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# Fuzzy Classification Based on Fractal Features for Undersea Image

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## Abstract

Because of the specialty of the undersea channel and the complexity of imaging environment, serious impact on image segmentation and target identification is caused by several uncertain factors in undersea image. This paper proposes a fuzzy pattern recognition approach for undersea image based on fractal features, and realizes reliable target classification in undersea image. Experiments prove that this approach is effective to identify the non-structural targets such as undersea rock and chimney.

**Keyword:** Fuzzy theory, fractal analysis, image classification, undersea image.

## 1 Introduction

Undersea robot plays an important role in undersea resources exploitation. The computer vision system is an important tool in environment information perception. With such information, robot can build environment model for planning and making decision, and at the same time, these information can also provide information for robot to detect and locate the undersea targets. Therefore, the ability of image processing and analysis is of very importance for robot to realize dynamic sensation, quick location and target tracing, and so on.

For the complex sea environment, uncertain factors and non-linear imaging bring about difficulties to image processing and feature extraction for vision system. For example, since the topography of undersea terrain and hydrothermal targets in the sea has different shapes and components, their characters are varied and cannot be forecasted in advance. Furthermore, the disadvantages, such as uneven lighting, low contrast, fuzzy edge, and the weak texture etc, result in difficult classification and segmentation with traditional structural features or gray features.

Benoit Mandelbrot first used the term fractal to designate objects that are self-similar at different scales [1], and the fractal concept provides a useful tool to explain a variety of naturally occurring phenomenon. A fractal is an irregular geometric object with an infinite nesting of structure at all scales. Fractal objects can be found everywhere in nature such as coastlines, fern trees, snowflakes, clouds, mountains, and bacteria. Some of the most important properties of fractals include that self-similarity, chaos, and non-integer fractal dimension (FD). Fractals are self-similar, which means that structures are repeated at different scales of size. The fractal dimension (FD) is a prefect measure to provide a quantitative measure of self-similarity and scaling. The FD analysis of objects has been successful in processing SAR image [2] and human face image [3], and the FD analysis is also used in medical image processing [4], [5]. The studies have also shown that the changes in the fractal dimension value reflect alterations of structural properties.

In this paper, a texture analysis approach based on fractal theory is designed to decompose directional and scaling texture information of different undersea objects, so as to enhance the subtle difference of texture between undersea targets. At first, textural parameters are extracted based on fractal theory. Then, fuzzy pattern recognition is implemented to achieve good classification of undersea targets. The result of experiments and comparing analysis are given in Section 4. Conclusions are summarized in Section 5.

## 2 Texture Feature Extraction Based on Fractal Theory

As well known, fractal dimension is the main tool to describe the complex structure of fractal object, so it can describe object's texture effectively. Theoretically, fractal dimension is constant while the scale is changing. It is also closely related to human sense of roughness of object surface. However, in practice, an abnormal phenomenon is found, that is, some different textures have similar fractal dimension. So single fractal dimension cannot provide enough information for character description. To overcome this difficulty, some features called on "Hole" character, correlation character and fractal dimension co-occurrence matrix are employed in this paper.

### 2.1 "Hole" Character of Texture Image Based on Fractal Theory

Mandelbrot proposed the concept of "Hole"[6]. "Hole" can reflect the roughness of texture. When the texture is exquisite, its value is small; otherwise, its value is large. So the character of "Hole" can be used to identify the fractal set that has the same fractal dimension, its definition is presented by (1).

$$\Lambda = E\left[\left[\frac{M}{E(M)} - 1\right]^2\right] \tag{1}$$

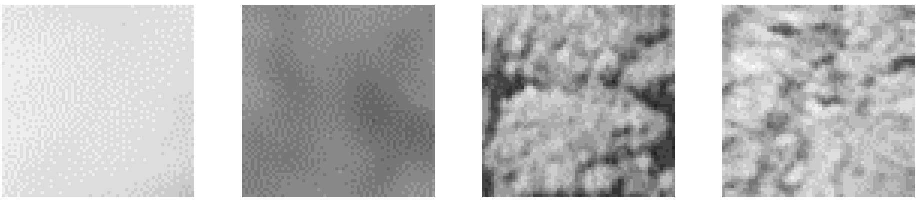
Here, M is the quality of fractal set，E（M）is the expectation quality. If the definition of M is different, then different character of "Hole" is obtained. In [7], a kind of description of "Hole" is proposed based on box dimension：

$$C(L) = \frac{M(L) - N(L)}{M(L) + N(L)} \tag{2}$$

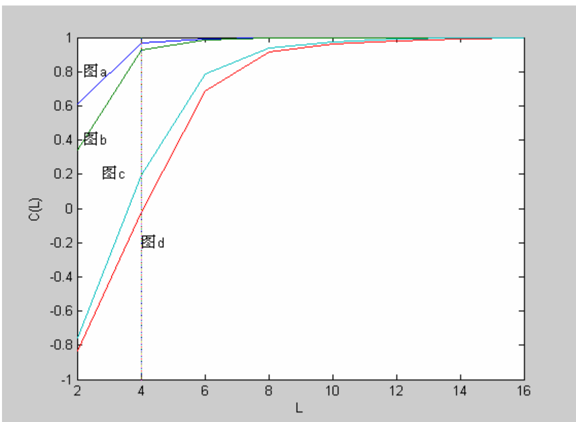
Here, L is the box scale, M(L) represents the average number of pixels in every box, N（L）represents the average number of box to cover one pixel. A simplified calculation method is given and shown by (3):

$$C(L) = \frac{P^2 - N_L^2}{P^2 + N_L^2} \tag{3}$$

Here, P is the total number of pixels in an image; $N_L$ is the number of boxes needed at the scale L. The value of C(L) is related to L. For images of different texture, the curves of C（L）are separated. Fig.1, (a) and (b) show two samples of chimney, (c) and (d) are the samples of rock, (e) is the curve of L-C(L). It is obvious that the curves of the same king have short distance, and the curves of different king have long distance. Furthermore, the texture of chimney is exquisite, the value of C(L) is large at certain L, and on the contrary, the texture of rock is rough, the value of C(L) is small. Hence, the value of C(L) which makes the maximum difference can be used as classification character.



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




(e)

**Fig. 1.** The curve of L-C(L) for samples of rock and chimney

### 2.2 Correlation Character of Texture Image Based on FBM

The fractal model based on FBM is a non-stationary model and often used to describe random phenomenon [8]. The key of the model is how to decide H. When H is decided, the fractal dimension can be easily calculated (Fd ＝3-H). H can be estimated by correlation function in case of discrete sequence. Discrete FBM can be defined as follows:

$$I_m(n) = B_H(n) - B_H(n-m) \tag{4}$$

$I_m(n)$ obeys the distribution of $N(0, \sigma^2 m^{2H})$， its correlation function is defined by (5):

$$R_{t_m}(k) = \frac{\sigma^2}{2}\left\{(k+m)^{2H} - 2k^{2H} + (k-m)^{2H}\right\} \tag{5}$$

In the formula (5), if $k = m$， we have

$$R_{t_m}(k) = \frac{\sigma^2}{2}\left\{(2m)^{2H} - 2m^{2H}\right\} = \frac{\sigma^2}{2}(2^{2H} - 2)m^{2H} \tag{6}$$

From (6), H can be estimated. Let m be equal to s and t ,respectively $(s \neq t)$ ,

$$\frac{R_{t_s}(s)}{R_{t_t}(t)} = \left(\frac{s}{t}\right)^{2H}$$

Therefore,

$$2H = \ln\left(\frac{R_{t_s}(s)}{R_{t_t}(t)}\right) \bigg/ \ln\left(\frac{s}{t}\right) \tag{7}$$

If $R_{t_s}(s)$ is calculated, H will be got. The method of calculating $R_{t_s}(s)$ can be described as follows:

Let the scale of texture image $B(i, j)$ be $M \times M, 0 \leq i, j < M$ . At first, calculate the gray scale difference of image for step s:

$$I_s(i, j) = B(i, j) - \frac{1}{N'(s)} \sum_{k,l \in N(s)} B(i+k, j+l) \tag{8}$$

Here, $N(s)$ is the set of pixels those are included in a circle loop. The inner radius of the circle loop is $s-1$ and the outer radius of the circle loop is s. That is , $N(s) = \{k, l \mid (s-1)^2 < k^2 + l^2 \le s^2\}$, $N^{'}(S)$ represents the number of pixels in N(s). Then $R_{t_s}(s)$ can be computed by (9):

$$R_{t_s}(s) = \frac{1}{M^2} \sum_{i,j=0}^{M-1} \left[ I_s(i,j) \bullet \frac{1}{N^{'}(s)} \sum_{k,l \in N(s)} I_s(i+k, j+l) \right] \quad (9)$$

It is apparent that the value of H is related to s and t. So H is changing with s and t. The optimal value of H is then selected as classification character.

### 2.3 Co-occurrence Matrix Character of Texture Image Based on Local Fractal Dimension

Co-occurrence matrix is the second order quantum of image. It is an effective tool for texture image analysis. It reflects multi-dimensional information including the direction of character distribution, the varied magnitude of local neighborhood and so on. Co-occurrence matrix can be described as follows:

$$P(g_1, g_2 \mid d, \theta) = \frac{\#\{[(x_1, y_1), (x_2, y_2)] \in S \mid f(x_1, y_1) = g_1 \,\&\, f(x_2, y_2) = g_2\}}{\#S} \quad (10)$$

Here, $(x_1, y_1)$ and $(x_2, y_2)$ mean the pixel pairs at distance *d* and direction $\theta$, $g_1$ and $g_2$ are the gray scale of the pixel pairs, respectively. *S* is the set of pixel pairs in target area, # is the number of pixel pairs that satisfies the conditions described in Eq. (10).

By co-occurrence matrix, some texture characters can be extracted, including energy, inertia, contrast, entropy, and so on. These characters can distinguish different textures effectively. They can be defined as follows:

Energy: $$W_E = -\sum_{g_1} \sum_{g_2} P(g_1, g_2) \log P(g_1, g_2) \quad (11)$$

Inertia: $$W_I = \sum_{g_1} \sum_{g_2} (g_1 - g_2)^2 P(g_1, g_2) \quad (12)$$

Contrast: $$W_C = \sum_{g_1} \sum_{g_2} | g_1 - g_2 | P(g_1, g_2) \quad (13)$$

Entropy: $$W_E = -\sum_{g_1} \sum_{g_2} P(g_1, g_2) \log P(g_1, g_2) \quad (14)$$

For undersea image, whose texture is weak, so fractal transformation is employed to enhance the texture difference. Then, texture characters are extracted based on local fractal dimension co-occurrence matrix as classification characters. In this way, the pattern recognition performance is promoted.

Blanket method is one of the traditional methods for calculating local fractal dimension. Its main idea can be expressed by follows: suppose the three-dimension surface is consisting of gray scale of pixels. If a certain pixel is selected as center, considering the surface which is at the distance of $\varepsilon$ from the center, it can be covered by a blanket whose thickness is $2\varepsilon$, then, the area of the surface will be equal to the ratio of the volume of blanket and it's thickness. In theory, the relation of grey surface, fractal dimension *d* and scale $\varepsilon$ can be described by (15):

$$A(\varepsilon) = c\varepsilon^{2-D} \tag{15}$$

If $\varepsilon$ is different, $A(\varepsilon)$ will be varied accordingly. Fit the pairs of （lg（1/2）, lg（A（2））, （lg（1/3）, lg（A(3)）,….. (lg(1/$\varepsilon$),lg(A($\varepsilon$)), … by means of least square, then, the slope *k* is obtained, the fractal dimension D can be calculated by (16):

$$D = 2 - k \tag{16}$$

## 3 Statistic-fuzzy Pattern Recognition

Pattern recognition is an important branch in computer vision; it can improve the sense ability of computer. Today, it have developed into an independent subject and been widely used in diverse domain. Traditional methods of pattern recognition include the nearest distance classification, neural network, fuzzy clustering and maximum grade of membership.

The premise of nearest distance classification is to suppose the model obeys normal distribution, the covariance matrix of each king be unit matrix and the transcendental probabilities of each king are equal. If the model X is to be classified, the Euclidean Distance between X and the mean value of each king need to be figured out firstly, then, X belongs to the king at the nearest distance. The advantage of this method is that the concept is obvious and can be realized easily. However, its disadvantage is also very evident, on one hand, this method does not take the impact of disperse samples on classification into account; on the other hand, it is not accurate to classify the model based on distance in multi-dimension space, especially, if the different kings are overlapped because of noise and aberrance, the same sample is in different kings, then, this method will not work well.

Classification with neural network relies on the neural network designed [9]. It also needs a learning procedure. This method is closely related to the sample, and the computing speed is slow, and also, in the case of noise and aberrance, the misjudge rate is high.

The method of fuzzy clustering and maximum grade of membership is similar in essence; they all perform a fuzzy transformation. But the method of fuzzy clustering is more stable and adaptive. Fuzzy C-mean algorithm (FCM) is one of the best know fuzzy clustering algorithms [10]. FCM is a data clustering algorithm in which each data point is associated with a cluster through a membership degree. This technique partitions a collection of N data points into r fuzzy groups and finds a cluster center in each group, such that a cost function of a dissimilarity measure is minimized. The algorithm employs fuzzy partitioning such that a given data point can belong to several groups with a degree specified by membership grades between 0 and 1.

All of these methods we mentioned above possess a common drawback. That is their performance for noise resisting is very limited and the misjudgment rate is not ideal when the characters of samples are overlapped or disperse. While for undersea image, as pointed out in previous section, some uncertain factors have great impact on them and the property of sample is unstable, the distribution of characters is also not concentrated, but overlapped. Furthermore, the dimension of different character is not the same. In order to improve the adaptability and the ability to resist aberrance of classification, this paper adopts statistic-fuzzy pattern recognition and introduces the criterion of "$3\sigma$". The algorithm is designed as follows:

Let target be X, and its character of dimension j is $f_{j,x}$, then its grade of membership relative to the center of class i and dimension j is defined by (17):

$$\mu_{i,j,x} = \begin{cases} 1+(f_{j,x}-m_{i,j})^2/\sigma^2{}_{i,j})^{-1}, m_{i,j}-3\sigma_{i,j} \le f_{j,x} \le m_{i,j}+3\sigma_{i,j} \\ 0, others \end{cases} \tag{17}$$

Here, $m_{i,j}$ and $\sigma_{i,j}$ are the average and standard deviation of sample characters of class i and dimension j, respectively.

Then, X is designated to certain class according the criterion of maximum grade of membership.

Through transformation above, the difference of dimension is eliminated, and also, the rule of "$3\sigma$" is introduced with the robustness of algorithm being promoted.

## 4 Experimental Results and Discussions

In this section, we select 18 samples of rock and chimney for the case study. In these samples, some textures of rock and chimney are very similar. Part of samples is shown as figure 1. Their gray character is overlapped and can hardly distinguish them directly. Furthermore, the lighting is uneven for most underwater image; this brings extra difficulties to the classification. In order to overcome the default, texture analysis base on fractal theory is employed to extract characters in this paper.

Some features are extracted for classification; they are "Hole" character, correlation character, co-occurrence matrix based on fractal dimension and so on. The mean value (av) and standard deviation (std) of samples are calculated and shown in table 1. Classification is carried out by means of nearest distance and fuzzy transformation, respectively. The result is compared in table 2.

Because the texture of chimney is exqusite, the charcter values of hole and energe are large, and the character values of correlation, contrast and inertia are small. But the texture of rock is rough, so the result is on the contrary. From Tabel 1, it is apprent to find that the differece of above characters between rock and chimney are distinct, so these characters can be used for classification.

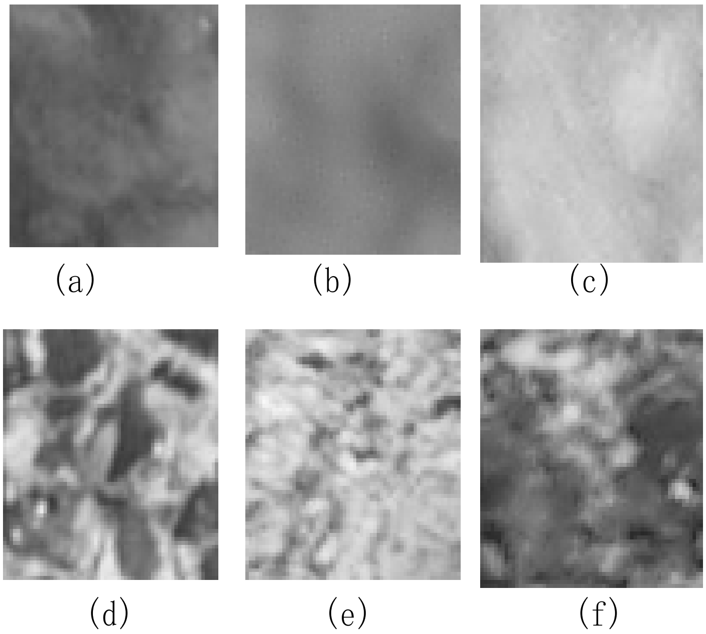


**Fig. 2.** (a), (b) and (c) are samples of rock, (d), (e) and (f) are samples of chimney.

**Table 1.** Distribution of features

| class | hole | | corelation | | energe | | inertia | | contrast | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Av | std | av | std | av | std | av | std | av | std |
| chimney | 0.92 | 0.04 | 1.1 | 0.36 | 0.26 | 0.15 | 3.4 | 1.3 | 0.56 | 0.36 |
| rock | 0.35 | 0.31 | 1.87 | 0.36 | 0.06 | 0.07 | 14.4 | 9.7 | 2.66 | 1.2 |

**Table 2.** Identification results by way of nearest distance and fuzzy transformation

| | Fuzzy | Nearest distance |
|---|---|---|
| Chimney | 94.12% | 94.12% |
| Rock | 94.44% | 83.33% |

Since the consistency of features for different undersea chimneys is comparatively good, the classification is almost the same by means of nearest distance and fuzzy transformation. But for undersea rocks, their features are diverse, with part of them being overlapped with the features of chimney, the well-judged rate is promoted obviously by way of fuzzy transformation than that by way of nearest distance. The approach in this paper shows strong ability to resist aberrance.

## 5 Conclusions

Due to several negative factors, for undersea circumstance, the classification is a challenge problem in nowadays. Feature extracting approach is very important. For undersea targets, their characters are not stable, and often overlapped, so single character cannot provide enough classification information, thus multi-dimension characters are needed in the classification procedure. But this is not to say that more characters, the better classification result will be. So it is a key issue and first step to select effective characters for classification. In practice, the combination of multi-characters can provide better classification result.

In this paper, several effective characters including "Hole" character, correlation character, co-occurrence matrix based on fractal dimension. These characters describe the undersea targets in different angles. And then, a fuzzy classification method is presented. This method has good performance of noise resisting. Experimental results illustrate the effectiveness of the method addressed in this article. Future works focus on the designation of fast and higher accuracy algorithm.

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