Localization algorithms in wireless sensor networks using Nonmetric Multidimensional scaling with RSSI for precision agriculture

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Abstract—**The positions of the sensor nodes in wireless sensor networks for precision agriculture must be required first. Position estimation generally includes errors due to the measurements of distance. Erroneous positions are propagated from a node to other nodes exacerbating the degree of errors in the estimation of the positions of these nodes. In this study, we evaluated the performance of NMDS-RSSI localization algorithms, using data from scenarios in farm. We concluded that the average value of the localization error deceased with signal propagation coefficient-μ increasing. And we proved the robust of NMDS algorithm for bad environment. Moreover, we obtained the relationship between the localization error and connectivity. The simulations show that the NMDS-RSSI localization algorithms yields better performance than the MDS-MAP in the same simulation conditions**

Keywords-Localization; Nonmetric Multidimensional scaling; wireless sensor networks; precision agriculture; RSSI

I. INTRODUCTION

A wireless sensor network (WSN) has enabled sensor nodes to be deployed in quantity to gather environmental parameters and to detect certain events by using inexpensive micro-controllers. Ning Wang et al [1] present an overview of recent developments in wireless sensor technologies in the food industry. Werner-Allen et al. advocate the deployment of a WSN in precision agriculture because of its small size, low fixed cost and simplicity of wiring [2]. In Europe, the Lofar Agro project is a study of precision agriculture that focuses on tailored management of a crop. This involves monitoring soil, crop and climate conditions in a field, generalizing the result and providing a decision support system for treatments or taking differential action such as real time variation of fertilizer or pesticide application. The DSS gathers information from a weather station by the wireless network. This is employed to map out a temperature and soil humidity distribution which is used to develop an effective strategy for controlling diseases such as Phytophthora [3,4].

To accomplish the mentioned applications in precision agriculture, the positions of the sensor nodes must be estimated first. As a result, the sensor localization is one of the important signal processing tasks in WSN. Sensor network localization algorithms estimate the locations of sensors with initially unknown location information by using knowledge of the absolute positions of a few sensors and inter-sensor measurements such as distance and bearing measurements. Sensors with known location information are called anchors and their locations can be obtained by using a global positioning system, or by installing anchors at points with known coordinates. In applications requiring a global coordinate system, these anchors will determine the location of the sensor network in the global coordinate system. Because of constraints on the cost and size of sensors, energy consumption, implementation environment and the deployment of sensors, most sensors do not know their locations. These sensors with unknown location information are called non-anchor nodes and their coordinates will be estimated by the sensor network localization algorithm [5,8].

Positioning algorithms in WSN can be categorized as centralized and distributed approaches. In centralized localization, all distance measurements are sent to a central unit for calculating the sensor positions. Centralized processing is advantageous in the sense that the solution obtained is generally more accurate and a global map is available. The measurement data of all the nodes in the network are collected in a central processor unit. In such a network, it is convenient to use a centralized localization scheme. A localization algorithm is less complex in terms of computations, communication overhead and increasing the overall lifetime of the network with low life-cycle costs [6].

In this paper we give details of a simple mathematical technique, Nonmetric Multidimensional scaling and how it solves the localization problem. This so called NMDS algorithm is able to find the relative positions of nodes and with few anchor nodes available derives or maps the relative coordinates to absolute coordinates. When using a complex localization algorithm highly sophisticated nodes must be deployed and this increases the overall cost of deployment of the network. With a tradeoff between complexity and accuracy this less complex NMDS algorithm derives absolute positions of nodes with accuracy sufficient enough for most of the applications in farm. At last, we present simulation results of the NMDS-RSSI algorithm by MATLAB.

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II. NMDS-RSSI

A. Multi-Dimensional scaling

Multidimensional scaling (MDS) is a set of related statistical techniques often used in information visualization for exploring similarities or dissimilarities in data. MDS is a special case of ordination. An MDS algorithm starts with a matrix of item–item similarities, and then assigns a location to each item in N-dimensional space, where N is specified a priori. For sufficiently small N, the resulting locations may be displayed in a graph [6].

MDS algorithms fall into two broad classes: metric algorithms, which seek an embedding with inter-point distances closely matching the input dissimilarities; and non-metric algorithms, which find an embedding respecting only the relative ordering of the input dissimilarities. Metric MDS is not appropriate in many of these applications since the magnitude of the input dissimilarities is unreliable, too difficult to measure, or simply unavailable. Therefore, we focus on the NMDS localization algorithms in this paper. The MDS is the course of repeated iteration [7]. The algorithm is following: the input is the initializing coordinate (x_i^0, y_i^0)of the nodes. The threshold ε and iteration number k is 0. Firstly, the initializing coordinate ((x_i^0, y_i^0)) is given and the Euclidean distance of each pair of nodes is derived by:

$$d_{ij}^k = \sqrt{(x_i^k - x_j^k)^2 + (y_i^k - y_j^k)^2} \tag{1}$$

$\hat{d}_{ij}^k$ is obtained by PAV for the dissimilarity matrix [P_{ij}] and [d_{ij}^k]. For $\forall$ i、j、u、v, if $p_{ij} < p_{uv}$,

If $d_{ij}^k > d_{uv}^k$, then $\hat{d}_{ij}^k = \hat{d}_{uv}^k = (d_{ij}^k + d_{uv}^k)/2$;

If $d_{ij}^k > d_{uv}^k$, then $\hat{d}_{ij}^k = d_{ij}^k$, $\hat{d}_{uv}^k = d_{uv}^k$.

Then, k increase 1, the new coordinate (x_i^k,y_i^k) is obtained by following formula.

$$x_i^k = x_i^{k-1} + \frac{a}{n-1}\sum_{j\in M, j=i}\left(1-\frac{\hat{d}_{ij}^{k-1}}{d_{ij}^{k-1}}\right)(x_j^{k-1} - x_i^{k-1})$$

$$y_i^k = y_i^{k-1} + \frac{a}{n-1}\sum_{j\in M, j=i}\left(1-\frac{\hat{d}_{ij}^{k-1}}{d_{ij}^{k-1}}\right)(y_j^{k-1} - y_i^{k-1}) \tag{2}$$

Then, the Euclidean distance of each pair of nodes is obtained by formula 1 and the STRESS1 is obtained by formula 3.

$$STRESS1 = \sqrt{\sum_{ij,i\neq j}(\hat{d}_{ij} - d_{ij})^2 / \sum_{ij,i\neq j} d_{ij}^2} \tag{3}$$

If STRESS1<10^{-3}, repeated iteration is over. Otherwise, the PAV is going on.

B. RSSI

The signal strength of a radio message decreases as distance increases. This signal strength can be measured with every known radio chip. This radio signal strength indicator (RSSI) can be converted to a distance estimate if there is mapping from this RSSI values to distances.

To use the RSSI value to run localization experiments on, a conversion function is needed to make distance estimates from the RSSI values. The relationship between RSSI and distance can be determined according to the following formula based on Friis transmission equation [7].

$$RSSI(d) = P_T - PL(d_0) - 10\mu \ln(d/d_0) + \delta_\sigma \tag{4}$$

RSSI (d) denotes the node receiving signal strength; P_T denotes sending energy; PL (d_0) denotes signal strength in reference node d_0; d_0 denotes the distance between the reference node and receiving node; μ denotes the signal propagation coefficient, which shows the damping of the signal. δ_σ denotes the Gaussian random variable with mean (0) and variance (σ^2). Some parameters must be determined empirically.

C. NMDS-RSSI

This subsection is description of NMDS-RSSI Localization algorithm [7]. In contrast to metric MDS, NMDS both finds a non-parametric monotonic relationship between the dissimilarities in the item-item matrix and the Euclidean distance between items, and the location of each item in the low-dimensional space. The relationship is typically found using isotonic regression. Here, The RSSI values of measure a pair of nodes is as input. The absolute coordinate of network nodes is as output.

The step of NMDS algorithm:

1. RSSI values are collected from network nodes, which structure dense matrix [r_{ij}]. RSSI value is zero when the distance between node i and node j is bigger than wireless communication radius.
2. Matrix [sij] is derived by that the constant which is bigger than r_{ij} subtract r_{ij}, which is due to that relationship between the RSSI value of node and their distance is inverse ratio approximate.
3. RSSI value is derived by shortest path algorithm dijstra according to the connectivity between [s_{ij}] and network nodes. Because a pair of nodes with belong not to wireless communication radius is not connected, the RSSI values of two nodes is zero. To meeting the demanding of similarity matrix, the RSSI value of two nodes is derived by shortest path algorithm dijstra.
4. The dissimilarity matrix [p_{ij}] in nodes is formed by the RSSI values of two nodes.
5. The relative coordinate is derived to the dissimilarity matrix [p_{ij}] by NMDS algorithm.
6. The relative coordinate of node is converted to absolute coordinate using the known beacon node.

III. EXPERIMENTAL

We conducted an experiment to investigate proposed the NMDS algorithm. All of these measurements were performed in the Matlab7.0. We performed algorithm performance measurements in the case of grid uniform distribution. The experimental parameters is following: the path loss factor - μ, the mean square deviation of Gaussian noise δ_σ, wireless communication radius-R, the node's average connectivity – β, the number of beacon node – m. In the simulation, the RSSI value can be determined according to the formula 4. In farm environment, the wireless channel has the disadvantage of reflection 、 multipath propagation and the background interference, which result to the different propagation loss in the same distance. Therefore, in order to simulate the reality situation, we introduce Gaussian noise ζ_σ. In the experimental, PT =5 dBm, PL (d0)=50 dBm, d0=1m.

In the case of grid uniform distribution, the nodes distribute uniform in the certain size grid with some distance. In order to simulate the reality situation, we introduce some placing error, which results to the deviation node to grid. The number of sensor nodes 、 the node distance 、 the wireless communication radius and the placing error can be set.

IV. RESULTS AND DISCUSSIONS

In simulation experiments, we performed algorithm performance measurements in the case of grid uniform distribution. The experiments were carried repeat in situation to changing denotes the signal propagation coefficient-μ and the Gaussian noise δ_σ. The 100 nodes with placing error were generated in 60m×60m grid with uniform distribution. The nodes distance is 4m. The wireless communication radius is 8m. The average connectivity is 10. The 4 nodes with random selecting is beacon node.

Fig 1 plots the average value of the localization error of NMDS-RSSI and MDS-MAP as a function of the signal propagation coefficient-μ with mean variance (σ=8). Observing the results reported in the figure, we conclude that the average value of the localization error decease with signal propagation coefficient-μ increasing.

Fig. 2 shows that the average value of the localization error of NMDS algorithm increase with the mean variance σ. At the same time, the value of the localization error is small even if Gaussian noise is the bigger, which proves the robust of NMDS algorithm for bad environment, for example, fields. In Fig. 1 and Fig. 2, the average localization error of NMDS algorithm is smaller than MDS-MAP is concluded.

Fig. 3 plots the relationship between the localization error and the node connectivity. When the node connectivity is relatively small, the localization error of NMDS-RSSI and MDS-MAP algorithm is bigger. With the increase of the node connectivity, the localization error of NMDS-RSSI will decrease. The localization error of NMDS-RSSI algorithm decreases much faster than the MDS-MAP algorithm. As the node connectivity continues to increase beyond 10, the both algorithm localization error will decrease slowly. This can be explained as follows [9]. When the node connectivity reaches a certain point, most sensor nodes can localize themselves. If we continue to increase the node connectivity, nodes will get to know more anchor nodes and have more choices to calculate their locations. Thus, the localization error will decrease. But, as shown in Fig. 3, this decrease is very limited.

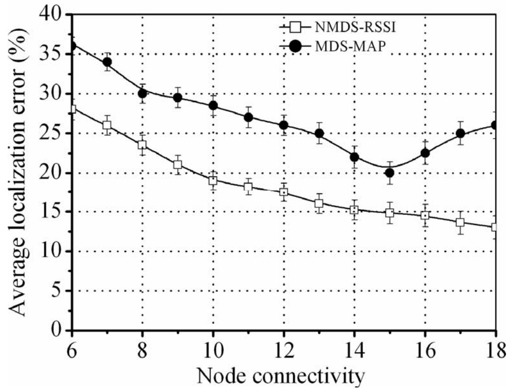

Figure 1. Localization error under different mean variance σ

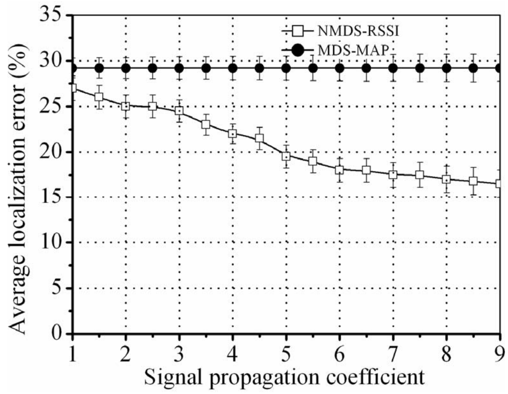

Figure 2. Localization error under different signal propagation coefficient-μ

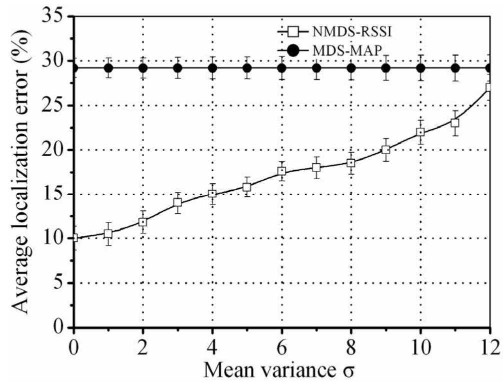

Figure 3. Localization error under different mean variance σ

V. CONCLUSION

In this paper, we analyzed the performance of NMDS-RSSI localization algorithms, using data from scenarios in farm. It concluded that the average value of the localization error decease with signal propagation coefficient-μ increasing. And we prove the robust of nonmetric Multidimensional scaling algorithm for bad environment. Moreover, we concluded relationship between the localization error and the node connectivity. The simulations show that the NMDS-RSSI localization algorithms yields better performance than the MDS-MAP in the same simulation conditions.

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