The Autonomous Underwater Vehicle Vision Denoising Method of Surfacelet Based on Sample Matrix

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Abstract. Through analyzing needs of the autonomous underwater vehicle vision, the autonomous underwater vehicle vision denosing method of Surfacelet based on sample matrix is proposed. N nosing image are produced by one image adding noise based on N sample matrix, which are circle shifted respectively and constructed image sequence. The image sequence is implemented Surfacelet transform and employed the hard thresholding denoising to coefficient and then linear average in airspace. The experimental results indicate that image de-noised has not Gibbs—like phenomena of Wavelet and nick effect. The method can restrain noise to underwater sonar image and hold detail and texture of image to target fringe of noise distribute strongly. The method has important significance to autonomous underwater vehicle planning for safe navigation routes and successful completion of the tasks.

Keywords: autonomous underwater vehicle; sonar image; image processing; Surfacelet transform; sample matrix.

1 Introduction

Autonomous underwater vehicle must equip with diversified water acoustic equipments for realizing exploretion, detection, position, navigation and communication tasks. Most of autonomous underwater vehicle only equip with image for sonar in the front of Autonomous underwater vehicle [1]. Water acoustic environment is complex, during the course of transmitting, many factor make signal to aberrance, such as more paths, strength noising and reverberation. This will cause the underwater acoustic imaging contrast goal difference, the details relatively small, marginal deterioration and difficult to determine edge [2] [3] [4] [5].

Yue Lu[6][7][8][9]and Minh N. Do proposed Surfacelet transform in 2005. Surfacelet transform has shift invariance. During the sonar image inhibit noising, most of methods obtain improvement of noising by decreasing resolution. Surfacelet transform has anisotropic characteristics in online and super plate. It can not only separate the band, but also has strong keeping details ability by multi-directions and translational invariance.

The outline of this paper is as follows: In section 2, we give an analysis of sonar image character. Then in section 3, Surfacelet transform theory is introduced. In section 4, the denoising method of Surfacelet based on sample matrix is proposed. Finally we briefly review the characteristics of the sonar image then compare the new

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methods with traditional denoising methods on the sonar images and some numerical experiments are showed in the end.

2 Imaging Mechanism and Statistical Properties of Underwater Target Sonar Image

Hai-Lan Zhang [10] analyzed the statistical properties of sonar image from the sound image of the imaging mechanism.

First, the correlation of the sonar image pixels is much weaker than the general optical images, and sometimes sonar image has strong anisotropy.

Second, gray-scale density of the general optical images is more complicated, and often has several peaks; but gray-scale density of the sonar images has only a peak.

Third, received the sonar echo is the bottom of the reverse scatter signal, which is caused by underwater irregular fluctuations. This scattering can be seen as random distribution of a large number of small scattering units produced. The phenomenon is similar to the laser speckle phenomenon. Hai-Lan Zhang theory draw a conclusions that the probability distribution of receive signals is zero mean the Gaussian distribution.

3 Surfacelet Transform

Yue Lu extended the DFB to higher dimensions, named NDFB. By combining the NDFB with a new multiscale pyramid, Yue Lu proposes the Surfacelet transform, which can be used to efficiently capture and represent surface-like singularities in multidimensional data.

In Figure 1, we use $L_i(\omega)(i=0,1)$ to represent the lowpass filters and $D_i(\omega)(i=0,1)$ to represent the highpass filters in the multiscale decomposition. $S(\omega)$ is an anti-aliasing filter used to cancel the aliasing caused by the upsampling operations. The NDFB is attached to the highpass branch at the finest scale and bandpass branches at coarser scales. To have more levels of decomposition, we can recursively insert at point a_{n+1} a copy of the diagram contents enclosed by the dashed rectangle in

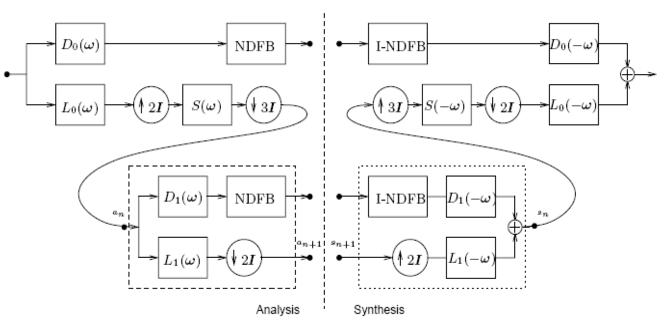


Fig. 1. Surfacelet transform structure

Figure 1, and at point s_{n+1} a copy of the diagram contents enclosed by the dotted rectangle in Figure 1.

In the new multiscale pyramid depicted in Figure 1, the lowpass filter $L_0(\omega)$ in the first level is downsampled by a non-integer factor of 1.5 (upsampling by 2 followed by downsampling by 3) along each dimension. Although this fractional sampling factor makes the new pyramid slightly more redundant than the Laplacian pyramid, the added redundancy to be very useful in reducing the frequency domain aliasing of the NDFB, which is concentrated on the boundaries of the frequency cell $[-\pi,\pi)^N$ and mainly caused by the 2π periodicity of the frequency spectrum of discrete signals. Intuitively, the new multiscale pyramid achieves the task of eliminating aliasing components by only keeping the middle (alias-free) portion of the NDFB filter responses. Consequently, the constructed surfacelets are well-localized in both the spatial and frequency domain. The lowpass filters $L_i(\omega)(i=0,1)$ in the frequency domain as

$$L_i(\omega) = d_i \cdot \prod_{n=1}^{N} L_i^{(1D)}(\omega_n) \tag{1}$$

Where $d_1 = 6^{N/2}$ and $d_2 = 2^{N/2}$; $L_i^{(1D)}(\omega_n)$ is a 1-D lowpass filter along the ω_n axis with passband frequency $\omega_{p,i}$, stopband frequency $\omega_{s,i}$ and a smooth transition band, defined as

$$L_i^{(1D)}(\omega) = \begin{cases} 1 & |\omega| \le \omega_{p,i} \\ \frac{1}{2} + \frac{1}{2}\cos\frac{(|\omega| - \omega_{p,i})\pi}{\omega_{s,i} - \omega_{p,i}} & \omega_{p,i} < |\omega| < \omega_{s,i} \\ 0 & \omega_{s,i} \le |\omega| \le \pi \end{cases} \tag{2}$$

for $|\omega| \le \pi$ and $i = 0,1$. Similarly, we also specify the antialiasing filter $S(\omega)$ as the separable product of 1-D lowpass filters having the same parameterized form as in (2), but with a different set of passband and stopband frequencies, denoted as $\omega_{p,A}$ and $\omega_{s,A}$ respectively.

The main advantage of designing the filters in the frequency domain is that we can let their frequency responses to be strictly zero beyond some cutoff frequencies. By choosing $\omega_{p,A}$, $\omega_{s,A}$ and $\omega_{s,i}$ properly, we can ensure that the aliasing introduced by the upsampling and downsampling operations will be completely cancelled, and the perfect reconstruction condition for the multiscale pyramid can be simplified as

$$\frac{|L_i(\omega)|^2}{d_i^2} + |D_i(\omega)|^2 \equiv 1 \quad i = 0,1 \tag{3}$$

4 Surfacelet Denosing Based on Sample Matrix

The resolution of sonar image is lower than normal optical image and the detail is small. So image edge is main important characteristics to recognition image. The image analysis ideal is analogous to the Contourlet. Compare to separated wavelet transform, the Surfacelet transform has improved in directional and anisotropic aspect, and it has shift invariance. To some extent, the Surfacelet transform decreases nick phenomenon. The represent the direction of the image information more focused at all levels in subband after Surfacelet transform. So this method has better results than other methods to use Surfacelet transform for processing under water target image. Gaussian noise after Surfacelet transform can be approximated as Gaussian noise. So most noise can be removed by threshold and image information can be reserved. Because noise distributes high-frequency part mainly, the threshold denoising isn't used in low-frequency subbands.

First, use sample matrix for image to sample and interpolation; second, image sequence is produced by cycle spinning; third, Surfacelet threshold denoising to image sequence; forth, reconstruct and fuse to denoising coefficient; at last, ideal denoising results can be obtained. Denoising course based on Surfacelet of sample matrix as shown in Figure 2.

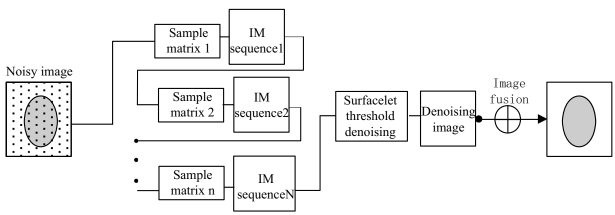


Fig. 2. Denoising course based on Surfacelet of sample matrix

4.1 Sample Matrix

$A(i, j)_{i,j \in I}$ is represented position (i, j) pixel value in a $N \times N$ image *I*. Sample process of image is sample $A(i, j)_{i,j \in I}$ of image respectively, so that many approximate images are obtained. With the following sample process:

(1) Construct sample basis matrix (for example 4×4 matrix)

$$S = \begin{pmatrix} 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 1 \end{pmatrix} \tag{4}$$

(2) According to image size, expand S to $S1$, if image size is 512×512, so

$$S1 = \underbrace{\begin{pmatrix} S & \cdots & S \\ \vdots & \ddots & \vdots \\ S & \cdots & S \end{pmatrix}}_{128} \tag{5}$$

(3) Sample to image. The sampled image A_s is obtained by (6)

$$A_s = A \bullet S1 \tag{6}$$

According to compute ability, sample basis matrix S is selected such as $S=\begin{pmatrix}0&1&0&1\\1&1&1&1\\0&1&0&1\\1&1&1&1\end{pmatrix}$、$S=\begin{pmatrix}1&0&1&0\\0&1&0&1\\1&0&1&0\\0&1&0&1\end{pmatrix}$、$S=\begin{pmatrix}0&1&0&1\\0&1&0&1\\0&1&0&1\\0&1&0&1\end{pmatrix}$ and so on. Only there are two 1 around each 0 that can satisfy require. By this method, we can obtain n different sample matrixes and sampled images. The paper use 12 kinds sample matrixes S.

4.2 ImageInterpolation Algorithms

The common image interpolation is as an estimation of potential unknown data. Interpolation is defined: within the scope of this unknown potential data is estimated by using within a certain range of known discrete data.

The common image interpolation algorithms have Nearest Interpolation, Bi-linear Interpolation, Bi-cubic Interpolation and Spline and so on. In order to test introduced method, the 2 Neighborhood mean interpolation is used in interpolating pixel value.

4.3 Denosing Method of Surfacelet Based on Sample Matrix

This paper proposed a denosing method of Surfacelet based on sample matrix as shown in figure 4, specific algorithm are as follows:

(1)*IM1* is obtained by sample matrix $S1$ sampling to noised image; then cycle shifts $m\times 1/n$ times from left to right and saves; according to cycle shifts order, *Sequences1* is produced that is $1/n\times m\times m\times m$ sequence at last.

(2) *IM2* is obtained by sample matrix $S2$ sampling to noised image; then cycle shifts $m\times 2/n$ times from left to right and saves; according to cycle shift order, according to cycle shift sequence, *Sequences2* is synthesize from $1/n$ to $2/n$ parts that is $1/n\times m\times m\times m$ sequence.

(3) *IMi* is obtained by repeating (2), different part is that cycle shifts $m\times i/n$ times from left to right and saves; according to cycle shift order, according to cycle shift sequence, *Sequencesi* is synthesized from $(i\text{-}1)/n$ to i/n parts that is $1/n\times m\times m\times m$ sequence.

(4) *Sequences* is obtained by synthesizing n-sequence *Sequencesi*, which is implemented Surfacelet transform and threshold denoising. Then De*Sequences* is produced by Surfacelet transform reconstruct to denoised coefficient.

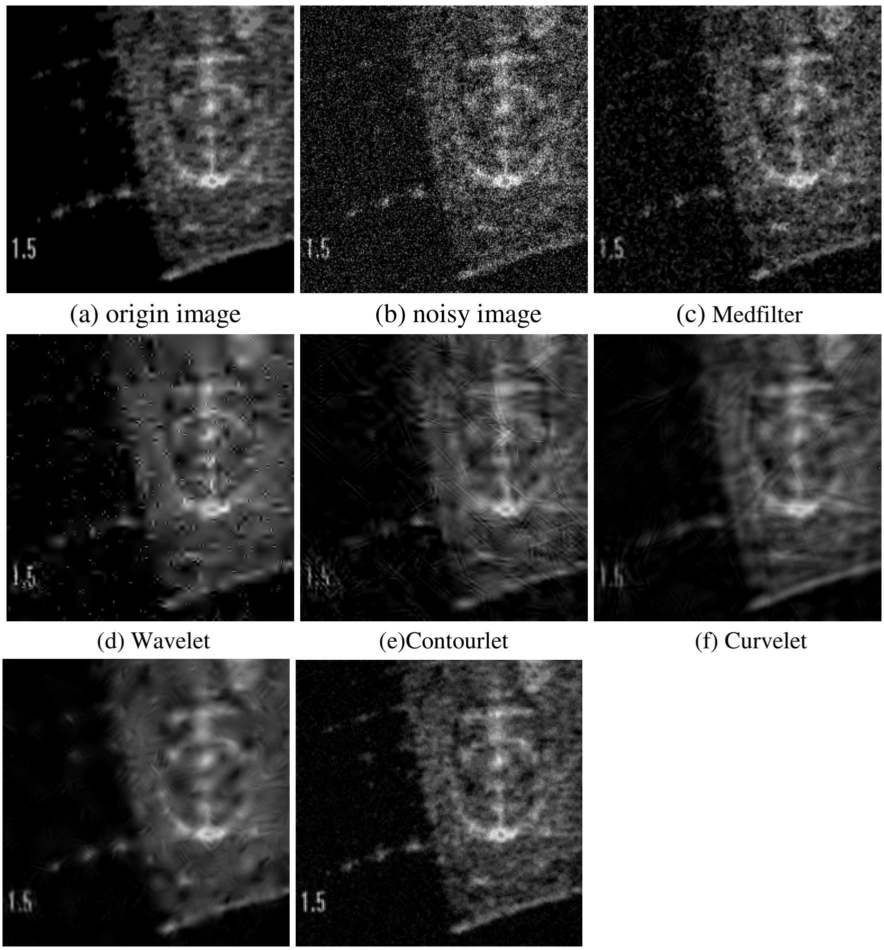
(5) Each frame of *DeSequences* cycle shift m times and shift direction is opposite to *Sequences1's*. The denoised image $IM_1^{T^{-1}}$ is obtained by computing *DeSequences1* linear average of each pixel gray value.

5 Experiments and Discussions

We perform numerical comparison on the underwater armor plate image shot by the DIDSON sonar with different character of angle of line and curve, which is convenient for detecting ability of target character. Using six transforms: Medfilter(MF),

Table 1. The results PSNR of the denoising methods

Input PSNR(db)	Output PSNR(db)					
	MF	WT	CT	CU	NT	SC
22.16	29.12	28.47	29.73	31.85	32.81	**34.76**
20.21	27.46	27.98	28.74	30.87	31.65	**32.97**
18.65	26.09	27.62	27.88	30.06	30.83	**31.67**
17.28	24.80	27.29	27.18	29.40	30.00	**30.74**
16.14	23.72	27.13	26.58	28.80	29.42	**29.65**



(a) origin image (b) noisy image (c) Medfilter

(d) Wavelet (e)Contourlet (f) Curvelet

(g) NSCT (h) method of the paper

Fig. 3. The contrast of sonar image denoising effect

Wavelet(WT), Contourlet(CI), Curvelet(CU), Nonsubsampled Contourlet Transform[11](NT) and denosing method of Surfacelet based on sample matrix (SC). Table 1 and Fig.3 express the effect and the PSNR plot of the approaches. All images implement 5 levels LP transform, and the first level is 16 directions, the others are 16, 8, 8, 4.

Experimental results indicate that the Medfilter offers keeping ability for image edges, but its denoising ability is limited with increasing noise strength. The wavelet transform keeps detail of image, but target edges keeping results is bad. The image has obvious nick phenomenon by Contourlet denoising method. Curvelet obtains good denoising effect, but the image has nick phenomenon and destroyed detail information. NSCT obtains better denoising effect than the formers, the image has obvious details and edges.

Method of this paper has best keeping ability of details and edges; it has high output SNR and little nick phenomenon. Fig.4 expresses the effect and the PSNR plot of the approaches. We can see that denosing method of Surfacelet based on sample matrix is best than others methods. So this method is an efficient denoising method of underwater sonar image.

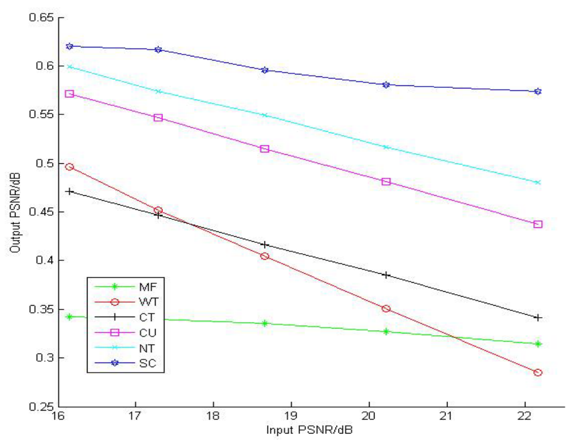


Fig. 4. The improved ratio of PSNR

6 Conclusions

This paper introduced sample matrix and Surfacelet transform and proposed. The autonomous underwater vehicle vision denosing method of Surfacelet based on sample matrix. The method can strong inhibit underwater sonar image of the noise, and can better keeping the edge effect in strong noise interference edge. Compare to other traditional denoising algorithms, the denoising algorithm of the paper proposed can obtain desired effect. The method has important significance to autonomous underwater vehicle planning for safe navigation routes and successful completion of the tasks.

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