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Three dimensional higher-order raypath separation in a shallow-water waveguide

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1	Abstract: Separating raypaths in a multipath shallow-water environ-
2	ment is a challenge problem due to the interferences between them and
3	colored noise existing in ocean environment, especially for two raypaths
4	arrive close to each other. Thus, in this paper, a three dimensional $(3D)$
5	higher-order raypath separation in an array to array configuration is
6	proposed. Performance tests using simulation data in a multipath en-
7	vironment, real data obtained in an ultrasonic waveguide and ocean
8	shallow-water data, respectively, illustrate that the proposed algorithm
9	achieves a higher resolution and a stronger robustness comparing to the
10	existing algorithms.

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11 1. Introduction

Acoustic rays are in multi-path propagation in a shallow-water waveguide due to the re-12 flection and (or) the refraction by the surface of the ocean and the continental shelf. The 13 multiple raypaths cover more parts of the ocean and provide more information than a single 14 emitted signal. However, they also produce interferences among them. Thus, separating 15 the raypaths is necessary in many important applications, such as passive sonar, ocean 16 acoustic tomography¹, etc. As a classical separation algorithm, the Multiple Signal Clas-17 sification (MUSIC) algorithm² was proposed to obtain a high-resolution separation of the 18 sources in a point to array configuration, which is composed of a point source and a verti-19 cal receiver array. The MUSIC algorithm improves separation resolution mainly exploiting 20 the orthogonality between the signal subspace and the noise subspace. However, it fails 21 when the signals are fully correlated or coherent. Jiang et el.³ proposed a smoothing active 22 wideband MUSIC (Smoothing-MUSICAL) algorithm, which is an extension of the MUSIC 23 algorithm to the case of separating fully correlated or coherent wideband signals by us-24 ing the spatial-frequency smoothing. In addition, comparing to the MUSIC algorithm, the 25 smoothing-MUSICAL algorithm improves the separation resolution through adding the ar-26 rival time of each raypath to the signal model as a new discrimination parameter. In addition 27 to second order moment-based algorithm, applying higher-order statistics to DOA estimation 28 has been focused on by the researchers and a group of algorithms have been developed⁴⁻¹⁰. 29 These algorithms exhibit superior estimation performance due to the properties of aperture 30 extension and noise suppression of higher-order cumulants. Recently, a wideband raypath 31

separation algorithm based on the fourth-order cumulant¹¹ is proposed in a point to array 32 configuration in a shallow-water waveguide. Higher resolution and more robust separation 33 is also obtained while at a cost of computation time. Sequentially, Jiang et el. propose a 34 fast algorithm using low-rank matrix approximation¹² to reduce the computation cost of the 35 4-smoothing-MUSICAL algorithm. On the other hand, Roux et el¹⁸ develop an array to ar-36 ray configuration, which is composed of a source vertical array and a receiver vertical array. 37 A double-beamforming algorithm is introduced experimentally in the configuration and a 38 high-resolution tomography inversion¹³ is finally obtained through using its separation re-39 sults, Moreover, Touzé et el¹⁴ present the double-capon algorithm and the double-MUSICAL 40 algorithm under the assumption of white Gaussian noise. To further improve both the resolu-41 tion and the robustness to the colored noise, we present a 3D higher-order raypath separation 42 algorithm in an array to array configuration in this paper. Its performance improvement is 43 achieved due to inheriting the merits of using both the higher-order cumulants and the array 44 to array configuration. 45

The rest of the paper is organized as follows. In Section 2, we give an elaborate description of the 3D higher-order raypath separation algorithm. In Section 3, we test the performance of the proposed algorithm using simulation data in a multi-path environment, real data obtained in an ultrasonic tank and ocean data, respectively. The paper is concluded in Section 4.

⁵¹ 2. The 3D higher-order raypath separation algorithm

52 2.1 Signal model

Assume the raypaths propagate in a double vertical array configuration, which is composed of an emission array (N sources) and a receiver array (M sensors). The P (P is assumed known^{15,16}) raypaths at the frequency ν produced by the n^{th} source and received on the m^{th} receiver is noted as $x_{m,n,\nu}$ and modeled as follows.

$$x_{m,n,\nu} = s_{\nu} \sum_{p=1}^{P} a_p e^{\Phi_p} + b_{m,n,\nu}$$
(1)

where s_{ν} is the source spectrum, $\Phi_p = -j2\pi\nu(T_p + (m - m_0)\tau_p^e + (n - n_0)\tau_p^r)$, $\tau_p^e = dsin(\theta_p^e)/c$ and $\tau_p^r = dsin(\theta_p^r)/c$. T_p notes the arrival time of the p^{th} raypath. m_0 (n_0) refers to the reference source (receiver). τ_p^e (τ_p^r) is the time delay for the p^{th} raypath propagates between two adjacent sources (receivers). d is the interval between two adjacent sources (receivers). θ_p^e (θ_p^r) is the direction of emission (reception) of the p^{th} raypath. a_p notes the amplitude of the p^{th} raypath. $b_{m,n,\nu}$ refers to the additive noise.

63 2.2 Data model

⁶⁴ Based on the signal model built in the above section, each signal received in the double-array ⁶⁵ configuration is a data cube for all N sources, M sensors and F frequencies of the wide-band ⁶⁶ signals considered in the algorithm. The data model is built through concatenating the data ⁶⁷ cube's elements into a long vector¹⁹. First, the elements corresponding to the source n^{th} at ⁶⁸ the frequency ν on all the M elements of the receiver array is concatenated into a vector as ⁶⁹ follows (+ notes transpose.) :

$$\mathbf{x}_{n,\nu} = [x_{1,n,\nu} \dots x_{M,n,\nu}]^+ \tag{2}$$

The elements corresponding to both the N source and the M sensors are further r1 concatenated into the following vector.

$$\mathbf{x}_{\nu} = [\mathbf{x}_{1,\nu} \dots \mathbf{x}_{n,\nu}]^+ \tag{3}$$

⁷² Finally, considering all the F frequencies, the long vector \mathbf{X} is obtained as follows.

$$\mathbf{X} = [\mathbf{x}_{\nu_1} \dots \mathbf{x}_{\nu_F}]^+ \tag{4}$$

Similarly, the steering vector $\mathbf{d}(\theta_p^e \theta_p^r, \mathbf{T}_p)$ and the additive noise **b** can be also concatenated into long vectors. Thus, the received signal in the frequency domain can be rewritten in the following matrix form.

$$\mathbf{X} = \sum_{p=1}^{P} a_p \mathbf{d}(\theta_p^e, \theta_p^r, \mathbf{T}_p) + \mathbf{b} = \mathbf{D}(\theta_p^e, \theta_p^r, \mathbf{T}_p) + \mathbf{b}$$
(5)

76 where

$$\mathbf{x} = [\mathbf{x}_{\nu_{1}}, \mathbf{x}_{\nu_{2}}, \cdots, \mathbf{x}_{\nu_{F}}]^{+}, \mathbf{x}_{\nu} = [\mathbf{x}_{1,\nu}, \mathbf{x}_{2,\nu}, \cdots, \mathbf{x}_{N,\nu}]^{+} \quad (\nu = \nu_{1}, \nu_{2}, \cdots, \nu_{F}), \text{ and } \mathbf{x}_{n,\nu} = [x_{1,n,\nu}, x_{2,n,\nu}, \cdots, x_{M,n,\nu}]^{+} \quad (n = 1, 2, \cdots, N). \quad \theta_{p}^{e} = [\theta_{1}^{e}, \theta_{2}^{e}, \cdots, \theta_{P}^{e}]^{+}, \quad \theta_{p}^{r} = [\theta_{1}^{r}, \theta_{2}^{r}, \cdots, \theta_{P}^{r}]^{+},$$

$$\mathbf{T}_{p} = [T_{1}, T_{2}, \cdots, T_{P}]^{+}.$$

$$\mathbf{d}(\theta_{p}^{e}, \theta_{p}^{r}, \mathbf{T}_{p}) = [\mathbf{d}_{\nu_{1}}(\theta_{p}^{e}, \theta_{p}^{r}, \mathbf{T}_{p}), \mathbf{d}_{\nu_{2}}(\theta_{p}^{e}, \theta_{p}^{r}, \mathbf{T}_{p}), \cdots, \mathbf{d}_{\nu_{F}}(\theta_{p}^{e}, \theta_{p}^{r}, \mathbf{T}_{p})]^{+}, \text{ with } \mathbf{d}_{\nu_{i}}(\theta_{p}^{e}, \theta_{p}^{r}, \mathbf{T}_{p}) = [\mathbf{s}_{\nu_{i}}e^{-j2\pi\nu_{i}(T_{p}+(1-n_{0})\tau(\theta_{p}^{e}))}\mathbf{d}(\theta_{p}^{r})_{\nu_{i}}, \cdots, \mathbf{s}_{\nu_{i}}e^{-j2\pi\nu_{i}(T_{p}+(N-n_{0})\tau(\theta_{p}^{e}))}\mathbf{d}(\theta_{p}^{r})_{\nu_{i}}]^{+} \quad (i = 1, 2, \dots, F) \text{ and}$$

$$\mathbf{d}(\theta_{p}^{r})_{\nu_{i}} = [e^{-j2\pi\nu_{i}(1-m_{0})\tau(\theta_{p}^{r})}, \cdots, e^{-j2\pi\nu_{i}(M-m_{0})\tau(\theta_{p}^{r})}]^{+}.$$

⁸³
$$\mathbf{b} = [\mathbf{b}_{\nu_1}, \mathbf{b}_{\nu_2}, \cdots, \mathbf{b}_{\nu_F}]^+$$
, with $\mathbf{b}_{\nu} = [\mathbf{b}_{1,\nu}, \mathbf{b}_{2,\nu}, \cdots, \mathbf{b}_{N,\nu}]^+$ $(\nu = \nu_1, \nu_2, \cdots, \nu_F)$, and

⁸⁴
$$\mathbf{b}_{n,\nu} = [b_{1,n,\nu}, b_{2,n,\nu}, \cdots, b_{M,n,\nu}]^+ (n = 1, 2, \cdots, N)$$

⁸⁵ 2.3 Principle of the Algorithm

⁸⁶ Using the data model built above, the trispectrum matrix of the received signal can be ⁸⁷ theoretically computed according to the following equation.

$$\mathbf{C} = E\{(\mathbf{X} \bigotimes \mathbf{X}^*) (\mathbf{X} \bigotimes \mathbf{X}^*)^H\}$$
$$-E\{(\mathbf{X} \bigotimes \mathbf{X}^*)\} E\{(\mathbf{X} \bigotimes \mathbf{X}^*)^H\}$$
$$(6)$$
$$-E\{(\mathbf{X}\mathbf{X}^H)\} \bigotimes E\{(\mathbf{X}\mathbf{X}^H)^*\},$$

where * notes conjugate, H notes conjugate transpose and \bigotimes notes kronecker product, 88 respectively. However, in a real ocean experiment, it is costly to obtain several realizations 89 for computing the expectation of the stochastic process. Moreover, the raypaths are reflected 90 or refracted by the emitted signal thus they are fully correlated or coherent, which will lead 91 to a rank deficiency of the trispectrum matrix. To resolve the problems, we use a three 92 dimensional smoothing technique¹⁴ to generate several realizations based on the received 93 signal. The spatial-frequency smoothing algorithm has two major advantages : (1) it is easy 94 to implement; (2) it first combines the spatial and frequency smoothing to provide more 95 useful information for estimation. To completely separate all the raypaths, it is necessary to 96 select the number of sub-antennas greater than the number of raypaths³. The smoothing is 97 performed in the dimensions of the emitted array, the receiver array and the frequency bins, 98 respectively. That is, the emitted (receiver) array is divided into K_e (K_r) subarrays for a 99 length of $N_e^s = N - K_e + 1$ $(N_r^s = M - K_r + 1)$. Similarly the K_f frequency subbands are 100 respectively composed of $N_f^s = F - K_f + 1$ frequency bins. Through these operation, we 101



Fig. 1. Schematic diagram of the smoothing technique for the cumulants. The **C** and $\mathbf{C}_{i,j,k}$ are computed based on the long vector trough the Eq. (7). The size of the matrix **C** is equal to $(N_e^s \times N_r^s \times N_f^s)^2$.

¹⁰² generate $K_e \times K_r \times K_f$ small data cubes, whose dimensions are $N_e^s \times N_r^s \times N_f^s$. The $\mathbf{X}_{i,j,k}$ is ¹⁰³ obtained through connecting the elements of all the three dimensions into a long vector. To ¹⁰⁴ be easily understood, the schematic diagram of the smoothing technique for the cumulants ¹⁰⁵ is provided in Fig. 1.

The expectation of the trispectrum matrix of the received signal is finally estimated 106 through an average of these smaller trispectrum matrices computed through the small data 107 cubes, which is specifically described in Eq. 7. 108

$$\widehat{\mathbf{C}} = \frac{1}{K_e K_r K_f} \sum_{k=1}^{K_f} \sum_{j=1}^{K_e} \sum_{i=1}^{K_r} \mathbf{C}_{i,j,k} = \frac{1}{K_e K_r K_f} \sum_{k=1}^{K_f} \sum_{j=1}^{K_e} \sum_{i=1}^{K_r} E\{(\mathbf{X}_{i,j,k} \bigotimes \mathbf{X}_{i,j,k}^*) (\mathbf{X}_{i,j,k} \bigotimes \mathbf{X}_{i,j,k}^*)^H\} - E\{(\mathbf{X}_{i,j,k} \bigotimes \mathbf{X}_{i,j,k}^H)\} \bigotimes E\{(\mathbf{X}_{i,j,k} \bigotimes \mathbf{X}_{i,j,k}^H)^*\},$$

$$(7)$$

109

Then, we apply the eigenvalue decomposition to $\widehat{\mathbf{C}}$ as follows.

$$\widehat{\mathbf{C}} = \mathbf{U}\mathbf{\Lambda}\mathbf{U}^{H} = \sum_{i=1}^{(N_{e}^{s} \times N_{r}^{s} \times N_{f}^{s})^{2}} \lambda_{i}\mathbf{u}_{i}\mathbf{u}_{i}^{H} = \sum_{i=1}^{P^{2}} \lambda_{i}\mathbf{u}_{i}\mathbf{u}_{i}^{H} + \sum_{i=P^{2}+1}^{(N_{e}^{s} \times N_{r}^{s} \times N_{f}^{s})^{2}} \lambda_{i}\mathbf{u}_{i}\mathbf{u}_{i}^{H}$$
(8)

where **U** is composed of $(N_e^s \times N_r^s \times N_f^s)^2$ eigenvectors, **A** is a diagonal matrix containing the 110 $(N_e^s \times N_r^s \times N_f^s)^2$ eigenvalues and \mathbf{u}_i denotes the i^{th} eigenvector. Arranging all the eigenvalues 111 from largest to smallest $\lambda_1 > \lambda_2 > \cdots$, $> \lambda_{(N_e^s \times N_r^s \times N_f^s)}^2$, the $(N_e^s \times N_r^s \times N_f^s)^2 - P^2$ eigenvectors 112 corresponding to the smallest eigenvalues project the noise subspace $\mathbf{U}_n \mathbf{U}_n^H$ where 113

$$\mathbf{U}_{n} = \left[\mathbf{u}_{P^{2}+1}, \mathbf{u}_{P^{2}+2}, \cdots \mathbf{u}_{\left(N_{e}^{s} \times N_{f}^{s} \times N_{f}^{s}\right)^{2}}\right]$$
(9)

114

Finally, the estimator $P_{Double 4-s-MUSICAL}$ in the double-array configuration can be constructed as follows. 115

$$P_{Double \ 4-s-MUSICAL} = \frac{1}{\mathbf{d}_4^H \mathbf{U}_n \mathbf{U}_n^H \mathbf{d}_4} \tag{10}$$

with the steering vector $\mathbf{d}_4 = \mathbf{d}(\theta_p^r, \theta_p^e, T_p) \otimes \left(\mathbf{d}(\theta_p^r, \theta_p^e, T_p)\right)^*$. 116

117 3. Performance test

In this section, the performance of the proposed algorithm is tested using simulation data in 118 a multi-path environment, small-scale data obtained in an ultrasonic tank and ocean data¹⁸, 119 respectively. The test parameters used in these experiments are shown in Table 1 and Table 120 2. $z_{s_1} \sim z_{s_M}$ notes the depths in which the first source to the M^{th} source is fixed under the 121 water while $z_{r_1} \sim z_{r_N}$ refers to the ranges which the first receiver to the N^{th} receiver cover. 122 D is the distance between the reference source and the reference receiver. c indicates the 123 acoustic velocity in which the raypaths propagate under the water. The central frequency of 124 the emitted signal is ν_c and its bandwidth is noted as ν_w . ν_n notes the number of frequencies 125 used in each test choosing the beginning frequency ν_b to the last frequency ν_e . N_s refers to 126 the number of samples used in each test in the time domain. 127

Figures 2 and 3 show the separation results of the proposed algorithm while the con-128 trast ones of the smoothing-MUSICAL algorithm and the 4-smoothing-MUSICAL algorithm 129 are also provided. Specifically, figure 2 (a), (c) and (e) illustrate the separation results of 130 a set of simulation data under the assumption that the waveguide provides nearly perfect 131 boundary conditions at the water-bottom interface. In the case, five raypaths propagate 132 between the double array configuration composed of four emitters and four receivers. The 133 signal to noise ratio is equal to 2dB. The SNR is defined as the power ratio of signal to 134 noise in the signal band. These powers are estimated in the time domain by the sum of 135 squares of samples (signal or noise). The reference source (receiver) is located at 50m under 136 the water. The smoothing-MUSICAL algorithm provides a two-dimensional (2D) separation 137

in a plan of the arrival time and the direction of arrival (DOA) in figure 2 (a) while the 138 other two algorithms give a 3D separation with the additional parameter: the direction of 139 emission (DOE) in figure 2 (c) and figure 2 (e), respectively. In figure 2 (a), (c) and (e), 140 each spot corresponds to a raypath and the black crosses mark the theoretical positions. It 141 is obviously that the smoothing-MUSICAL algorithm fails in finding the raypath with the 142 DOA around at -5° in figure 2 (a) and the raypath with the DOA around at 0° is deficient 143 in the results of the double-MUSICAL algorithm in figure 2 (c). In contrast, the proposed 144 algorithm successfully separates all the five raypaths without any artifact in figure 2 (e), 145 where the deficient raypaths in figure 2 (a) and figure 2 (c) are highlighted by the red circles. 146

Figure 2(b), (d) and (f) illustrate the performance contrast of the three algorithms 147 using a set of real data obtained at a small-scale ultrasonic tank. The small-scale experiment 148 reproduces the actual physical phenomena occurring in the real ocean environment in a 149 smaller scale inside the laboratory based on the operation multiplying the frequency of the 150 signals by a factor and dividing the spatial distances by the same factor. Thus, the small-scale 151 experiment is a reduced cost and a totally controlled experiment. Specifically, in this tank, 152 a steel bar acts as the bottom, for which the boundary conditions are nearly perfect at the 153 water-bottom interface, and a 1.10m-long, 5.4-cm-deep acoustic waveguide is constructed¹⁷. 154 Two coplanar 64-element vertical line arrays (VLA) are placed and the central frequency of 155 the transducer is 1 or 3 MHz with a 50% frequency bandwidth. The transducer dimensions 156 $0.75mm \times 12mm$ are used to make the linear arrays omni-directional in the plane defined 157 by the source-receiver arrays and the beams collimated in the plane perpendicular to the 158

waveguide axis. Figure 2(b), (d) and (f) show a group of separation results with a set of real 159 data obtained in the small-scale experiment. There are seven predictable raypaths in the 160 example, whose theoretical positions are indicated by the black crosses. Figures 2(b) and 161 2(d) show the separation results using the smoothing-MUSICAL algorithm and the double-162 MUSICAL algorithm, respectively. It can be clearly seen that both of the two algorithms 163 are deficient in detecting one raypath with the DOA around at 5°. Comparing to them, the 164 proposed 3D higher order algorithm correctly find all the seven raypaths in figure 2(f), where 165 the red circle highlights the deficient raypath in figures 2(b) and 2(d). 166

Finally, the performance of the double-4-smoothing algorithm is tested using ocean 167 data. The experiment has been performed in July 2005 north of Elba Island, Italy¹⁸. It uses 168 a similar experimental setup to the small-scale ultrasonic experiment, although at a much 169 larger scale. Two equally spaced vertical linear arrays are implemented in 120 m water and 170 the distance between them is 4.071 km. The source array (SA) is composed of 29 transducers 171 covering 78 m and the receiver array (RA) has 32 hydrophones spanning 62m. The central 172 frequency of the transducers is 3.2 kHz with 1 kHz bandwidth. Figure 3 shows the contrast 173 of separation results using a set of ocean data, which has been acquired in a down-refraction 174 profile. There are three expected rays, a surface-reflected ray and two refracted rays. Each 175 refracted ray has a turning point near the depth of maximum sound-speed variability. Due 176 to the sound speed variation described in the Ref.¹⁸, the three raypaths arrived at close 177 time. Figure 3(a) shows that the separation result of the smoothing-MUSICAL algorithm 178 in the plan of the arrival time and the DOA. It detects just a mixed spot for two of the 179

three raypaths due to their close arrival times and DOAs. Figure 3(b) shows that the 180 separation result of the double-MUSICAL algorithm in the plan of the emitted angle and 181 the DOA, which has a raypath deficiency with the DOA around at 10° . However, the 182 proposed algorithm gives an accurate separation for the three raypaths shown in the plan of 183 the emitted angle and the DOA in Figure 3 (c) because of the different emitted angles and 184 a strong robustness of the proposed algorithm to the fluctuant ocean. Figure 3(d) displays 185 the three raypaths in Figure 3(a)-(c), which propagate between the centers of source and 186 receive arrays. 187

¹⁸⁸ Moreover, we test the performance of the double-4-smoothing-MUSICAL algorithm ¹⁸⁹ using the simulation data at different SNRs in a red noise inference environment and compare ¹⁹⁰ its separation performance in terms of root-mean-square errors (RMSE) with that of the ¹⁹¹ double-MUSICAL algorithm. In these Monte Carlo experiments, we define the average ¹⁹² RMSE of the 3D separation result $\hat{R_p}$ for the p^{th} raypath as follows.

$$RMSE_{R_p} = \sqrt{\frac{1}{K_p} \sum_{k=1}^{K_p} \|\hat{R}_p - R_p\|^2}$$
(11)

¹⁹³ where K_p is the number of the trials, which is equal to 20 for these Monte Carlo experiments. ¹⁹⁴ That is, the simulations are performed 20 times at each different SNR. 400 simulations in ¹⁹⁵ total are performed in red noise environments with their SNRs ranging from -20 dB to 20 ¹⁹⁶ dB. The configuration parameters used in the simulations are consisted with those shown in ¹⁹⁷ Table I and Table II. For those raypaths which can be separated by both the two algorithms, ¹⁹⁸ the RMSEs are computed at each dimension of the 3D separation result. Specifically, figures

	M	N	$z_{s_1} \sim z_{s_M}(m)$	$z_{r_1} \sim z_{r_N}(m)$	<i>d</i> (m)
Simulation	4	4	$47.5 \sim 52.5$	$47.5 \sim 52.5$	2.5
Small-scale experiment	4	5	$26.375 \times 10^{-3} \sim 28.625 \times 10^{-3}$	$25.625 \times 10^{-3} \sim 28.625 \times 10^{-3}$	0.75×10^{-3}
Ocean data	4	4	$93.098 \sim 101.456$	$94 \sim 100$	2

Table 1. The configuration parameters of simulation, small-scale experiment and the at-sea experiment.

4 (a), (b) and (c) show the curves of the average RMSEs for the DOE, the DOA and the time 199 of arrival (TOA) produced by the two algorithms, respectively. In figure 4 (a), the double-4-200 MUSICAL algorithm generally produces a smaller bias in the low SNR range (from -20dB to 201 0dB) and a relatively stable performance in moderate-to-high SNR. For the average RMSEs 202 shown in the Figures 4(b) and 4(c), the double-4-MUSICAL algorithm generally shows a 203 better and stable performance. Based on the performance contrasts with the simulation 204 data, small-scale data and ocean data, a conclusion is drawn that the double-4-smoothing-205 MUSICAL algorithm enables to achieve an aperture extension, a stronger robustness to the 206 fluctuant environment and a resolution improvement for the extension of cumulants-based 207 algorithm to the double-array configuration. 208

209 4. Conclusion

²¹⁰ In this paper, we extended a higher-order algorithm to a double-array configuration. Higher-²¹¹ resolution and more robust separation for close arrivals even in a fluctuant ocean environment



Fig. 2. Separation results comparison of different algorithms using simulation datas ((a), (c) and (e)) or using real data obtained in an ultrasonic tank ((b), (d) and (f)). The black crosses denote the theoretical values. The red circles highlight the raypaths used to differentiate the separation ability of the algorithms. (a) and (b) show the results of the smoothing-MUSICAL algorithm; (c) and (d) show the results of the double-MUSICAL algorithm; (e) and (f) show the results of the double-MUSICAL algorithm; (e) and (f) show the results of the double-MUSICAL algorithm; (e) and (f) show the results of the double-MUSICAL algorithm; (e) and (f) show the results of the double-MUSICAL algorithm; (e) and (f) show the results of the double-MUSICAL algorithm; (e) and (f) show the results of the double-MUSICAL algorithm; (f) and (f) show the results of the double



Fig. 3. Separation results comparison of different algorithms using ocean datas. The black crosses denote the theoretical values. The red circles highlight the raypaths used to differentiate the separation ability of the algorithms (a) the smoothing-MUSICAL algorithm; (b) the double-MUSICAL algorithm; (c) the double-4-MUSICAL algorithm; (d) Raypaths between the source and the reference sensor for the three rays.



(c)

Fig. 4. The RMSE comparison of different algorithms using simulation data interfered by red noise.(a) the RMSE (in degree) of the direction of emission (DOE) vs SNR variation; (b) the RMSE (in degree) of the direction of arrival (DOA) vs SNR variation; (c) the RMSE (in 0.1ms) of the time of arrival (TOA) vs SNR variation.

	$\nu_c ({\rm Hz})$	ν_w (Hz)	$ \nu_n(\nu_b \sim \nu_e) \ (\text{Hz}) $	N_s	D(m)	$c \ (m/s)$
Simulation	1.5×10^3	5×10^3	75 $(0 \sim 5 \times 10^3)$	135	2000	1500
Small-scale experiment	1.2×10^{6}	5×10^6	$150(0 \sim 5 \times 10^6)$	132	1	1473
Ocean data	3.2×10^3	6×10^3	$50 \ (0 \sim 6 \times 10^3)$	60	4.701×10^3	1509

Table 2. The test parameters used in the simulations, the small-scale experiment and the at-sea experiment.

is achieved by the higher-order 3D algorithm. In future work, we will study the inversion for
ocean acoustic tomography based on the separation results.

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