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High-Resolution DOA of Coherent Sources Based on Single Acoustic Vector-hydrophone

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Abstract

Aiming at the situation of two coherent sources, their bearings are estimated of high resolution by single acoustic vector-hydrophone. The pressure and particle-velocity channels of single acoustic vector-hydrophone can be considered as an array at one point with special spatial directivity. The reception model of two coherent sources is gained and the signal covariance matrix of single acoustic vector-hydrophone is decorrelated by the method of phasic smoothing, then the performances of different high-resolution algorithms are compared. The computer simulation indicates that a single vector hydrophone can realize two coherent sources DOA estimating and the method of vector optimization robust beamforming (VORB) gives the best DOA estimating result.

Keywords: *single acoustic vector-hydrophone, decorrelation, high-resolution algorithm*

1. Introduction

Vector hydrophone can measure sound pressure at the spot and vibration velocity at three directions in the sound filed simultaneously and concurrently. That means by using single acoustic vector-hydrophone bearing estimation of underwater target can be finished. As a result its application is attracting more and more attentions. Thus bearing estimation based on single vector hydrophone is a very important domain in the research field of submarine sound signal disposal [1-2]. In the past few years, some research results have been gained both at home and abroad about single vector hydrophone bearing estimation. Nehoria [3] in his article proposed two bearing estimation algorithms based on sound intense flow vector decombearing and velocity covariance decombearing. In literature [4] and [5] improved MVDR and MUSIC algorithms are introduced and used to conduct bearing estimation to single target and coherent acoustic sources. Academician Shi'e Yang [6] from Harbin Engineering University with the help of simultaneous system of equations combined by broadband sound pressure and even-time-order matrix has calculated the intensity and bearing and so on of each target.

When there exist two coherent acoustic sources under actual working conditions, the measured of single vector hydrophone is vector addition of two signals. Bearing of a single target cannot be estimated by using traditional acoustic energy flow method. Given this, single acoustic vector-hydrophone can be regarded as a common lattice with special space directivity [7]. When the signals received are two coherent signals, data rank of covariance matrix received by vector hydrophone is lowered down to 1. That will make dimension of signal subspace smaller than number of signal sources and thereby the direction of signal source cannot be estimated correctly [8-9]. This thesis introduces

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phasic smoothing method in electromagnetic signal disposal and attempts to use it to conduct de-correlation to covariance matrix of single-vector received signal, successfully recover data rank of covariance matrix. After that high-resolution algorithm which is often used in array signal processing and vector optimization algorithm introduced in this paper are adopted to conduct bearing estimation to coherent signals. By doing so single vector hydrophone has got the ability of distinguishing bearings of two coherent acoustic sources. And these all offer the basis to practical engineering application of this method.

2. Signal Reception Model of Single Vector Hydrophone

This paper only considers two-dimensional problem. What that concerns are sound pressure path of single vector hydrophone and orthorhombic two-dimensional vibration velocity paths V_x , V_y .Considering that L far-field narrow-band signals are input into the single vector hydrophone, use $x_l(t)$ to represent l th incident signal and $\mathbf{a}(\theta_l)$ to represent steering vector of single vector hydrophone to l th signal. That comes to:

$$\mathbf{a}(\theta_l) = \begin{bmatrix} 1 \\ \cos\theta_l \\ \sin\theta_l \end{bmatrix} \tag{1}$$

In the equation, θ_l is horizontal angle of incidence of l th signal. The three factors represent sound pressure path of single vector hydrophone and orthorhombic two-dimensional vibration velocity paths V_x , V_y respectively. Then output of single vector hydrophone can be represented as:

$$\mathbf{X}(t) = \mathbf{A}S(t) + \mathbf{N}(t) \tag{2}$$

In the equation, $\mathbf{X}(t)$ means the number of snapshots data vectors in 3×1 dimension of single vector hydrophone. $\mathbf{N}(t)$ means noisy data vectors in 3×1 dimension. $\mathbf{S}(t)$ refers to $L\times 1$ dimensional vector of space signals. $\mathbf{A} = [a(\theta_1) \quad a(\theta_2) \quad \cdots \quad a(\theta_l)]$ is $3\times L$ dimensional flow-pattern matrix of single vector hydrophone.

3. Covariance Matrix De-correlation of Received Data

As to the mathematic model of equation (2), under circumstances of white Gaussian noise, covariance matrix of data received from three paths of single vector hydrophone is:

$$\mathbf{R} = E\left\{\mathbf{X}\mathbf{X}^{\mathrm{H}}\right\} = \mathbf{A}E\left\{\mathbf{S}\mathbf{S}^{\mathrm{H}}\right\}\mathbf{A}^{\mathrm{H}} + E\left\{\mathbf{N}\mathbf{N}^{\mathrm{H}}\right\} = \mathbf{A}\mathbf{R}_S\mathbf{A}^{\mathrm{H}} + \mathbf{R}_N \tag{3}$$

In the equation, $\mathbf{R}_S$ and $\mathbf{R}_N$ are covariance matrix of signal and covariance matrix of noise respectively. For white space noise when noise power is σ^2 , the following equation works:

$$\mathbf{R} = \mathbf{A}\mathbf{R}_S\mathbf{A}^{\mathrm{H}} + \sigma^2\mathbf{I} \tag{4}$$

When signal sources are completely coherent, rank of covariance matrix of signal received by single vector hydrophone is lowered to 1. That will make number of dimension of signal subspaces smaller than number of signal sources. And the result is steering vector of some coherent sources and noise subspaces are not completely coherent. So direction of signal source cannot be estimated correctly. Therefore, the key to find out the bearing of coherent sources by using single vector hydrophone is how to recover effectively the sequence of covariance matrix of signal through a series of disposals or transformations so that the bearings of coherent acoustic sources can be estimated correctly. With regard to data covariance matrix of coherent acoustic sources received by such a special 'array', single vector hydrophone, this paper uses phasic smoothing method to conduct de-correlation to it with working principles as [10]:

Suppose two signals with completely same frequencies are $k_1 s(t) e^{j\phi_1}$ and $k_2 s(t) e^{j\phi_2}$ among which k_1, k_2 are signal amplitudes and ϕ_1, ϕ_2 are initial phases of the two signals. Define $\bar{\mathbf{R}}$ as:

$$\bar{\mathbf{R}} = \frac{1}{2}(\mathbf{R} + \mathbf{R}^*) \tag{5}$$

In the equation, $\mathbf{R}$ is covariance matrix of received data of single vector hydrophone and $\mathbf{R}^*$ is conjugate of covariance matrix, which refers to:

$$\mathbf{R}^* = \mathbf{A}\mathbf{R}_S^*\mathbf{A}^{\mathrm{H}} + \sigma^2\mathbf{I} \tag{6}$$

So,

$$\begin{aligned}\bar{\mathbf{R}} &= \frac{1}{2}(\mathbf{R} + \mathbf{R}^*) = \frac{1}{2}(\mathbf{A}\mathbf{R}_S\mathbf{A}^{\mathrm{H}} + \mathbf{A}\mathbf{R}_S^* A^{\mathrm{H}} + 2\sigma^2\mathbf{I}) \\ &= \frac{1}{2}(\mathbf{A}(\mathbf{R}_S + \mathbf{R}_S^*)\mathbf{A}^{\mathrm{H}}) + \sigma^2\mathbf{I}\end{aligned} \tag{7}$$

In the equation,

$$R_S = E(S(t)S^{\mathrm{H}}(t)) = \sigma_S^2 \begin{bmatrix} k_1 e^{j\phi_1} \\ k_2 e^{j\phi_2} \end{bmatrix} \begin{bmatrix} k_1 e^{j\phi_1} \\ k_2 e^{j\phi_2} \end{bmatrix}^H \tag{8}$$

σ_S^2 is signal power. Substitute equation (8) into (7) is:

$$\mathbf{R}_S + \mathbf{R}_S^* = \sigma_S^2 \begin{bmatrix} k_1^2 & k_1 k_2 \,\mathrm{Re}(\mathrm{e}^{j(\phi_1 - \phi_2)}) \\ k_1 k_2 \,\mathrm{Re}(\mathrm{e}^{j(\phi_2 - \phi_1)}) & k_2^2 \end{bmatrix} \tag{9}$$

In the equation (9), when $\varphi_1 - \varphi_2 \neq n\pi$ ($n = 0, \pm 1, \pm 2$), rank of matrix is 2, explaining that rank of covariance matrix of data in $\bar{\mathbf{R}}$ has been recovered by means of phasic smoothing method. Searching $\bar{\mathbf{R}}$ by using high-resolution algorithm can conduct bearing estimation to the two coherent acoustic sources.

4. Vector Optimization Algorithm

4.1. Introduction of Robust Algorithm

Suppose current scanned azimuth is θ_t, then according to the space bearing relationship, the practical steering vector at this direction can be obtained as $\mathbf{A}(\theta_t)$; the actual steering vector is $\bar{\mathbf{A}}(\theta_t)$. Taking influence of steering vector error Δ_{NM} into consideration, redefine actual source vector $\mathbf{A}(\theta_t)$ as the following form:

$$\mathbf{A}(\theta_t) = \bar{\mathbf{A}}(\theta_t) + \Delta_{NM} \tag{10}$$

Norm of Δ_{NM} can be restricted by constant $\varepsilon > 0$:

$$\|\Delta_{NM}\| \leq \varepsilon \tag{11}$$

Then actual steering vector $\mathbf{A}(\theta_t)$ will belong to the following set:

$$\mathbf{C}_{NM}(\varepsilon \mid \theta_t) = \{\mathbf{A}(\theta_t) \mid \mathbf{A}(\theta_t) = \bar{\mathbf{A}}(\theta_t) + \Delta_{NM}, \|\Delta_{NM}\| \leq \varepsilon\} \tag{12}$$

Restrict steering vector that belongs to set $\mathbf{C}_{NM}(\varepsilon \mid \theta_t)$, which means the absolute value of array response is smaller than 1:

$$\left|\mathbf{w}_{MN}^{\mathrm{H}}(\theta_t)\mathbf{A}(\theta_t)\right| \geq 1, \mathbf{A}(\theta_t) \in \mathbf{C}_{NM}(\varepsilon \mid \theta_t) \tag{13}$$

Therefore, robust algorithm can be expressed as the limited optimized question [11]:

$$\begin{cases} \min\limits_{\mathbf{w}_{NM}(\theta_t)} w_{NM}^{\mathrm{H}}(\theta_t)\mathbf{R}_{true}\mathbf{w}_{NM}(\theta_t) \\ s.t. \left|\mathbf{w}_{NM}^{\mathrm{H}}(\theta_t)\mathbf{A}(\theta_t)\right| \geq 1 \quad for \quad all \quad \mathbf{A}(\theta_t) \in \mathbf{C}_{NM}(\varepsilon \mid \theta_t) \end{cases}$$
$$\Updownarrow \tag{14}$$
$$\begin{cases} \min\limits_{\mathbf{w}_{NM}(\theta_t)} \mathbf{w}_{Nm}^{\mathrm{H}}(\theta_t)\mathbf{R}_{true}\mathbf{w}_{NM}(\theta_t) \\ s.t. \mathbf{w}_{nm}^{\mathrm{H}}(\theta_t)\overline{\mathbf{A}}(\theta_t) \geq \varepsilon \left\|\mathbf{w}_{NM}(\theta_t)\right\| + 1 \quad , \mathrm{Im}\{\mathbf{w}_{NM}^{\mathrm{H}}(\theta_t)\overline{\mathbf{A}}(\theta_t)\} = 0 \end{cases}$$

Applying vector optimized restriction algorithm into bearing estimation of coherent acoustic sources based on single vector hydrophone will restrict original vector mismatch and limited sampling effect and the others in a joint way. The algorithm can be described as:

$$\begin{cases} \min\limits_{\mathbf{w}_{NM}(\theta_t)} (\mathbf{w}.r.t.R_+^2) \ (\left\|\mathbf{U}\mathbf{w}_{NM}(\theta_t)\right\|_2, \left\|\mathbf{w}_{NM}(\theta_t)\right\|_2) \\ s.t. \ \ \mathbf{w}_{NM}^{H}(\theta_t)\overline{\mathbf{A}}(\theta_t) \geq \varepsilon \left\|\mathbf{w}_{NM}(\theta_t)\right\| + 1 \quad , \quad \mathrm{I}m\left\{\mathbf{w}_{NM}^{H}(\theta_t)\overline{\mathbf{A}}(\theta_t)\right\} = 0 \end{cases} \tag{15}$$

In the equation, $\mathbf{U}$ can be obtained through Cholesky decombearing conducted to $\mathbf{R} = \mathbf{U}^{\mathrm{H}}\mathbf{U}$ with R being known. $(\mathbf{w}.r.t.R_+^2)$ in the objective function refers to discussion of values of $\left\|\mathbf{U}\mathbf{w}_{NM}(\theta_t)\right\|_2$ and $\left\|\mathbf{w}_{NM}(\theta_t)\right\|_2$ in positive real number field. Equation (12) is vector optimization problem related to two objective functions $\left\|\mathbf{U}\mathbf{w}_{NM}(\theta_t)\right\|_2$ and $\left\|\mathbf{w}_{NM}(\theta_t)\right\|_2$. $\left\|\mathbf{w}_{NM}(\theta_t)\right\|_2$ is penalty term and it is used to ensure that stable weighting vector $\mathbf{w}_{NM}^{\mathrm{H}}(\theta_t)$ can be acquired by original objective function under conditions of turbulence.

4.2. Lagrange Fast Solving of Robust Algorithm

In line with Tikhonov regularization method, equation (15) can be described equally as:

$$\begin{cases} \min\limits_{\mathbf{w}_{NM}(\theta_t)} \left(\left\|\mathbf{U}\mathbf{w}_{NM}(\theta_t)\right\|_2^2 + \tau\left\|\mathbf{w}_{NM}(\theta_t)\right\|_2^2\right) \\ s.t. \quad \mathbf{w}_{NM}^{\mathrm{H}}(\theta_t)\overline{\mathbf{A}}(\theta_t) \geq \varepsilon\left\|\mathbf{w}_{NM}(\theta_t)\right\| + 1 \quad , \quad \mathrm{Im}\{\mathbf{w}_{NM}^{\mathrm{H}}(\theta_t)\overline{\mathbf{A}}(\theta_t)\} = 0 \end{cases} \tag{16}$$

In the equation $\tau > 0$ is restriction parameter and the restriction function of the equation above can be simplified further as:

$$\begin{cases} \min\limits_{\mathbf{w}_{NM}(\theta_t)} \left(\left\|\mathbf{U}\mathbf{w}_{NM}(\theta_t)\right\|_2^2 + \tau\left\|\mathbf{w}_{NM}(\theta_t)\right\|_2^2\right) \\ s.t. \quad \left|\mathbf{w}_{NM}^{\mathrm{H}}(\theta_t)\overline{\mathbf{A}}(\theta_t) - 1\right|^2 = \varepsilon^2\mathbf{w}_{NM}^{\mathrm{H}}(\theta_t)\mathbf{w}_{NM}(\theta_t) \end{cases}$$
$$\Updownarrow \tag{17}$$
$$\begin{cases} \min\limits_{\mathbf{w}_{NM}(\theta_t)} (\mathbf{w}_{NM}^{\mathrm{H}}(\theta_t)\mathbf{R}\mathbf{w}_{NM}(\theta_t) + \tau\mathbf{w}_{NM}^{\mathrm{H}}(\theta_t)\mathbf{w}_{NM}(\theta_t)) \\ s.t. \quad \left|\mathbf{w}_{NM}^{\mathrm{H}}(\theta_t)\overline{\mathbf{A}}(\theta_t) - 1\right|^2 = \varepsilon^2\mathbf{w}_{NM}^{\mathrm{H}}(\theta_t)\mathbf{w}_{NM}(\theta_t) \end{cases}$$

Use Lagrange multiplier method to solve the function above, optimization weighting vector after derivation can be expressed as:

$$\mathbf{w}_{NM}(\theta_t) = \frac{\xi_{NM}(\theta_t)}{\xi_{NM}(\theta_t)\overline{\mathbf{A}}^{\mathrm{H}}(\theta_t)\left(\hat{\mathbf{R}} + \xi_{NM}(\theta_t)\mathbf{I}\right)^{-1}\overline{\mathbf{A}}(\theta_t) - \varepsilon^2}\left(\mathbf{R} + \xi_{NM}\mathbf{I}\right)^{-1}\overline{\mathbf{A}}(\theta_t) \tag{18}$$

Among it, $\hat{\mathbf{R}}$ is the covariance matrix of sample data, ξ_{NM} is the optimization opposite-angle loaded factor which is expressed as:

$$\xi_{NM}(\theta_t) \approx \frac{\varepsilon^2(\sigma_n^2 + \sigma_s^2\left\|\mathbf{A}_n(\theta_t)\right\|^2) + \delta\left\|\overline{\mathbf{A}}_n(\theta_t)\right\|^2}{\left\|\overline{\mathbf{A}}(\theta_t)\right\|^2 - \varepsilon^2} \tag{19}$$

In the equation above, $\|\mathbf{A}_n(\theta_t)\|$ is projection of $\mathbf{A}(\theta_t)$ in noise subspace and $\bar{\mathbf{A}}_n(\theta_t)$ is projection of $\bar{\mathbf{A}}(\theta_t)$ in noise subspace. Vector optimization algorithm can finally be written as generalized opposite-angle loaded form. Its optimization opposite-angle loaded factor $\xi_{NM}(\theta_t)$ is related to white space noise power σ_n^2, target power σ_s^2, ε^2, δ and $\|\mathbf{A}_n(\theta_t)\|^2$, $\|\bar{\mathbf{A}}(\theta_t)\|^2$.

4.3. Robust Bearing Estimation Result

Substitute the target optimized weighting coefficient $\mathbf{w}_{NM}(\theta_t)$ at the time of t into target function $\mathbf{w}_{NM}^H(\theta_t)\mathbf{R}\mathbf{w}_{NM}(\theta_t)$, output power under optimized weighting coefficient us:

$$\mathbf{P}_{VORB}(\theta_t) = \mathbf{w}_{NM}^H(\theta_t)\mathbf{R}\mathbf{w}_{NM}(\theta_t) \tag{20}$$

Conduct spectrum peak searching within the interested angle range, space spectrum map formed of single vector hydrophone based on vector optimization stable beam is obtained.

5. Analysis of Simulation Experiment

For the purpose of testing the performance of high-resolution algorithm based on single vector hydrophone in coherent acoustic sources bearing estimation, the following experiments are designed to conduct analysis. The incidence azimuths of coherent acoustic sources with frequencies both being 300Hz are $\theta_1 = 210^\circ$ and $\theta_2 = 220^\circ$ respectively, the initial phases are $\pi/3$ and $\pi/6$, the sampling frequency is 3000Hz, number of snapshots is 1000, step size in search is $\Delta\theta = 0.1^\circ$, total 100 times of Monte Carlo experiments are conducted. Figure 1 shows the spatial spectrum results of decoherent data based on single vector hydrophone when SNR (signal-to-noise ratio) is 20dB using different algorithms, namely conventional beam-forming (CBF), Minimum Variance Distortionless Response (MVDR), multiple signal classification algorithm (MUSIC) and VORB algorithm. Among them CBF and MVDR algorithms both only have one peak value being both 215°. That illustrates that resolving abilities of these two methods are not strong enough to recognize multiple targets under this simulation condition. MUSIC and VORB algorithms can conduct bearing estimation to double targets. Results estimated by MUSIC are 213.2° and 239.8°; those estimated by VORB are 208.9° and 221.7°. Obviously VORB algorithm demonstrates better accuracy while keeping enough resolving ability, generating the optimized bearing estimation results if coherent acoustic sources.

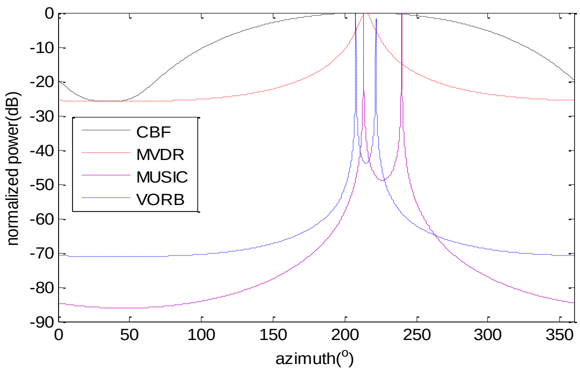

Figure 1. The spatial Spectrum Comparison and Analysis by Different Algorithms

Since under these simulation conditions, resolving abilities of CBF and MVDR cannot distinguish targets with angle degree difference being 10°, no further discussion is conducted to these two algorithms.

Suppose double-target SNR (signal-to-noise ratio) lifted from 0dB to30dB and use MUSIC and VORB methods to conduct a bearing searching to the target every 1dB. Fixed number of snapshots is 1000; other simulation conditions remain the same.

Figure 2 and 3 give different SNR (signal-to-noise ratio) and calculation results of double coherent acoustic sources bearing estimation RMSEs under different number of snapshots. From them it can be seen that 1) under conditions of SNR (signal-to-noise ratio) and number of snapshots being the same, bearing estimation performance of VORB algorithm is much better in comparison with MUSIC algorithm; 2) along with the decrease of SNR (signal-to-noise ratio), performances of two algorithms get worse in varying degrees while downtrend of performance curve of VORB is more gentle, which illustrates that this method has better performance in terms of noise suppression influence; 3)along with increase of number of snapshots, performance of MUSIC algorithm has obvious improvement and impacts of number of snapshots on VORB algorithm are not big. VORB algorithm maintains very strong bearing estimation ability for always.

To sum up, VORB has lower RMSEs in comparison with MUSIC algorithm and higher stability. It can effectively lower square noise's influences on bearing estimation and at the same time maintain good bearing estimation capacity when number of snapshots is small, giving the optimized bearing estimation results.

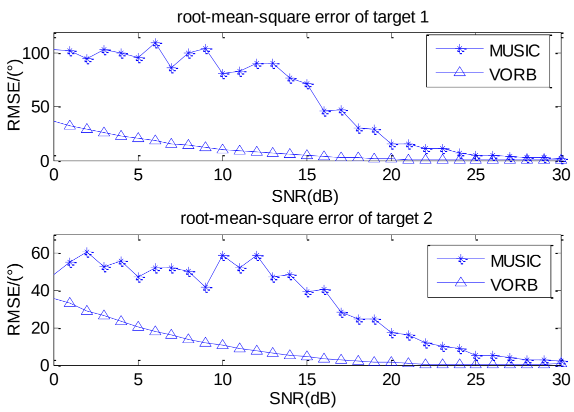

Figure 2. RMSEs of Bearing Estimation for the Coherent Sources under Different SNRs

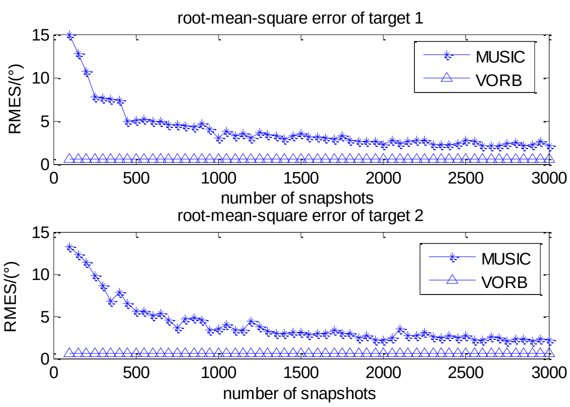

Figure 3. RMSEs of Bearing Estimation for the Coherent Sources under

Different Snapshots

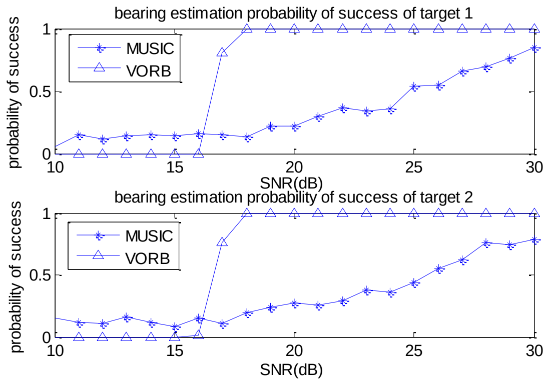

Figure 4. The Probability of Success of Bearing Estimation for the Coherent Sources under Different SNRs

Figure 4 presents probability curves of these two methods' realizing multi-target resolution under simulation conditions mentioned above. From the Figure it can be seen that under these experimental conditions, the algorithm proposed by this paper has higher probability of success in multi-target resolution.

Table 1. Resolving Comparison of the Multiple Targets' Azimuth Estimations by Four Algorithms under Different Conditions

SNR/dB	10			20			30		
azimuth/(°)	20	50	100	20	50	100	20	50	100
CBF	×	×	×	×	×	×	×	×	×
MVDR	×	×	×	×	×	√	×	√	√
MUSIC	√	√	√	√	√	√	√	√	√
VORB	√	√	√	√	√	√	√	√	√

Table 1 shows the comparison of the multiple targets' azimuth estimations by four algorithms under different SNR (signal-to-noise ratio). √ means bearing estimation can be done to two targets and × means double targets cannot be recognized. Since the number of single vector hydrophone paths is limited (only three paths are used in this paper), CBF algorithm cannot recognize double targets and MVDR can only conduct bearing estimation to two target in situations of SNR(signal-to-noise ratio) being so high and azimuth being so big. MUSIC and VORB algorithms can both conduct bearing estimation to two acoustic sources in situations of SNR (signal-to-noise ratio) and azimuth being different. However, it must be pointed out that number of signal sources must be known beforehand in the application of MUSIC algorithm but not in that of VORB algorithm. As is shown in the previous simulation, VORB gave the optimized bearing estimation result.

6. Conclusions

This paper uses phasic smoothing method to have covariance matrix of double coherent signals received by single vector hydrophone de-correlated and also applies high-resolution algorithm which is often used in array signal processing into single vector hydrophone. The paper proposed a new coherent acoustic sources bearing estimation method based on single vector hydrophone method. This method adds stable restriction conditions to array original vectors to enhance stability and resolving ability of high-resolution bearing estimation method. Simulation experiment has shown that bearing estimation can be conducted to two coherent acoustic sources only by using single vector hydrophone. Moreover, method proposed in this thesis has stronger resolving ability and anti-noise jamming ability in comparison with traditional high-resolution methods. This method gave the best results of coherent acoustic sources bearing estimation. All these established the basis for later engineering application.

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