Fuzzy Clustering Based Source Direction Estimation Method Using Acoustic Energy Measurement with UWSN

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***Abstract*—A Fuzzy clustering based fusion location method is presented for acoustic source direction estimation in underwater wireless sensor network. This method based on acoustic signal energy measurements taken at the received acoustic signal of a stationary sensor. Using fuzzy K-Means clustering, we could get centers of clusters with different orders. According to the new centers with their coordinates calculated, three least-square methods of source localization based on energy decay model(LS, WLS and F-WLS) are used to estimate the direction of the source. Numerous simulation results show that weighted least-square (WLS) method of localization outperforms least-square (LS) localization for different SNR. The experimental results shown that this direction method could also perform well in lower SNR. The average error of F-WLS yield the approximately same direction accuracy, but outperforms WLS in lower SNR. And for a certain network, the optimal order of clusters could be found not the bigger the better.**

Keywords—underwater sensor networks; source direction; acoustic energy measurement; fuzzy clustering; weighted least square

I. INTRODUCTION

In recent years, wireless sensor networks have been widely studied in various safety-related applications. Many researchers have paid attention to underwater wireless sensor networks (UWSN) in data collection and environment monitoring [1]. The underwater wireless sensor network often performs monitoring tasks such as detection, classification, localization, and tracking of one or more targets in the sensor field[2-3]. However, the underwater sensors are battery powered and have limited wireless communication bandwidth. And due to the extremely environment, there always presented researchers with many challenges[4].

In this paper, we will focus on the task of source direction, using passive and stationary acoustic sensors. As is known that the intensity of an acoustic signal emitted Omni-directionally from a point sound source and propagating through water will attenuate at a rate that is inversely proportional to the distance from the source. Actually in a sensor network, we could always find a sensor that is closest to the source, and its intensity measured should be the largest one. For the whole sensor network, the measured signal intensity of all sensors would distributed around a center line in axis-symmetric way. Therefore, the source must be laid on the center line of the whole network in a statistic sense.

Motivated by this property, using source energy decay model, an energy-based acoustic source direction method is proposed for single target in an open-terrain acoustic sensor field. With noise taken into account, the problem is solved as all the hyper-spheres formed by all energy ratios in the least square sense. According to this, an energy based Fuzzy K-Means clustering method is used with different orders, and the centers of each cluster should be laid beside the center line in a statistic sense. In this way, the direction of the source could be calculated using least square location method.

The rest of this paper is organized as follows. In section II, the acoustic energy decay model is developed. In Section III, an energy based fuzzy K-Means clustering method is given. In Section IV, the LS-based source localization methods in underwater wireless sensor networks (UWSN) were investigated and presented. At last, we completed some simulations to verify the performance with Monte Carlo experiments.

II. ENERGY DECAY MODEL OF SENSOR SIGNAL

Energy-based source direction is motivated by a simple assumption that the sound level decreases when the distance between sound source and the listener becomes large. By modeling the relation between sound level (energy) and distance of the source, one may estimate the source using multiple energy reading at different, known sensor locations[5].

Let n be the number of acoustic sensors in the sensor field. The acoustic signal received at the i^{th} $i=1,2,\cdots,n$ sensor during time interval t_i , , denoted by $e_i(t)$, then can be expressed as:

$$e_i(t)=\gamma_i\frac{s(t-t_i)}{\left\|r_s(t-t_i)-r_i\right\|}+\varepsilon_i(t) \tag{1}$$

where $s(t)$ is the intensity of the acoustic source measured 1 meter away from that source, and t_i is the time delay for the acoustic signal propagates from the target (acoustic source) to

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the i^{th} sensor. $\varepsilon_i(t)$ is the background noise that is modeled as a zero-mean additive white Gaussian (AWGN) noise random variable with variance ς_i. $r_s(t)$ is a $d\times1$ vector denoting the coordinates of the target during time interval t; r_i is a $d\times1$ vector denoting the Cartesian coordinates of the i^{th} stationary sensor.

III. Energy Based Fuzzy K-Means Clustering

Fuzzy K-Means clustering is basically a partitioning method to analyze data and treats observations of the data as objects based on locations and distance between various input data points [6-7]. In this paper, the method is used to solve the problem of how to estimate the center line. In a statistic sense, the average coordinates of all the sensors is probably near the center line, and can be considered as a result of one cluster based on energy distribution. For each sensor, sensor location and the received energy are known and written as $X_i=\{x_i,y_i,e_i\}, i=1,2,\cdots,n$. Where (x_i,y_i) is the location of sensor, e_i is the received energy. According to the received energy the K-Means clustering method is used as classification method and partitioning the objects into k mutually exclusive clusters $k=2,3,\cdots,m$ that objects within each cluster remain as close as possible to the others in the same cluster but as far as possible from objects in other clusters. Select an appropriate m, there will be z centers of these clusters, $z=\sum_{i=1}^{m} i$, and these centers are also regarded near the center line, as shown in Fig.1.

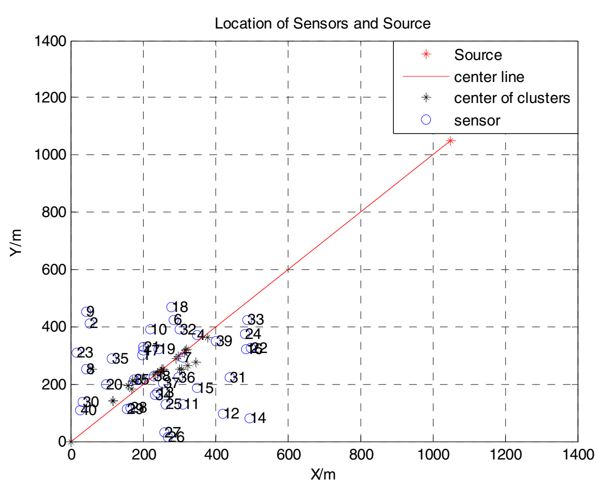

Fig.1 Location of sensors and source

Let $Z=\{X_1,X_2,...X_n\}$ be a set of n objects. To cluster X into k clusters by the fuzzy K-Means algorithm[35] is to minimize the following objective function:

$$\min\ P(U,Z)=\sum_{j=1}^{k}\sum_{i=1}^{n}u_{ij}D_{ij}+\lambda\sum_{j=1}^{k}\sum_{i=1}^{n}u_{ij}\log u_{ij} \qquad (2)$$

subject to

$$\sum_{j=1}^{k}u_{ij}=1,\ \ u_{ij}\in(0,1],\ \ 1\le i\le n$$

where $U=\{u_{ij}\}$ is an n-by-k partition matrix, u_{ij} represents the association degree of membership of the i^{th} object e_i to the j^{th} cluster is an k-by-m matrix containing the cluster centers, and D_{ij} is a dissimilarity measure between the j^{th} cluster center and the i^{th} object. Here, the square of the Euclidean norm is used as the dissimilarity measure,

$$D_{ij}=\sum_{l=1}^{m}(z_{jl}-e_{il})^2$$

The first term in eq. (2) is the cost function of the standard K-Means algorithm. The second term is added to maximize the negative objects-to-clusters membership entropy in the clustering process. With the weight entropy term, the clustering process can simultaneously minimize the within cluster dispersion and maximize the negative weight entropy to determine clusters to contribute to the association of objects.

IV. Weighted Least Square Method of Source Direction

Using the clustering method of Section III, we could get z centers with their locations calculated by the known sensor locations. By using linear least square fitting to the z new points, we could fit a line that is close to the center line in theory. According to the new z observation data $(x_i,y_i), i=1,2,\cdots,z$, The least square (LS) estimation of the source direction is to minimize the following cost function:

$$f(k,b)=\sum_{i=1}^{z}\frac{1}{2}(kx_i+b-y_i)^2$$

$$\frac{\partial f}{\partial k}=0,\quad \frac{\partial f}{\partial b}=0$$

Because of the limited z, polynomial weights will be used to enhance estimation performance. In this section weighted least-square (WLS) method and fusion weighted least-square (F-WLS) method are proposed to reduce the source direction error, and ensuring the estimation performance[8-9].

V. Numerical Experiment

The source direction performance of different least square methods (LS, WLS, and F-WLS) are compared by the MATLAB. N sensors were placed randomly and uniformly in the region of sized 2_D 100×100 cubic meters. Assumed that the source was located without the 2-D field. The root mean square error (RMSE) and signal to noise ratio (SNR) are defined as follows:

$$RMSE = \sqrt{\sum_{i=1}^{N_i} \sum_{j=1}^{N_j} \frac{\left\| \hat{k} - k \right\|^2}{N_i N_j}} \;, \quad SNR = 10 \log \frac{S}{\sigma_i^2}$$

In order to eliminate the effect of UWSN deployment, different number of sensors topologies with 100 Monte-Carlo trials per topology are used. The source direction performance (SDP) of LS, WLS and F-WLS method are analyzed with different SNR, which number of sensors are varied from N=40 to N=300, the order of clusters *m*=6 and samples L=4000. The average errors are shown in Fig.2, and the RMSE when different numbers of sensors are presented in Fig.3, which SNR=0dB. Fig.4 and Fig.5 gives the SDP with lower SNR(-10dB).

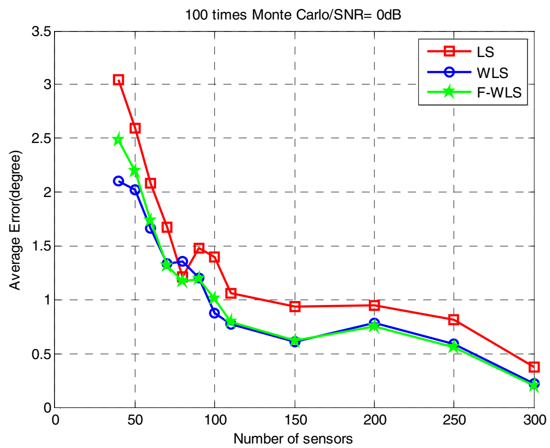

Fig.2 Average error of source direction with different number of underwater wireless sensors nodes

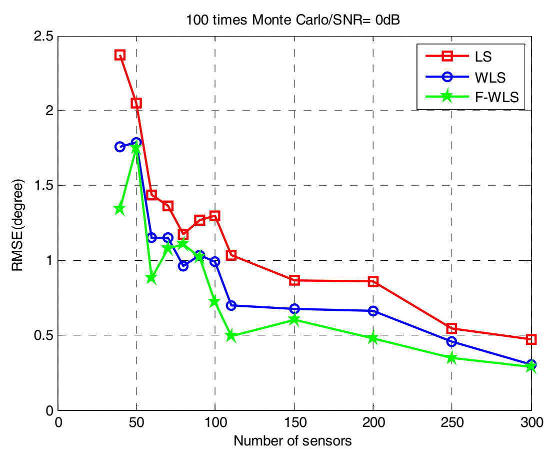

Fig.3 RMSE of source direction with different number of underwater wireless sensors nodes

From Fig.2 and Fig.3, we can see that the average error and RMSE decrease fast at first with the increasing number of sensors. After the number of sensors over 100, the estimation performance increase slowly, we could find that the optimal number of sensors equal 100 for the consideration of increasing cost with sensors. Compared the RMSE of these three methods, F-WLS methods outperform WLS and LS method .

As shown in Fig.4 and Fig.5, for lower SNR (-10dB), these three methods also have a good performance. WLS and F-WLS yield the approximately same direction accuracy. However the estimation performance of F-WLS is more stable than WLS method.

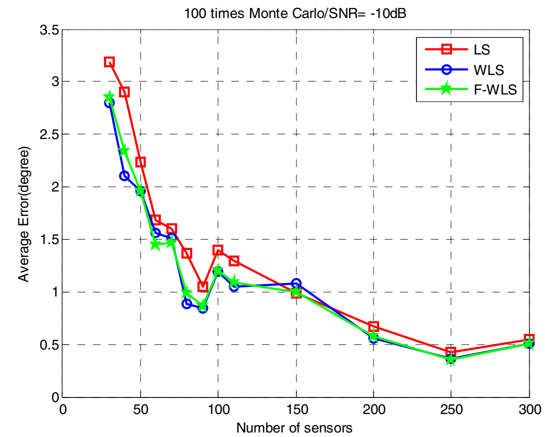

Fig.4 Average error of source direction with different number of underwater wireless sensors nodes

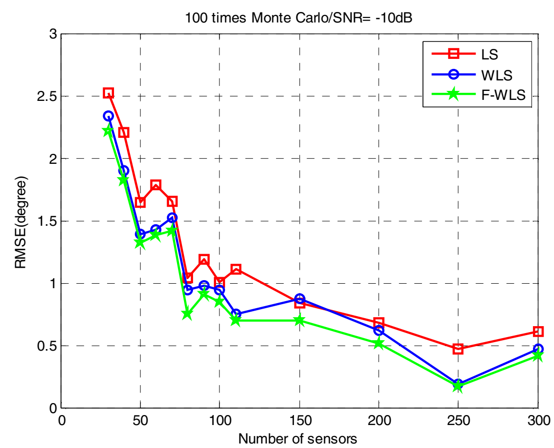

Fig.5 RMSE of source direction with different number of underwater wireless sensors nodes

As shown in Fig.6 and Fig.7, an constant N was given to analyze the estimation performance of different order of clusters. Let number of sensors N=100, SNR=-10dB, samples L=4000, the order of clusters *m* varied from 1 to 7.

In Fig.6, we could see that the average error of LS, WLS and F-WLS in this conditions have the same change trend. For N=100, the optimal performance is obtained when *m=5*. In Fig.7, the RMSE have shown in this conditions, and the performance of these three method decrease when the order of clusters *m* is small, but become bigger with the further increase of *m*. Compared these three methods, F-WLS methods outperform WLS and LS method. For a certain network, to ensure the estimation performance, number of sensors contained with a cluster should not be to small. Therefore, an appropriate order of clusters could be found not the bigger the better.

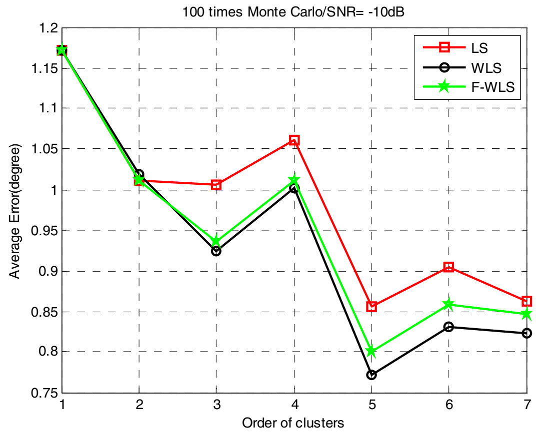

Fig.6 Average error of source direction with different order of clusters

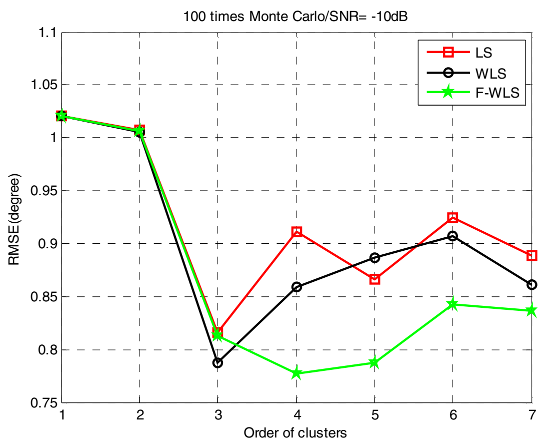

Fig.7 RMSE of source direction with different order of clusters

VI. . CONCLUSION

This paper focus on source localization method based on the energy measurement of network sensors. according to energy decay model, the source must be laid on the center line of the whole network in a statistic sense. Using Fuzzy K-Means method with different orders, we could get center of clusters with their coordinates near the center line. Simulated with three different least-square method, the performance of different algorithm with different SNR are analyzed. The WLS outperforms the LS, and could have a good performance in lower SNR. At last of this paper, the SDP of a constant number of sensors with different order of clusters shown that for a certain network, the optimal order of clusters could be found not the bigger the better.

For further research we will focus on the energy fluctuate model of underwater sensor network.

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