Side-scan Sonar Image De-noising Based on Bidimensional Empirical Mode Decomposition and Non-local Means

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Abstract. In order to suppress the multiplicative specular noise in side-scan sonar images, a denoising method combining bidimensional empirical mode decomposition and non-local means algorithm is proposed. First, the sonar image is decomposed into intrinsic mode functions(IMF) and residual component, then the high frequency IMF is denoised by non-local mean filtering method, and finally the processed intrinsic mode functions and residual component are reconstructed to obtain the de-noised side-scan sonar image. The paper's method is compared with the conventional filtering algorithm for experimental quantitative analysis. The results show that this method can suppress the sonar image noise and retain the detailed information of the image, which is beneficial to the later image processing.

1 Introduction

With the development and utilization of marine resources and the in-depth exploration of the ocean, seabed topographic survey and ocean target detection have become hot issues. Due to the advantages of wide operating range, high resolution and scanning of the entire seabed area of the target, side-scan sonar is widely used in the mapping of seabed topography and geomorphology, marine resource survey and seabed object imaging, etc^[1].

Sonar image is an important achievement of side-scan sonar work and a manifestation of ocean information. Under the influence of imaging mechanism and working environment, sonar image has serious noise, especially the influence of seabed reverberation. Reverberation appears as randomly distributed speckles in side-scan sonar images, which is called speckle noise^[2]. Side-scan sonar image denoising is a pre-processing work, which is of great significance for obtaining image information and provides guarantee for subsequent image segmentation, mosaic and target recognition.

For noise suppression of side-scan sonar images, optical images' spatial domain noise removal algorithms, such as median filtering and mean filtering, are mostly used at present^[3]. These methods are not very skilled in suppressing speckle noise in side-scan sonar images. In this paper, a denoising method is proposed that combines bidimensional empirical mode decomposition(BEMD) and non-local means(NLM) algorithm. Through experimental verification, compared with median filtering and mean filtering, the evaluation indexes of this method, such as MSE, PSNR, and SSIM, are all superior to the above two methods. The denoising effect of this method is obvious, and the details and edge information of the image are effectively retained.

2 Bidimensional empirical mode decomposition

Empirical mode decomposition(EMD) is a signal decomposition method proposed by N.E.Huang[4] et al. According to the characteristics of the signal, EMD decompose the nonlinear and unsteady signal from high to low frequency into several intrinsic mode functions (IMF) and a residual component(Res) which expresses the change trend of the signal. The criteria of IMF must meet two conditions :

a. In the whole data sequence, the number of signal extreme points is equal to the number of zero crossing points, or one at most.

b. At any time node, the average value of the local maximum envelope and the local minimum envelope is zero.

It is these two conditions that prevent the instantaneous frequency of the signal from being affected by the asymmetric waveform, and use the envelope average value of the local extreme value to constrain the local symmetry, so that the EMD can maintain the characteristics of the signal itself in the decomposition process.

The bidimensional empirical mode decomposition proposed by Nunes^[5] et al. is a two-dimensional extension of EMD and is mainly used to process and analyze multiscale characteristics of image signals. BEMD can extract the global structure information of the image, and is more effective than wavelet transform in image texture analysis, edge extraction and image noise reduction^[6-8]. The BEMD decomposition of image I(x, y) which size is

(m,n) can be summarized as the following steps:

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Step 1 Image initialization, denote the image sequence $H_{1,1}(x, y) = I(x, y)$

Step 2 The maximum and minimum points of $H_{l,k}(x, y)$ were calculated according to the 8-neighborhood method, where *l* was the *l*-th IMF component and *k* was the *k*-th screening

Step 3 Envelope fitting was performed for the extremum, and obtaine the upper envelope $U_{l,k}(x, y)$ and the lower envelope $D_{l,k}(x, y)$ of the image

Step 4 Calculate the image envelope mean surface $M_{lk}(x, y)$:

$$M_{l,k}(x,y) = \frac{U_{l,k}(x,y) + D_{l,k}(x,y)}{2}$$
(1)

Step 5 The input image $H_{l,k}(x, y)$ minus the image envelope mean surface $M_{l,k}(x, y)$ to obtaine $J_{l,k}(x, y)$

$$J_{l,k}(x,y) = H_{l,k}(x,y) - M_{l,k}(x,y)$$
(2)

Step 6 Judge whether $J_{l,k}(x, y)$ meets IMF's constraint SD. If so, $J_{l,k}(x, y)$ is the *l*-th IMF. Otherwise, let $H_{l,k+1}(x, y) = J_{l,k}(x, y)$ return Step 2 and repeat the above steps until the condition is satisfied after *K* screening.

When the screening constraint *SD* is less than a certain threshold, the screening is stopped :

$$SD = \sum_{x=0}^{x=m} \sum_{y=0}^{y=n} \frac{\left| J_{l,k}(x,y) - J_{l,k+1}(x,y) \right|^2}{J_{l,k}^2(x,y)} < \sigma$$
(3)

The value of threshold σ affects the number and quality of IMF decomposition, which is generally between 0.2 ~ 0.3 ^[9].By experimental comparison, in this paper σ =0.2

Step 7 Calculate the residual component:

$$R_{l+1,1}(x,y) = H_{l,1}(x,y) - J_{l,K}(x,y)$$
(4)

Step 8 If $R_{l+1,1}(x, y)$ contains no less than two extreme points, return $R_{l+1,1}(x, y)$ as a new image sequence Step 1 to continue decomposition, until the residual component $R_L(x, y)$ has no more than two extreme points, and the whole BEMD decomposition ends. The original image sequence can be expressed as:

$$I(x, y) = \sum_{l=1}^{L} J_{l,K}(x, y) + R_{L}(x, y)$$
(5)

Figure 1 is the result image obtained by BEMD decomposition of 153*121 side-scan sonar image as the input initial image according to the above steps. As shown in the figure, a is the original image, b, c, d and e are the decomposed components $IMF_1 \sim IMF_4$, and f is the residual component obtained after the decomposition. It can be seen from the image and screening process that the first two IMF components obtained after decomposition contain the high-order frequency components of the original image signal. A large amount of noise of the image signal exists in the high-order frequency components. The purpose of denoising can be realized by removing the noise in the high-order frequency components and then reconstructing the remaining images. Different from EMD decomposition signals, the residual

components obtained by BEMD decomposition contain the image details and edge information after removing the high-order frequency components, so the residual components cannot be simply omitted in the final image reconstruction.



Fig. 1. Sonar image with BEMD

3 Side-scan sonar image de-noising based on BEMD and NLM

3.1 Non-local means algorithm

Acoustic images will generate speckle noise when sidescan sonar receives echo signal. Speckle noise affects the interpretation of acoustic images, and in severe cases, it will hide or distort the real seabed topography[3]. Compared with traditional optical image denoising method, NLM can suppress speckle noise more effectively.

Traditional filtering algorithms only deal with a single pixel of an image. Buades^[10] et al. proposed NLM algorithm based on block similarity theory on the basis of bilateral filtering. The core idea of NLM is that the estimate of the current pixel is obtained by a weighted average of pixels with similar neighborhood structures.

An image noise model :

$$V(i) = I(i) + N(i) \tag{6}$$

I(i) is the original image, N(i) is the noise, and V(i) is the image polluted by noise.

For each pixel value in V(i), the NLM algorithm uses the weighted average value of all pixels in the whole noisy image to obtain the estimation of the pixel point^[10]:

$$NLM[v(i)] = \sum_{j \in I} w(i, j)v(i)$$
(7)

The value of weight w(i, j) depends on the similarity of pixels *i* and *j*, which is measured by the Gaussian weighted Euclidean distance d(i, j) of the matrix centered on *i* and *j*:

$$d(i, j) = \left\| v(N_i) - v(N_j) \right\|_{2,\alpha}^2$$
(8)

Formula(8) represents the L^2 norm of gauss weighted Euclidean distance between neighborhood matrix N_i and N_j , α is the standard deviation of the Gaussian, Gaussian weighting represents the use of a discrete Gaussian function template to weight Euclidean distance, which means that the closer the pixel is to the center, the higher the weight will be.

The weight w(i, j):

$$w(i, j) = \frac{1}{c(i)} e^{-\frac{d(i, j)}{h^2}}$$

$$c(i) = \sum_{j \in I} e^{-\frac{d(i, j)}{h^2}}$$
(9)

c(i) is the normalized coefficient, and h is the attenuation coefficient of the exponential function.

In practical applications, the neighborhood matrix is usually selected as a small part around the pixel point, and the search window also selects a part of the range of the image. It can be seen from the principle of the algorithm that compared with the traditional denoising algorithm, NLM algorithm combines the local idea and uses the similarity between image blocks to replace the similarity between pixels, which can make full use of the redundant information in the image and retain the detailed features to the maximum extent while denoising.

3.2 Image de-noising based on BEMD and NLM

The sonar image can be decomposed into IMF components and a residual component by BEMD. According to the algorithm principle, each component represents different frequency components of the original signal from high to low, and the noise basically exists in the previous high-frequency IMF components. The

purpose of noise removal can be achieved by simply removing the high-frequency IMF directly. However, some image details are still retained in the high-frequency IMF, so this simple denoising method eliminates the image details while suppressing the noise, and the reconstructed image is not ideal. In view of BEMD's good decomposition ability of non-stationary signals, a denoising method is proposed with NLM. Figure 2 is the flow diagram of this method.

Assuming I(x, y) is the original image to be processed, the steps of BEMD-NLM processing are as follows:

Step 1 Feature extraction was carried out for I(x, y), according to the screening parameter SD and conforming to the conditions, screen out IMF components IMF(x, y) and a residual component R(x, y)

Step 2 NLM filtering was performed on the highfrequency $IMF_h(x, y)$ to obtain the processed component $NIMF_h(x, y)$ in noise reduction

Step 3 The processed high-frequency $IMF_h(x, y)$, low-frequency $IMF_l(x, y)$ and the residual component R(x, y) were reconstructed to obtain the noise reduction image processed by BEMD-IMF :

 $N(x, y) = NIMF_h(x, y) + IMF_l(x, y) + R(x, y)$ (10)

The high-frequency IMF contains the main information and noise of the original image, while the residual component still retains part of the image details, so the residual component should be retained in the final image reconstruction.



Fig. 2. BEMD-NLM method

4 Experimental analysis

In order to verify the practicability and effectiveness of this method, the measured data of shipwreck in a certain sea area was selected and the instrument was Edgetech 4200-MP. The original XTF format file was read to generate the sonar waterfall diagram, as shown in fig.3.a. It can be seen from the original waterfall map that the shipwreck target is obvious, but the speckle noise is serious in the image, so the original image is denoised by the method proposed in this paper.



a. Original image

b. Denoised image



Fig. 3. Shipwreck image with BEMD-NLM

Firstly, BEMD was performed on fig.3.a to obtain four IMF c, d, e, f and a residual component g. Among them, noise signals were mainly distributed in two high-frequency components of IMF1 and IMF2. IMF3 and IMF4 contain the low-frequency information of the original image. As can be seen from fig.3.g, part of the image information is still retained in the residual component. NLM filtering was performed on two high-frequency components, and then reconstructed the four components to obtain the denoised image fig.3.b.

For the convenience of comparison and analysis, a 130*120 noisy image was intercepted at the bow part of the original image for median filtering, mean filtering and application of the proposed method.



Fig. 4. Denoising results of the image

It can be concluded from the filtered image that median filtering, as a nonlinear smoothing technique, can suppress some speckle noise, but the denoising effect is limited, and the detailed information after filtering is poorly retained. Mean filtering not only reduces some noises but also blurs the image, especially the edges and details of the target. The proposed method can suppress the speckle noise effectively and retain the edge and detail information of the sonar image effectively.

In order to objectively and quantitatively evaluate the denoising effect of the three methods, common evaluation criteria[11] are introduced: Mean Square error (MSE), the expectation of the square of the difference between the real value of the target and the estimated value; Peak Signal-to-noise Ratio (PSNR) is the ratio between the energy of the peak signal and the average energy of the noise; Structural Similarity (SSIM) refers to the similarity of image structure and reflects the similarity of image outline and details.

Table.1. Evaluation index of three methods

	MSE	PSNR	SSIM
median filter	101.315	28.074	0.752
Mean filter	95.078	28.350	0.761
Paper method	58.912	30.428	0.795

Table 1 is a very objective and intuitive representation of the performance of the three methods. The smaller the MSE value is, the better the algorithm performance will be. The larger the value of PSNR is, the better the denoising effect will be. As can be seen from the table, the MSE of the method presented in this paper is greatly improved compared with the median filtering and mean filtering, the value of PSNR is also significantly improved. The method in this paper is obviously superior to the other two methods in these two indexes. The closer the value of SSIM is to 1, the closer the de-noised image is to the original structure. The method in this paper is more effective in retaining the outline and details of the image.

5 Conclusion

In this paper, a side-scan sonar image denoising method combining BEMD and NLM is proposed. First, the original side-scan sonar image was decomposed by BEMD to obtain IMF component and Res component, the high frequency IMF with noise was processed by NLM, then the processed IMF component and Res component were reconstructed to obtain the sonar image after denoising. In order to quantitatively compare the performance of this method, the processed image is compared with the image after median filtering and mean filtering. In terms of MSE, PSNR and SSIM, this method is obviously superior to the above two filtering methods. As the speckle noise is the main feature of side-scan sonar image noise, the method presented in this paper has a good denoising effect. While effectively suppressing the speckle noise, the contour and detail features of the image object can be retained.

The denoising of side-scan sonar image is the foundation of image segmentation and mosaic and other subsequent processing. The internal operation structure of the method in this paper is complex, and the running time is obviously longer than that of ordinary filtering method, which is not conducive to real-time image processing. Therefore, the following research contents should focus on the improvement of algorithm efficiency and enhancement of speckle noise removal effect to lay a solid foundation for side-scan sonar image processing in the later stage.

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Reference

- 1. Li Q W, Huo G Y. *Sonar image processing*. Science Process (2015).
- Zhang K H, Yuan F, Cheng E. Analysis of side-scan sonar image noise model. J Xiamen Univ Nat Sci, 57(3): 390-395, (2018).
- Xiong C L, Xia W, Sun X X, Pei W B. Application of 1D wavelet transform in denoising side-scan sonar images. Hydrographic Surveying and Charting, 33(03): 29-32, (2013).
- Huang N E, Shen Z, Long S R, et al. The empirical mode decomposition and the Hibert spectrum for nonlinear and non-stationary time series analysis. Proceedings of the Royal Society of London, 454 : 903-995, (1998).
- Nunes J C, Bouaoune Y, Delechelle E, et al. Image analysis by bidimensional empirical mode decomposition. Image & Vision Computing, 21(12):1019-1026, (2003).
- Shen B, Cui F, Peng S L. Texture analysis and instantaneous frequency estimation of BEMD. Journal of Computer Aided Design and Graphics, (10): 205-212, (2005).
- Liu B, Lin Y, Wang Y L. BEMD adaptive algorithm for edge feature extraction of underwater images. Journal of Harbin Institute of Technology, 45(02) : 117-122, (2013).
- Liu D, Chen X Y, Fang W H. An improved BEMD threshold denoising algorithm for monocular vision positioning. Chinese Journal of Inertial Technology, 26(06): 737-746, (2018).
- Xue Z W. An improved BEMD algorithm for screening stopping condition and its application. Heilongjiang Science and Technology Information, (13): 68+182,(2011).
- 10. Buades A, Coll B, Morel J M. A non-local algorithm for image denoising. *IEEE computer society conference on computer version and pattern recongnition*. IEEE, (2005).
- Li F, Zhu L L. Comparetive Research on Denoising Effects of Common Filtering Algorithms Based on Sonar Image. Mine Warfare & Ship Self-Defence, 25(04): 82-86, (2017)