Localization in Sensor Networks with Fading Channels Based on Nonmetric Distance Models

Viet-Duc Le, Young-Koo Lee, and Sungyoung Lee

Department of Computer Engineering, KyungHee University
Seocheon-dong, Giheung-gu, Youngin-si, Gyeonggi-do 446-701, Korea
{levietduc,sylee}@oslab.khu.ac.kr, yklee@khu.ac.kr

Abstract. Wireless Sensor Network (WSN) applications nowadays are an emerging avenue in which sensor localization is an essential and crucial issue. Many algorithms have been proposed to estimate the coordinate of sensors in WSNs, however, the attained accuracy in real-world applications is still far from the theoretical lower bound, Crame-Rao Lower Bound (CRLB), due to the effects of fading channels. In this paper, we propose a very simple and light weight statistical model for rang-based localization schemes, especially for the most typical localization algorithms based on received signal strength (RSS) and time-of-arrival (TOA). Our proposed method infers only the order or the nomination of given distances from measurement data to avoid significant bias caused by fading channels or shadowing. In such way, it radically reduces the effects of the degradation and performs better than existing algorithms do. With simulation of fading channels and irregular noises for both the RSS-based measurement and the TOA-based measurement, we analyze and testify both the benefits and the drawbacks of the proposed models and the localization scheme.

Keywords: Localization, Nonmetric, Fading channel, Shadowing.

1 Introduction

Node Localization plays a fundamental role in Wireless Sensor Network applications which are rapidly growing. Especially, in applications for dynamic environment such as manufacturing logistics, asset tracking, context aware computing, where sensors may change their locations time by time without notice. In addition, in large scale WSN applications where sensors are deployed randomly in vast areas, for instant, environment monitoring, conservation biology and precision agriculture, the measured information must stick with location information so that the data are meaningful. Hence, it is critical that self-localization or node localization must be implemented in those applications.

Many localization algorithms have been proposed to compromise the trade-offs between low cost, low energy consumption, and high accuracy and robustness. These algorithms are categorized into range-based schemes and range-free schemes. The range-based schemes estimate the location of sensors based on

O. Gervasi et al. (Eds.): ICCSA 2009, Part II, LNCS 5593, pp. 419–431, 2009.

given pairwise distances transformed from measurements such as received signal strength (RRS), time-of-arrival (TOA), time of different of arrival (TDOA), angle of arrival (AOA). Usually, TOA, TDOA are suitable for applications requiring high accuracy (in order of centimeters) but it will be costly to equip those measurements. Meanwhile, if the first priority is low cost, RSS is the best candidate. However, the drawback of using RSS is that it is difficult to overcome the bias due to the irregular distribution of radio rank. To improve the accuracy, in case of using RSS, Patwari et al. proposed a novel localization algorithm based on maximum likelihood relative estimation (MLE) [1]. Recently Costa et al. [2] introduced a scalable, distributed weighted-multidimensional scaling (dwMDS) algorithm. The main issue of range-based schemes is the adding cost of hardware to measure the distance. Therefore, in recent years, other scholars proposed range-free schemes.

The locations of sensor, in range-free schemes, are estimated from the connectivity or the number of hops between each pair of sensors. Thus, range-free schemes do not require any hardware to determine the pairwise distances. Obviously, it significantly reduces cost and power consumption as well. Consequently, range-free schemes are suitable for the resource-limited WSNs. Some of the best papers working on the range-free scheme should be mentioned here including MDS-MAP [3], Isomap [4], area-based approach [5], DV based positioning [6], mobile and static sensor network localization [7]. Recently, some novel approaches in range-free schemes were proposed such as the distributed localization algorithm with improved grid-scan and vector-based refinement [8]. Naturally, range-free schemes take precedence over range-base schemes when cost and energy are the main concerns. However, the range-free scheme has its own drawback, that is, it is very hard to obtain high accuracy, particularly, in real-world applications with fading channels and unpredictable noises.

To deal with the effects of fading channels and irregular noises in measuring distances, some novel approaches have been proposed recently. V. Vivekanandan and W.S Wong [9] improved MDS-MAP [3] by using ordinal Multidimensional Scaling (MDS) instead of classical MDS. In Ordinal MDS/MDS-MAP(O), which will be described more details in the section XX, it only requires a monotonicity constraint between the shortest path distance and the Euclidean distance for each pair of nodes. The results show that ordinal MDS gives higher accuracy than classical MDS. However, MDS-MAP(O) [9] still uses the metric model as the input of algorithm. N. Patwari and P. Agrawal [10] build up an algorithm which infers localization information from link correlations in order to avoid significant effects from correlated shadowing on links, in connectivity, localization, and in radio tomographic imaging. Even so, current literatures estimate the coordinates of sensor mostly from a given matrix of pairwise distances. This kind of approach inherits the bias of measurements as well as the converting measurements into Euclidean distances.

Unlike previous work, in this paper, we proposed a very simple model based on nonmetric model MDS [11] to reduce the effects of fading channels and irregular noises. This method is technically similar to averaging (AR) in signal processing.

In such way, the major errors of measured distances will be somewhat canceled. For that reason, when integrated with range-based algorithms as the input, the model will perform significantly better than the stand-alone algorithms do. We also remark that only Gaussian noise in the localization problem is concerned in most existing work. We however focus on how to cope with non Gaussian noise, fading channels, and artifacts. In this paper, first we define the problem formulation, then we propose the nonmetric distance model, so-called NoDis Model, for the most common measurements in nowadays, the received signal strength (RSS) and the time-of-arrived (TOA). Next section, we will show and analyze the performance of our proposed scheme via simulation the NoDis model with MDS-MAP [3] and MDS-MAP(O) [9]. Finally, we end the paper with our conclusions and future work.

2 Problem Formulation

In this section, we first introduce the mathematical localization problem. Then we talk over models of RSS and TOA in realistic and simulate WSN networks. Finally, we explain the rough challenges of fading channels in real applications and how to model such phenomena.

2.1 Localization Problem

In this paper, we consider a network which includes n sensors, normal nodes, randomly deployed in d-dimensional space (d=2 or 3) without location information, and very few m beacons ($m \ll n$) with location information. Let N=n+m denote the total number of sensors in the considering WSN, $X = \{x_i : i = 1..N\}, x_i \in \Re^d$, be the actual vector coordinates of sensors and $\widehat{X} = \{\widehat{x}_i : i = 1..N\}, \widehat{x}_i \in \Re^d$, be the estimate vector coordinates of sensors. The problem of localization in Wireless Sensor Networks is formalized as follows: Given n normal nodes, m beacons, and a set of pairwise vector distances $\{\delta_{ij} : i, j = 1..N\}$, the locations of normal nodes must be estimated. We assume that all measured pairwise vector distances, $\{\delta_{ij} : i \neq j$ and $i, j = 1..N\}$, are available and $\|\delta_{ij}\| = \|\delta_{ji}\|$, ($\|.\|$ is the 2-norm). This assumption doesn't restrict the application of the proposed algorithms. The more pairwise vector distances are given, the higher accuracy is achieved. Note that our method is developed to adapt any type of range measurements, for instance, RSS, TOA, or AOA. However, in this paper, we mainly discus on RRS and TOA model because of their low cost and most typically used in WSN applications.

2.2 No Fading Channels

For most existing work, they only solve the localization problem with Gaussian noise on the distance only. In other words, there is no noise that is much greater than the data containing location information. In this paper, we concern only two typical measurement models, received signal strength (RSS) and time of arrival (TOA) because of their popularity.

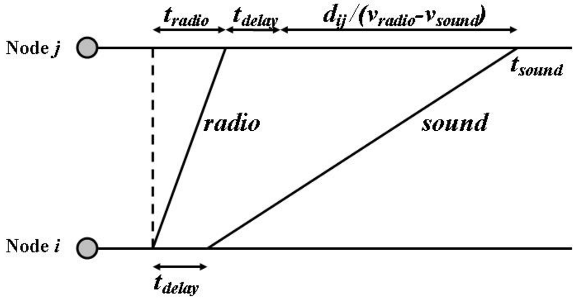


Fig. 1. Time of Arrival illustrated

In RSS-based, distances are measured by converting power of radio signal with the following formula:

$$d_{ij} = d_0 10^{(P_0 - P_{ij})/(10 n_p)}, \tag{1}$$

where, d_{ij} is the converted distance between sensor i and j. P_0 and P_{ij} are the power in decibel milliwatts at distance d_0 and d_{ij} respectively. n_p is the path loss and depends on the environment and can be known from calibration and measurement.

Naturally the equation 1 reflects the degradation of received signal strength with corresponding distances. Furthermore, RF channel measurements of P_{ij} is mainly constant over path length [Rappaport 1996] and [1]. Thus, it is possible to model P_{ij} as a Gaussian model in form

$$P_{ij} \sim N(\bar{P_{ij}}, \sigma_{dB}^2), \tag{2}$$

where $\bar{P_{ij}}$ is the mean value of signal power received at distance d_{ij} and σ_{dB}^2 is the variance of the irregular distribution of radio range.

In TOA-based, sensors are commonly equipped hardware ranging mechanism such as a speaker and a microphone or ultrasound. The mathematical transformation physical measurements into Euclidean distance is independent of particular hardware. To measure the distance between sensor i and j, sensor i first sends a radio message and waits some interval of time, t_{delay}, to ensure that node j receives the message. Then node i emits a sound. Node j, based on the time of receiving the radio signal, it notes the current time t_{radio}. When node j hears the sound, it again note the current time t_{sound}. Using the fact that radio signal travels very much faster than sound in the air, the distance between node i and j is simply computed as

$$\begin{aligned} d_{ij} &= (v_{radio} - v_{sound}) * (t_{sound} - t_{radio} - t_{delay}) \\ &= \triangle v * \triangle t, \end{aligned} \tag{3}$$

where v_{radio} and v_{sound} are the speed of radio and sound traveling in the air, respectively. Assume that the air is unique and there is no obstacle on the traveling path of sound, the bias in TOA case is mostly caused by the error in time measurement. Therefore, the $\triangle t$ can be modeled as

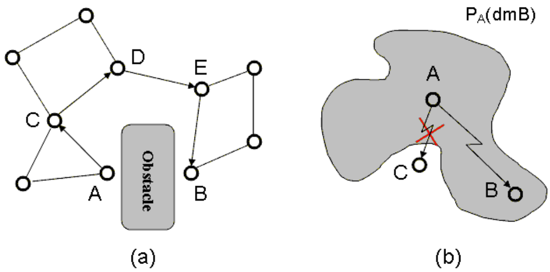


Fig. 2. Effects on measured data in real application: (a)from fading channel; (b)from irregular radio range

$$\triangle t \sim N(\bar{\triangle t}, \sigma_s^2), \tag{4}$$

where $\bar{\triangle t}$ is the mean value of $\triangle t$ and σ_s^2 is the variance of the traveling time of sound.

2.3 Fading Channel Models

The physical location of sensors is critical for both network operation and data gathering. Nowadays, network communication in WSNs mostly use radio signal to transmit or receive data and many localization algorithms execute relied on the connectivity or the propagation of the transmission. However, the connectivity or hop-counting must face with fading channels due to unexpected obstacles in real-world environment. In Fig. 2a, sensor A and sensor B can not directly communicate with each other because of the obstacle between them. The number of hops or the distance estimated between sensor A and B, through the path $A \to C \to D \to E \to B$, consequently is much greater than the actual distance. Fig. 2b illustrates the effect of irregular radio range in WSNs. In practical, the radio range is not symmetric. Therefore, based on measured data, one will think that node B is closer to node A than node C is, even that is not true.

To simulate these phenomena, non Gaussian noise or artifacts, we proposed a method as hereafter. For the RSS model, the radio signal is significantly degraded when there are obstructions on the link. And the ratio of sigma over path loss σ_{dB}/n_p represents this phenomenon, fading channels or artifacts. As a consequence, if we increase the σ_{dB}/n_p of some random links in a wireless sensor network by adding a constant C, their corresponding measured distances will be significantly larger than true values.

To simulate the fading channel in TOA case, analogously, we randomly multiply a number of measured time values, $\triangle t$, by a fixed coefficient α.

$$d_{ij}^{*} = \alpha * \triangle v * \triangle t. \tag{5}$$

In summary, by creating fading channels on some random links like our method, the corresponding measured distances are radically different from the actual distances. In order to cope with both non fading channels (Gaussian noises) and fading channels (non Gaussian noise), we propose a new model which based on nonmetric models and will be described in next section.

3 Our Proposed Model

3.1 Nonmetric Distance Modeling

The input $\{\delta_{ij} : i \neq j \text{ and } i, j = 1..N\}$ of a localization scheme is a set of pairwise distances among sensors in a network, which is a metric space or so-called metric distance model. That is, it represents various properties of the data related to algebraic operations (addition, subtraction, multiplication, division). The pairwise distances are converted from other measurements such as RF signal (RSS), Time of Arrival (TOA) or hop-distances (connectivity). Because of the present of fading channels and unpredictable obstacles in real-world applications, there are some measured distances which are significantly different from their actual values. This phenomenon consequently biases the output of a localization scheme, coordinates of normal nodes. To lessen the effect of noise, we convert metric distance models into nonmetric distance models [11].

Metric distance models only preserve the rank or the order of the metric data. For example, if $\delta_{12} = 12$ and $\delta_{34} = 9$, a nonmetric distance model maintains only the property as $\delta_{12} > \delta_{34}$. Therefore, we constructs a new model of given distance $\delta_{ij} \longrightarrow \widehat{\delta}_{ij} = f(\delta_{ij})$ so that

$$if\ \delta_{ij} > \delta_{kl}\ then\ \widehat{\delta}_{ij} > \widehat{\delta}_{kl}. \tag{6}$$

Note that we also can use the requiring monotonicity $\widehat{\delta}_{ij} \geq \widehat{\delta}_{kl}$, however, neither $\widehat{\delta}_{ij} > \widehat{\delta}_{kl}$ nor $\widehat{\delta}_{ij} \geq \widehat{\delta}_{kl}$ strengthens models in practice, because one can always add a very small number ϵ to one side of the equality.

There are many ways to obtain a nonmetric distance model $\widehat{\delta}_{ij}$ satisfying (6). In this paper, we propose a simple and lightweight method as follows and name it the NoDis model. First we create a vector $v = \{v_i : \ i = 1..n(n-1)/2\}$ from elements below the diagonal of the given pairwise distances δ_{ij}. Then we derive an index vector $u = \{u_i : \ i = 1..n(n-1)/2\}$ from sorting vector V in ascending order. Obviously, each element u_i contains the index of corresponding v_i, and $u_i \leq \ n(n-1)/2, \ i = 1..n(n-1)/2$. We also stress that the index of u is the order of elements of v. Next step is that we construct a nonmetric vector $\widehat{v} = \{\widehat{v}_i : \ i = 1..n(n-1)/2\}$ where,

$$\widehat{v}_{u_i} = i, \ i = 1..n(n-1)/2. \tag{7}$$

Finally, one easily builds the nonmetric distance model $\widehat{D}$ by converting $\widehat{v}$ into a square, symmetric format matrix, in which $\widehat{d_{ij}}$ denotes the nonmetric distance between the ith and jth sensors in the given metric distances, and satisfies (6). We use this nonmetric model $\widehat{D}$, a square symmetric matrix with all elements on the diagonal are zero, as the input of algorithms based on the MDS technique. A

Table 1. Symbolic metric distances δ_{ij}, order (index of v), nomination vector v, index vector u, nonmetric nomination vector $\widehat{v}$ and symbolic nonmetric distances $\widehat{\delta}_{ij}$

d_{ij}	Order	v	u	$\widehat{v}$	$\widehat{d_{ij}}$
d_{12}	1	9	3	2	$\widehat{d}_{12}$
d_{13}	2	3	5	3	$\widehat{d}_{13}$
d_{14}	3	5	7	4	$\widehat{d}_{14}$
d_{23}	4	7	9	1	$\widehat{d}_{23}$
d_{24}	5	15	12	6	$\widehat{d}_{24}$
d_{34}	6	12	15	5	$\widehat{d}_{34}$

very simple example with only 4 nodes ($n = 4$) given in Tab. 1 would be useful to understand converting nonmetric distances from given metric distances. Let d_{24} and d_{34} be kind of fading channels, apparently the discrepancies between them and other distances are reduced in vector $\widehat{v}$. This sort of transformation weakens the effects of large bias on input data. It consequently somewhat improve the accuracy and convergence speed as well.

3.2 Model Limitations

We note that our proposed NoDis model has hereafter limitations. Firstly, NoDis is mainly developed for range-based schemes. We only test the NoDis model with rang-based algorithms in our simulation. However, it is possible to apply our proposed with range-free schemes by calculating pairwise distances analogously to DV-HOP [6].

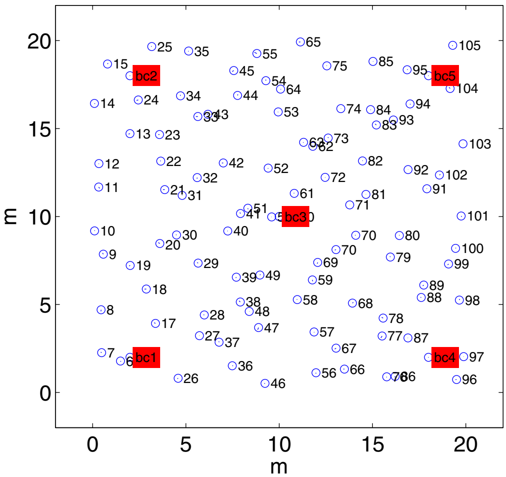
Secondly, the NoDis model is most appropriate to localization algorithms which perform well on networks in which sensors are randomly deployed. In this paper, we analyze and investigate our proposed model 5 and 6 with classical (MDS) and ordinal MDS. With some other localization algorithms, our proposed model may not suffice to improve the performance.

Finally, the NoDis model has not integrated the effects of multi-paths which impairs given distances. The power received at a receiving sensor may be the multi-path components transmitted by many sensors, not only the considering sensor in pair with receiving sensor. The NoDis assume that the receiver only receives power from only one of its neighbors at a time. An update model, which considers the correlation between multi-paths, should be developed to archive better solution.

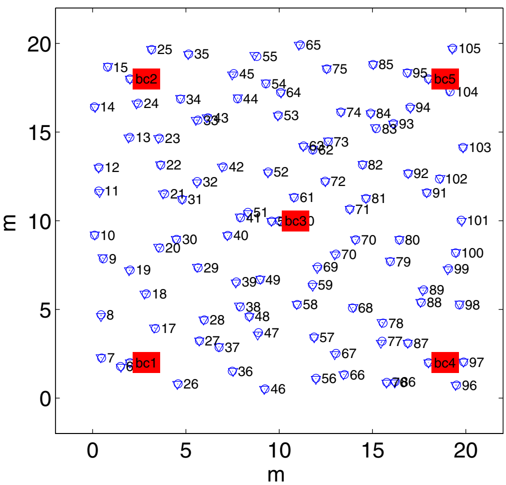
The proposed nonmetric distance model does not perfectly represent for all cases of noises in wireless sensor network localization, however, it does simplify the existing algorithms, makes them applicable for real world applications.

4 Experimental Results

In our experiments, we access the performance of our proposed NoDis modle when using the model as the input for MDS-MAP [3] and ordinal MDS [9]. To



(a) 100 sensors, marked as "∘", are randomly deployed in an area 20m x 20m. 5 beacons are in "red".



(b) The result of localization with TOA measurement, ratio of noise is 25%. The estimate locations are marked as "$\bigtriangledown$". RMSE = 0.0592m.

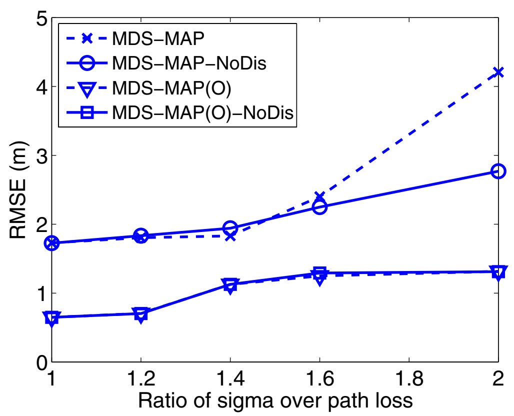
Fig. 3. Illustration of 100 randomly deployed sensors and their estimated locations marked as "$\bigtriangledown$"

compare the performance of our proposed localization scheme, we also implement MDS-MAP and ordinal MDS (MDS-MAP(O)). For comparable convenience, all experiments run on a same network topology. That is, 100 nodes are deployed randomly in a 20m x 20m square. 4 reference nodes or beacons are placed at 4 corners and one at the center of the area (see Fig. 3.a). For instant, Fig. 3.b shows the result of the localization problem in TOA case with the ratio of noise is

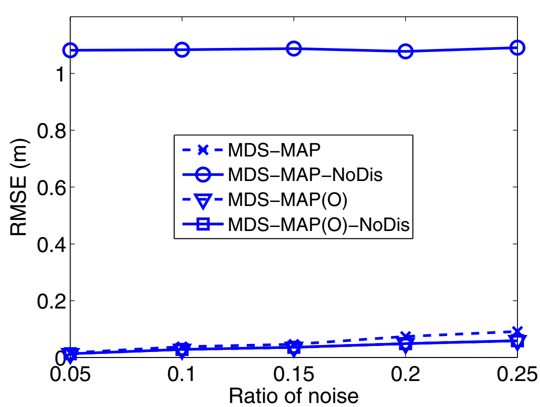
25% and the obtained RMSE is $0.0592m$. Noises and artifacts are generated for (non) fading channel models for both RSS and TOA measurements. The initial coordinate of sensors is randomly assigned for each trial of our simulations. We conduct the simulations on two phrases, the former is without fading channels and the latter includes fading channels.

4.1 Simulations without Fading Channels

To model the errors in the simulation network, we add Gaussian noise to the received signal strength for the RSS model and to the distance for TOA model. For RSS case, the ratio of sigma over path loss σ_{dB}/n_p varies from 1 to 2. For TOA case, the ratio of noise σ_s varies from 5%(0.05) to 25%(0.25). We run 10 trials for each type of considering algorithms, the Root Mean Square Error of each algorithms is plotted in Fig. 4.



(a) RSS measurement



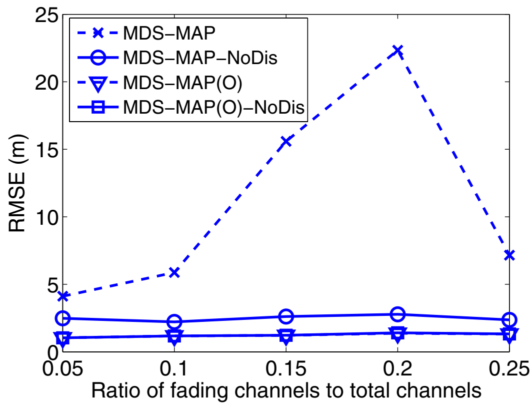
(b) TOA measurement

Fig. 4. Root Mean Square Error for the simulations without fading channels

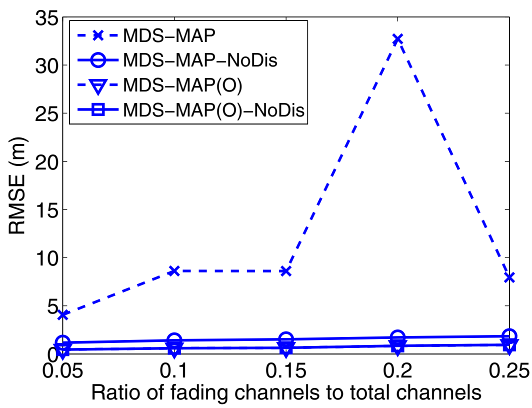
From the graph, it is easy to realize that the performances of our proposed, RMSE of MDS-MAP-NoDis and MDS-MAP(O)-NoDis are similar to those of MDS-MAP and MDS-MAP(O) when the ratio of noise is low. However, NoDis seems to give better accuracy when the noise increases, particularly with the MDS-MAP algorithm in RSS model. The reason is that MDS-MAP suffers from large bias when noise is increasing but NoDis. However, the NoDis model also reduces the resolution of TOA measurement, MDS-MAP-NoDis in the Fig 4.b therefore can not get high accuracy like the MDS-MAP can.

4.2 Simulations with Fading Channels

To add fading channels into the above network topology to analyze the performance of algorithms, we vary the percentage of channels in the network from 5%(0.05) to 25%(0.25). We note that the channels or links selected to transform



(a) RSS measurement



(b) TOA measurement

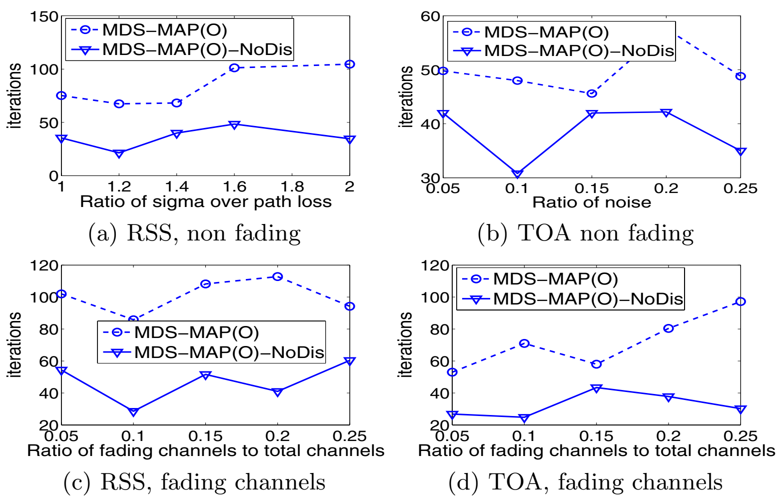
Fig. 5. Root Mean Square Error for the simulations with fading channels

into fading channels are random. To transform a normal channel to a fading channel, we fix parameters σ_{dB}/n_p and σ_s at 1.6 and 20% respectively and double distances calculated by (1) and (3). The fading channels only vary in quantity, indeed.

Again, we run 10 trials for each type of considering algorithms. Fig. 5 shows their results on the fading channel cases. This time, MDS-MAP-NoDis is much better than MDS-MAP, and achieving as good results as MDS-MAP(O) or MDS-MAP(O)-NoDis. Obviously, the NoDis model works very well in the case of having a lot of fading channels and it is suitable for the real -world application where there are many unpredictable obstacles. We also remark that MDS-MAP, the basic MDS-MAP [3], can not work appropriately when the number of fading channels excesses 10%(0.1) of total channels in the network. This limitation can be explained by that optimizing with Mean Square Error (MSE) technique in a metric space can not perfectly remove artifacts or fading channels. That is why its graphs are irregular in the Fig. 5.

4.3 Convergence

As we have studied, the accuracy attained by MDS-MAP(O) [9] and our proposed MDS-MAP(O)-NoDis are almost similar in both cases of with and without fading channels. However, when the irregular noises are high, especially when occurring many fading channels, MDS-MAP(O)-NoDis converges much faster than MDS-MAP(O) does. The reason is the NoDis model discards the significantly different distances in the given pairwise distances δ_{ij}. In addition, MDS-MAP algorithms are technically based on minimizing Mean Square Error which largely depends on the value of bias and MDS-MAP(O) is not an exception. Thus, MDS-MAP(O) require many more iterations to get convergence than



(a) RSS, non fading (b) TOA non fading

(c) RSS, fading channels (d) TOA, fading channels

Fig. 6. Convergence vs. level of noise and fading channels

MDS-MAP(O)-NoDis. Their results are plotted in Fig. 6. The iterations are the averaging of 10 trials.

5 Conclusions

We propose a new approach for localization that works well with networks containing fading channels. The proposed model, when used as the input for rang-based schemes or even rang-free schemes, can radically eliminate or reduce the effects of fading channels and artifacts. Previous methods often use the metric pairwise distances to estimate the coordinate of sensors. In such way, it is hard to overcome the problem caused by fading channels. Our approach does not have this limitation. It estimates the location of sensors from the nomination or the order of pairwise distances in nonmetric space. Simulations using various network measurements and different levels of noise illustrate that our proposal gives higher accuracy and convergence speed than the previous work, especially when there are many fading channels.

Acknowledgment

This research was supported by the MKE (Ministry of Knowledge Economy), Korea, under the ITRC(Information Technology Research Center) support program supervised by the IITA (Institute of Information Technology Advancement)" (IITA-2009-(C1090-0902-0002)).

References

1. Patwari, N., Hero III, A., Perkins, M., Correal, N., O'Dea, R.: Relative localization estimation in wireless sensor networks. IEEE Trans. Signal Processing 51(8), 2137–2148 (2003)
2. Costa, J., Patwari, N., Hero III, A.: Distributed weighted-multidimensional scaling for node localization in sensor networks. ACM Transactions on Sensor Networks 2(1), 39–46 (2006)
3. Niculescu, Y.S., Ruml, W., Zhang, Y., Fromherz, M.: Localization from connectivity in sensor networks. IEEE Transactions on Parallel and Distributed Systems 15(11), 961–974 (2004)
4. Shang, Y., Ruml, W., Zhang, Y., Fromherz, M.: Localization from mere connectivity. In: Proc. Mobihoc., pp. 201–212 (2003)
5. He, T., Huang, C., Blum, B., Stankovic, J., Abdelzher, T.: Range-free localization schemes for large scale sensor networks. In: Proc. ACM MobiCom, pp. 81–95 (2003)
6. Niculescu, D., Nath, B.: Dv based positining in ad hoc networks. Telecommunication Systems 22, 267–280 (2003)
7. Rudafshani, M., Datta, S.: Localization in wireless sensor networks. In: Proc. Information Processing in Sensor Networks (IPSN), pp. 51–60 (2007)
8. Sheu, J.P., Chen, P.C., Hsu, C.S.: A distributed localization scheme for wireless sensor networks with improved grid-scan and vector-based refinement. IEEE Transactions on Mobile Computing 7(9), 1110–1123 (2008)

9. Vivekanandan, V., Wong, V.: Ordinal mds-based localization for wireless sensor networks. In: Proc. IEEE Vehicular Technology Conference, pp. 1–5 (2006)
10. Patwari, N., Agrawal, P.: Effects of correlated shadowing: Connectivity, localization, and rf tomography. In: Proc. Information Processing in Sensor Networks, pp. 82–93 (2008)
11. Borg, I., Groenen, P.J.: Mordern Multidimenstional Scaling Theory and Applications. Springer, Heidelberg (2005)