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Study on Multi-Source Localization of Wireless Sensor Network Based on Quantitative Information

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Abstract

Against the problem that quantitative localization is concentrated on single-source localization, this paper studies the quantitative multi-source localization methods based on wireless sensor network. Firstly, the log-quantization strategy which reflects the characteristics of acoustic source is proposed. The sensor node transmits the quantized information to base station according to the measurements and log-quantization strategy. Secondly the based station estimates the location of the sources according to the proposed method termed as multiple source localization based on possibilistic C means clustering algorithm. Finally the efficient of the proposed method is verified by the simulation under different parameters. The simulation results show that the proposed method could accurately estimate the location of source. And the proposed method is robust to the packet loss rate.

***Keywords**: Wireless Sensor Networks, Localization, Quantized Information, Acoustic Source, Possibilistic C Means Clustering*

1. Introduction

With the constant development of micro-electronics, short-distance communication and sensing technology, wireless sensor networks (WSNs) have become a research hotspot [1]. Signal source (or target) localization is an important research direction of WSNs, and the results of the researches can be widely applied into the areas of the localization of vehicles, large underwater creatures and humans. WSNs-based signal source localization can be categorized into three types according to the methods of measurement, namely TDOA (Time Difference of Arrival)-based, RSS (Received Signal Strength)-based and AOA (Angle of Arrival)-based localization. Among them, TDOA-based method places a relatively high demand on the time synchronization of nodes and AOA-based method places a relatively high demand on node hardware for the need of array antenna. However, RSS-based method places a relatively low demand on node hardware and the power dissipation is relatively small, so it best suits the application of WSNs [2].

WSNs-based multi-source localization has attracted the attention of scholars from both China and beyond. Sheng [3] put forward the maximum likelihood estimation (MLE) to establish the objective function for multi-source localization, and then the localization of signal sources is searched and estimated through adopting the expectation maximization and multi-resolution. Ampeliods [4] propose to adopt the alternate mapping algorithm to divide the localization issue of multi-sources into several non-convex optimization problems, which significantly lowers the computing complexity when compared with MLE-based method. Shen [5] break the complex multi-source localization problem into

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several convex optimization ones, based on which TTS (Tractable Three-Step) algorithm is put forward to estimate the location of signal sources.

The above algorithms require the sensor nodes to transmit the measured original data to base stations, which then estimate the localization of signal sources according to measurements and sensor nodes. However, the energy of sensor nodes and the communication bandwidth are extremely limited and the transmission of original data consumes relatively much energy, so the measured original data can be quantized so that the nodes only need to transmit several bits of information after quantization, hence significantly lowering the transmission quantity of data and lowering the energy consumption of nodes. Ozdemir [6] propose a target localization method based on quantitative data, which establishes the objective function through MLE-based method, obtains the estimated localization of targets through optimizing the objective function, and integrates the channel uncertainty into it, so this method has certain fault tolerance for the channel disturbance. Masazade [7] put forward cyclic source localization algorithm against heterogeneous sensor networks, which firstly obtains the posterior probability density function through the Monte-Carlo method, then proposes two node selection methods, and finally estimates the location of signal sources according to the selected nodes and objective function. Vempaty [8] put forward a cyclic localization method based on coding theory. In each cycle, the base stations estimate the location of signal sources though solving the problem of M-nary hypothesis testing and meanwhile determine the areas of interest of the next cycle. Compared with the maximum likelihood estimation, this method lowers the computing complexity.

At present, researches on quantitative localization are mostly concentrated on single-target (single-source) localization, so there are few literatures relevant to the multi-source localization methods based on quantitative information. Based on the above analyses, this paper studies the multi-source localization methods based on quantitative information, and puts forward a multi-source localization method based on modified possibilistic C-means Clustering Algorithm.

2. System Mobel

Suppose that N sensor nodes are randomly deployed in the sensing field, the location of each sensor node is known, there are K acoustic sources in the field with each one of them sending acoustic signals evenly to all around, and the influence of obstacles on signal propagation is not considered, then the signal intensity received at the *i-th* sensor node is [3]:

$$y_i = \sum_{k=1}^{K} \frac{S_k}{d_{ik}^{\gamma/2}} + n_i \tag{1}$$

Where, y_i is the received energy of acoustic signal at *i-th* sensor node, n_i is the measurement noise and it is modeled as zero mean Gaussian noise with variance σ^2; S_k is the energy of *k-th* signal source, and γ is the path loss coefficient, $d_{ik} = \|\rho_k - r_i\|$ is the Euclidean distance between the *i-th* node and the *k-th* signal source, ρ_k is the coordinate of the *k-th* signal source, and r_i is the coordinate of the *i-th* sensor node.

Measurement y_i at *i-th* sensor node is quantized into M bits, shown as D_i. Assume L=2^M, and D_i is an integer within the range of [0, L-1]. The quantization of *i-th* sensor node can be shown as:

$$D_i = \begin{cases} 0, & y_i \le \eta_1 \\ 1, & \eta_1 < y_i \le \eta_2 \\ \vdots & \vdots \\ L-1, & y_i > \eta_{L-1} \end{cases} \tag{2}$$

Where, η_i is the quantization threshold.

As shown in Fig. 1, in the situation of one signal source, measurement y_i decreases sharply with the increase of distance. The adoption of traditional uniform quantization will lower the resolution when the measurement is relatively small. Therefore, this paper proposes the logarithmic quantization strategy. Aiming at a certain target source measured by the sensor network, its energy value will often fall into the range of $S_{MIN} \le S_k \le S_{MAX}$, then the quantization threshold can be defined as follows:

$$\eta_i = 10^{\left[a_1 + \frac{(i-1)(a_2-a_1)}{L-2}\right]}, i = 1, \ldots, L-1 \tag{3}$$

Where, $a_1 = \log_{10}\left(K \cdot S_{\min}\right)$, $a_2 = \log_{10}\left(K \cdot S_{\max}\right)$.

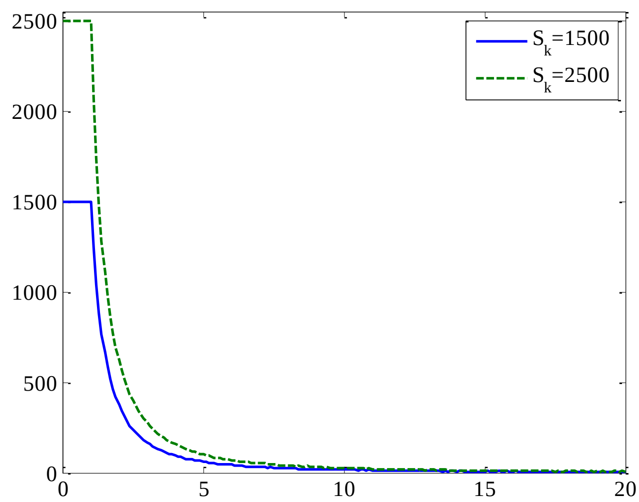

Figure 1. The Relationship between Measurement and Distance

The maximum likelihood estimation is a multi-source localization algorithm that has been widely applied, but its computing complexity is high, so it is unsuitable for the sensor nodes with limited calculation and storage capacity.

3. Multi-Source Localization Algorithm Based on Modified Possibilistic C-Means

3.1. Possibilistic C-Means Clustering Algorithm

In 1993, R. Krishnapuram and J. Keller introduced possibility theory into clustering and put forward Possibilistic C-Means Clustering Algorithm (PCMC) [9]. Compared with fuzzy C-means, it lifts the restrictions on sample membership degree, or in other words, the sum of membership degree will not be limited to 1.

Given the data set that has been classified into C types, through minimizing the following function we can obtain as [10]:

$$J(t)=\sum_{i=1}^{C}\sum_{j=1}^{q}\left(t_{ij}\right)^{m}\left\|x_j-p_i\right\|^{2}+\sum_{i=1}^{C}\lambda_i\sum_{j=1}^{q}\left(1-t_{ij}\right)^{m} \tag{4}$$

Where $t_{ij}\in[0,1]$, $0<\sum_{j=1}^{q}t_{ij}<q$, p_i is the *i-th* clustering center, C is the number of clustering, t_{ij} is the probable subdivision value of xj to i type, m is the weighted index (m=2 in this paper), and is the penalty factor.

The expression of penalty factor is as follows:

$$\lambda_i=W\frac{\sum_{i=1}^{q}t_{ij}^{m}\left\|x_j-p_i\right\|^{2}}{\sum_{i=1}^{q}t_{ij}^{m}} \tag{5}$$

Where W=1.

Through iteration, we can obtain the probable subdivision value and clustering centers as:

$$t_{ij}=\left[1+\left[\frac{\left\|x_j-p_i\right\|^{2}}{\lambda_i}\right]^{\frac{1}{m-1}}\right]^{-1} \tag{6}$$

$$p_i=\frac{\sum_{j=1}^{q}t_{ij}^{m}x_j}{\sum_{j=1}^{q}t_{ij}^{m}} \tag{7}$$

3.2. Multi-Source Localization Algorithm

Assume that nodes with D_i>0 are the alarm nodes, each alarm node directly transmit the quantized data D_i to base stations, and base stations will estimate the location of signal sources according to the proposed multi-source localization algorithm. $R=\left[r_1,r_2,\ldots,r_q\right]$ is the coordinate set of alarm nodes, and $q\le N$. Adopting the following modified possibilistic C-means algorithm can estimate the location of signal sources.

D_i is normalized:

$$D_i'=\frac{D_i}{\sum_{i=1}^{n}D_i} \tag{8}$$

Based on (1) and (2), the larger the quantized value D_i, the larger the measurement of sensor nodes, which indicates that if the sensor node is closer to signal source, then its weight in calculating clustering center will be bigger. Therefore, this paper takes D_i' as the weight to redefine the clustering center as follows:

$$p_i = \frac{\sum_{j=1}^{n}\left(t_{ij}\right)^m D'_j x_j}{\sum_{j=1}^{n}\left(t_{ij}\right)^m D'_j} \tag{9}$$

The steps of the proposed algorithm are as follows:

Step 1. Initialize parameters: the number of clustering $C=K$, the number of initial iteration t=1, the biggest number of iteration is t_{max}, and the stopping threshold $\varepsilon = 0.01$. Initialization probable subdivision value is $t_{ij}^{(0)}$ and the clustering center is $p_i^{(0)}$. Based on (5), the penalty factor λ_i can be calculated.

Step 2. Calculate probable subdivision values according to (6).

Step 3. Calculate clustering center according to (9).

Step 4. Calculate objective function value according to (4), and $t=t+1$.

Step 5. If $\left\|J(t) - J(t-1)\right\| < \varepsilon$ or $t>t_{max}$, then stop; or if otherwise, repeat step 2-4.

Clustering center $P = \left[p_1, ..., p_K\right]$ will be regarded as the estimated location of the signal sources.

4. Simulation Results

The simulation environment in this paper is as follows: in a field with an area of 100m×100m, randomly deploy N sensor nodes and K signal sources, and all default parameters are shown in Table 1.

Table 1. The Default Parameters

Parameter	Symbol	Default
Node number	N	400
Signal source number	K	2
Measurement noise SD	σ	1 m
Quantized bit number	M	3 bit
Energy at k signal source	S_k	1500

The simulation results of this paper are obtained through running the Monte Carlo experiments for 2000 times, and following indexes are adopted in assessing the localization errors:

$$\frac{1}{R \cdot K}\sum_{i=1}^{R}\sum_{k=1}^{K}\sqrt{\left(x_k - \hat{x}_k(i)\right)^2 + \left(y_k - \hat{y}_k(i)\right)^2} \tag{10}$$

Where (x_k, y_k) is the real location of the *k-th* signal source, $\left(\hat{x}_k(i), \hat{y}_k(i)\right)$ is the estimated location of the *k-th* signal source after running Monte Carlo experiment for the *i-th* time, and R=2000.

Fig. 2 presents the relationship between the noise standard deviation σ and the localization error under different quantization bit numbers. As can be seen from the Fig. 2, the localization error of the proposed algorithm increases with the increase of σ. The reason lies in the fact that a larger σ will cause the bigger the disturbance of noise to measurement, and the larger probability for errors of quantized value D_i. With increasing number of quantization bit M, the localization error gradually decreases. The reason lies in the fact the bigger M is, the more the quantitative information supplied by nodes to base stations will be, thus uplifting the accuracy of localization.

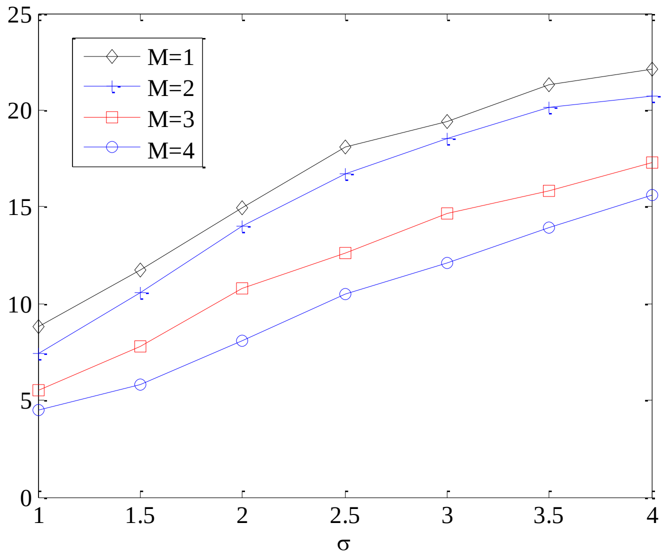

Figure 2. The Relationship between Localization Error and Standard Variance of Noise under Different Quantization Bit Numbers

Table 2. Presents the Influence of Node Number and Signal Source Energy. S_k on localization error. It can be seen that the accuracy of the proposed algorithm increases with the increase of node number, because the more the number of node, the more effective information is supplied, hence improving the accuracy of localization. Due to the fact the disturbance among signals will increase as the signal energy S_k becomes bigger, the accuracy of localization is negatively influenced.

Table 2. The Localization Error

	N=200	N=250	N=300	N=350	N=400
S_K=1500	6.0581	5.8402	5.756	5.624	5.624
S_K=2000	7.3731	7.2468	7.1978	7.1559	7.0534
S_K=2500	8.763	8.6856	8.5772	8.5056	8.38

The above two conclusions are from relatively ideal situations, or in other words, sensor nodes can all transmit quantized value D_i to base stations. In real situations, due to reasons like node malfunction or channel congestion, packet loss might arise, or in other words, base stations fail to receive the quantized values of some nodes. Fig. 3 presents the relationship between packet loss rate and localization error. It can be seen that with increasing packet loss rate, the localization error of the proposed algorithm does not vary basically. Therefore, the proposed algorithm has certain robustness. Meanwhile, with increasing noise standard deviation σ, the localization error climbs up.

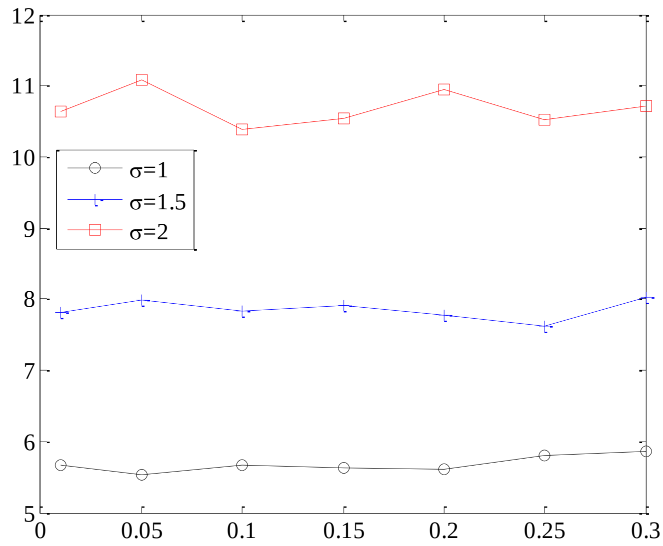

Figure 3. The Relationship between Packet Loss Rate and Localization Error

Assume that the node communication radius is 75m, and each node transmits its own 16 bits of ID information (network address) and measured energy information to base stations in a single-hop manner. If the energy of the *k-th* signal source S_k=1500, then the data packet required to be transmitted according to traditional methods based on measurement is 27 bits in size (16bit+11bit). If the method based on quantization proposed in this paper, then only 19 bits of data need to be transmitted (16bit+3bit, here assume the quantization bit number M=3).

Given that the measurement data is sent in a single-hop manner with no need to transmit data from other nodes, so the experimental model adopted in this experiment is as follows [11]:

$$E_{tx}(l,d) = l \times E_{ele} + l \times d^2 \times E_{amp} \tag{11}$$

Where, E_{ele} is the energy consumed by non-transmission equipment (frequency synthesizer, mixer and filter), E_{amp} is the energy consumed by projectors, l is the size of data packet, and d is the transmission distance.

From the above, it can be seen that under the condition that the transmission distance is fixed, the node energy consumption is in direct proportion to the size of data packet. Default parameters adopted in this experiment are as shown in the following Table 3.

Table 3. Default Parameters of the Energy Simulation

Parameter	Value
E_{ele}	3.63μJ/bit
E_{amp}	16.3μJ/bit
d	75m

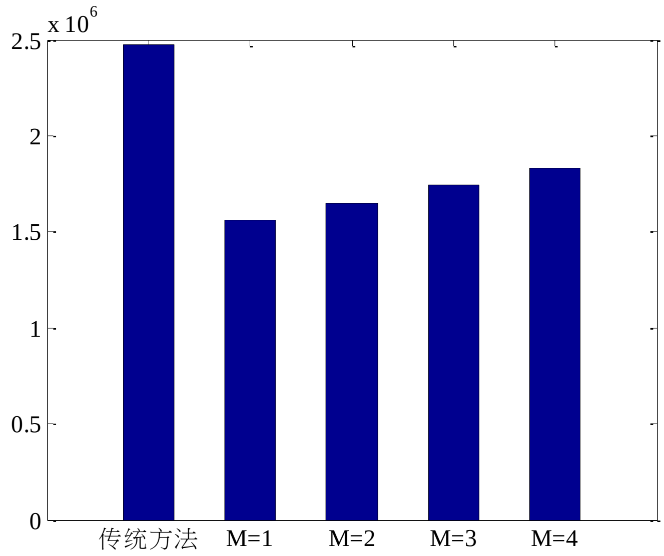

Figure 4. Comparison of Energy Consumption

5. Conclusions

This paper studies the multi-source localization methods of quantitative information based on wireless sensor network. Firstly, aiming at the propagation features of acoustic sources, it proposes logarithmic quantization strategy, which can better reflect the relationship between acoustic source and distance. Then, a multi-source localization method based on possibilistic C-means clustering (PCMC) is proposed to transform multi-source localization problem into clustering problem, with a view to obtaining the estimated location of signal sources through calculating the clustering center. The simulation results show that the algorithm in this paper can accurately estimate the location of multiple signal sources, with certain robustness against packet loss probability. Compared with traditional localization methods based on measurement, the algorithm proposed in this paper can effectively reduce energy consumption.

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