4. **Experimental simulation and analysis.** In the beginning of the simulation, this paper first describes two definitions. The localization success rate is the ratio of the number of unknown nodes that can be located and the number of all unknown nodes. The relative error is the error between locating position and real position for the unknown nodes, which is described as times the distance of communication radius.

In Matlab7.0, 400 nodes, including 120 anchor nodes, are distributed randomly in an area of 300m $\times$ 300m. The communication radius is 20m. The maximum moving speed is 1.4m/s. The maximum moving angle is $\pm 22.5°$.

Figure 5 shows the success rate of the traditional RSSI localization algorithm and the proposed localization algorithm based on cooperated prediction. The success rate of new localization algorithm increases from 25% to 50% before the first ten rounds. Then the localization success rate has been maintained at around 50%. The reason is that the proposed localization algorithm can solve the problem that the unknown nodes cannot be located when the number of anchor nodes are less than three.

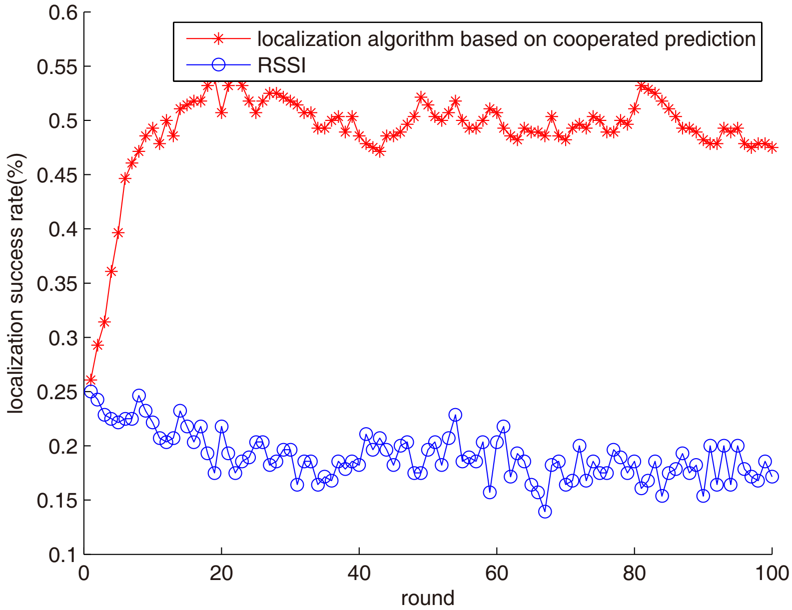


Figure 5. Localization success rate comparison

Figure 6 shows the average localization error of the traditional RSSI localization algorithm and the proposed localization algorithm based on cooperated prediction. The average relative error per each round of the improved algorithm is 0.54 improved by 24%. It is due to the introduction of moving speed and direction of prediction, with the increase of the localization success rate, the relative localization error will inevitably increase.

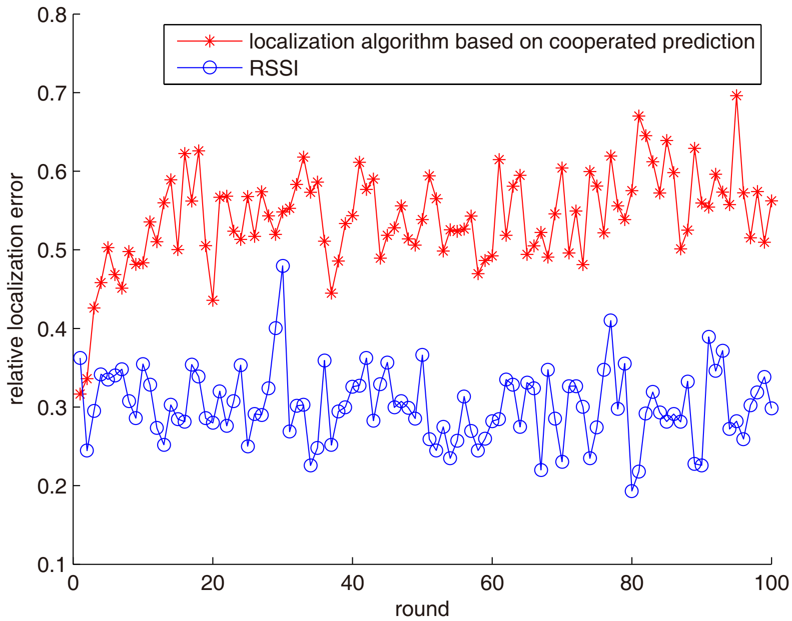


Figure 6. Comparison of average relative error

Figure 7 shows the effect of communication radius on localization success rate. When the communication radius becomes larger, the localization success rate becomes higher. When the communication radius is 40m, the localization success rate is nearly 100%. Only the individual isolated nodes cannot be located.

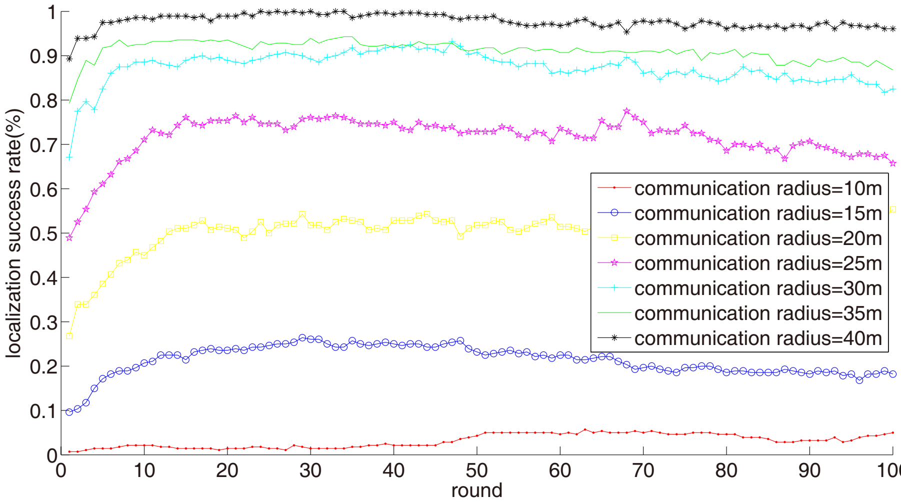


Figure 7. The effect of communication radius on localization success rate

Figure 8 shows the effect of the communication radius on relative localization error. The smaller the communication radius is, the greater the average relative error is. When the communication radius is 10m, the average relative error is 0.65. When the communication radius is 40m, the average relative error is 0.25. The smaller communication radius is, the larger fluctuation of the relative error of each round is. It is because when the communication radius is larger, the unknown node can communicate with more anchor nodes, thus the unknown node localization error will be smaller.

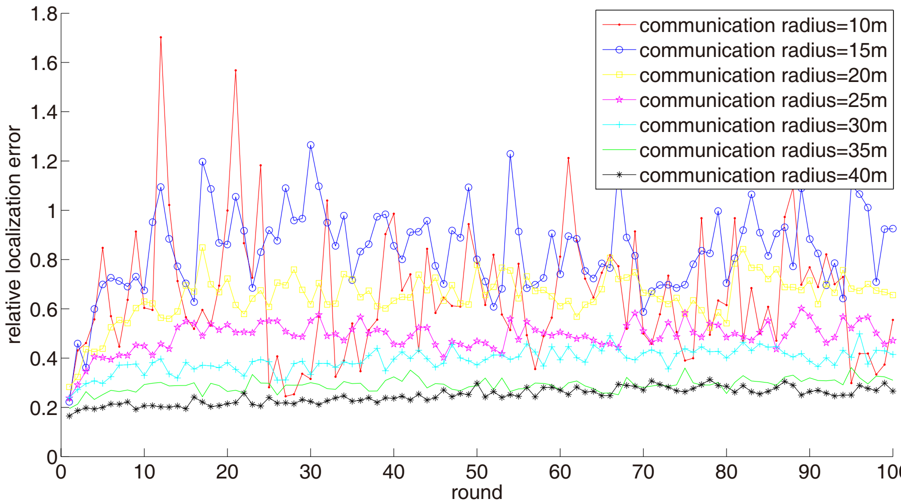


Figure 8. The effect of communication radius on relative localization error

Figure 9 shows the effect of moving speed on localization success rate. The average localization success rate ranges from 49% to 54% in different speeds. So the effect of moving speed on the localization success rate is not very large. The reason is that maximum speed of all nodes are the same, isolated nodes may well find the anchor nodes. This shows that the algorithm has a good adaptability to moving speed.

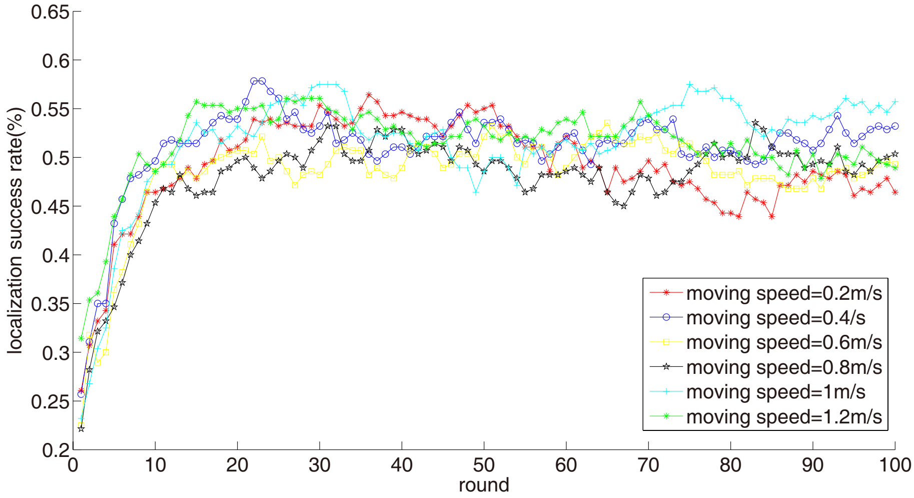


FIGURE 9. The effect of moving speed on localization success rate

Figure 10 shows the effect of moving speed on relative localization error. With the increase of the number of rounds, relative localization error fluctuates in the range of 0.5 to 0.9. The effect of moving speed on relative localization error is not obvious. So the algorithm has a good adaptability to moving speed.

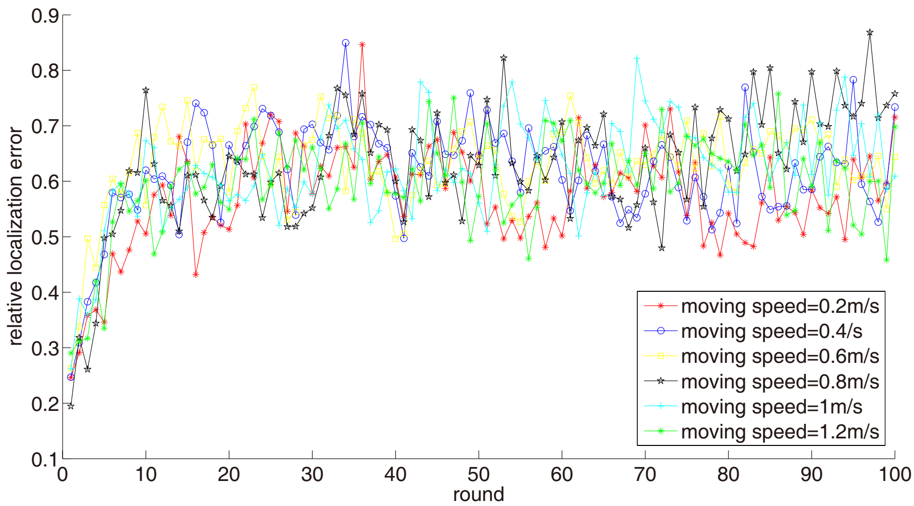


FIGURE 10. The effect of moving speed on relative localization error

5. **Conclusion.** This paper proposes a moving node localization algorithm based on cooperated prediction for wireless sensor networks. In order to obtain more actual parameters, we adopt fitting method to get distance-power transforming model. In this paper, RSSI localization algorithm is applied in wireless sensor networks where all anchor nodes and unknown nodes move randomly. The unknown node can be located by using trilateration when it can communicate with three or more anchor nodes. The unknown node can be located by utilizing the historical localization coordinates of unknown nodes when it can communicate with two anchor nodes. When the unknown node can communicate with only one anchor node, it judges its coordinate by utilizing the historical localization coordinates and predictable incline angle. Therefore the algorithm successfully solves the problem that the unknown nodes cannot be located when the number of anchor nodes

is less than three. Simulation results show that, compared with the traditional RSSI localization algorithm, localization success rate of the proposed algorithm is improved by about 30%, but the average relative error is improved by about 24%.

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