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Seafloor Classification Based on the Texture Analysis of Sonar Images Using the Gabor Wavelet

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Abstract

In the process of the sonar image textures produced, the orientation and scale factors are very significant. However, most of the related methods ignore the directional information and scale invariance or just pay attention to one of them. To overcome this problem, we apply Gabor wavelet to extract the features of sonar images, which combine the advantages of both the Gabor filter and traditional wavelet function. The mother wavelet is designed with constrained parameters and the optimal parameters will be selected at each orientation, with the help of bandwidth parameters based on the Fisher criterion. The Gabor wavelet can have the properties of both multi-scale and multi-orientation. Based on our experiment, this method is more appropriate than traditional wavelet or single Gabor filter as it provides the better discrimination of the textures and improves the recognition rate effectively. Meanwhile, comparing with other fusion methods, it can reduce the complexity and improve the calculation efficiency.

Keywords: *Seafloor classification, Sonar images, backscattering, Texture feature, Gabor wavelet, Multi-orientation; Multi-resolution*

I. Introduction

In recent years, side scan sonar (SSS) images become the most important way to inspect the seafloor [1,8], with the advances of underwater acoustic digital signal processing technology. Lots of methods have been developed for classification and recognition of the seafloor based on the sonar images. Among these researches, texture-based methods have been widely applied in both spatial and frequency space.

Fractal theory [2], neural networks [3,4], Markov random field theory [5], co-occurrence matrices [6] and many other methods have been used to analyze SSS images so far. However, all of these methods ignore the orientation information of the sonar images. The importance of the relative orientation of sonar process on image texture directionality is illuminated by J. M. Bell and Chantler [7]. But they can't solve this problem successfully. The Gabor filter has been proposed to solve the orientation problem in the reference [8]. However, this method pays no attention either to another important factor influencing the sonar image significantly, which is called scale or resolution.

Y. L. Wang et al. [9] present a supervised classification method of sonar images to overcome the orientation and scale problem, which takes advantages of the directional wavelet and fuzzy fractal dimension. However, to each image, it needs to extract the feature twice using wavelet and fuzzy fractal dimension respectively, which results in wasting of time and memory. Meanwhile, this method needs to design a complex classifier to combine the two features, which leads to a low recognition rate.

In this paper, we analyze the main factors influencing the classification rate in the process of generation the sonar images. Furthermore, according

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to the analysis, we propose a scheme to extract the texture feature of sonar images using Gabor wavelet with different parameters, which can solve the direc-tional and scale problems perfectly.

The analysis of the main problem in the sonar image generation is discussed in detailed in section II. A brief introduction and analysis of the Gabor function and the theory of wavelet are presented in section III. In section IV, The proposed Gabor wavelet is introduced. Finally, discussions based on the experiments and the conclusion about this proposed method is given in section V and VI, respectively.

II. Analysis of the problems in the sonar image generation

In the process of image generation, the orientation of the tow fish relative to a directional seabed texture has a profound effect on the classification of the texture-based feature. As illustrated in Fig. 1, the same sand ripple features of the seabed appear completely different from each other, since the textures are dependent on the reflectivity of the seabed.

In order to illuminate the importance of the orien-tation information, we simulate extracting the textur feature from different direction for the same sona image, as shown in Fig. 2.(a), which is composed o sand. It is easy to find that the texture is totall different. In the orientation of 45^0, the ripple textur is similar as the original image. On the contrary, i the orientation of 135^0, there is no obvious featur of sand.

Therefore, if we do not take these directional effect into consideration, variation in the tow fish track ma result in the failure of classification.

On the other hand, the change of the slant angl along the swath or the perpendicular position of th tow fish will result in the variety of the size of th object, as well as the variety of the texture characte of the seafloor. This problem can cause an effect o the classification feature, which is suitable for on image but not for another one. In order to overcom this limitation, we may need the filter which can kee the scale invariable or has the multi-resolution charac-teristic.

The Gabor filter and the wavelets transform ar proposed to solve these two problems. In the ne section, we will introduce these two different method

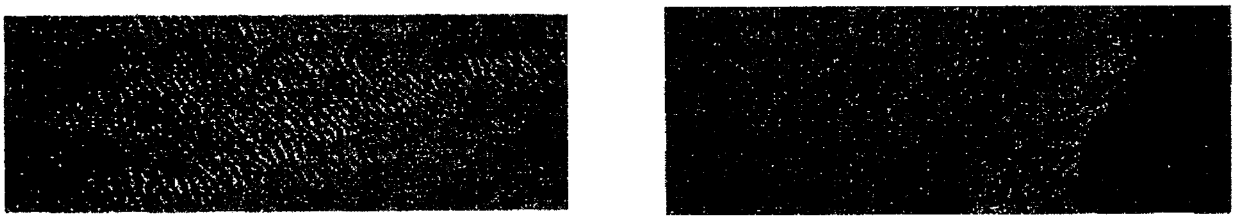

(a) (b)

Fig. 1. (a) Side scan sonar image, (b) Side scan image of the same region of seabed but traversed in a perpendicular direction.


(a) (b) (c)

Fig. 2. (a) the original image, (b) the texture of 45^0, (c) the texture of 135^0.

and analyze the advantages and disadvantages of them to classify seabed physiognomy, respectively.

III. Wavelets and Gabor function

The wavelet transform is defined as decomposition of a signal $f(t) \in L^2(R)$ into a family of functions $\psi_{m,n}(t)$:

$$w_\psi(m,n) = \int_{-\infty}^{+\infty} f(t)\overline{\psi_{m,n}(t)}dt \tag{1}$$

The shape of the complex Gaussian wavelet of order 4 is given in figure 3.

In the equation (1), $\psi_{m,n}(t)$ is obtained through translation and dilation of a kernel function $\psi(t)$ known as mother wavelet:

$$\psi_{m,n}(t) = m^{-1/2}\psi\left(\frac{t-n}{m}\right) \tag{2}$$

where m and n are the scale and translation factors, respectively. Combing equations (1) and (2), we get the expression of wavelet in frequency domain as

$$W_\psi(m,n) = \frac{\sqrt{m}}{2\pi}\int_{-\infty}^{+\infty} X(\omega)\psi(m\omega)e^{j\omega t}d\omega \tag{3}$$

If the scale factor m is changed, the center frequency and the bandwidth will be different, as shown in Fig.

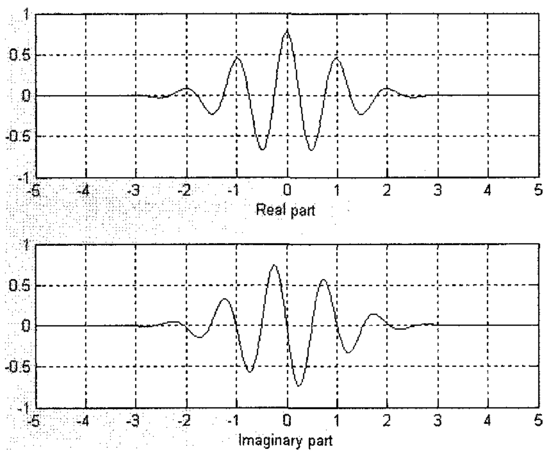


Fig. 3. The real part and imaginary part of wavelet.

4. This character of the wavelet is called multi-resolution, which is suited to solve the scale invariable problem of sonar image.

In the process of generating the sonar image, we change the time axis to spatial axis for further analysis. Under this situation, as m gets larger, the spatial observational range of the seafloor will become larger. In the frequency domain, it is equivalent to generate a coarse sonar image with the large scale characteristics of the seafloor having a low frequency. If m gets smaller, it will provides a high density picture of small area of the seafloor with a high frequency.

2D Gabor function is defined by equation (4) based on the Gaussian-modulated [8]:

$$g(x,y) = \frac{1}{2\pi\alpha\beta} e^{-\frac{1}{2}\left[\frac{(X'-X'_0)^2}{\alpha^2}+\frac{(Y'-Y'_0)^2}{\beta^2}\right]} e^{j2\pi(uX'+vY')} \tag{4}$$

Where, α and β are the scale factors of x-axes and y-axes respectively. (X'_0, Y'_0) is the center of spatial domain and (u, v) is the spatial frequency of the filter in the frequency domain. Its real and imaginary parts can be used as two real filters, of which the former is an even-symmetry and the latter is an odd-symmetry Gabor filter. We will not discuss the odd-symmetry Gabor function here because only the even-symmetry Gabor function will be used in this paper. The definition of the even-symmetry Gabor function is as follows:

$$g_r(x,y) = \frac{1}{2\pi\delta_x\delta_y}\exp\left\{-\frac{1}{2}\left[\frac{X'^2}{\delta_x^2}+\frac{Y'^2}{\delta_y^2}\right]\right\}\times\cos[2\pi f X'] \tag{5}$$

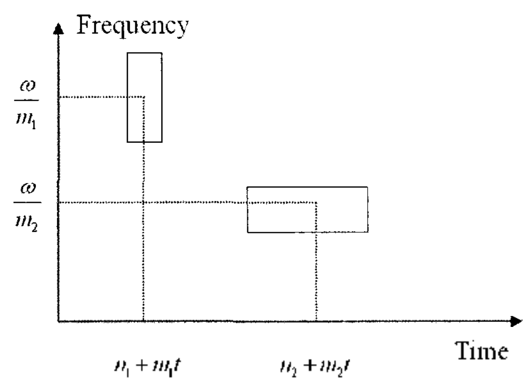


Fig. 4. Time-frequency windows in wavelets transform.

where, δ_x and δ_y is the standard deviation of the Gabor filters of x-axes and y-axes respectively, and

$$\begin{cases} X' = x\cos\theta + y\sin\theta \\ Y' = -x\sin\theta + y\cos\theta \end{cases} \qquad (6)$$

In the equation (6), θ is called orientation factor. Different orientational feature can be extracted by θ, as presented in figure 5.

In the defining the Gabor function, α and β are also the scale factors of x-axes and y-axes, respectively, which can control the shape of the Gabor function. However, to each image, α and β are constant as figure 6 show, which means the scale is time invariant. It indicates that the Gabor filter cannot solve the multi-resolution problem of sonar images. Thus a design of Gabor wavelet is proposed to combine both advantages of Wavelets and Gabor function to the sonar image.

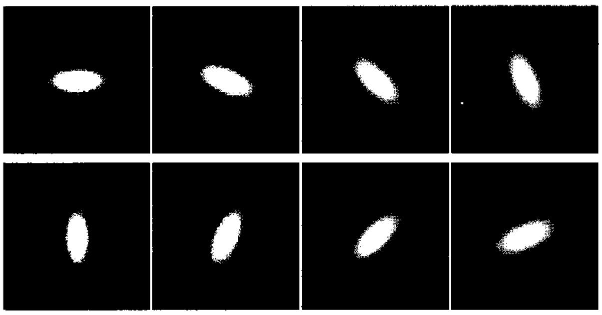


Fig. 5. Different orientation from 0 to π with the interval $\theta = \frac{\pi}{8}$ of Gabor function.

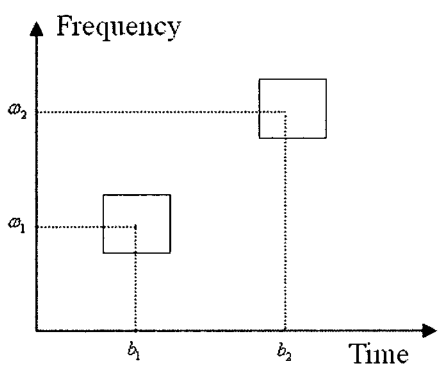


Fig. 6. Time-frequency windows in Gabor transform.

IV. Design of the Gabor wavelet

The Gabor wavelet is a familiar complex-valued wavelet. The generating function of the Gabor wavelet is

$$\psi(t) = h^{1/2}\pi^{1/4}\exp\left\{-\frac{(t-t_0)^2}{2h^2} + i\omega_0 t\right\} \qquad (7)$$

where h>0, ω_0 is the center of frequency, t_0 is the center of time.

Its Fourier transform

$$\hat{\psi}(\omega) = \frac{1}{\sqrt{2\pi}}\int_{-\infty}^{+\infty}\psi(t)e^{-i\omega t}dt \qquad (8)$$

is given by

$$\hat{\psi}(\omega) = h^{-1/2}\pi^{-1/4}\exp\left\{-\frac{h^2(\omega-\omega_0)^2 + 2it_0(\omega-\omega_0)}{2}\right\} \qquad (9)$$

The Gabor wavelet is

$$\psi^{a,x}(t) = |a|^{-1/2}\psi\left(\frac{t-x}{a}\right) \text{ for } a,x \in R, a \neq 0 \qquad (10)$$

and the Gabor wavelet transform with respect to this wavelet family is defined by

$$(T^{wav}f)(a,x) = \langle f, \psi^{a,x}\rangle = \int_{-\infty}^{+\infty} f(t)|a|^{1/2}\overline{\psi\left(\frac{t-x}{a}\right)}dt$$

for $f \in L^2(R)$ (11)

A class of self-similar functions referred to as the Gabor wavelet, is now considered. Let $g_r(x,y)$ be the mother Gabor wavelet, then this self-similar filter can be obtained by appropriate dilations and rotations of $g_r(x,y)$ through the generating function :

$$g_{mn}(x,y) = aG(x',y'), \qquad (12)$$

where $\alpha>1$, m,n are integers, and

$$x' = a^{-m}X' = a^{-m}(x\cos\theta + y\sin\theta) \quad (13)$$

$$y' = a^{-m}Y' = a^{-m}(-x\sin\theta + y\cos\theta) \quad (14)$$

where, $\theta = \frac{n\pi}{k}$, and k is the total number of orientations. The scale factor a^{-m} is to ensure that the energy is independent of m.

VI. Experiment

16 SSS images with a size of 512*512 are chosen as our training and testing set. The images were obtained with 50 kHz sampling rate and the frequency of 400 kHz as shown in figure 7. The total depth of the sea-bottom varies from 75 m to 100 m.

In order to get enough training and testing samples, sub-sampled images have been segmented into small sub-images with the size of 64*64 pixels using the method in reference [8]. Finally, we can sample 4096 sub-images in total, including 1600 training samples and 2496 testing samples. Each small image may include more than one sediment type, such as sand, rock, mud or combinations of them. Some of the sample images used in the experiments are shown in figure 8.

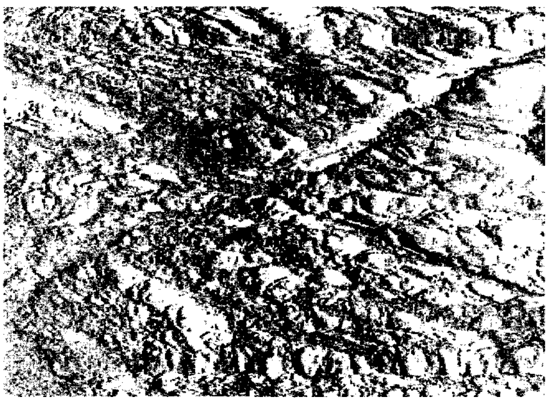


Fig. 7. One of testing images for experiments.

In this paper, we design the Gabor mother wavelet using constrained parameters to reduce the complexity and to improve the calculation efficiency. Meanwhile, at each orientation, we can search the optimal Gabor parameters with the help of bandwidth parameters based on the Fisher criterion [8].

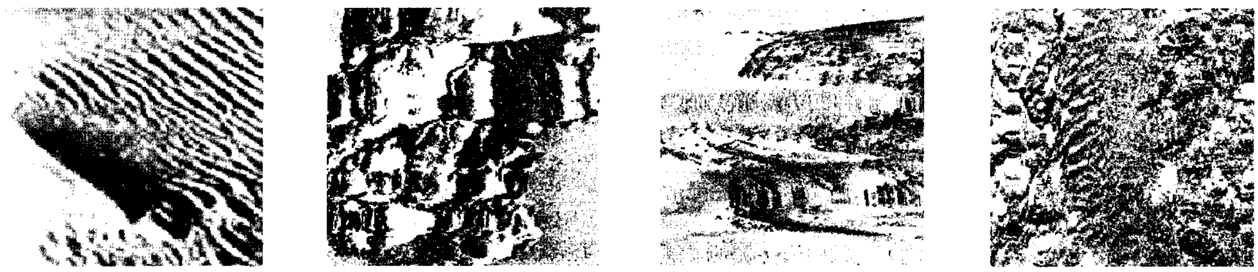
To get the best result, the Gabor wavelet was tested for different values of the number of scales and the number of orientations. The classification rate computed for each setting. After extracting the texture features of SSS images using Gabor wavelet, k-nearest neighbor classifier is used to determine the class [10].

The results are presented in Table 1. As it suggests, the total number of scales and the orientations are important for texture classification of sonar images since the process of texture discrimination is improved by using more features.

In order to compare the advantage and disadvantage of the traditional wavelet and Gabor wavelet, we choose half of our training and testing set and make them rotated with a small angle. We design the dyadic wavelet taking Fourier transform as the mother wavelet

Table 1. The classification rate of GW.

Number of scales	Number of orientation	Classification rate(%)
6	6	92.3
8	6	94.8
6	8	94.8



(a) (b) (c) (d)

Fig. 8. (a) sand, (b) rock, (c) mud, (d) rock and sand.

[11]. The classification rate of the original and rotated images is shown in table 2.

From the above table, for original textures, the dyadic wavelet transform results 90.4% classification rate, while Gabor wavelet leads to an 93.8% classification rate. When the test textures are rotated, the classification rate of dyadic wavelet was 86.4%, while for Gabor wavelet it still suitable with a 93.1% classification rate.

In order to see the effect of the scale variety on the performance of the algorithm, we compared the classification rate for different changes in the size of the texture for both Gabor function and Gabor wavelets, as shown in Table 3. When the input image is the original image without scale variety, the Gabor wavelet shows 93.8% of correct classification rate, which is comparable to 91.9% of the Gabor filter. However, to the image zoomed, the GW method still can keep a 93.2% classification rate, which indicates this proposed method has a good robustness to the scale or the resolution of the sonar image. To compare these three methods obviously, the database is reorganized. It's composed of half of the original images, the rotated images and the zoomed images, which are referred in Table 2 and Table 3. The classification results are illustrated in Table 4. Comparing the classification rate, the GW is also much more effective than the other two methods to the reorganized database.

Table 2. The comparison between Wavelet and GW.

Classification Rate Input Images	Wavelet classification Rate (%)	GW Classification rate (%)
Original image	90.4	93.8
Rotated image	86.4	93.1

Table 3. The comparison between Gabor filter and GW.

Classification Rate Input Images	Gabor filter Classification Rate (%)	GW Classification Rate (%)
Original image	91.9	93.8
Zoomed image	88.2	93.2

Table 4. The comparison of three classification methods.

	Wavelet classification rate (%)	Gabor filter classification rate (%)	GW classification rate (%)
Testing images	88.6	90.5	94.8

Finally, concluding from the experiments, Gabor wavelet not only contains multi-resolution information of images but also indicates the multi-orientation feature of the images, which is useful to classify the sonar image perfectly.

V. Conclusion

Automated recognition and classification of sonar images become increasingly important with the development of underwater acoustic digital signal processing technology. In this paper, we analyze the main factors to influence the classification result during the generating process of a sonar image. Taking the orientation and resolution problems of texture-based analysis into consideration, Gabor wavelet has been applied to extract the features, which can have the characteristic of both Gabor function and wavelet. Based on the various experiments, the test results show that the classification rate could be improved considerably by our proposed method.

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[Profile]

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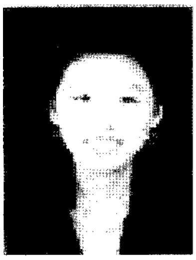

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