Three-Dimensional Node Localization Algorithm for WSN Based on Differential RSS Irregular Transmission Model

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Abstract —The localization accuracy of the conventional three-dimensional (3D) node localization algorithm based on received signal strength (RSS) is restricted by the random signal strength fluctuation caused by the irregular propagation environments. In this paper, we propose an improved localization algorithm based on a differential RSS distance estimation algorithm to minimize the influence of the path loss exponent error. Furthermore, considering the influence of degree of irregularity (DOI), we propose a new radio model and obtain numerically the relation between DOI and the variation of signal transmission ranges. A spherical shell with certain finite thickness is then used to characterize the transmission range irregularity. The simulation results show the path loss exponent has no effect on localization error in the proposed algorithm. The localization errors for various DOIs are significantly lower than the conventional 3D algorithm for different densities of anchor nodes.

Index Terms—Three-dimensional node localization, RSS, irregular transmission model, DOI, WSN

I. Introduction

In recent years, node localization technologies of wireless sensor networks (WSN) are applied widely in target tracking, event monitoring, positioning and routing, et al. WSN nodes are often distributed in complex three-dimensional (3D) environments such as mountain, forest and sea where two-dimensional localization technologies cannot be applied directly. Therefore, it is important to research 3D localization technologies for practical applications.

Among the existing localization algorithms, the received signal strength (RSS) based approach is most widely used in large-scale networks because of its low-complexity and low-cost. However, in order to obtain high localization accuracy, the RSS-based algorithm needs an accurate relation between the RSS and the distance for each transmitter-receiver pair. Several empirical models are proposed to correlate the path loss with the distance. But different models are for different environments; and the parameters of a model also depend on the specific site where the measurements are taking place. It is very difficult to choose the right parameters and the right model for each transceiver pair in a large WSN. Moreover, these models do not take into account severe propagation effects such as multipath, fading, shadowing, etc. [1]. Thus, the distance estimations by RSS-based approaches are usually not accurate and consequently the node localization is also not accurate.

There have been many research results for improving the accuracy of node localization using the RSS-based approaches. The method in [2] called TR2S2 (Trilateration based on Ratio of Received Signal Strength) takes advantage of the fact that the ratio of RSS from a pair of base stations (BS) varies little when the environment changes as the RSS from either BS increases or decreases simultaneously. TR2S2 uses the RSS ratio between BS1 and BS2 as an intrinsic data entity to pinpoint a reference point in the radio map of the environment. Using training processes, the authors create a 3D radio map by recording every reference point. A Three-Dimensional Compressive Sensing (3D-CS) approach is proposed for node localization [3] where a 3D sparsity basis and a 3D measurement matrix are used as radio map and noisy measurements, respectively, in order to recover the target position. Reference [4] utilizes the estimated error in distance to decrease the error of the RSS-based localization to a certain extent. The method has better performances than the initial RSS algorithm in locating accuracy and responding time. But the required angle information is difficult to acquire in practical applications. Reference [5] attains more accurate results by selecting the max-RSS point instead of the two end points of the chord. Its error decreases by about 50%. This method in [6] utilizes the RSS loss formula to weight the localization process to get more accurate estimates with a nearly invariant locating time. Meanwhile, it reduces the occurrence probability of the “in-to-out error”. Reference [7] proposes a method based on RSS when the sensors are placed in optimal 3D environment. The source can be localized optimally at various non-coplanar sensors under Lognormal Shadowing. Reference [8] uses Kalman filter to process the RSS in order to calculate the absolute position and estimate the relative values. The preprocessing algorithm can significantly reduce the distance estimation error, but the communication and computation overheads increase.

Manuscript received December 27, 2013; revised April 14, 2014.
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doi:10.12720/jcm.9.5.391-397

To improve the localization precision, reference [9] introduces into the RSS-based localization algorithm a link quality indicator (LQI), which has a larger dynamic range and a higher resolution than the original RSS-based algorithm. However, this algorithm requires in advance the relative distance information, which is difficult to obtain in practice. Considering the path loss of outdoor environment, the authors in [10] put forward an improved outdoor localization method based on RSS, which uses target tracking and analyzes the raw RSS data taken in the outdoor environments to calculate the distance between the anchor nodes and the unknown node. But, it increases the network complexity and communication burden. Reference [11] proposes an indoor 3D localization algorithm based on RSS which utilizes Artificial Neural Networks (ANN) and Support Vector Machines (SVM) to improve the localization accuracy. But this algorithm mainly focuses on the theoretical analysis. In addition it also increases the complexity.

In summary, the main factors causing the localization estimation errors by RSS-based approaches are the use of inaccurate propagation model and the neglect of path loss irregularity. Firstly, although the propagation models should change with different environment conditions in order to reflect the complex propagation effects, the existing improved RSS-based localization algorithms mostly rely on accurate information of the environments in order to yield accurate location estimates. However, since the environments are usually unknown, it is very likely to use a wrong propagation model or a wrong propagation parameter. This will inevitably cause significant localization errors. Secondly, the other main factor causing location estimation errors is the neglect of path loss irregularity due to various fading effects. Since the environments are very complex, the path loss is random in nature. Thus, the relation between distance and RSS is then uncertain even an appropriate propagation model in employed. However, the existing improved RSS-based localization algorithms mostly either rely on averaging over a large number of measurements which increases the communication and computation overheads or ignore the random effects and sometimes even require additional propagation information which is not practical.

In this paper, we propose a low complexity RSS-based localization algorithm to improve the node localization accuracy. Based on a differential RSS transmission model, the path loss exponent effects are canceled and the errors caused by using an inaccurate path loss exponent are minimized. In addition, in order to improve the localization accuracy under transmission irregularity, we propose a revised degree of irregularity (DOI) model for node localization where we study the relation between the DOI and transmission range. The computational complexity of the proposed approach is very low, which is the same as the original unimproved RSS-based node localization algorithm. We test the performance of the proposed algorithm using numerical simulations.

II. 3D RSS-BASSED NODE LOCALIZATION

The RSS-based node localization algorithms generally consist of two steps. Firstly, based on some empirical path loss models, derive the distances between some transceiver pairs from the corresponding RSS's. Secondly, based on some localization schemes, calculate the coordinates of the unknown nodes using the derived distances.

A. The Relation between Distance and RSS

At present, the radio propagation path loss models include Free Space Propagation Model, Two-Ray Ground Reflection Model, Log-Distance Path Loss Model, Log-Normal Shadowing Model, and Hata model [1,2,12，13,14,15], etc. In this paper, we use the Log-Normal Shadowing Model. The path loss is 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 and 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, typically $k = 2 \sim 6$. X_σ is a zero mean Gaussian random variable that reflects the random variation in the path loss due to shadow fading, namely $X_\sigma \sim [0, \sigma^2]$. The values of k and σ also depend on the environment, and line-of-sight (LOS) or non-line-of-sight (NLOS) illumination. The values of k and σ in some specific environments are shown in Table I [16]. Note that, in practice, the best-fit path loss parameters k and σ are usually unknown. A better choice of k will result in a smaller σ .

TABLE I. TYPICAL PATH LOSS PARAMETERS IN DIFFERENT ENVIRONMENTS

Environment	k		σ (dB)	
	LOS	NLOS	LOS	NLOS
Residential	1.79	4.58	2.22	3.51
Office	1.63	3.07	1.9	3.9
Outdoor	1.76	2.5	0.83	2
Open outdoor	1.58		3.96	
Industrial	1.2	2.15	6	6

Let P_T denote the transmitting power and G denote the antenna gain. The RSS by the i^{th} receive node with respect to the j^{th} transmit node, $P(d_{ij})$, is defined as

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

Then, the distance d_{ij} between nodes i and j is

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

Since X_σ is not known in practice, there will be error on estimating d_{ij} . As the distribution of X_σ is a zero mean Gaussian, the maximum likelihood estimation $\hat{d}_{ij}$ of d_{ij} is to assume $X_\sigma=0$. Thus,

$$\hat{d}_{ij} = d_0 \cdot 10^{\frac{P_T+G-PL(d_0)-P(d_{ij})}{10k}} \quad (4)$$

Obviously, a better choice of the path loss exponent k will result in a smaller average estimation error $E(\left|d_{ij}-\hat{d}_{ij}\right|)$.

B. The Conventional 3D Localization Scheme

The conventional localization algorithm in 3D WSN uses the estimated distances between the unknown node and some known anchor nodes to calculate the positions of the unknown node. Each unknown node needs to communicate with at least four neighboring anchor nodes to obtain the corresponding RSS values. Using (4), an unknown node can estimate its distance to each anchor node. If there are four or more anchor nodes, the unknown node can use the estimated distances to estimate its coordinates [6], [17].

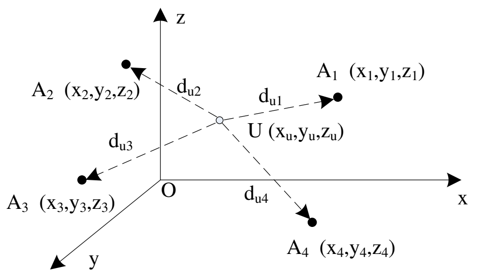

Fig. 1. The schematic diagram of the node localization algorithm

As illustrated in Fig. 1, the known coordinates of the four anchor nodes A_1 , A_2 , A_3 , and A_4 are (x_1, y_1, z_1) , (x_2, y_2, z_2) , (x_3, y_3, z_3) , and (x_4, y_4, z_4) , respectively. The coordinate of the unknown node U is (x_u, y_u, z_u) . The distances from the unknown node to the four anchor node A_1 , A_2 , A_3 , and A_4 , respectively are d_{u1} , d_{u2} , d_{u3} , and d_{u4} . Since there are estimation errors on these distances, there will also be estimation errors on the unknown coordinates. The estimated coordinates $(\hat{x}_u, \hat{y}_u, \hat{z}_u)$ of node U can be calculated by solving the following system of nonlinear equations

$$(x_j-\hat{x}_u)^2+(y_j-\hat{y}_u)^2+(z_j-\hat{z}_u)^2=\hat{d}_{uj}^2,\ j=1,2,3,4 \quad (5)$$

There will usually be no solution to (5) if there is any distance estimation error. Instead, the coordinates are estimated as follow

$$(\hat{x}_u, \hat{y}_u, \hat{z}_u) = \arg\min_{(x_u,y_u,z_u)} \sum_{j=1}^{4} \left|(x_j-x_u)^2+(y_j-y_u)^2+(z_j-z_u)^2-\hat{d}_{uj}^2\right| \quad (6)$$

Since (5) is nonlinear, an error in distance estimation could result in a much larger error in coordinate estimations, especially when node U is not at or near the center of the region surrounded by the anchor nodes.

III. 3D Differential RSS Node Localization Based on Irregular Transmission Model

As discussed in Sec. II, there are two drawbacks in conventional RSS-based localization algorithms. The first drawback is regarding the mapping from RSS to node distance according to an empirical path loss model. Since the path loss exponent k is usually unknown and may vary with the changes of environments, an inappropriate choice of k will result in large distance estimation errors. The second drawback is regarding the set of nonlinear equation in (5) where an error in distance estimation could result in much larger errors in coordinate estimations. To mitigate these two drawbacks, we propose a differential RSS localization algorithm based on an irregular transmission model. The proposed new algorithm has the following two main improvements over the conventional RSS-based localization algorithms.

A. Differential RSS Distance Estimation

To avoid the effects of the path loss exponent, k , error on the distance estimation, a differential RSS distance estimation is proposed. For convenience and without loss of generality, assume all the anchor nodes have the same transmitting power P_T and the same antenna gain G . When some nodes are in the same cluster or in short distances with one another, they are most likely in the same propagation environment and have the same path loss exponent. Denote the distance between an anchor node A_t and the unknown node U as d_{ut} . Also let $P(d_{ut})$ be the RSS received by the unknown node U with respect to the transmission from the target anchor node A_t . According to (2),

$$P(d_{ut}) = P_T + G - PL(d_0) - 10k\lg(d_{ut}/d_0) - X_{\sigma 1} \quad (7)$$

Let A_i and A_j be two nearby reference anchor nodes. Denote the distance between A_i and A_j as d_{ij} , the RSS from A_j to A_i as. $P(d_{ij})$ Then

$$P(d_{ij}) = P_T + G - PL(d_0) - 10k\lg(d_{ij}/d_0) - X_{\sigma 2} \quad (8)$$

Assume $d_0=1$. Since (7) and (8) have the same path loss exponent k , combine (7) and (8) to obtain

$$d_{ut} = 10^{\frac{P_T+G-PL(d_0)-P(d_{ut})-X_{\sigma 1}}{P_T+G-PL(d_0)-P(d_{ij})-X_{\sigma 2}}\lg d_{ij}} \quad (9)$$

Note that the target anchor node could also be used as one of the two reference anchor nodes. That means A_t could be A_i or A_j . To simplify (9), define

$$W_n = P_T + G - PL(d_0) - X_{\sigma n},\quad n = 1,2 \tag{10}$$

and substitute (10) into (9) to obtain

$$d_{ut} = 10^{\frac{W_1 - P(d_{ut})}{W_2 - P(d_{ij})}\lg d_{ij}} \tag{11}$$

Since $X_{\sigma 1}$ and $X_{\sigma 2}$ are unknown, W_1 and W_2 in (11) are also unknown. The maximum likelihood estimate is

$$\hat{d}_{ut} = 10^{\frac{W - P(d_{ut})}{W - P(d_{ij})}\lg d_{ij}} \tag{12}$$

where

$$W = P_T + G - PL(d_0) \tag{13}$$

If there is no anchor node nearby can be used as the reference, d_{ut} will be estimated using the communication range R as the reference. Usually, the longer the distance between the two transceiver nodes is, the smaller the RSS is. Then the smallest RSS is corresponding to the longest separation between the two transceiver nodes, which is approximated as R. Let $P(d_{\min})$ be the minimum RSS of the unknown node. Thus,

$$d_{ut} = 10^{\frac{W - P(d_{ut})}{W - P(d_{\min})}\lg R} \approx 10^{\frac{W - P(d_{ut})}{W}\lg R} \tag{14}$$

B. DOI Propagation Model

It is a very common phenomenon that the propagation ranges of RF signals in different directions can be quite different. In[18], the authors proposed to characterize this kind of RF signal transmission irregularity using the DOI model where DOI is defined as the maximum radio range variation per unit degree change in the direction of radio propagation. As shown in Fig. 2, when DOI=0, there is no transmission irregularity and the transmission range is an ideal spherical shell. With the increasing of DOI value, the transmission range becomes more and more irregular.

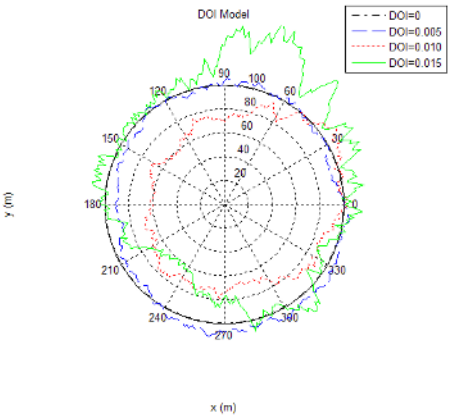

Fig. 2. The effect of DOI on propagation ranges

The DOI model in [18] also defines an upper bound and a lower bound on the radio propagation range. When the distance between a transceiver pair is larger than the upper bound, the transceiver pair is said to be out of the communication range. When the distance is less than the lower bound, the transceiver pair is guaranteed to be within the communication range. If the distance is between these two bounds, the probability for the transceiver pair to be within the communication range is determined by the actual distance value and the DOI value.

To take the transmission irregularity into consideration for differential RSS distance estimations, we include DOI in (12) and (14) as following:

$$\hat{d}'_{ut} = 10^{\frac{W - (1+doi)P(d_{ut})}{W - (1+doi)P(d_{ij})}\lg d_{ij}} \tag{15}$$

$$d'_{ut} = 10^{\frac{\hat{W} - (1+doi)P(d_{ut})}{\hat{W}}\lg R'} \tag{16}$$

$$R' = \frac{\sum_{n=1}^{360} R(1 + doi(n))}{360} \qquad (n = 1,2,\ldots,360) \tag{17}$$

where doi is a uniformly distributed random variable, namely $doi \sim U[-DOI, DOI]$. Note that (15) or (16) is similar to (9) except that the random variables $X_{\sigma 1}$ and $X_{\sigma 2}$ in (9) are Gaussian and the random variable DOI in (15) or (16) is uniformly distributed. It is found numerically that the DOI model is preferred because the estimation errors caused by transmission irregularity in the DOI model are bounded.

The signal transmission distance varies with the different values of DOI. When the DOI changes, the communication range R' changes within a certain range, namely $R' \in [R - R \cdot doi, R + R \cdot doi]$. R' is defined as the statistical average value of the communication range variation per unit degree change in the direction of radio propagation in (17). It is effective to improve the adaptability to the environment.

The influence of different DOI values on the signal transmission range estimation by (15) or (16) is studied through many numerical experiments. The results are summarized in Table II.

TABLE II. RELATION OF DOI AND SIGNAL TRANSMISSION RANGE

DOI	Radius of spherical shell
0	R
0.005	0.9R-1.1R
0.01	0.85R-1.15R
0.015	0.8R-1.2R
0.02	0.75R-1.25R

This is illustrated in Fig. 3, in which the upper bound is denoted by sphere a and the lower bound is denoted by sphere c. The irregular curve d denotes typical radio ranges of an anchor node, which are less than the upper bound but larger than the lower bound. Note that the typical radio ranges are direction dependent. Also shown in Fig. 3 is the sphere b which denotes an ideal case where the communication range R is a constant in all directions. From Fig. 3, we conclude that the unknown source is located within a spherical shell with the upper bound as the outer radius and the lower bound as the inner radius.

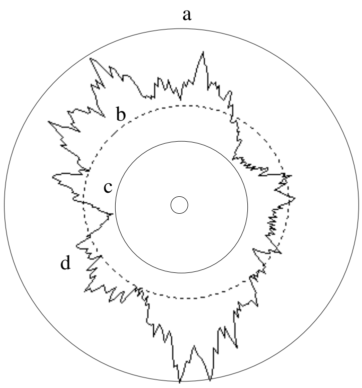

Fig. 3. Upper and lower bounds of transmission ranges

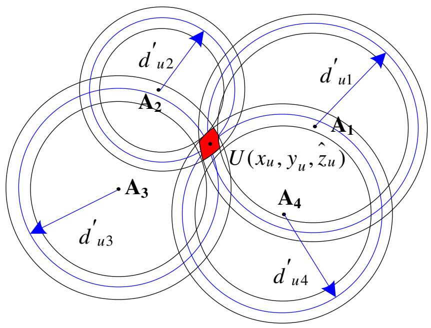

Fig. 4. Node localization diagram

Substitute (15) or (16) into (6), one can then solve (6) for finding the location estimate $(\hat{x}_u, \hat{y}_u, \hat{z}_u)$ of the unknown node U where the transmission irregularity effects are taken account for. Since each of the four equations in (5) defines a spherical shell, (6) can be solved alternatively as a centroid of the intersection regions of the four spherical shells (see Fig. 4). This approach will be denoted as the Centroid Algorithm [19]. In summary, the DOI model is incorporated into the differential RSS range estimation formulas to take the transmission irregularity into considerations. The node localization problem can then be solved by the Centroid Algorithm to estimate the nodes position.

IV. Experimental Analysis

In Matlab7.0, we distribute randomly 100 nodes (including anchor nodes and unknown nodes) in an area of $500\times500\times500\text{m}^3$. The number of anchor nodes is variable. The communication radius of all nodes is 100m. We repeat the test 50 times for each algorithm under the same network environment to calculate the average localization error. The localization error is defined as the ratio of the Euclidean distance between estimated position and actual position to the communication radius. The numerical experiment consists of the following four steps:

1) The first step is to establish the network model. Given a 3D network, $Z=(V,E)$ is the network structure, where V is the set of the anchor nodes in the network, E is the set of the unknown nodes in the network. Let $i\in V$ and $j\in E$. Define d_{ij} as the distance between node i and node j; $P(d_{ij})$ is the signal strength between node i and node j.

2) The anchor nodes transmit their node ID and coordinates. The path loss is calculated using (1) with $X_\sigma \sim [0,\sigma^2]$, σ=2. The unknown nodes record RSS and location information of the anchor nodes after receiving the transmitted signals of the anchor nodes. At the same time, the unknown nodes will rank the anchor nodes according to RSS.

3) Adopt (15) or (16) to calculate the distances between unknown nodes and anchor nodes. Obtain the distance matrix for the whole WSN.

4) Adopt DOI propagation model and relations of DOI and signal transmission range in TABLE II to confirm the actual spherical shells with certain thickness.

5) Use Centroid Algorithm to estimate the positions of the unknown nodes.

Fig. 5 shows the result of proposed 3D localization algorithm. There are 36 anchor nodes in the 3D area. DOI=0.01. "☆"represents the anchor nodes with known locations. "○"represents the target nodes with unknown locations. "□"represents estimated positions of the target nodes using the proposed algorithm.

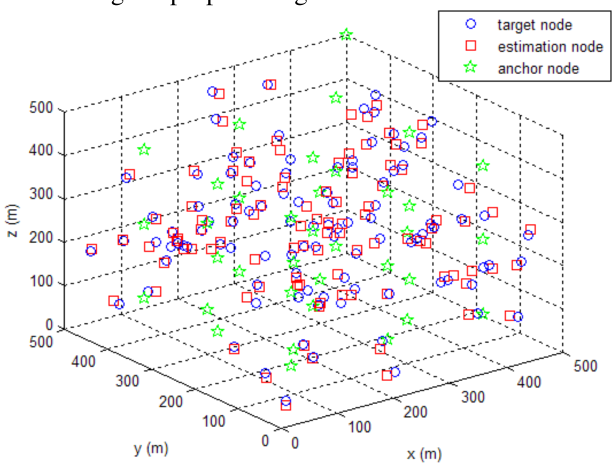

Fig. 5. 3D localization result

Fig. 6 shows the average localization error of the conventional RSS-3D algorithm and the proposed localization algorithm based on a differential RSS irregular transmission model for different numbers of anchor nodes and DOI. Firstly, when the number of anchor nodes increases, average localization error of two algorithms reduces. The average localization error of the proposed algorithm is about 10% less than the conventional RSS-3D algorithm as DOI=0. Secondly, with the increase of DOI, more and more radio propagation irregularities cause the localization error to increase. When DOI=0~0.015, the localization error of the proposed algorithm is smaller than traditional RSS-3D algorithm. When DOI=0.02, the localization error of the proposed algorithm is larger than traditional RSS-3D algorithm.

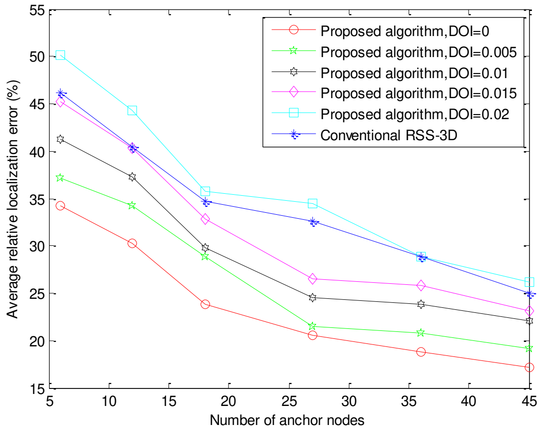

Fig. 6. Comparison of localization errors for different numbers of anchor nodes and different DOI

Fig. 7 shows the effects of the path loss exponent k and the number of anchor nodes on the average localization error as DOI=0. Assume the real path loss exponent $k = 2.5$. For the conventional algorithm, a better choice of the path loss exponent k will result in a smaller average localization error. But the best-fit path loss exponent is usually unknown. From Fig. 7, we can observe that unsuitable values of k will cause obvious errors and a bigger deviation from the true k will cause a larger error. However, for the proposed algorithm, there is no need to choose the path loss exponent k .

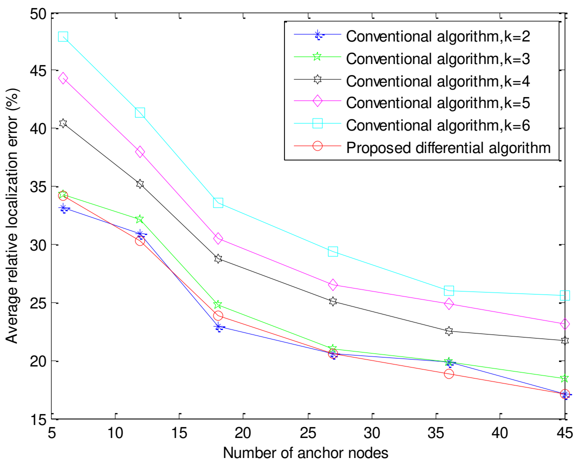

Fig. 7. Comparison of localization errors for different numbers of anchor nodes and different path loss exponents *k*.

V. CONCLUSION

Considering the disadvantages of the conventional RSS-based mode localization algorithm, we propose an improved 3D localization algorithm to mitigate the main factors that cause the localization errors. To reduce the influence of path loss exponent k , we put forward a differential RSS distance estimation algorithm which can be applied to different environments. To reduce the influence of path loss irregularity, we put forward a revised DOI model and obtain numerically the relation between DOI and signal transmission range. The simulation experiments show, comparing with the conventional RSS-3D algorithm, the proposed algorithm improves the WSN node localization accuracy for different numbers of anchor nodes, different values of DOI and different propagation environments (characterized by different path loss exponents k).

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