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Classification of Seabed Physiognomy Based on Side Scan Sonar Images

Ning Sun* and Taebo Shim*
*Underwater Acoustic Communication Institute, Soongsil University, Korea
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Abstract

As the exploration of the seabed is extended ever further, automated recognition and classification of sonar images become increasingly important. However, most of the methods ignore the directional information and its effect on the image textures produced. To deal with this problem, we apply 2D Gabor filters to extract the features of sonar images. The filters are designed with constrained parameters to reduce the complexity and to improve the calculation efficiency. Meanwhile, at each orientation, the optimal Gabor filter parameters will be selected with the help of bandwidth parameters based on the Fisher criterion. This method can overcome some disadvantages of the traditional approaches of extracting texture features, and improve the recognition rate effectively.
Keywords: *Seabed physiognomy classification; Sonar images ;backscattering; Texture feature; Gabor filter; Parameter constraint; Optimal parameter*

I. Introduction

In recent years, detection and analysis of seabed physiognomy has played an important role in both civilian and military applications [1]. Many methods are used to acquire seabed images for further analysis. With the advances of underwater acoustic digital signal processing technology, side scan sonar (SSS) images become a most important way to inspect the seafloor [2].

A tow fish, which contains an acoustic transmitter and receiver arrays, operating in the backscattering mode, is towed by a ship. The tow fish follows a straight trajectory with a constant altitude or a constant depth. SSS arrays are arranged on the port and starboard sides of the tow fish. One array emits an acoustic wave perpendicular to the track followed by the tow fish. As the bottom of the ground area is insonified by the projector, the receiver array collects the energy backscattered from the sea bottom for each beam. The sonar image is built by allocating one beam per image line [3]. Fig. 1 shows an acquired SSS image, which will be used as a training image.

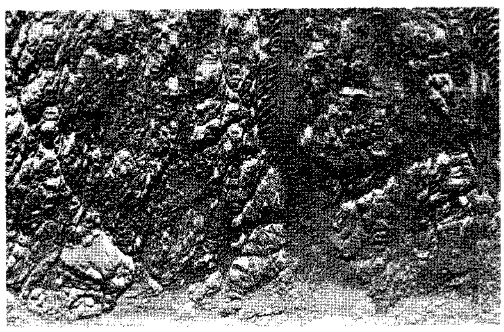


Fig. 1. Side scan sonar image as a training sample.

Lots of methods have been developed for recognition and classification of sonar images. Among these researches, texture-based methods have been widely applied in both spatial and frequency space.

Object detection of sonar images based on fractal theory was presented in the references [4, 5]. Zhong Liu et al.

Corresponding author: Taebo Shim (tbshim@ssu.ac.kr)
Dept. of Electric Engineering, Soongsil Univ. 447-1, Sangdo 5-Dong, Dongjak-Gu, Seoul, 156-743

[6] found that an important characteristic based on the fractal texture feature is to have scale invariance, which is suitable for the sonar images. Then, the multi-scale fractal theory and the Zipf law were adopted to detect the object in the sonar image. There has been much interest in utilizing artificial neural networks (ANNs) for classification of sonar images, due to the nature of their parallel structure of simple computational elements and good classification performance [7, 8, 9]. In the following research, Jiang et al. [10] introduced a new method based on the Markov random field theory. The adaptive maximum-entropy arithmetic was introduced by Jiang et al combining images with pre-segmentation arithmetic based on fractal theory. Meanwhile, co occurrence matrices [11] and many other methods have been used to segment and classify SSS images so far.

As we know, when an acoustic pulse interacts with the seabed, it is scattered in all directions. However, the backscattering is the most important aspect of the image generation process, and hence the most crucial in determining the directionality of the SSS images. However, most of the above texture-based methods ignore the directional information of SSS images, which is fundamental for exact classification.

J. M. Bell and Chantler [12] illuminate the importance of the relative orientation of sonar process on image texture directionality. They pointed out that the direction of the tow fish relative to a directional seabed texture has a profound effect on the mean output, and hence the suitability for classification, of this texture-based feature. Therefore, variation in the tow fish track may result in the failure of classifiers that do not take these directional effects into consideration [12]. But they can't solve the directional problem successfully. Techniques combining both directional wavelet and fuzzy fractal dimension have been proposed in reference [13]. But it only uses two kinds of special directional information.

In this paper, we propose a scheme to extract the texture feature of sonar images using Gabor filter with different parameters, which can solve the directional problem perfectly.

The paper is organized as follows. The definition of Gabor filter is given in section Ⅱ. A detailed way of selecting the filter parameters is presented in section Ⅲ. In section Ⅳ, the classification result is discussed based on a lot of experiments. The conclusion is given in section Ⅴ.

Ⅱ. Definition of Gabor filters

Gabor filters are widely used in image processing because of its multi-scale, multi orientation and multi-frequency abilities [14, 15].

The Gaussian-modulated 2D Gabor function is defined by equation (1):

$$g(x,y) = \frac{1}{2\pi\alpha\beta} e^{\frac{1}{2}[\frac{(X'-X'_0)^2}{\alpha^2}+\frac{(Y'-Y'_0)^2}{\beta^2}]} e^{i2\pi(uX'+vY')} \quad (1)$$

Here 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:

$$g_r(x,y,\delta_x,\delta_y,\theta,f) = \frac{1}{2\pi\delta_x\delta_y}\exp\{-\frac{1}{2}[\frac{(x\cos\theta+y\sin\theta)^2}{\delta_x^2}+\frac{(y\cos\theta-x\sin\theta)^2}{\delta_y^2}]\}\times \cos[2\pi f(x\cos\theta+y\sin\theta)] \quad (2)$$

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

$$\begin{cases} X' = x\cos\theta + y\sin\theta \\ Y' = -x\sin\theta + y\cos\theta \end{cases} \quad (3)$$

If the image function f (x, y) convolve with the Gabor filters, the output G (x, y) is

$$G(x,y) = g(x,y) * f(x,y) \quad (4)$$

To the discrete image of size M×N, the result, passing through the even-symmetry Gabor filter, is

$$G_r(x,y,\delta_x,\delta_y,\theta,f)$$
$$=\sum_{x=1}^{M}\sum_{y=1}^{N} f(x,y)\,g_r(x,y,\delta_x,\delta_y,\theta,f)$$
$$=\sum_{x=1}^{M}\sum_{y=1}^{N} f(x,y)\frac{1}{2\pi\delta_x\delta_y}\times$$
$$\exp\{-\frac{1}{2}[\frac{(x\cos\theta+y\sin\theta)^2}{\delta_x^2}+\frac{(y\cos\theta-x\sin\theta)^2}{\delta_y^2}]\}\cos[2\pi f(x\cos\theta+y\sin\theta)] \tag{5}$$

Detailed parameters selection based on sonar images will be discussed in the next section.

III. Design of Gabor filters

Equation (5) shows that the crucial problem is to gain the optimal values of $\delta_x,\delta_y,\theta,f$. Many people select the optimal parameters through experiences or experiments.

Our process for gaining optimal parameters is as follows.

First of all, the range of f will be discussed. According to Sun in reference [14], it is useless to convolve a signal with the even Gabor function of high radial frequency because few signals or parts of the signal are similar to those of the even filter. So the Gabor filters are always used as a low band pass filter. This makes people often choose the value of f near to 0 or 1.

We define δ_r in two dimensions as

$$\delta_r=\sqrt{\delta_x^2+\delta_y^2} \tag{6}$$

In order to get the desired filters in two dimensions, f must be adapted to two inequalities [14] as

$$\frac{2\delta_r}{\sqrt{\Delta x^2+\Delta y^2}}\le\frac{1}{2f}\le\frac{6\delta_r}{\sqrt{\Delta x^2+\Delta y^2}} \tag{7}$$

and

$$\frac{2\delta_r}{\sqrt{\Delta x^2+\Delta y^2}}\le\frac{1}{2(1-f)}\le\frac{6\delta_r}{\sqrt{\Delta x^2+\Delta y^2}} \tag{8}$$

In the above inequalities, Δx and Δy denotes a sampling interval of sonar images along the x-axes and y-axes, respectively

Then f will be constrained as

$$f\in[\frac{\sqrt{\Delta x^2+\Delta y^2}}{12\delta_r},\frac{\sqrt{\Delta x^2+\Delta y^2}}{4\delta_r}]\cup[1-\frac{\sqrt{\Delta x^2+\Delta y^2}}{4\delta_r},1-\frac{\sqrt{\Delta x^2+\Delta y^2}}{12\delta_r}] \tag{9}$$

Here, we only consider the even symmetry Gabor function, so it is just modulated in x-direction. When we acquire the sonar images, the sampling interval in x-direction and y-direction are always to take one pixel. Then $\Delta x=1$, and $\Delta y=1$. In this condition, (9) become

$$f\in[\frac{1}{12\delta_x},\frac{1}{4\delta_x}]\cup[1-\frac{1}{4\delta_x},1-\frac{1}{12\delta_x}] \tag{10}$$

The shape of the Gabor filter with different f's is given in the figure 2, which is our desired shape with f within the constrained range.

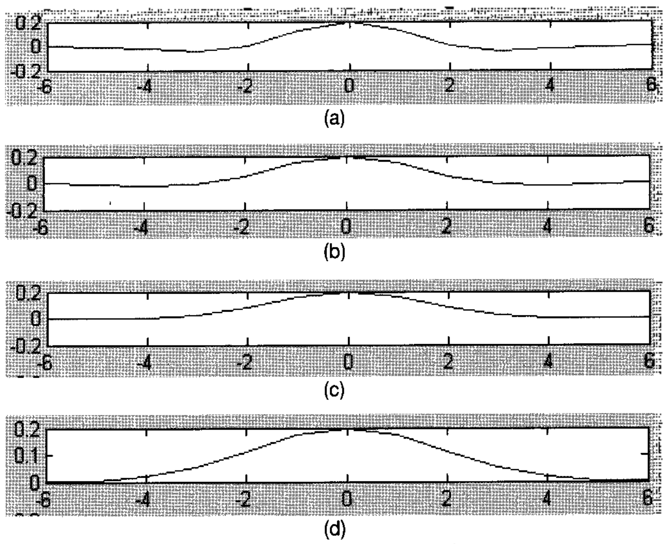


Fig. 2. (a) Gabor function with f=0.031, (b) f=0.063, (c) f=0.093, (d) f=0.125.

When we take the value of f in the constrained range, i.e., $f=f_{opt}$, it is robust to the noise and also can keep the features of the edges well. When $f=f_{opt}$, the filtering result is the optimum as fig.3 (c) shows. However, if f goes beyond this boundary, the filter will be sensitive to the noise. If $f<f_{opt}$, the image is blurred seriously and we can't get the texture feature effectively. On the contrary, If $f>f_{opt}$, the filter will take the noise as signal

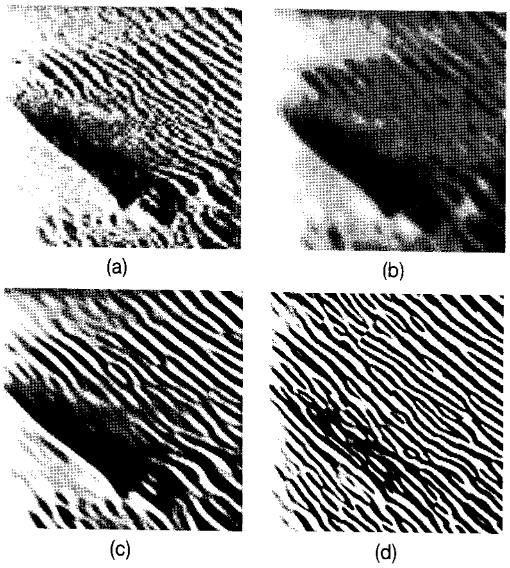


Fig. 3. (a) One image of our database (b $f < f_{opt}$),
(c) $f = f_{opt}$, and (d) $f > f_{opt}$.

and get an anamorphic filtering result as fig.3 (d) shows.

Next, we will propose a detailed process to gain the optimal value of δ_x, δ_y, θ, and f.

First, wset the orientation parameters as

$$\theta_k = \frac{\pi}{n}(k-1) \qquad k=1,2,\cdots,n, \tag{11}$$

Secondly, at each orientation, we will search the optimal Gabor filter with the help of bandwidth parameters based on Fisher rule. Finding the Fourier transform of equation (1), we can get the half peak bandwidth of Gabor filter B as

$$B=\log_2\left[\frac{\pi F\delta_r+\alpha}{\pi F\delta_r-\alpha}\right] \tag{12}$$

where $F=\sqrt{X'^2+Y'^2}$ is the central frequency of Gabor filter, X' and Y' are defined in (3), and $\alpha=\sqrt{(\ln 2)/2}$. Given B, we can get the value of δ_r as

$$\delta_r=\frac{\pi(2^B-1)F}{\alpha(2^B+1)} \tag{13}$$

Thirdly, suppose the two kinds of features f_1 and f_2. In order to classify these two targets, we use Fisher rule as a criterion, which states

$$J=\frac{\|m_1-m_2\|^2}{T_1+T_2} \tag{14}$$

where

$$m_i=(1/n_i)\sum_i f_i$$

$$T_i=tr((1/n_i)\sum(f-m_i)(f-m_i)^T),\quad i=1,2$$

Combining (5) and (10), the features of the sample images are extracted by the Gabor filters.

At last, the optimal value can be gained by searching the maximal value of J. At the same time, we can estimate the feature value of the sample images in the optimal parameters.

After extracting the texture features of SSS images, k nearest neighbor classifier is used to determine the class.

IV. Experiment

Our training and testing set consists of 16 SSS images with a size of 512*512. The images were obtained with 50 kHz sampling rate and the frequency of 400khz as shown in figure 4. The total depth of the sea bottom varies from 75m to 100m.

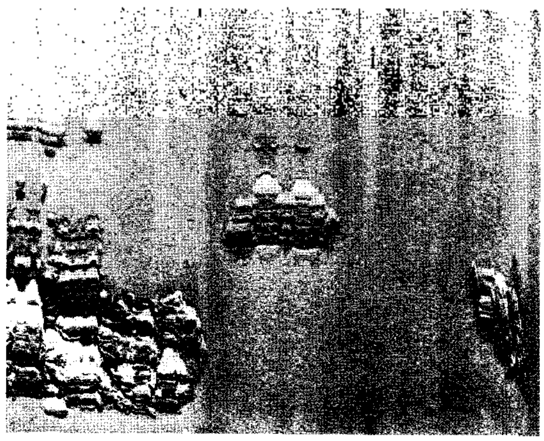


Fig. 4. One of testing images for experiments.

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. By sub sampling on every 32 pixels, we get 256 sub images from each original image. From these 256 images, we choose 100 images as training samples and the remainders are taken as testing samples. Therefore, 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 5.

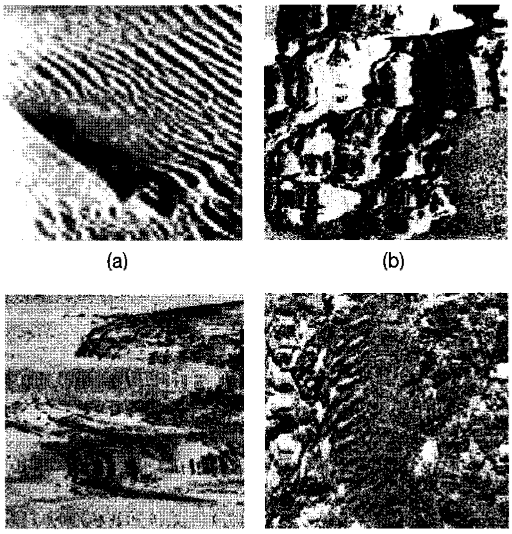

(a) (b) (c) (d)

Fig. 5. (a) sand, (b) rock, (c) mud, (d) rock and sand.

In equation (11), the value of n is taken as 8. To each simple image, we can get a 8D eigenvector with θ taken at 0, $\frac{\pi}{8}$, $\frac{2\pi}{8}$ $\cdots$ π. Then, the optimal parameters are acquired by our method at each orientation. In this experiment, the bandwidth of the Gabor filters is from 0.6 to 2.0, with the interval of 0.1. In the end, we get the 8D eigenvector as $[a_1, a_2, a_3 \cdots a_8]$.

The main process of obtaining the optimal values of Gabor filters is given in Fig.6:

We use the k nearest neighbor classifier to determine the class [16].

The rule suggested is

(1) Find k−nearest neighbors of the unknown vector from the training vectors.

(2) Assign the unknown vector to the class which appears most frequently in the vectors identified in the previous step.

Orientations obtained by the optimal filtering are

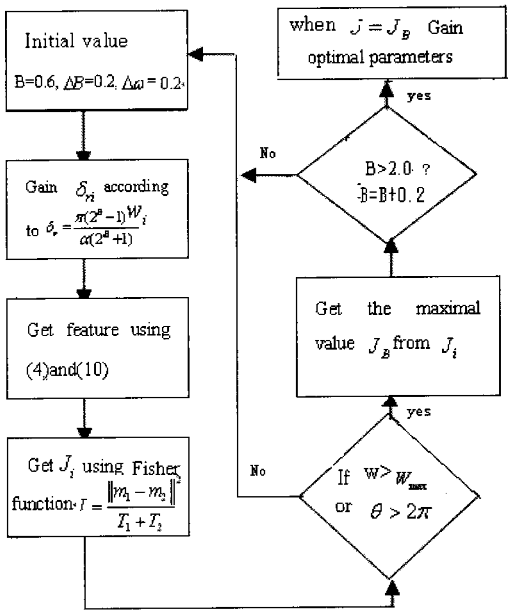
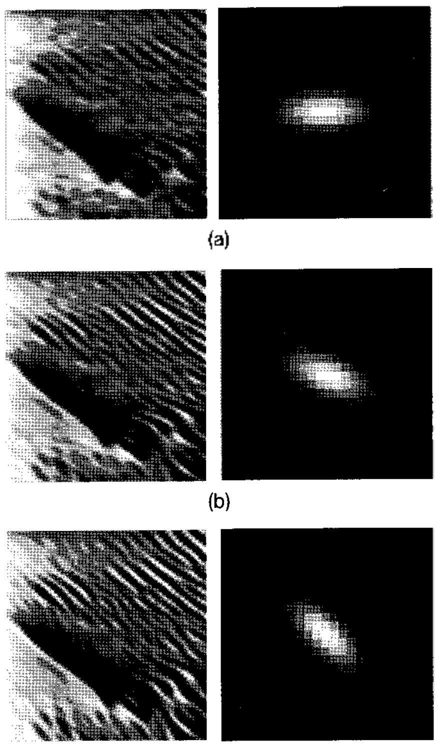


Fig. 6 The main flow chart.

presented in Fig.7. If we take $\theta = 0$ as an example, we gain the optimal parameters as

δ_x =3.0, δ_y =4.0, and f=0.08

From the output we can also conclude that, the response of Gabor filters is strongest when the direction of the parameter is vertical to the direction of texture feature, as Fig.7(c) show.


(a)

(b)

(c)

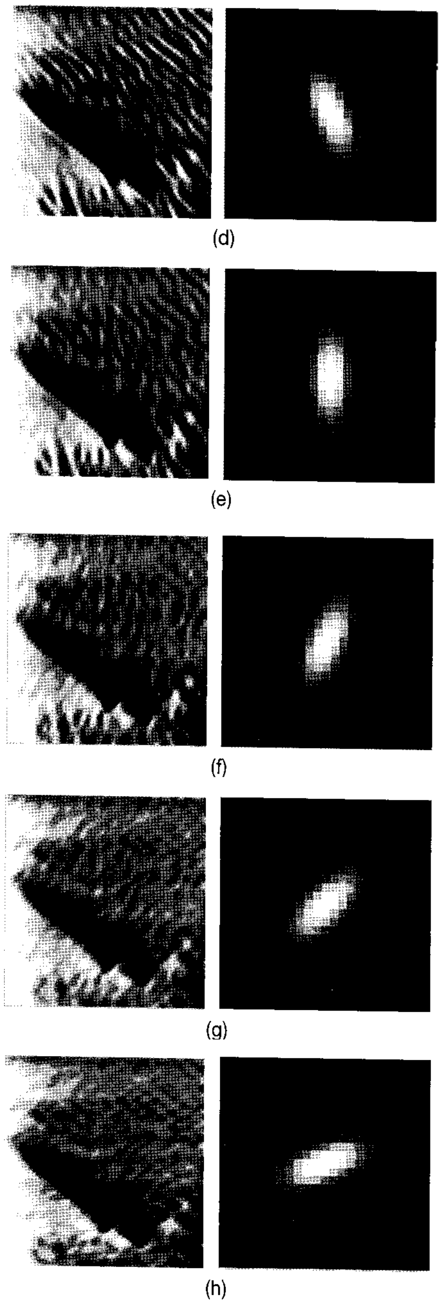


Fig. 7. (a)-(h) is the optimal filtering result at each orientation from 0 to π. The interval is $\theta = \frac{\pi}{8}$.

Some SSS images have so much noise that they make the classification process harder and the causes uncorrect results. Meanwhile, the texture similarities can also result in a low rate of correct classification. In order to analyze the factors influencing the classification rate exactly, we choose four classes of images from our database for further study: 1.Sand 2.Rock 3.Mud. 4. Rock and Sand.

The percentages of correct classification are shown in table 1. We found that, 90.43%of pixels of sand were

Table 1. Classification result.

Class	Result	Gabor filters (%)
1	1	90.43
	2	0
	3	9.36
	4	0.21
2	1	0
	2	99.50
	3	0
	4	0.5
3	1	5.32
	2	1.93
	3	91.9
	4	0.85
4	1	10.24
	2	0
	3	1.16
	4	88.60
Total result (%)		94.5

correctly classified as belonging to that class, none were classified as rock, while 9.36% of them were classified as mud, and 0.21% were recognized as rock and sand incorrectly. From the figure, we can conclude that it is effective to classify the single sediment because of their different features, such as with sand, rock. However, it is more difficult to classify images which include more than one sediment type.

The last row of table 1shows the overall percentages of correct results for our method.

Gabor filters not only contain detailed information of images but also indicates the directional feature of the images. In order to compare this with the other methods such as Co-occurrence matrix, Neural network, and Wavelet transform, classification rates for the sonar images using the same image is provided in Table 2.

As we can see on table 2, our method is better than the other classification algorithms.

Table 2. The comparison of different image classification methods.

	Co-occurrence matrix	Neural network	Wavelet transform	Fuzzy fractal	Gabor filter
Classification nate(%)	81.7	84.4	90.8	83.6	94.5

V. Conclusion

Automated recognition and classification of sonar images become increasingly important with the development of underwater acoustic digital signal processing technology. Considering the orientation problem of texture based analysis, we have applied 2D Gabor filters to extract the features, using constrained parameters to reduce the complexity and improve the calculation's efficiency. Meanwhile, at each orientation, we can search the optimal Gabor filter parameters with the help of bandwidth parameters based on the Fisher criterion. The test results show that the classification rate could be improved considerably by our proposed method.

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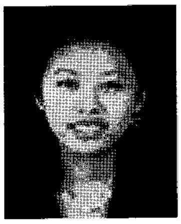
[Profile]

• Ning Sun



2005: B.S. Electronic Engineering, Shandong university of science and technology, China
2007: M.S. Pattern recognition and intelligent system, Shandong university of science and technology, China
2007-Present: Master Student, Underwater Acoustic Communication Institute, Department of Electric Engineering, Soongsil University
Interested area : Underwater image processing

• Taebo Shim

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