Weighted Least-Squares Solutions for Energy-Based Collaborative Source Localization Using Acoustic Array

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Summary
The Least-Squares (LS) acoustic source location estimation technique is reported for the application in a wireless sensor network. The technique uses acoustic signal energy measurements taken at individual sensors of a wireless sensor network to estimate an acoustic source location. In this paper, an improved formulation of this localization problem, which clarifies the LS estimation errors, is firstly presented. Then two weighted solutions, weighted nonlinear LS and weighted linear LS, are given. The weighting coefficients are derived from the energy measurements, which directly relate the energy strength with the estimation errors. Compared with existing LS methods, the weighted LS solutions deliver more accurate results and offer flexible implementation to reduce computational load. Extensive simulations are conducted to confirm the performance advantages.

Key words:
Acoustic sensors, Collaborative signal processing, Least squares, Sensor network, Source localization

1. Introduction

Efficient collaborative signal processing algorithms that consume less energy for computation and less communication bandwidth are highly important for the applications of the wireless sensor network [1], [2]. Source localization is one of the important collaborative signal processing tasks. Its objective is to estimate the positions of one or more targets within a sensor field monitored by the sensor network. The existing acoustic source localization techniques are typically based on three types of sensor measurements from physical variables: time delay of arrival [3]-[6], direction of arrival [7]-[9] and received sensor signal strength or energy [10]-[12]. It is found that the energy-based methods derived from the received signal energy are much appropriate for the application to sensor networks [11]. In this paper, we focus on collaborative source localization of a single target with acoustic sensors.

Let there be N sensors deployed randomly but with known positions in a sensor field in which a target emits omnidirectional acoustic signal from a point source. It has been shown that the acoustic energy in ground surface will attenuate at a rate that is inversely proportional to the square of the distance from the source [11]. The energy measurement y_i at the i^{th} sensor can be modeled as

$$y_i = g_i \cdot \frac{s}{\left\| r - r_i \right\|^2} + n_i, \quad i = 1, 2, \cdots N \tag{1}$$

where g_i is the gain factor of the i^{th} sensor, s is the signal energy radiated by the acoustic source, r and r_i are the $p \times 1$ coordinates of the source and the i^{th} sensor (p=2 or 3), n_i ($i = 1, 2, \cdots N$) are measurement noise approximated well as Gaussian noise with $n_i \sim N(\mu_i, \sigma_i^2)$ and independent at different sensors. The problem is to estimate the source coordinate from the measurements.

In [10], starting from the acoustic energy decay model, the authors formulate the source localization as a maximum-likelihood (ML) estimation problem. By introducing the concept of energy ratio and approximating the measurement noise as its mean value, the estimation problem is further formulated respectively as solutions of nonlinear and linear least-squares (LS) ones (in [11], they are named as ER-NLS and ER-LS methods, respectively). Simulation and field experiments show that these LS methods yield promising results. Fundamental is the concept of the energy ratio, which eliminates the estimation of source energy in the ML estimation. In addition, the energy ratio also gives us elegant geometric explanation of the source localization. As shown in [10], the source location can be restricted to a hypersphere (a circle in 2-D coordinates) whose center and radius are functions of the energy ratio and the two sensor locations. If more sensors are used, more hyperspheres can be determined. If all sensor measurements contain no noise, the corresponding hyperspheres will intersect at a particular point that corresponds to the source location.

However, it should be noted that the LS estimation formulations of source location assume additive white Gaussian noise (AWGN). In practice, although it is reasonable to assume that the sensors have AWGN, the LS model error may not be AWGN. In this paper, we reformulate the LS estimation problems by incorporating the measurement noise into estimation models and find that weighted LS approaches are more appropriate for estimating the source location. Keeping in mind that the

Manuscript received January 5, 2007.
Manuscript revised January 25, 2007.

less energy for computations is needed in sensor network applications, we derive simple weighting matrices from the sensor measurements. The resulting weighted LS approaches (denoted as ER-WNLS and ER-WLS) take a bit more computational load than the LS ones in [10], however, the estimation accuracy is greatly improved. Another advantage of the weighted LS methods is able to choose those hyperspheres or hyperplanes, which have great contributions to the accurate estimation of the source location, according to the weighting coefficients. In this sense, the ER-WNLS and ER-WLS can be implemented in smaller size of LS estimators than the ER-NLS and ER-LS can do.

This paper is organized as follows. In Section 2, an improved estimation model of target location is formulated. The weighted solutions (ER-WNLS and ER-WLS) are presented in Section 3. In Section 4, extensive simulations are performed to show superior performance of the weighted solutions over ER-NLS and ER-LS methods. Section 5 is the conclusion.

2. Estimation Model

Instead of using model (1) directly, we consider a mean-removed one. Define $h_i = (y_i - \mu_i)/g_i$ as normalized and mean-removed sensor measurement. Then (1) can be expressed as

$$h_i = \frac{s}{\|r - r_i\|^2} + \varepsilon_i , \quad i = 1,2,\cdots N \tag{2}$$

where $\varepsilon_i \sim N(0, \sigma_i^2 / g_i^2)$. From (2), the source energy is related with any sensor measurement h_i as

$$s = \|r - r_i\|^2 h_i - d_i^2 \varepsilon_i , \quad i = 1,2,\cdots N \tag{3}$$

where $d_i = \|r - r_i\|$ is the distance between the source and the i^{th} sensor. For any two sensors, we have

$$\|r - r_j\|^2 h_j - d_j^2 \varepsilon_j = \|r - r_i\|^2 h_i - d_i^2 \varepsilon_i$$
$$i = 1,2,\cdots N-1 \quad \text{and} \quad j = i+1,\cdots,N \tag{4}$$

Define the energy ratio [10] κ_{ij} of the i^{th} and j^{th} sensors as

$$\kappa_{ij} = \left(\frac{h_i}{h_j} \right)^{-1/2}$$

For $0 < \kappa_{ij} \neq 1$, (4) can be reexpressed as[1]

$$\left| r - c_{ij} \right|^2 = \rho_{ij}^2 + \zeta_{ij} ,$$
$$i = 1,2,\cdots N-1 \quad \text{and} \quad j = i+1,\cdots,N \tag{5}$$

where c_{ij} and ρ_{ij} are the center and the radius of the hypersphere defined in [10],

$$c_{ij} = \frac{r_i - \kappa_{ij}^2 r_j}{1 - \kappa_{ij}^2} , \qquad \rho_{ij} = \frac{\kappa_{ij} \left| r_i - r_j \right|}{1 - \kappa_{ij}^2}$$

and

$$\zeta_{ij} = \frac{d_i^2 \varepsilon_i - d_j^2 \varepsilon_j}{h_i - h_j} \tag{6}$$

is a composite noise twisting the hypersphere. The noise is a zero-mean variable depending on measurement noise, sensor reading and distance between source and sensors. Its variance is different from one (i,j) to another (i,j).

Equation (5) is the estimation model of the source location we will use in the following discussions. A great difference between (5) and (8) in [10] is that (5) clearly defines the estimation error, which depends on the sensor measurement noises, sensor measurements and distances from source to sensors. For N acoustic sensors, there will be C_N^2 equations similar to (5). For the brevity of notations, suppose that $M \leq C_N^2$ hyperspheres are used for locating the source and let us denote these hypersphere equations as

$$\left| r - c_i \right|^2 = \rho_i^2 + \zeta_i , \quad i = 1,2,\cdots,M \tag{7}$$

3. Energy Ratio-Based Weighted Least Squares Solutions

Based on (7), two least squares formulations can be defined. In [10], the noise terms ζ_i are assumed to be linear, independent Gaussian random variables with zero mean and identical variance. Obviously, such an assumption may not be true as revealed in (6) and hence may cause some performance degradation. In this sense, as is well-known, weighted least-squares formulations [13] will give improved solutions. Parallel to the development in [10], we derive two weighted least-squares solutions.

3.1 Energy ratio-based weighted nonlinear least

[1] For $\kappa_{ij} = 1$, Eq. (5) is reduced to the twisted hyperplane equation between r_i and r_j. For simplicity of presentations, we will only discuss the case of $0 < \kappa_{ij} \neq 1$ in the following development.

squares solution (ER-WNLS)

Define three $M \times 1$ vectors $a(r)$, b_1 and n_1 with $|r-c_i|^2$, ρ_i^2 and ζ_i as their elements, respectively. Then (7) is given in matrix form as

$$a(r) = b_1 + n_1 \tag{8}$$

The weighted nonlinear least-squares solution to (8) is given by minimizing

$$J_1(r) = \left(a(r) - b_1\right)^T W_1 \left(a(r) - b_1\right) \tag{9}$$

where W_1 is an arbitrary $M \times M$ positive definite weighting matrix. The ER-NLS method [10] assumes that the noise terms ζ_i ($i = 1, 2, \cdots, M$) in the noise vector n_1 are independent and identically distributed, and therefore the unit weighting matrix is used. As expected, the optimal weighting is the inverse of the noise covariance matrix $Q_1 = E\left\{n_1 n_1^T\right\}$ if the matrix is nonsingular [14]. However, as indicated in (6), the noise term ζ_i in the noise vector n_1 is due to the composition of the two sensor noises. Any sensor noise may be used to formulate several noise elements in the vector n_1. Therefore, the noise terms ζ_i are generally not independent and thus results in singular covariance matrix Q_1. To overcome this, we still assume that the noise terms are independent, but not identically distributed. Then the noise covariance matrix will be diagonal one with the variance of ζ_i as its elements. This assumption will sacrifice some estimation performance but can save computational resources, which is highly desired in energy-saving sensor networks.

From (6) and (8), we see that the diagonal elements of Q_1 will be given by $E\left\{\zeta_{ij}\zeta_{ij}\right\}$, which concerns two sensor measurements. Note from (2) that the $d_i^2 = \|r - r_i\|^2$ can be approximated as $\frac{s}{h_i}$. Then

$$\zeta_{ij} = \frac{d_i^2 \varepsilon_i - d_j^2 \varepsilon_j}{h_i - h_j} \approx \frac{s}{h_i - h_j}\left(\frac{\varepsilon_i}{h_i} - \frac{\varepsilon_j}{h_j}\right) \tag{10}$$

Thus

$$E\left\{\zeta_{ij}\zeta_{ij}\right\} \approx \left(\frac{s}{h_i - h_j}\right)^2 \left(\frac{\sigma_i^2}{h_i^2 g_i^2} + \frac{\sigma_j^2}{h_j^2 g_j^2}\right) = s^2 \omega_{ij} \tag{11}$$

where $\omega_{ij} = \frac{1}{\left(h_i - h_j\right)^2}\left(\frac{\sigma_i^2}{h_i^2 g_i^2} + \frac{\sigma_j^2}{h_j^2 g_j^2}\right)$. With the double indices *ij* replaced by a single index *m* for the brevity of notations, the weighting matrix W_1 can be selected as

$$W_1 = diag.\left\{\cdots, \frac{1}{\omega_m}, \cdots\right\} \tag{12}$$

where $\omega_m = \omega_{ij}$. Discarding s^2 will not affect the minimization of (9). If the noise variances at different sensors are equal, the noise variance terms can also be discarded from ω_m.

After finding the weighting matrix, the source location can be estimated from (9) by some nonlinear optimization methods, such as exhaustive search, multiresolution search, and gradient-based steepest descent search methods. In Section IV, we will use multiresolution method [11] to conduct simulation experiments.

Finally, we note that the (9) can be transformed into a linear LS problem with quadratic constraint, as discussed in [16].

3.2 Energy ratio-based weighted linear least squares solution (ER-WLS)

The optimization objective $J_1(r)$ is a 4-th order nonlinear equation, caused by quadratic term $\|r\|^2$. The ER-WLS formulation eliminates the quadratic term and has a closed form solution. For any two equations (7), subtracting each side and arranging their terms, we get hyperplane equations

$$2\left(c_i^T - c_j^T\right) r = \left(\|c_i\|^2 - \rho_i^2\right) - \left(\|c_j\|^2 - \rho_j^2\right) + \left(\zeta_j - \zeta_i\right)$$
$$i = 1, 2, \cdots M-1 \text{ and } j = i+1, \cdots, M \tag{13}$$

Define a matrix C with $2\left(c_i^T - c_j^T\right)$ as each row, an observation vector b_2 with $\left(\|c_i\|^2 - \rho_i^2\right) - \left(\|c_j\|^2 - \rho_j^2\right)$ as its element, and a noise vector n_2 with $\left(\zeta_j - \zeta_i\right)$ as its element. In matrix form, (13) is rewritten as

$$Cr = b_2 + n_2 \tag{14}$$

Then the ER-WLS solution reads as minimizing

$$J_2(r) = \left(Cr - b_2\right)^T W_2 \left(Cr - b_2\right) \tag{15}$$

where W_2 is a positive definite weighting matrix. The optimal weighting is the inverse of the noise covariance matrix, $Q_2 = E\left\{n_2 n_2^T\right\}$.

As in last subsection, we only consider the diagonal elements. Referring to (14), (5), and (6), any diagonal element of Q_2 will concern four sensor measurement noises. There are two possibilities for the generation of (13): four different sensors and three sensors with one common. Let us denote the diagonal element as $E\left\{\left(\zeta_{ij}-\zeta_{kl}\right)\left(\zeta_{ij}-\zeta_{kl}\right)\right\}$, which can be expanded as

$$\begin{aligned} &E\left\{\left(\zeta_{ij}-\zeta_{kl}\right)\left(\zeta_{ij}-\zeta_{kl}\right)\right\} \\ &= E\left\{\zeta_{ij}\zeta_{ij}\right\} + E\left\{\zeta_{kl}\zeta_{kl}\right\} - 2E\left\{\zeta_{ij}\zeta_{kl}\right\} \end{aligned} \tag{16}$$

The last term is given by

$$E\left\{\zeta_{ij}\zeta_{kl}\right\} \approx \begin{cases} 0, & i \neq j \neq k \neq l \\ \dfrac{s^2}{\left(h_i-h_j\right)\left(h_k-h_j\right)} \cdot \dfrac{\sigma_j^2}{h_j h_l g_j^2}, & i \neq j \neq k,\ j = l \end{cases} \tag{17}$$

Thus, using (10) and (17), we have

$$E\left\{\left(\zeta_{ij}-\zeta_{kl}\right)\left(\zeta_{ij}-\zeta_{kl}\right)\right\} \approx s^2 \tau_{ijkl} \tag{18}$$

where

$$\tau_{ijkl} = \begin{cases} \omega_{ij} + \omega_{kl}, & i \neq j \neq k \neq l \\ \omega_{ij} + \omega_{kl} + \dfrac{\sigma_j^2}{\left(h_i-h_j\right)\left(h_k-h_j\right) h_j h_l g_j^2}, & i \neq j \neq k,\ j = l \end{cases} \tag{19}$$

For the first possibility, there are $3 \cdot C_N^4$ hyperplanes. For the second possibility, there need three sensors to determine a hyperplane, so there are C_N^3 hyperplanes. With the four indices *ijkl* replaced by a single index *p* for the brevity of notations, the weighting matrix W_2 is given by

$$W_2 = diag.\left\{\cdots, \frac{1}{\tau_p}, \cdots\right\} \tag{20}$$

where $\tau_p = \tau_{ijkl}$.

With the weighting matrix defined by (20), the estimated source location is given by

$$r = \left(C^T W_2 C\right)^{-1} C^T W_2 b_2 \tag{21}$$

4. Performance Simulations

We have conducted extensive simulation experiments to assess the performance of the ER-WNLS and ER-WLS methods. Two simulation results are presented here. The first experiment compares the performance of the ER-WNLS and ER-WLS methods to that of the ER-NLS and ER-LS methods. The improved performance of the ER-WNLS and ER-WLS methods in terms of location estimation errors and range estimation errors is apparent in the simulation results. The second experiment shows the performance variations as the weighting number. It is found that the ER-WNLS and ER-WLS methods have the advantages to choose important hyperspheres and/or hyperplanes for estimations. Therefore, small number of hyperspheres and/or hyperplanes can be used to implement the source location estimations with undeteriorated performance.

We assume there are *N* sensor nodes, which are randomly scattered in a 2-D (*p*=2) sensor field of size 100m by 100m. All the sensor gain calibration is set at 1, and the measurement noise at different sensors is assumed i.i.d with the variance σ^2. A single source location is also chosen randomly from within the sensor field. Equation (1) is used to generate the acoustic energy readings and $s = 10000$.

For the ER-NLS and ER-WNLS methods, we use multiresolution (MR) search solution with three levels of grid sizes at 10 meters, 2 meters, and 0.4 meter, respectively.

A. Performance Comparison for different sensor numbers and noise levels

In this study, we compare the source location estimation errors and the range estimation errors for different sensor numbers and noise levels with four methods of ER-NLS, ER-LS, ER-WNLS and ER-WLS. First, at the noise level $\sigma = 0.2$, we calculate the estimation errors (recorded in x- and y-coordinates and ranges, respectively) with sensor number *N*=6, 10, and 25. Then, with *N*=10, we calculate the range estimation errors at different noise levels. For each σ and *N* setting, we conduct 2000 repeated trials which are averaged to obtain the estimation errors.

Table 1 shows the mean and covariance matrices of the location estimation errors. From the table, it is seen that the mean values of these four methods do not show any statistically significant bias and, hence, the four estimates are unbiased. Furthermore, the location errors in different dimensions are uncorrelated and the related variances are approximately equal. It is also noted that the variances in both x- and y-coordinates of all the methods decrease as the sensor number increases. The ER-WNLS and ER-WLS methods consistently outperform the

ER-NLS and ER-LS methods. The superiority of the ER-WNLS method to the ER-NLS method is obvious, and as sensor number increases, the ER-WNLS method performs best.

The range estimation errors can be further analyzed by calculating its probability density distribution. We use the histograms of the errors as approximations of the distribution. The results are shown in Fig.1, with 5-m increment bin. In this figure, each row represents results obtained from a particular method. Each column represents results from a particular sensor number. The mean and the standard deviation of the error are also calculated and listed in each subfigure. It is again seen that ER-WNLS method performs best among all these methods.

Table 1. Mean covariance matrices of location estimation errors

	6 sensors	10 sensors	25 sensors
NLS	$[0.52\ \ 0.04]$ $\begin{bmatrix} 270 & 2 \\ 2 & 294 \end{bmatrix}$	$[0.16\ \ -0.38]$ $\begin{bmatrix} 245 & -1 \\ -1 & 259 \end{bmatrix}$	$[-0.02\ \ 0.15]$ $\begin{bmatrix} 225 & -11 \\ -11 & 226 \end{bmatrix}$
WNLS	$[0.00\ \ 0.33]$ $\begin{bmatrix} 147 & 5 \\ 5 & 165 \end{bmatrix}$	$[0.11\ \ -0.12]$ $\begin{bmatrix} 84 & -2 \\ -2 & 87 \end{bmatrix}$	$[-0.07\ \ -0.04]$ $\begin{bmatrix} 23 & 1 \\ 1 & 19 \end{bmatrix}$
LS	$[-0.32\ \ 0.07]$ $\begin{bmatrix} 351 & 33 \\ 33 & 378 \end{bmatrix}$	$[0.21\ \ 0.01]$ $\begin{bmatrix} 140 & 3 \\ 3 & 147 \end{bmatrix}$	$[0.03\ \ -0.08]$ $\begin{bmatrix} 44 & -1 \\ -1 & 41 \end{bmatrix}$
WLS	$[0.01\ \ 0.20]$ $\begin{bmatrix} 326 & 54 \\ 54 & 369 \end{bmatrix}$	$[-0.08\ \ -0.02]$ $\begin{bmatrix} 104 & 5 \\ 5 & 106 \end{bmatrix}$	$[-0.07\ \ 0.00]$ $\begin{bmatrix} 25 & 0 \\ 0 & 25 \end{bmatrix}$

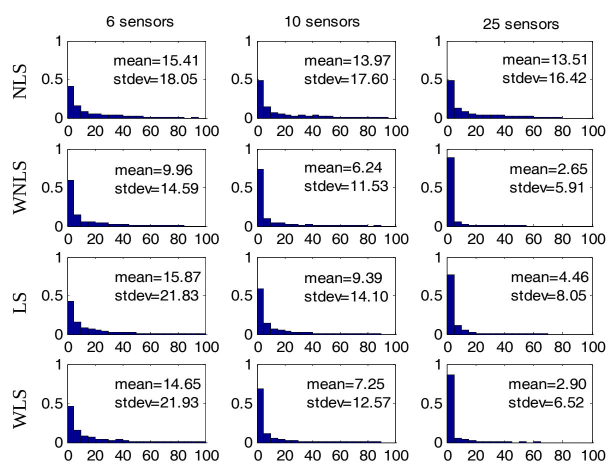

Fig. 1. Distribution of the range estimation errors of the four methods

Next, the root-mean-squared errors (RMSEs) of the range estimations of the four methods are simulated at different noise levels and N=10. Fig.2 gives the variations of the RMSEs versus noise levels σ. From this figure, we can see that the RMSEs increase as the noise level increases. The ER-WNLS and ER-WLS methods yield smaller errors than the ER-NLS and ER-LS methods can do. Again, the ER-WNLS method outperforms other methods.

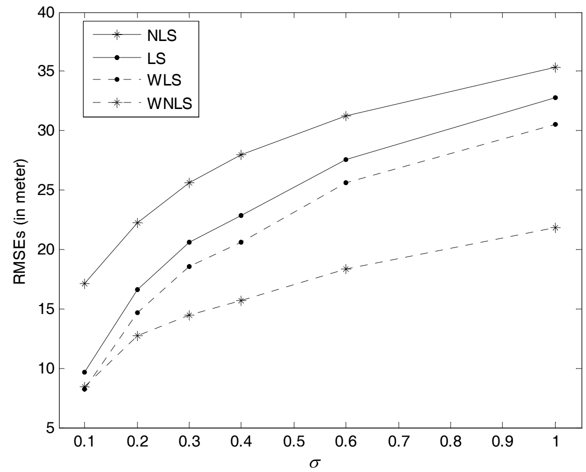

Fig.2. RMSEs of the range estimation at different noise levels σ (N=10)

B. Localization Accuracy with Reduced Hyperspheres and Hyperplanes

If N sensors are used to detect the source, as analyzed before, there will be C_N^2 hyperspheres for the nonlinear LS solutions and $C_N^3 + 3 \cdot C_N^4$ hyperplanes for the linear LS solutions. However, in theory, the nonlinear LS methods only need 3 hyperspheres, and the linear LS methods only need 2 hyperplanes. In another world, there will be large redundant hyperspheres/hyperplanes in LS estimators. The weighted LS solutions proposed in this paper enable us to choose the important (large weighting) hyperspheres or hyperplanes for location estimations.

In this simulation, we study the effect of weighting numbers on estimation accuracy. Let N=10. Then there are all $C_{10}^2 = 45$ hyperspheres for the ER-WNLS method and $C_{10}^3 + 3 \cdot C_{10}^4 = 750$ hyperplanes for the ER-WLS method, i.e., there are equal numbers of weights to be computed. We conduct 2000 trials, and in each trial, all the weights of the hyperspheres or hyperplanes are computed ahead and arranged in descending order. Figs.3 and 4 show the variations of the mean values of the weights for $\sigma = 0.2$. As is seen, there are only small numbers of weights with large weighting coefficients. The estimation accuracy of the source location is largely due to these weights.

Figs. 5 and 6 give the RMSE variations of the location estimation errors with ER-WNLS and ER-WLS methods as the number of weights. The estimated RMSEs decrease as the number of weighting coefficients increases. When the number increases to certain values, the RMSEs do not decrease significantly and even ascend slightly for the ER-WLS method. For the simulation example, 11 hyperpheres for the ER-WNLS method or 100 hyperplanes for the ER-WLS method are enough to ensure the estimation accuracy. The numbers of the hyperspheres/hyperplanes are greatly less than those required in ER-NLS and ER-LS estimators.

The advantage of the weighted methods in applications is quite obvious. A threshold is set to select the weighting coefficients and then the computation source can be saved without significantly sacrificing the localization accuracy.

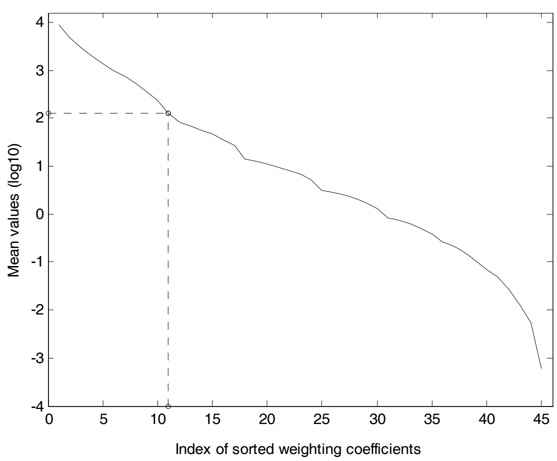

Fig.3. Mean values ($\log_{10}$) of the sorted weighting coefficients for the hyperspheres

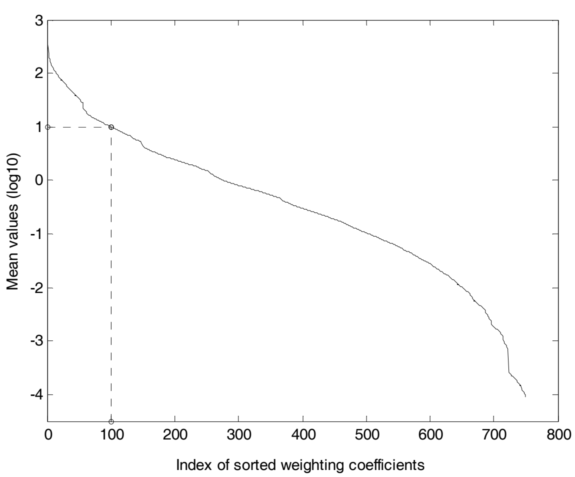

Fig.4. Mean values ($\log_{10}$) of the sorted weighting coefficients for the hyperplanes

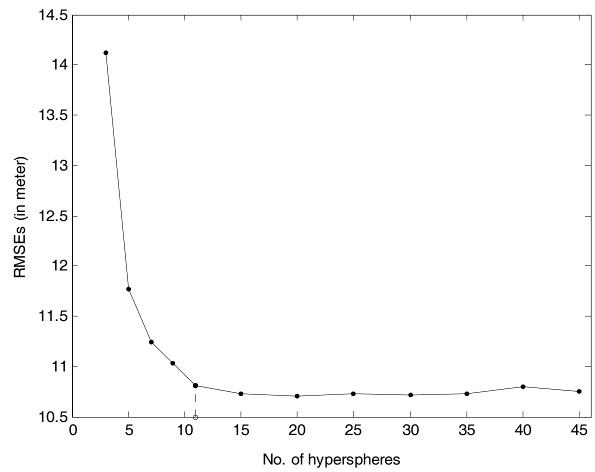

Fig.5. RMSEs of the ER-WNLS method versus the number of hyperspheres

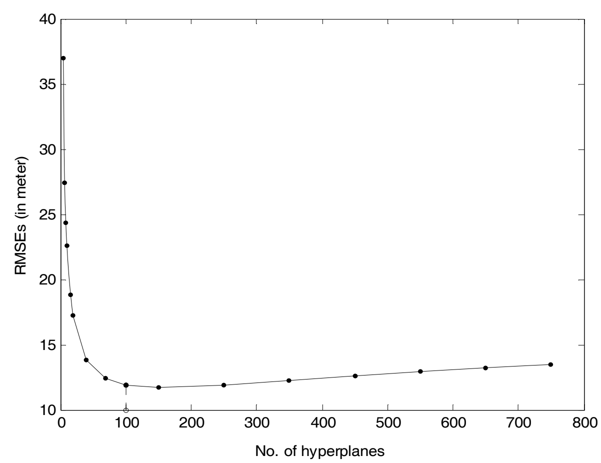

Fig.6. RMSEs of the ER-WLS method versus the number of hyperplanes

5. Conclusions

In this paper, an improved energy based acoustic source localization estimation model is proposed and two weighted least squares solutions are presented. Extensive simulations show that these weighted solutions yield performance superior to that of the existing least square solutions. The weighted formulations enable us to remove redundant hyperspheres and/or hyperplanes in original formulations and save computational source.

Acknowledgment

The work was partially supported by the National Natural Science Foundation of China through the grant number 60472059.

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