Multiple Nodes Signal Localization Algorithm Based on Integration of Sub-frame Estimation and Cluster Analysis

Hongqing Liu [1]

1 Modern Logistics
Hunan Vocational College
Changsha Hunan, 410131, China

***Abstract* — Node positioning system can quickly determine the position of the multiple nodes. On how to improve the performance of multiple nodes localization, multiple nodes localization algorithm based on integration of subframe estimation and cluster analysis is proposed. First, a signal is divided into 8 subframes. Each subframe signal using the phase variation is calculated in response to the power control weighting function, which searches the node signal source position to obtain the maximum value of the subframe estimation. Because the signal in the time domain node is sparse, these estimates correspond to a plurality of node signals position. Then the estimated values of the sub-frames are divided into several categories using the convergence of clustering algorithm. Finally controlled in response to the sub-frame by the average estimated value of the power function was evaluated to give the final node source location estimation. Experimental results show that in the case of 2-3 nodes, the positioning performance of the algorithm is much higher than traditional algorithms.**

Keywords - node positioning system; cluster analysis; node signals signal; multiple nodes source; sub-frame, anti-terror attacks

I. INTRODUCTION

Microphone array system can be widely used in car hands-free communication [1], speech separation [2], the node source monitoring [3] and other fields. Node source localization based on microphone array technology has played a key role in these systems. Such as hands-free communication systems, it may use the beam source array according to the estimated orientation algorithm to suppress the formation of interference and noise. Since the 1970s, researchers at home and abroad to node positioning method conducted in-depth research, the various positioning algorithm and used the actual node signals localization system [4-6]. At present, a single node signal source localization based on a growing number of researchers has begun to focus on multiple nodes signal localization techniques.

In the real environment, such as ordinary buildings environment, in addition to an array of received signals direct node but also have reflected node and background noise. Reflected in a number of obstacles repeatedly claimed to reverb, which is an important factor affecting the positioning performance. In the case of multiple sources signals, the node signals localization algorithm must also have the ability to distinguish between multiple sources.

Literature [7] proposed multiple node signals localization algorithm to simulate the human auditory, in the real world can achieve 4 positions of the node signals, but the algorithm is computationally expensive and still difficult practical. Literature [8] proposed the formation of pyramid-based multiple node signals localization algorithm. The algorithm uses the sparsity of the speech signal, multiple frame signals in time-frequency analysis, based on formation objective function, using a histogram clustering multiple node signals localization. The algorithm relies on the formation and the observed signal takes a long time, and therefore cannot be used to locate the node signals moves. Literature [9] proposed a phase transformation guided weighted response power (Steered Response Power-Phase Transform, SRP-PHAT) node signals localization algorithm. The algorithm computes an array of guided responses received signal power (Steered Response Power, SRP), looking to make the maximum point SRP node signals location is estimated node signals space. As a result of PHAT weighted, SRP-PHAT algorithm has strong robustness in reverberant environments, which also makes it one of the most popular node signals localization algorithm. In the case of a node signals, the node signals location corresponding space SRP highest peaks. Under the multiple source case, theoretically each node signals will generate a spatial spectrum peak, therefore, SRP-PHAT cluster algorithm can also be combined with multiple node signals localization. According to this principle, the literature [10] proposed multiple node signals localization algorithm based on large aperture array. This algorithm requires only one frame of data can be achieved for the node signals 5 positioned for movement in the case of the node signals. However, SRP-PHAT is difficult to overcome the interference between the node signals, each node signals to produce overlapping peaks. Peak node signals generated less likely to be covered by strong signals, so the algorithm multiple node signals lower positioning performance. Literature [11] proposed to divide the sub-band approach to overcome the interference between the node signals position to improve performance, but in order to avoid the high frequency band produced scripts phase winding [12], array element spacing is not too large. In addition, sub-band division method also with the signal sampling frequency; these problems make the algorithm application is limited.

II. THE PROPOSED ALGORITHM

A. Traditional SRP-PHAT Multiple Node Signals Localization Algorithm

Based on the received sub-frame node signals localization techniques divided the array microphone array into subframe first. Then estimate the location of the node signal according to one or more frames. As mentioned above, the time-frequency analysis algorithm requires tens to hundreds of frame signal in order to estimate the position of the plurality of node signals. The length of frame signal is several tens of milliseconds, so this type of algorithm is used only for a stationary node signals positioning. SRP-PHAT algorithm only needs one data to estimate the location of the node signals, with a wider range of practical value.

We used $x_m(n)$ to represent the mth microphone receives a frame data. $X_m(k)$ indicates its discrete Fourier transform. In the far-field assumption, the positioning algorithm only estimated arrival angle of the node signals direction (Direction of Arrival, DOA), that is node signals direction, denoted as $\boldsymbol{q}=(\theta,\phi)$. Where, θ and ϕ respectively represent the horizontal angle and the elevation of the node signals. PHAT weighted pilot signals received by the array response may be expressed as:

$$\hat{Y}^{\mathrm{PHAT}}(k,\boldsymbol{q})=\sum_{m=1}^{M}\frac{X_m(k)}{\left|X_m(k)\right|}e^{-j\omega\tau_{ml}(\boldsymbol{q})} \tag{1}$$

Where $\tau_{ml}(\boldsymbol{q})$ represents the delay of mth microphone signal reaches the reference primitive l . ω represents the frequency point k corresponding analog angular frequency, M is the number of array primitives. The expression is:

$$\tau_{ml}(\boldsymbol{q})=\boldsymbol{\zeta}\cdot(\boldsymbol{r}_m-\boldsymbol{r}_l)/c \tag{2}$$

Where "·" represents the vector dot product. $\boldsymbol{\zeta}$ is a representative of the node signals direction vector, its length is 1, can be expressed as

$$\boldsymbol{\zeta}=[\cos\phi\cos\theta,\ \cos\phi\sin\theta,\ \sin\phi]^{\mathrm{T}} \tag{3}$$

$\boldsymbol{r}_m=[x\ y\ z]^{\mathrm{T}}$ is the coordinate vectors for the mth microphone in the rectangular coordinate system. c is the air speed of node(about 342m/s). Imaginary the SRP-PHAT function of node signals location $\boldsymbol{q}$ for

$$\hat{P}^{\mathrm{PHAT}}(\boldsymbol{q})=\sum_{k=0}^{K-1}\hat{Y}^{\mathrm{PHAT}}(k,\boldsymbol{q})\hat{Y}^{\mathrm{PHAT}*}(k,\boldsymbol{q}) \tag{4}$$

Where "*" denotes taking conjugate. K is the number of FFT points. According to the symmetry of the power spectrum in order to save computation, the actual calculation only need to calculate half of the frequency. The formula (4) can be written as

$$\hat{P}^{\mathrm{PHAT}}(\boldsymbol{q})=\sum_{k=0}^{K/2-1}\hat{Y}^{\mathrm{PHAT}}(k,\boldsymbol{q})\hat{Y}^{\mathrm{PHAT}*}(k,\boldsymbol{q}) \tag{5}$$

Suppose there is only one node signals, Q represents the interested node signals space, then $\hat{P}^{\mathrm{PHAT}}(\boldsymbol{q})$ reaches a maximum at the location of the real node signals, namely the location of the node signals is estimated to be

$$\hat{\boldsymbol{q}}_s=\arg\max_{\boldsymbol{q}\in Q}\hat{P}^{\mathrm{PHAT}}(\boldsymbol{q}) \tag{6}$$

In the case where a plurality of node signals, each source would theoretically produce a peak, that $\hat{P}^{\mathrm{PHAT}}(\boldsymbol{q})$ function has a plurality of peaks, each peak to identify the position of multi-node signals localization can be achieved. Literature algorithm is according to the principle, which uses the converging clustering algorithm (AC: Agglomerative Clustering) to obtain the position estimate of the plurality of node signals. As mentioned above, since the mutual interference between the node signals, the peak of the node signals overlap, positioning performance of the algorithm is low.

B. AC Cluster

The proposed algorithm obtained from each sub-frame of node signals position estimation, we call subframe estimates. Each subframe estimate is representing a different node signals, it must have the same or close to a few points, which correspond to the same source. Therefore, you need to estimate the subframe cluster analysis. Assuming clustering obtained after classes N_c, each corresponding to a possible source. AC clustering does not need to know the number of classes for solving the problem of unknown the number of node signals. In addition, the question of this article, the estimated number of subframes set of data points is the need of clustering, its size is very small. AC clustering efficiency is very high.

We use i to represent the iteration number, k indicates the class number, u represents the sequence number represents the point. For the ith iteration, the class $C^{(i)}(k)$ has $\left|C^{(i)}(k)\right|$ point, where the operator $|\cdot|$ said class potential, that is the number of points in this class. $\boldsymbol{q}_k^{(i)}(u)$ represents the points in the class $C^{(i)}(k)$, apparently $1\le u\le\left|C^{(i)}(k)\right|$. AC clustering using Euclidean distance (Euclidean distance) to represent the distance between two points, the operator is $\|\cdot\|$. We used d_{th} represent the Euclidean distance threshold. This question of the threshold represents the minimum distance between the two node signals, which can be pre-set. Suppose the points of a data set is N , AC clustering algorithm using pseudo-code description of the process as shown in Table 1.

TABLE I AC CLUSTER ALGORITHM PROCESS

1. Input data points N, each point for a class, so $i=0$, $N_c=N$. Initial class: $C^{(i)}(k), k=1,...,N$,selected coupling parameter L ('average', 'simple' or 'complete')
2. According to L, calculated the distance $d_{kl}^{(i)}$ between $C^{(i)}(k)$ and

$C^{(i)}(l)$ for any two classes: If L = 'average', then $d_{kl}^{(i)} = \underset{u,v}{\text{mean}} \left\| \boldsymbol{q}_k^{(i)}(u) - \boldsymbol{q}_l^{(i)}(v) \right\| \forall k, l$. If L = 'simple', then $d_{kl}^{(i)} = \min_{u,v} \left\| \boldsymbol{q}_k^{(i)}(u) - \boldsymbol{q}_l^{(i)}(v) \right\| \forall k, l$. If L = 'complete', then $d_{kl}^{(i)} = \max_{u,v} \left\| \boldsymbol{q}_k^{(i)}(u) - \boldsymbol{q}_l^{(i)}(v) \right\| \forall k, l$.
3. Calculation $d_{\min} = \min_{k,l}(d_{kl}^{(i)})$, if $d_{\min} \geq d_{\text{th}}$, clustering end, save the results, otherwise continue.
4. Merge satisfy $C^{(i)}(k_1)$ and $C^{(i)}(k_2)$ any two classes, which meet the conditions $d_{k_1k_2}^{(i)} = d_{\min}$.
5. The combined number of statistical categories, update N_c , and make $i = i+1$, go back to step 2

The clustering problem in this paper, the coupling parameter L can be chosen according to N . The larger N , take L = 'average', while N is small, then take L = 'simple'.

C. Improved SRP-PHAT Node Signals Localization Algorithm

The basic idea of the improved algorithm is based on speech signal sparsity in the time domain. The signal frame is divided into several sub-frame to process. Suppose that frame length is T , which is divided into N_{SF} subframes. The subframes do not overlap, the subframe size is $T_{SF} = T/N_{SF}$. For each subframe using the algorithm described in Section 2 to give the SRP functions $\hat{P}_n^{\text{PHAT}}(\boldsymbol{q})$ of each sub-frame, the node signals position to obtain the subframe estimation [24].

$$\hat{\boldsymbol{q}}_n = \arg\max_{\boldsymbol{q} \in Q} \hat{P}_n^{\text{PHAT}}(\boldsymbol{q}), \quad n = 1, 2, \ldots, N_{SF} \tag{7}$$

According to the sparsity of assumptions, these estimates include multiple node signals location.

AC clustering will be divided into N_c classes, but not every class corresponds to a node signals. Similar to a single node signals, due to the influence of reverberation and noise, some of the subframe may get the wrong estimate. These estimates are far away from the true value, which will become a separate category clustering. The number of class $C(k)$ elements is $|C(k)|$, which means that subframes have been estimated that there are similar. The greater the $|C(k)|$ value, $C(k)$ contained in the real node signals location estimates that the greater the possibility. We set the threshold γ_{th} , leaving only the classes $|C(k)| > \gamma_{\text{th}}$ that can be expressed as $\{C(k),\ k = 1 : \tilde{N}_c\}$, apparently $\tilde{N}_c \leq N_c$. The larger γ_{th} helps to reduce the estimated error, but may discard some of the correct estimate. Its value should be appropriately selected according to the number of signals. A class has a number of estimates, they correspond to the same source, from these estimates also need to select a best estimate. In order to evaluate these estimates, we define the function of the average sub-frame SRP.

$$\hat{P}_{\text{avg}}^{\text{PHAT}}(\boldsymbol{q}) = \frac{1}{N_{SF}} \sum_{n=1}^{N_{SF}} \hat{P}_n^{\text{PHAT}}(\boldsymbol{q}) \tag{8}$$

The kth class in the best estimate for

$$\hat{\boldsymbol{q}}_k^* = \arg\max_{\boldsymbol{q} \in C(k)} \hat{P}_{\text{avg}}^{\text{PHAT}}(\boldsymbol{q}),\ k = 1, \ldots, \tilde{N}_c \tag{9}$$

Due to the sudden of signals signal, multiple signals in a frame signal is not necessarily completely overlap. For example two signals, one frame of a signal may contain multiple signals or may contain only one repeated node. We use N_s represent the number of the signals source, assuming its value is known, N_a represents a number of signals echo. The value is unknown, $\hat{N}_a$ represents the estimated values, said there should be $\hat{N}_a \leq N_s$. The target of multiple node signals localization algorithm is based on a frame data to estimate the number and location of node source. According to formula (9), we obtain the node signals position estimated at $\{\hat{\boldsymbol{q}}_k^*,\ k = 1 : \tilde{N}_c\}$. If $\tilde{N}_c \leq N_s$, the above estimate is the final output, and $\hat{N}_a = \tilde{N}_c$. If $\tilde{N}_c > N_s$, but also choose an estimated value of $\hat{N}_a$ from $\{\hat{\boldsymbol{q}}_k^*,\ k = 1 : \tilde{N}_c\}$, then $\hat{N}_a = N_s$. According to the value of $|C(k)|$ and $\hat{P}_{\text{avg}}^{\text{PHAT}}(\hat{\boldsymbol{q}}_k^*)$ evaluating the pros and cons of $\hat{\boldsymbol{q}}_k^*$. For example, two estimation values $\hat{\boldsymbol{q}}_k^* \in C(k)$ and $\hat{\boldsymbol{q}}_l^* \in C(l)$, if $|C(k)| > |C(l)|$, $\hat{\boldsymbol{q}}_k^*$ is considered superior to $\hat{\boldsymbol{q}}_l^*$, and vice versa. If $|C(k)| = |C(l)|$, then compare the value of $\hat{P}_{\text{avg}}^{\text{PHAT}}(\hat{\boldsymbol{q}}_k^*)$ and $\hat{P}_{\text{avg}}^{\text{PHAT}}(\hat{\boldsymbol{q}}_l^*)$, where the larger the value corresponding to the estimated better. The proposed modified SRP-PHAT multiple node signals localization algorithm using pseudo-code description of the process, as shown in Table 2.

TABLE II IMPROVED SRP-PHAT NODE SIGNALS LOCALIZATION ALGORITHM PROCESSES

1. one input signal was divided into N_{SF} subframes, to calculate SRP functions $\hat{P}_n^{\text{PHAT}}(\boldsymbol{q})$
2. According to the formula (7) to give N_{SF} subframes estimate value $\hat{\boldsymbol{q}}_n$ $\hat{\boldsymbol{q}}_n$
3. Select L = 'simple', use AC clustering estimated marge N_{SF} subframes together into N_c class
4. retain the classes only meet the conditions $|C(k)| \geq \gamma_{\text{th}}$, which is expressed as $\{C(k),\ k = 1 : \tilde{N}_c\}$
5. According to the formula (8), calculated $\hat{P}_{\text{avg}}^{\text{PHAT}}(\boldsymbol{q})$ .In accordance with formula (9) to give $\{\hat{\boldsymbol{q}}_k^*,\ k = 1 : \tilde{N}_c\}$
6. Make $\hat{N}_a = \min(\tilde{N}_c, N_s)$, depending on the value of $|C(k)|$ and $\hat{P}_{\text{avg}}^{\text{PHAT}}(\hat{\boldsymbol{q}}_k^*)$ to evaluate $\hat{\boldsymbol{q}}_k^*$, whichever is optimal points $\hat{N}_a$, denoted

as $\hat{\boldsymbol{q}}_{sk}$, $k=1,\ldots,\hat{N}_a$
7. Output ultimate source position estimation node $\hat{\boldsymbol{q}}_{sk}$, $k=1,\ldots,\hat{N}_a$

III. EXPERIMENT AND ANALYSIS

In order to contrast the performance of improved algorithm with the original algorithm, this research recorded a 7.62 mm assault rifle firing at the time of the blast wave signal as the node signals. The maximum position measurement error is taken 2cm in the simulation, and the maximum delay estimation error is 5 microseconds, for pure node signals localization experiment. The microphone array for collecting signals is a radius of 1.5 m of uniform circular array, which is placed in a level. The number of microphones is 8, shown in Figure 1. DOA vector pointing from the origin point to the node signals, and the vector is defined as ζ by formula (3). We take collection database Numbers "recorder-2014-04-0001" as a group of data, which has three shots. The microphone array and signals location are shown in Figure 2.

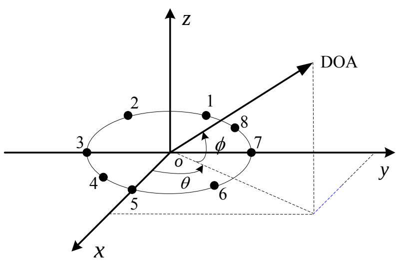

Figure 1. Microphone array and node signals DOA vector

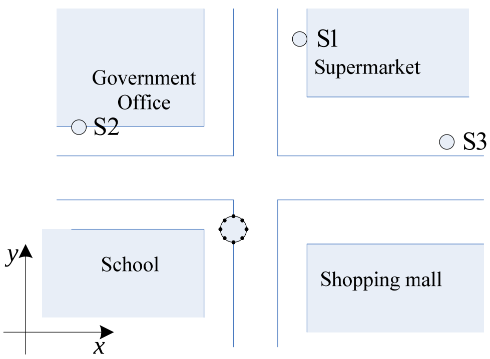

Figure 2. Microphone array and signals source location

Three signals orientation are: $\boldsymbol{q}_{s1}=(74^{\circ},21^{\circ})$, $\boldsymbol{q}_{s2}=(-7^{\circ},24^{\circ})$ and $\boldsymbol{q}_{s3}=(-50^{\circ},14^{\circ})$. In the process of shooting incident, shot first single occurrence, which is s1 and s2, s1 and s3, s2 and s3, then three people shot together. In each case, we take 12.5s data, a total of 50s data. Signal sampling frequency is 16kHz. The frame length is $T=1024$ points (64ms). The number of sub-frames per frame is $N_{SF}=8$. Each sub-frame is added Henning window; the frame overlap rate is zero. After removing the silent gap, a total of 625 frames data used in the experiment, including 439 of two signals, and 186 frames of three signals.

The main purpose of the algorithm is to calculate the minimum area containing the target. First, freely choose two nodes detected the target information to calculate the intersection boundary of two circular detection areas. Then find the intersecting circular detection area between the line and $[T_1,T_2]$ through an iterative approach. After these two steps, can find the node satisfying the condition, and may calculate the straight line d_2 passing through the two points $\{R_1,R_2\}$. Then we use the same method to calculate a straight line d_2 through the circular area of $[R_1,R_2]$. Finally, the area obtained is the cross area of c_i, c_j and c_k, as shown in Figure 3. "+" represents the target position.

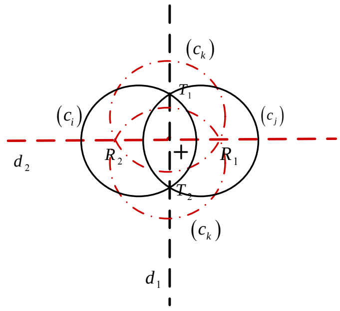

Figure 3. Several simple node signals estimates

Whether traditional SRP-PHAT algorithm, or the proposed algorithm, must be in source space search to get the node signals position estimation. According to the positional relationship between the array and the node signals, we set the search range of the horizontal angle θ is $-180^{\circ}\sim180^{\circ}$, and the range of the elevation ϕ is $0^{\circ}\sim45^{\circ}$, steps are 1°. Uniform circular array was used in the experiment plane array, and has smaller aperture. The array for elevation resolution is very low, so only in accordance with horizontal positioning accuracy to evaluate the performance of the algorithm. Each frame data input can get $\hat{N}_a$ point estimate results. If the horizontal angles of the kth point estimate with a mobile shooting angle true value is less than 5°, this point is the correct estimate, otherwise is the error estimate. The correct estimation of the cumulative number of points obtained in all the frames, and then divided by the total number of frames to get the estimated activity node signals correct rate:

$$R_c=\frac{\sum_{i=1}^{I}\alpha_c(i)}{\sum_{i=1}^{I}N_a(i)} \tag{10}$$

Similarly the estimated error rate can be obtained

$$R_e = \frac{\sum_{i=1}^{I} \alpha_e(i)}{\sum_{i=1}^{I} N_a(i)} \tag{11}$$

In the above two formulas, I is used for signal frame of the experiment, $\alpha_c(i)$ and $\alpha_e(i)$ represent the number of correct estimate and the number of error estimate obtained by the *ith* frame data. $N_a(i)$ is the true value of the number of signals moving for *ith* frame data. It is noteworthy that the number of moving signals of each frame is unknown, so that the sum of correct rate and error rate is not to 1, which reflects the performance of positioned algorithm.

In order to facilitate researchers conducted node signals localization experiments, AV16.3 database also provides a single pure node signal, these recordings synchronized with the array recordings, so we can determine in the *ith* frame time. Each node signals is not active, the *ith* frame data $N_a(i)$ can be obtained.

We first consider the case of two signals. Because each frame of data is divided into eight subframes, the probability that each node signals frame occurs in two or more subframes. Therefore we set $\gamma_{\text{th}} = 2$ in Table 2. Consider the extent and source close to the estimate of discrete subframe is large, set $d_{\text{th}} = 16^{\circ}$ in Table 1. For convenience of description, the literature (Muniz A S G. *et al*, 2011) algorithm referred to as SRP-PHAT, the proposed improved algorithm referred to as SRP-PHAT-SF. Two algorithms were used to make two signals node signals localization experiments, the results is shown in table 3.

TABLE III TWO SIGNALS CASES POSITIONING PERFORMANCE COMPARISON OF TWO KINDS OF ALGORITHM

Algorithm and evaluation index	SRP-PHAT		SRP-PHAT-SF	
	R_c (%)	R_e (%)	R_c (%)	R_e (%)
s1 and s2	70.4	12	76	8
s1 and s3	59.93	16.85	62.92	15.36
s2 and s3	68.05	10.9	68.8	6.39
average	66.03	13.28	69.09	9.96

From Table 3 can be seen, the proposed algorithm has significantly improved positioning performance than the literature. Where the average correct rate increase by about 3%, the average error rate reduced by 3.32%.

We then consider the case of three signals. Due to the number of node signals are more, in order to raise the correct rate, set $\gamma_{\text{th}} = 1$, the same as the rest of the parameters with two signals. The experimental results are shown in Table 4. Seen from Table 4, the case of three signals, the proposed algorithm can greatly improve the correct rate, and error rate increased slightly.

TABLE IV THREE SIGNALS CASES POSITIONING PERFORMANCE COMPARISON OF TWO KINDS OF ALGORITHM

Algorithm	R_c (%)	R_e (%)
SRP-PHAT	50.3	18.05
SRP-PHAT-SF	64.71	18.46

Randomly placed three tetrahedral arrays, according to the geometric relationships to calculate blast wave arrival times of the three microphone array. Then the coordinates of the three microphone array, the arrival time as a known quantity, respectively SRP-PHAT-SF location algorithm with this algorithm simulation 50 times, the distribution of node signal positioning error as shown in Figure 4. According to calculations, SRP-PHAT-SF location algorithm node signal positioning error is 1.704m, the average location error node signal algorithm is 1.576m, which can achieve more accurate than the SRP-PHAT-SF position location algorithm.

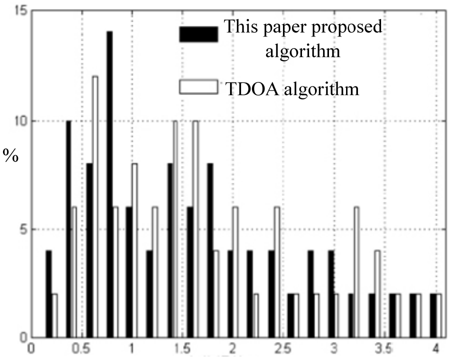

Figure 4. Nodes Positioning Error Distribution

SRP-PHAT-SF location algorithm cannot eliminate the practical application of multipath interference caused by the delay estimation errors, in order to show the superiority of the proposed method, add 1-4 8ms in TDE 8 array delay estimation errors positioning the two methods is shown in Figure 5.

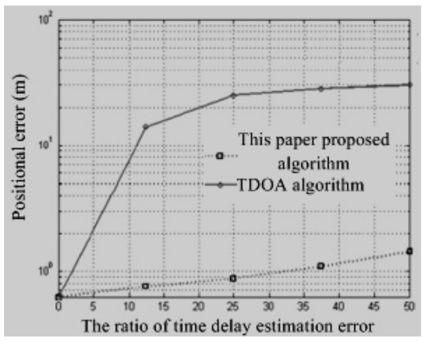

Figure 5. Delay Estimation Errors Affect the Proportion of Positioning Error

As can be seen in Figure 5, when the proportion of time delay estimation error is 0%, the two methods positioning error is almost the same. When the proportion of time delay estimation error increases, SRP-PHAT-SF positioning error increases linearly. When the number of the microphone array increases, the position error increases and decreases the number of the array shown in Figure 6. But with the increase in the number of arrays, the hardware requirements are also increased by the simulation results, so it should be between the array and the number of positioning accuracy trade-off.

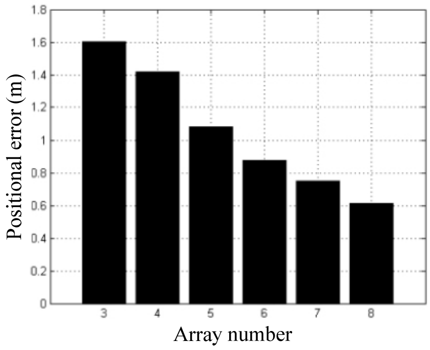

Figure 6. The influence of array number of positioning error

IV. CONCLUSIONS

In the real environment, noise around is an important factor affecting the performance of node signals localization algorithm. SRP-PHAT algorithm of reverberation has stronger robustness and has been widely applied. But the spatial resolution of SRP-PHAT is low. In the case of multiple signals, the space for each node signals peaks often overlap, resulting in this algorithm has poor performance of the multiple node signals localization. This paper proposed fusion subframe estimate and cluster analysis of multiple node signals localization algorithm. One frame of node signal is divided into eight subframes. The subframe is calculated SRP function to search the strongest node signals position sub-frame in each sub-frame. Since the speech signal has time domain sparsely, most node signals localization estimates obtained for each subframe cannot correspond to the same source, include multiple node signals location. Using AC cluster algorithm to these estimates is divided into several classes, and using the average to evaluate the estimate through function SRP, thereby obtain the final node signals position estimation. Use real environment 2 ~ 3 node microphone array data recording experiment. The results show that the improved algorithm can effectively improve the positioning performance.

The authors confirm that this article content has no conflicts of interest.

REFERENCES

[1] Alex Tek, Benoist Laurent, Marc Piuzzi, Zhihan Lu, Matthieu Chavent, Marc Baaden, Olivier Delalande et al. “Advances in Human-Protein Interaction-Interactive and Immersive Molecular Simulations”. InTech, 2012.

[2] Andrew R, Peters G P, Lennox J. “Approximation and regional aggregation in multi-regional input-output analysis for national carbon footprint accounting”. Economic Systems Research, Vol. 21, No. 03, pp. 311-335, 2009.

[3] Kwak S J, Yoo S H, Chang J I. The role of the maritime industry in the Korean national economy: an input-output analysis. Marine Policy, Vol. 29, No. 04, pp. 371-383, 2011.

[4] Degui Zeng, Yishuang Geng, “Content distribution mechanism in mobile P2P network”, Journal of Networks, Vol. 9, No. 03, pp. 1229-1236, 2014.

[5] Gan Yan, Yuxiang Lv, Qiyin Wang, Yishuang Geng, “Routing algorithm based on delay rate in wireless cognitive radio network”, Journal of Networks, Vol. 9, No. 04, pp. 948-955, 2014.

[6] Gan Yan, Yuxiang Lv, Qiyin Wang, Yishuang Geng, “Routing algorithm based on delay rate in wireless cognitive radio network”, Journal of Networks, Vol. 9, No. 04, pp. 948-955, 2014.

[7] Guanqun Bao, Liang Mi, Yishuang Geng, Mingda Zhou, Kaveh Pahlavan, “A video-based speed estimation technique for localizing the wireless capsule endoscope inside gastrointestinal tract”, 2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Aug. 2014

[8] Guanqun Bao, Liang Mi, Yishuang Geng, Mingda Zhou, Kaveh Pahlavan, “A video-based speed estimation technique for localizing the wireless capsule endoscope inside gastrointestinal tract”, 2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Aug. 2014

[9] Guanxiong Liu, Yishuang Geng, Kaveh Pahlavan, “Effects of calibration RFID tags on performance of inertial navigation in indoor environment”, 2015 International Conference on Computing, Networking and Communications (ICNC), Feb. 2015

[10] Jie He, Yishuang Geng, Fei Liu, Cheng Xu, “CC-KF: Enhanced TOA Performance in Multipath and NLOS Indoor Extreme Environment”, IEEE Sensor Journal, Vol. 14, No. 11, pp. 3766-3774, 2014.

[11] Jie He, Yishuang Geng, Kaveh Pahlavan, “Toward Accurate Human Tracking: Modeling Time-of-Arrival for Wireless Wearable Sensors in Multipath Environment”, IEEE Sensor Journal, 14(11), 3996-4006, Nov. 2014

[12] Jie He, Yishuang Geng, Yadong Wan, Shen Li, Kaveh Pahlavan, “A cyber physical test-bed for virtualization of RF access environment for body sensor network”, IEEE Sensor Journal, Vol. 13, No. 10, pp. 3826-3836, 2013