Curvelet Approach for Deep-sea Sonar Image Denoising, Contrast Enhancement and Fusion

Huimin Lu†, Akira Yamawaki* and Seiichi Serikawa*

Abstract – Side-scan sonar acquires high quality imagery of the seafloor with very high spatial resolution but poor locational accuracy. However, multi-beam sonar obtains high precision position and underwater depth in seafloor points. In order to fully utilize all information of these two types of sonars, it is necessary to fuse the two kinds of sonar data. This paper gives curvelet transform for enhancing the signals or details in different scales separately. It also proposes a new intensity sonar image fusion method, which is based on curvelet transform. Considering the sonar image forming principle, for the low frequency curvelet coefficients, we use the maximum local energy method to calculate the energy of two sonar images. For the high frequency curvelet coefficients, we take absolute maximum method as a measurement. The main attribute of this paper is: Firstly, the multi-resolution analysis method is well adapted the cured-singularities and point-singularities. It is useful for sonar intensity image enhancement. Secondly, maximum local energy is well performing the intensity sonar images, which can achieve perfect fusion result. The experimental results show that the method can be used in the flat seafloor or the isotropic seabed. Compared with wavelet transform method, this method can get better performance.

Keywords: Curvelet transform, Side-scan sonar, Multi-beam sonar, Image processing, Deep-sea terrain detection

1. Introduction

Acoustic sensing is the imaging modality of choice for the analysis of deep-sea environments [1]. Acoustic waves propagate well in water, as opposed to electro-magnetic waves, which is used by optical cameras to reconstruct the real scene. The optical camera gives high resolution images and can exploit rich vision literature applied in air; however, it is hindered by the limited range of light in water and by the turbidity of the water in most no-ideal conditions. So, several acoustic sensors are routinely used to study the underwater environment, such as multi-beam sonar [2], side-scan sonar [3] et al.

Multi-beam sonar (MES) can obtain high precision position and underwater depth in seafloor points. At the same time, it also can obtain low-resolution seabed images. To obtain images of the seafloor, side-scan sonar (SSS) are used. It can obtain low precision position and depth with high-resolution. In order to fully utilize all information, the digital information of MES and SSS can be fused for explaining and exploring seabed. The fused image is helpful to make more comprehensive, quantitative and qualitative analysis, which is of great significance to understand seafloor topography, underwater target detection and digital seabed topography.

Because the images of MES and SSS are not measured from the same sensor, their deformations are also not at the same. It is necessary to register the two type images to get the converted parameters of corresponding pixel. T. Lebas et al. [4] adopt Chamfer registration method to acquire MES combination image and the SSS image. It didn’t consider whole image, and may lead to registration parameters inconsistent in the part of image mosaic. K. Behrooz et al. [5] proposed the seabed contour method to co-register images. The result was satisfactory, but the results must be obtained from the same sensor. In 1998, S. Daniel et al. [6] suggested using a pair of goals and shadows to register images. This method is only applicable to the slant range uncorrected SSS image. In the same year, Z. Zhang [7] adopted a fast automatic registration method for co-registration of remote sensing imagery. But the method is only applicable to the slant range uncorrected SSS image. In the same year, Z. Zhang [7] adopted a fast automatic registration method for co-registration of remote sensing imagery. But the method is not fit for sonar image processing. In 2003, F. Yang et al. [8] proposed the maximal correlate coefficient-based co-registering method. The method can fully utilize useful information of two types of sonars. In this paper, we take this method as an image preprocessing method.

In [9], Y. Han et al. proposed a wavelet based multi-beam
sonar and side-scan sonar fusion method. It adapted dyadic wavelet transform for fusion. During some research, people found that the wavelet only can express point singularities very well. In two-dimensional signal or higher, because of limited directional, the wavelets do nothing. To solve this problem, several theoretical papers have called attention to the benefits of beyond wavelets.

Curvelet [10], as a new multiscale analysis method in beyond wavelets, which is an extension and latest development of wavelet and ridgelet, is a kind of multiscale, multi-directional and anisotropic transform. This paper proposes curvelet transform in sonar image denoising, enhance the sonar image’s global contrast in the low-frequency subbands, and enhance the details of image at each scale in the high-frequency. After that, an intensity-based curvelet transform fusion method is proposed.

The outline of the paper is as follows. Sections 2 introduce the fundamental of curvelet transform. Given this, the curvelet transform-based sonar image denoising, image enhancement, and MES and SSS image fusion is derived in Section 3. In Section 4, the experimental results are shown, at the same time, we discuss the results. We conclude this paper in Section 5.

2. Curvelet Transform

In this section, we review the theory of ridgelet and curvelet transforms, which is used in this subject.

**Definition:** let \( \psi : \mathbb{R} \rightarrow \mathbb{R} \) satisfy the condition

\[
K_\psi = \int \left| \frac{\hat{\psi}(\xi)}{\xi} \right|^2 d\xi < \infty,
\]

where \( \psi \) is called an Admissible Neural Activation Function (ANAF). We will suppose that \( \psi \) is normalized so that \( K_\psi = 1 \).

For each \( a > 0, b \in \mathbb{R} \) and \( \theta \in [0, 2\pi) \) ridgelet basis functions are defined by

\[
\Psi_{a,b,\theta}(x) = a^{-1/2} \psi \left( \frac{x_1 \cos \theta + x_2 \sin \theta - b}{a} \right).
\]

We can see that ridgelet function is a constant in the direction of line: \( x \cos \theta + x \sin \theta = C \). In the vertical direction of the line, it is a wavelet function. Given an integrable bivariate function \( f(x_1, x_2) \), we define its ridgelet coefficients (i.e. Continuous Ridgelet Transform) by

\[
\text{CRT}_f(a, b, \theta) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \Psi_{a,b,\theta}(x_1, x_2) f(x_1, x_2) dx_1 dx_2
\]

Then the exact reconstruction formula is

\[
f(x_1, x_2) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \text{CRT}_f(a, b, \theta) \psi_{a,b,\theta}(x_1, x_2) \frac{d\theta}{a} d\theta d\xi
\]

where \( a \) and \( b \) are selected for the functions which are both integrable and square integrable. A basic tool for calculating ridgelet coefficients is to view ridgelet analysis as a form of wavelet analysis in the Radon domain. The Radon transform for function \( f(x_1, x_2) \) is given by

\[
R_f(\theta, t) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x_1, x_2) \delta(x \cos \theta + x \sin \theta - t) dx_1 dx_2
\]

where \( \delta \) is the Dirac function. The ridgelet coefficients \( \text{CRT}_f(a, b, \theta) \) of function \( f(x_1, x_2) \) are given by analysis of the Radon transform via

\[
\text{CRT}_f(a, b, \theta) = \int_{-\infty}^{\infty} R_f(\theta, t) a^{-1/2} \psi[(t - b) / a] dt
\]
Hence, we clearly see that the ridgelet transform is precisely the application of one-dimensional wavelet transform to the slices of the Radon transform where the angular variable \( \theta \) is constant and \( t \) is varying. Through discrete Radon transform, we can turn an array of \( n \times n \) to that of \( n \times 2n \). And then one-dimensional wavelet transform is done, and \( 2n \times 2n \) array discrete ridgelet transform is gotten. The flowchart of ridgelet transform is presented in Fig. 1.

Curvelet transform [11,12] provides a sparse expression for image smoothing and edge section at the same time. Unlike the results in wavelet transform, the coefficient of the edge can be concentrated. Let \( Q \) be the collection of all dyadic squares of scale \( s \) and it can be defined by

\[
Q_s = \left[ \frac{k_1}{2^s}, \frac{k_1+1}{2^s} \right] \times \left[ \frac{k_2}{2^s}, \frac{k_2+1}{2^s} \right] \tag{7}
\]

where \( k_1, k_2 \in \mathbb{Z} \). For \( Q \in Q_s \), let \( w_Q \) be a window near \( Q \), obtained by dilation and translation of a single \( w \), and is satisfied

\[
\sum_{Q \in Q_s} w_Q^2 (x_1, x_2) = 1 \tag{8}
\]

Then we have the reconstruction formula as

\[
f(x_1, x_2) = \sum_{Q \in Q_s} f(x_1, x_2) w_Q^2 (x_1, x_2)
\]

\[
= \sum_{Q \in Q_s} \int_{-\infty}^{2\pi} \int_{-\infty}^{2\pi} \left\{ f, w_Q T_Q \phi_{a,b,\theta} \right\}_{L^2(R^2)}
\times w_Q (x_1, x_2) T_Q \phi_{a,b,\theta} (x_1, x_2) \frac{da}{a^2} \frac{db}{b^2} \frac{d\theta}{4\pi} \tag{9}
\]

3. Sonar Image Processing Technologies

3.1 Soft-thresholding Denoising

We now briefly report the 2D Fast Discrete Curvelet Transform (2D FDCT) [13, 19] as a soft thresholding sonar image denoising method in this paper. 2D FDCT via wrapping is simpler, faster, and less redundant. The 2D FDCT is expressed as

\[
c^D(j,l,k) = \sum_{0 \leq t_1, t_2 < n} f(t_1, t_2) \varphi^D_{j,l,k}[t_1, t_2] \tag{10}
\]

where \( f(t_1, t_2) \) is an input of Cartesian arrays with \( t_1 \geq 0, t_2 < n \).

c^D(j,l,k) are curvelet coefficients and \( \varphi^D_{j,l,k} \) are Riesz representers. \( l = 0, 1, ... \), \( 2^l \), \( k = (k_1, k_2) \), \( k_1, k_2 \in \mathbb{Z} \) is a translation parameter, \( j = 0, 1, 2, ... \) is a scale parameter.

Since the 2D FDCT is not normpreserving, the variance of each curvelet coefficient depends on its index [14]. Let \( C \) denote the 2D FDCT matrix and curvelet transform an image with noise distribution given by \( N(0,1) \), then the outcome has noise distribution given by \( N(0, CC^*) \). After that, use the Monte-Carlo simulation method to estimate the noise variance of each curvelet index. Suppose an image \( I \) with standard with noise, \( N(0,1) \) is discrete curvelet transformed and the variance, \( \sigma^2 \) is estimated where \( \lambda \) indicates its index. The denoising algorithm by soft thresholding the curvelet coefficients \( c \) with

\[
\tilde{c}_\lambda = \begin{cases} 
  c_\lambda & |c_\lambda| \geq k \sigma \lambda \sigma \\
  0 & |c_\lambda| < k \sigma \lambda \sigma 
\end{cases} \tag{11}
\]

where \( \sigma \) is estimation of the standard deviation of the noise of image \( I \) and \( k \) is subband dependent value, estimated by denoising few know images and letting \( k \) variate.

3.2 Piecewise Function based Enhancement

Science the curvelet transform is well-adapted to represent images containing edges; it is good can didate for edge enhancement [15]. In Ref. [15], a non-linear image contrast enhancement method was proposed, which is based on modify the curvelet coefficients. This method needed \( c, p, s, \) and \( m \), four parameters to determine Starc \( k \) operator. It requires repeated adjustment parameters in practice experience. In this paper, we propose a new method. The curvelet coefficients at scale \( j \) and location \( l \) are multiple with \( y \), where \( y \) is defined by:

\[
y(x) = x_{jl} - (G-1) \delta \quad \text{if } x_{jl} < -\delta \\
y(x) = G x_{jl} \quad \text{if } |x_{jl}| \leq \delta \\
y(x) = x_{jl} + (G-1) \delta \quad \text{if } x_{jl} > \delta \tag{12}
\]

where, the threshold \( \delta = \max(|x_{jl}|) \frac{e^{-j}}{1+e^{-j}} \). Gain factor \( G = \frac{c}{1+e^{-j}} \), which can be adapted by \( c \). This method only uses one parameter to determine the coefficients \( c \).

3.3 Local Energy based Fusion

Back to review the sonar camera imagery principle, the
acoustic camera emits acoustic beams and returns two sets of data, the intensity of the return from a point, and the distance from the camera. Based on intensity (or energy) of receiver and imaging principle, the intensity-distance information can be imaged as gray level image.

Consider the energy distribution of the gray image, this paper takes the maximum local energy (MLE) \([16,17]\) as a measurement to fuse MES and SSS sonar images. In image multiscale analysis, due to the incompleteness of multi-scale decomposition, image details are still retained in the low frequency. Therefore, proposed edge filters to get a good result. But because of the edge filter coefficients distribute as non-Gaussian distribution, so, combine with local energy, can solve this problem well. Select the maximum energy of two images as output. Due to the partial human visual perception characteristics and the relationship of decomposition about local correlation coefficients, the statistical characteristics of neighbor should be considered. Therefore, the statistic algorithm is based on the \(3 \times 3\) sliding window. The algorithm is described as follows:

\[
LE_\xi(i,j) = \sum_{i=M,j=N} p(i+i,j+j) \cdot f_\xi^{02}(i+i,j+j)
\]

where \(p\) is the local filtering operator, \(M, N\) is the scope of local window. \(\xi \in A\) or \(B\) (\(A, B\) is the window for scanning two images). \(f_\xi^{02}(i,j)\) is low frequency coefficients.

Maximum Local Curvelet Energy is

\[
LCE^{i,k}_{\xi}(i,j) = E_1 \ast f_\xi^{02}(i,j) + E_2 \ast f_\xi^{02}(i,j) + \ldots + E_K \ast f_\xi^{02}(i,j).
\]

where \(E_1, E_2, \ldots, E_{K-1}\) and \(E_K\) are the filter operators in \(K\) different directions. \(l\) is the scale layer.

\[
E_1 = \begin{bmatrix} -1 & -1 & -1 \\ 2 & 2 & 2 \\ -1 & -1 & -1 \end{bmatrix}, E_2 = \begin{bmatrix} -1 & 2 & -1 \\ -1 & 2 & -1 \\ -1 & 0 & 0 \end{bmatrix}, E_3 = \begin{bmatrix} 0 & -1 & -1 \\ -1 & 2 & -1 \\ -1 & 0 & 1 \end{bmatrix}
\]

(15)

where, \(LCE_{\xi}(i,j)\) \([18]\) reflects the intensity information of horizontal, vertical and diagonal direction. It is well represent the image details information. Define the average local energy of image \(A\) and \(B\) is

\[
ALCE_{AB} = \frac{LCE_A(i,j) + LCE_B(i,j)}{2}
\]

The Correlation Coefficient (CC) of the two source image is \(R_{AB}\). Suppose the Probability Distribution Function (PDF) of \(ALCE_{AB}\) is \(\alpha\), which is calculated by the proportion of edge pixels. If \(R_{AB} < \alpha\), the low coefficient \(c_{low}\) as output. Otherwise output the weighted coefficient \(w_{c_{low}} + (1-w)c_{high}\). The weighting factor \(w\) is set by hand. For the high frequency coefficients, absolute maximum method is used.

4. Experimental Results and Discussions

The following data are obtained from the offshore of the East China Sea. MES and SSS sonar systems are both used. Fig. 2(a) is the intensity-based seafloor terrain obtained by MES, and Fig. 2(b) is the same area intensity-based terrain obtained by SSS. The maximal depth is 100.8 m, and the minimal depth is 27.3 m. The data have been preprocessing. Fig. 3(a) is the curvelet transform-based MES image denoising and Fig. 3(b) is the curvelet transform-based SSS image denoising. Fig. 4(a) is the curvelet transform-based MES image contrast enhancement, and Fig. 4(b) is the curvelet transform-based SSS image contrast enhancement. The PSNR of MES and SSS is 38.697, 40.6898, respectively. From this figure, the edge details are more clearly than that in Fig. 4(a). Fig. 5 reports the comparison of wavelet transform-based fusion and curvelet transform-base fusion. Beside visual analysis, we compare the results in numerical analysis. The quantitative analysis result is shown in Table 1. We use the evaluation functions in PSNR, \(Q\), \(Q_w\), \(Q_E\) to measure the results. From Table 1, we also confirm that the curvelet transform based fusion method is obviously better than wavelet transform based fusion method.
5. Conclusion

This paper proposed a method that combines the multi-beam water depth data and side-scan image information, based on curvelet transform. It is firstly considered the maximum local energy method and curvelet transform for MES and SSS sensor image fusion. During the results using human visual system (HVS) and some well-defined mathematical frameworks, the proposed methods have perfect preformation on solving sonar data. The methods can be used not only in the flat seafloor that has different intensities, but also in the isotropy seabed that has an uneven terrain. In future, in order to achieve more remarkable visual effect results, we will consider using most recent optical imaging method to solve the problems in underwater vision [20-22].

Acknowledgements

This work was partially supported by Grants-in-Aid for Scientific Research of Japan (No. C19500478) and fully supported by Research Found for Young Scientists by Japan Society for the Promotion of Science (No.25・10713). The authors also gratefully acknowledge the helpful comments and suggestions of the reviewers.

References


Huimin Lu was born in Yangzhou, China, on November, 1985. He received the B.S. degree in Electronics Information Science and Technology from Yangzhou University in 2008. And he received M.S. degrees in Electrical Engineering from Kyushu Institute of Technology and Yangzhou University in 2011, respectively. Recently, he is a Ph.D. candidate in Kyushu Institute of Technology. His current research interests include computer vision, communication and deep-sea information processing. He is a student member of IEEE, IEICE, ACM and JSPS.

Akira Yamawaki was born in Chiba, Japan, on November, 1974. He received M.S. degrees in Electrical Engineering from Kyushu Institute of Technology, Japan in 1999. During 1999-2000, he was a system-on-chip designer of Mitsubishi Electric Corporation. He received Ph.D. in Electrical and Electronic Engineering from Kyushu Institute of Technology in 2006. From 2000-2007 he was an assistant in Kyushu Institute of Technology. Since 2007, he has been an Assistant Professor in Kyushu Institute of Technology. His current research interests include computer vision, digital hardware system, smart sensor system, sensor network and reconfigurable hardware.
system. He is a member of IEICE, senior member of IIAE.

Seiichi Serikawa was born in Kumamoto, Japan, on June, 1961. He received the B.S. and M.S. degrees in Electronic Engineering from Kumamoto University in 1984 and 1986. During 1986 -1990, he stayed in Tokyo Electron Company. From 1990 to 1994, he was an assistant in Kyushu Institute of Technology. He received the Ph.D. degree in Electronic Engineering from Kyushu Institute of Technology, in 1994. From 1994 to 2000, he was an Assistant Professor at the Kyushu Institute of Technology. From 2000 to 2004, he was an Associate Professor at the Kyushu Institute of Technology. Science 2004, he has been a Professor at the Kyushu Institute of Technology. He worked as Vice President of School of Engineering in Kyushu Institute of Technology from 2010 to 2012. Recently, he is the Dean of Department of Electrical Engineering and Electronics of School of Engineering in Kyushu Institute of Technology. His current research interests include computer vision, sensors, and robotics. He is a member of IEEJ, and IEICE, and the president of IIAE.