



Adaptive Matched Field Processing for Source Localization Using Improved Diagonal Loading Algorithm

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Received: 8 March 2017 / Revised: 27 April 2017 / Accepted: 30 April 2017
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Abstract Matched field processing (MFP) has been a method widely applied for shallow underwater target localization, which is a critical issue in underwater acoustic. To enhance the efficiency of conventional MFP methods, different adaptive MFP algorithms have been developed; the white noise constraints (WNC) MFP or diagonal loading (DL) algorithm is such a typical one. The WNC or DL one has been considered to be the most desirable method because it is more robust to environment mismatch in practical in comparison with the minimum-variance distortionless response MFP algorithm, a popular high-resolution method. Although having exceptional ability to localize underwater sources in mismatch scenarios, the DL method has still been not reach high resolution in certain cases. In the paper, we proposed an adaptive method known as improved diagonal loading algorithm to make an increase in the resolution and the peak background rate in the ambiguity surface of source localization results in comparison with DL one. The proposed algorithm works by adding one more parameter that is adjusted in the steering vector of the DL algorithm. The simulation results show that the new algorithm attains better beamforming performance in terms of high resolution than the existing adaptive MFP algorithms in the case of environmental mismatch caused by noise effects and the limitation of the snapshots.

Keywords Matched field processing (MFP) · Mismatch · Source localization · Acoustic underwater

1 Introduction

MFP algorithms have commonly used in shallow underwater for source detection and localization [1–6]. Conventional approaches constructing MFP algorithms commonly apply a vertical or horizontal array of hydrophones. The match between the received signals from the hydrophones and the replica signal in a full-wave acoustic propagation model provides an estimate of the source's position. Scanning the source position produces the ambiguity surface. The ambiguity surface obtained from the conventional MFP algorithms contains high sidelobes beside a main lobe, causing a difficulty to localize the source target. A way to overcome this problem in conventional MFP algorithms is to apply numerous adaptive MFP algorithms. The standard adaptive MFP

(AMFP) processor, so-called minimum-variance distortionless response (MVDR) is effective in noise rejection as well as sidelobe cancellation, yielding an increase in resolution for the localization results in the absence of mismatch in comparison with CMFP [6, 7]. Although having good resolution performance, MVDR has a shortcoming of great sensitive to mismatch problems that commonly occur in practical situations. The consequence of this mismatch sensitivity makes the source hardly be localized in a number of practical cases. Hence, another adaptive MFP algorithm known as white noise constraints (WNC) or diagonal loading (DL) is employed in an attempt to counteract mismatch issues. The DL algorithm uses diagonal loading technique to the weight vector of the MVDR method by choosing the load level parameter that satisfies the white noise constraint [6–8]. In the process of adjustment of the load level parameter, DL algorithm has ability to resolve the mismatch problem, however loses its high-resolution characteristic in some cases.

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In this paper, we propose an adaptive algorithm known as improved diagonal loading technique (IDL) as an improvement of DL algorithm, which shows a better resolution in the ambiguity surface in a number of scenarios in a shallow water area. The proposed algorithm works by adding one more adjusted parameter to the DL weight vector; therefore, the performance of the method has a relation to the choice of the two parameters which are the load level factor previously existing in the DL algorithm and the adding adjusted parameter put in IDL. For comparison and evaluation purpose, the localization performance of CMFP, MVDR, DL and IDL algorithms is simulated in both match and mismatch cases. Though the mismatch comes from many causes, the paper only focuses mismatch scenarios as a result of the effects of noises and the limitation of the number of snapshots.

The body of the paper is organized as follows. In Sect. 2, a number of MFP algorithms are investigated. Next, in Sect. 3, the paper presents environment model used for evaluating the proposed algorithm. Next, the simulation results is given in Sect. 4. The Sect. 5 is the conclusion of the paper.

2 MFP Algorithms

2.1 Conventional MFP Algorithm

Conventional beamforming is created by delaying the signals from individual channels so that the waves coming primary beam direction are aligned in the same phase and then summed to make the coherent gain in the main beam direction [7]:

$$b = w^H p \quad (1)$$

where w is the weight vector, p is the received spectral value and H shows the Hermitian transpose operation.

Power output of the beamforming is calculated by:

$$\begin{aligned} B &= |w^H p|^2 \\ &= w^H (p p^H) w \\ &= w^H R w \end{aligned} \quad (2)$$

The matrix R refers to sample-average cross-spectral density matrix (CSDM) that is calculated based on spectral of received signal at the hydrophones. A better estimate of the signal can be obtained by averaging several snapshots in the condition of the received time series are long enough. Therefore, the CSDM is given by:

$$R = \frac{1}{M} \sum_{m=1}^M p_m p_m^H \quad (3)$$

where p_m is the m th snapshot.

Weight vector w is conventional MFP processor, which is calculated by acoustic model as:

$$w = v = \frac{G(r, z)}{|G(r, z)|} \quad (4)$$

where G is Green function, which is calculated by acoustic models.

When using the Normal mode method, Green function is calculated by [9]:

$$G(r, z) = \frac{i}{\rho(z_s) \sqrt{8\pi r}} e^{-j\frac{\pi}{4}} \sum_{m=1}^{\infty} \psi_m(z_s) \psi_m(z) \frac{e^{jk_m r}}{\sqrt{k_m}} \quad (5)$$

where r is the range, z is the depth, ρ is density, z_s is the depth of the source, ψ_m is the mode amplitude and k_m is eigenvalue.

Therefore, the power output is:

$$B = v^H R v \quad (6)$$

The maximum value of the power output will determine the source location.

2.2 The DL Algorithm

In conventional MFP algorithm, the sidelobes exist next to the main lobe; therefore, to minimize the number of the sidelobes and the influence of the noises, adaptive adjustment of weight vectors is exploited automatically. MVDR is an algorithm that is applied to reduce noise effects and sidelobes. The output power of MVDR processor is expressed by [7]:

$$B = w^H R w, \quad (7)$$

Weight vector is calculated by resolve the constraint:

$$\min(w^H R w) \text{ subject to } w^H v = 1 \quad (8)$$

The weight vector of the MVDR algorithm is given by [7]:

$$w_{\text{MVDR}} = \frac{R^{-1} v}{v^H R^{-1} v} \quad (9)$$

Replacing the weight vector w_{MVDR} in Eq. (7), the power output of MVDR processor is [7]:

$$B_{\text{MVDR}} = w_{\text{MVDR}}^H R w_{\text{MVDR}} \quad (10)$$

Therefore:

$$B_{\text{MVDR}} = \frac{1}{v^H R^{-1} v} \quad (11)$$

To robust the MVDR algorithm, white noise constraint which is based on adding a constant value to diagonal elements of CSD matrix is used for the weight computation:

$$w_{DL} = \frac{(R + \varepsilon I)^{-1}v}{v^H(R + \varepsilon I)^{-1}v} \tag{12}$$

The value of ε is chosen to satisfy some white noise gain constraint [7]. Finally, replacing weight vector w_{DL} in Eq. (7), the power output of DL processor is:

$$B_{DL} = w_{DL}^H R w_{DL} \tag{13}$$

The value of ε equal to zero implies pure MVDR algorithm. The value of ε equal to infinitive implies conventional MFP algorithm.

2.3 The Proposed IDL Algorithm

The IDL algorithm is a developed version of the diagonal loading algorithm. It is based on adjusting the diagonal loading factor of DL technique along with the parameter which is added to the weight vector in DL algorithm. The diagram of IDL is described in Fig. 1.

The weight vector of IDL algorithm is calculated as follows:

$$w_{IDL} = \frac{[(R + \varepsilon I)^{-1} + \beta I]v}{v^H[(R + \varepsilon I)^{-1} + \beta I]v} \tag{14}$$

The power output of IDL (B_{IDL}) is presented as:

$$B_{IDL} = w_{IDL}^H R w_{IDL} \tag{15}$$

The adaptive level is based on making adjustments to choose two parameters ε and β in the weight vector. Particularly, controlling the parameter ε is to deal with the degree of the mismatch, while controlling the parameter β is to increase resolution level of the ambiguity. When the parameter β is equal to zero, the proposed algorithm becomes the DL method. When both two parameters ε and β are equal to zero, the IDL algorithm becomes the MVDR one.

3 Environmental Model

The configuration of the environment is demonstrated in Fig. 2 in which the parameters are described in detail.

The ocean environment contains three layers: upper water layer, sand layer and bottom layer; each of them is characterized by its own parameters.

In water layer, the acoustic velocity varies from 1522 to 1543 ms, the density ρ is 1.024 g/cm³, and the depth of the layer is 112 m.

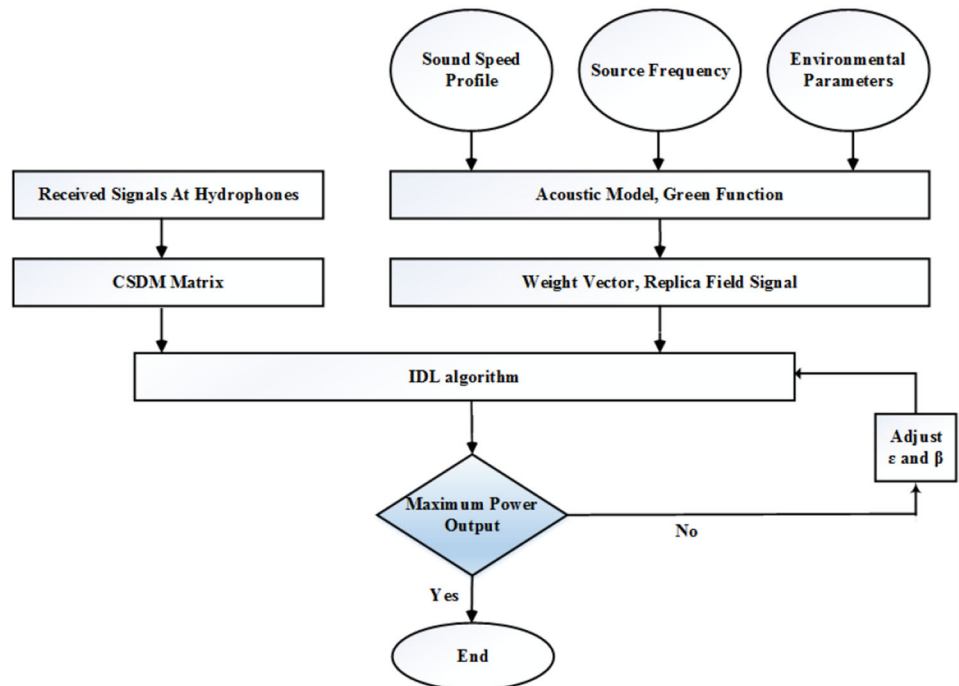


Fig. 1 The diagram of the IDL algorithm

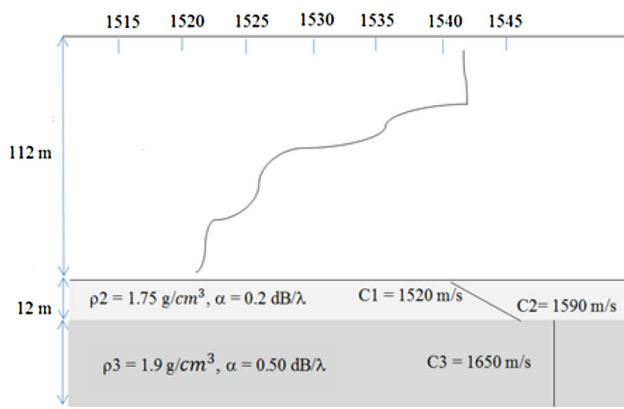


Fig. 2 The environmental model

In sand layer, the acoustic velocity varies from 1520 to 1590 m/s, the absorption parameter α is 0.2 dB/ λ , the density ρ is 1.75 g/cm³ and the depth of the layer is 12 m. In bottom layer, the acoustic velocity is 1650 m/s, the density ρ is 1.9 g/cm³, the absorption parameter α is 0.5 dB/ λ . The sound speed is the most important parameter because it depends on other factors such as the temperature, the salinity and the depth of the layer. The density parameter describes the reflection ability of acoustic waves, while the absorption characterizes the acoustic absorption.

4 Simulation Results

4.1 Input Parameter

Environmental parameter is described in Sect. 3. The source is assumed to be located at range 2 km and 59 m depth and sent at 110 Hz in the case of fixed target observation. The hydrophone array includes 50 elements that are put at the range from 6 to 104 m depth, in which the distance between each hydrophone is 2 m. In this simulation, the signals at the hydrophones which contain signal-to-noise ratio (SNR) equal to -5 dB are simulated under the effects of Gaussian noise.

4.2 Simulation Results

To evaluate the efficiency of the IDL algorithm, the simulation is carried out in both match and mismatch cases.

4.2.1 Simulation in the Match Case

The simulation results in the match case are demonstrated in Figs. 3 and 4. The simulation results in Fig. 3 show that the source can be localized when applying MFP algorithm; how-

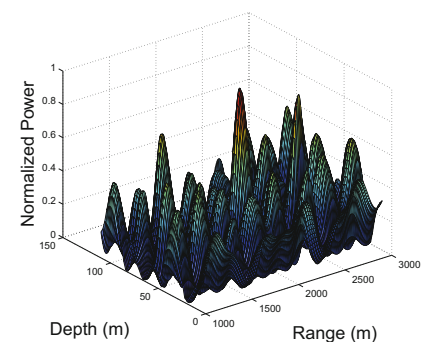
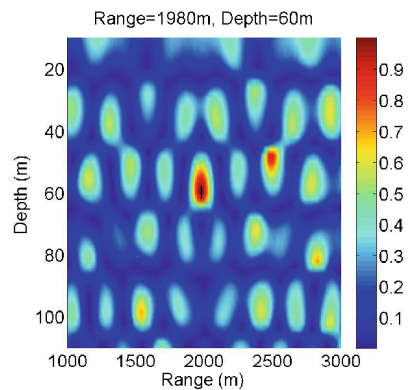


Fig. 3 The ambiguity surface of conventional MFP algorithm

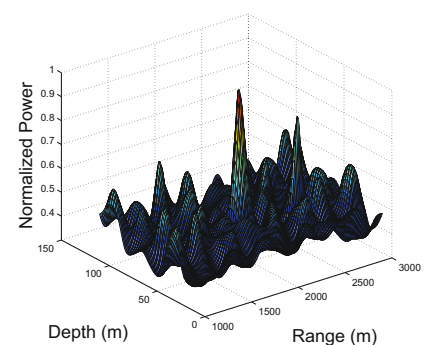
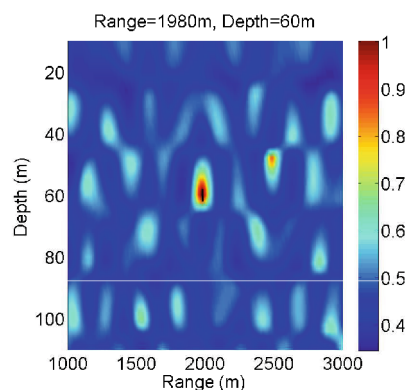


Fig. 4 The ambiguity surface of MVDR algorithm in the match case

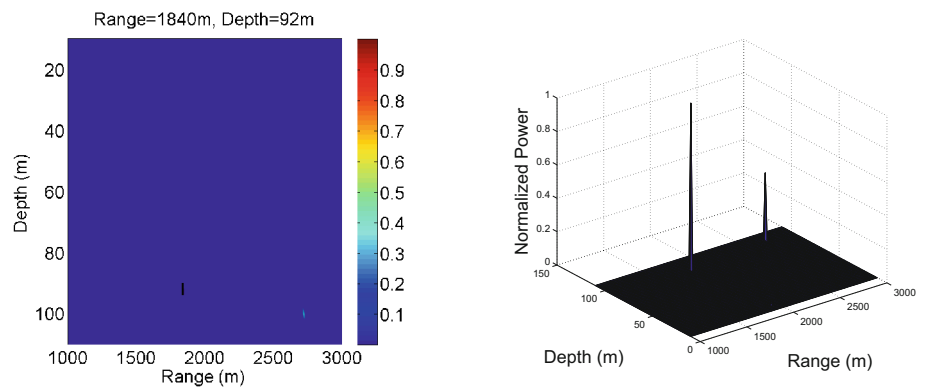


Fig. 5 The ambiguity surface of MVDR algorithm in the mismatch case

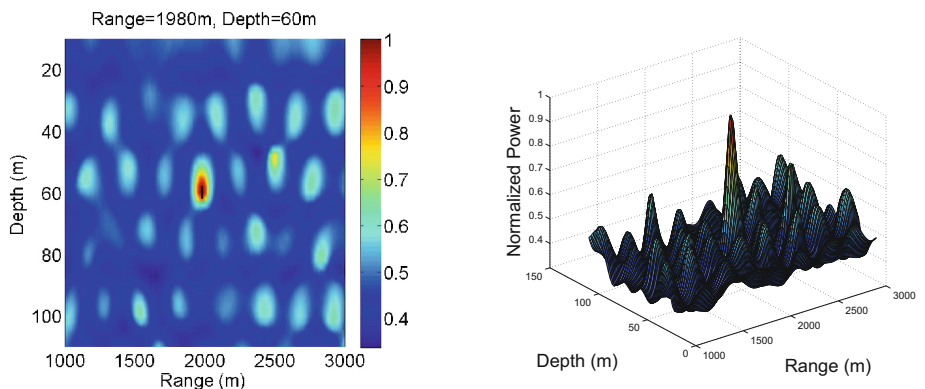


Fig. 6 The ambiguity surface of the DL algorithm with $\varepsilon = 1$

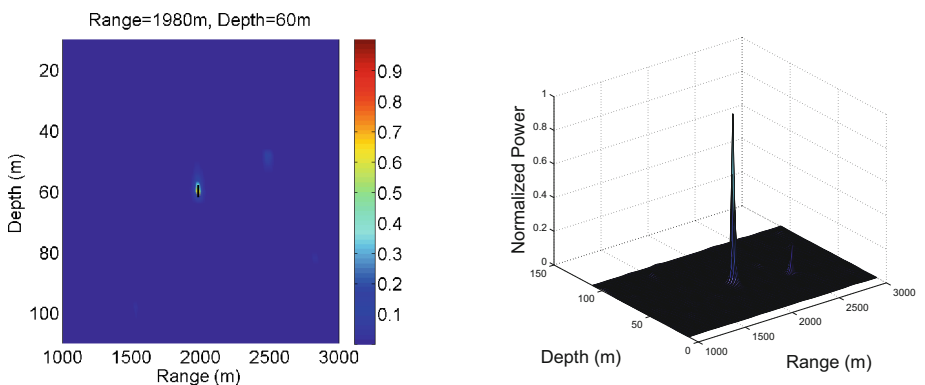


Fig. 7 The ambiguity surface of IDL algorithm with $\varepsilon = 1$ and $\beta = 0.2$

ever, the ambiguity surface contains some sidelobes beside the main lobe. The results in Fig. 4 show that MVDR ambiguity surface displays a sidelobe suppression as well as an increase in resolution, presenting an improvement of the performance compared to MFP algorithm.

4.2.2 Simulation in the Mismatch Case

The simulation results in the mismatch case in which the number of the snapshot is limited to $N = 40$ and Gaussian Noise level is -5 dB are presented in Figs. 5, 6 and 7.

Based on the results in Fig. 5, it is shown that MVDR algorithm under environmental mismatch provides inaccurate localization result. The simulation results in Fig. 6 indicate that DL algorithm has better tolerance to mismatch than the MVDR has, yet the DL still has not given a high resolution of the ambiguity surface ($PBR = 8.2$). This disadvantage of ambiguity surface is improved by using IDL algorithm. It is seen from Fig. 7 that when applying IDL algorithm, the localization performance significantly increases in both ability to resist mismatch and the resolution level in comparison with

MVDR and DL while retaining the localization error value to an acceptable value and the high PBR level ($PBR = 480.8$).

5 Conclusion

The paper studies a number of underwater source localization algorithms by using a hydrophone array in shallow water and applying the proposal of IDL algorithm, which is derived by adjusting two loading parameters, to improve the resolution and the degree of robustness to the environmental mismatch. The simulation results show that the localization performance of the Passive Sonar System not only obtains higher level of accuracy and robustness to the mismatch but also gives a better resolution for the ambiguity surface in the case of applying IDL than applying the MVDR and the DL algorithms.

For the future work, the IDL algorithm can be investigated in the case of mismatch problems caused by other potential factors along with the noise effects and the limitation of the number of the snapshots. The effectiveness of the proposed algorithm on these mismatches will be compared with that of the existing adaptive MFP algorithms.

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