Abstract—In order to perform autonomous manipulation in underwater surveys, a robust seabed type classification technique is crucial. Seabed images convey a lot of information about seabed types and various image segmentation methods have been implemented to classify seabed types by analyzing the features of images such as contour and region. However, these strategies are not robust for diverse underwater environments. Therefore, this paper proposes a novel method based on multifractal spectrum to describe and classify the deep seabed types by analyzing the textures. The applicability of multifractal approach to seabed type classification is verified by different samples of deep seabed.

Keywords—multifractal spectrum; seabed type classification; texture analysis

I. INTRODUCTION

Overall, more than 70 percent of the surface of the earth is covered by the sea. And the sea contains extremely large mineral resources including oil, gas, polymetallic nodules. Different from other mineral resources buried in the seabed, polymetallic nodules such as manganese nodules commonly cover on surface of the seabed. Also the benthos on the seabed are used to analysis the ecological status of oceans. Consequently, in the recent decades, the seabed survey is becoming the research focus for locating the large mineral resources and collecting information of biological organisms on the seabed.

Autonomous Underwater Vehicles (AUVs) have already been widely used in oceanic survey mission. They are used not only to measure physical and chemical properties of the water, but also to collect informations of sea floor where they move. AUVs provide technology supports exactly as submersible for these missions to collect informations of seabed.

Seabed classification and identifying is an important technology for improving the autonomic performance capacity of AUVs while performing survey missions. Acoustic remote sensing technique is a conventional approach widely used in many marine applications. Whereas travel time of acoustic signals is used for the bathymetry measurements, the intensity and shape of the received signal can provide useful information on the composition of the seabed [1]. Many studies are currently ongoing to research and find the features of acoustic signals in different seabed types [2-7]. However, the amount of information is limited for mechanism of acoustic sonar. Therefore, for some particular survey to specific small-scale oceanic areas, acoustic remote sensing technique cannot provide excellent performance.

Underwater robot vision system instead or cooperate with acoustic sonar system with has been utilized to study hydrothermal vents, document ancient and modern wrecks, characterize benthic habitats and inspect underwater man-made structures, and has been provided excellent performance. Optical imagery is rich in detail and is easily interpretable by scientists. Therefore, most of underwater robots install with vision system to collect image data of interested area and to do other works, such as targets tracking, navigation and localization. Ortiz et al. established a perfect underwater vision system using ROV or AUV to detect various video information of underwater cables [8]. Kia and Arshad introduced a new technique for AUV target tracking and navigation [9].

Follow the developments of image processing and robot vision technologies, various techniques for image processing are widely applied on the research of seabed survey, as examples mosaicking for seabed mapping, segment sonar images with the aim of seabed classification and reef monitoring [10-11]. To improve the visual sensing ability of underwater vehicles or submersibles in seabed survey, a robust visual method of seabed classification is proposed in our study. Multifractals are considered to be an extension of fractals with multiple scales [12-15], introduced for numerous applications in pattern recognition, including image feature extraction [16-17]. Notably, multifractals are effective in texture analysis of images and small size feature extractions [18-19]. Here, in this study we focus on a new method based on the multifractal theory, which characterizes seabed texture, and classifies seabed types by comparing their multifractal spectrums.

The paper is organized as follows. Section II describes several kinds of deep seabed types and presents the method proposed in this article by using multifractal theory in image analysis. Section III provides details of the experiments and discusses the experimental results. Finally, Section IV concludes the paper and presents the future work.
II. MATERIALS AND METHODS

A. Seabed Images

Underwater vehicles or submersibles with a towed camera system have been used in deep seabed surveys. The common and typical samples of deep seabed images are shown in Fig.1. Images of the seabed are often lacking sharp pronounced features (such as corners, edges or regions) which are used for feature extraction [20].

Fig. 1. Deep seabed types: a) manganese nodules; b) sand; c) biota habitat; d) rock.

B. Basics of Multifractal Theory

The fractal dimension measures the degree of irregularity and complexity of an object. The multifractal dimension has been proposed as an extension of fractal dimension to describe more sophisticated, structured objects on different scales. Local and global characters of the object are concurrently measured to extract data features [21].

The following equation, defined as [22]

\[
I_{i,j,x} = \left[ \frac{i}{v_x}, \frac{i+1}{v_x} \right] \times \left[ \frac{j}{v_y}, \frac{j+1}{v_y} \right]
\]

(1)

where \( v_x \) is an increasing sequence of positive integers, and let \( \mu \) is a measure of probability of a domain defined as \([0,1] \times [0,1]\), considering that

\[
\tau_x(q) = \frac{1}{\log v_x} \log \sum_{y} \mu(I_{i,j,x})^q
\]

(2)

where \( \Sigma_y \) presents the summation of \( \mu(I_{i,j,x}) \), except \( \mu(I_{i,j,x}) = 0 \). When the limit of \( \tau_x(q) \) exists, then

\[
\lim_{q \to x} \tau_x(q) = \tau(q)
\]

(3)

The Legendre transform of \( \tau(q) \) is defined as

\[
f(\alpha) = \inf_{\alpha} [\alpha q - \tau(q)]
\]

(4)

Considering the sets

\[
E_x = \left\{ (x,y) \in [0,1] \times [0,1], \lim_{x \to \infty} \frac{\log \mu(I(x,y))}{\log v_x} = \alpha \right\}
\]

(5)

where \( I(x,y) = \{ I_{i,j,x} | (x,y) \in I_{i,j,x} \} \), \( \alpha \) is the local Hölder exponents, and \( f(\alpha) \) is defined as the Hausdorff dimension of \( E_x \). Consider the following double limit,

\[
f(\alpha) = \lim_{x \to \infty} \lim_{\epsilon \to 0} \frac{\log N_x(\alpha)}{\log v_x}
\]

(6)

where \( N_x(\alpha) = \text{card} \{ I_{i,j,x} | (x,y) \in \{x - \epsilon, x + \epsilon\} \} \). The symbol \( \alpha \) is the coarse-grained Hölder exponent of \( \mu \) at \( I_{i,j,x} \), defined as

\[
\alpha_x(I_{i,j,x}) = \frac{\log \mu(I_{i,j,x})}{\log v_x}
\]

(7)

In multifractal theory, the central issue is to select the description of the singularities of the measure \( f(\alpha) \), a detailed mathematical description can be found in other literature [12,13,21].

C. Multifractal Image Analysis

The Hölder exponent \( \alpha \) identifies singularities for each image pixel, which describes the local regularity of the image object. If multifractal analysis is applied to analyze an image object, the calculation of the Hölder exponent at point \((x,y)\) is represented as:

\[
\alpha(x,y) = \lim_{i \to \infty} \frac{\log \mu(V(i))}{\log(i)} , \quad i = 2n + 1, \quad n = 0,1, ...
\]

(8)

where \( \mu(V(i)) \) is the measure of the area \( V(i) \). \( V(i) \) is a square of \( i \times i \) area centered at a point on the image with a current of intensity \( I(x,y) \). Different measures of \( \mu(V(i)) \) may be used for estimating \( \alpha \). Some of the most frequently used measures known as capacity measures, are represented as follows:

Maximum: \( \mu(V(i)) = \max_{I(x,y)} I(x,y) \)

(9)

Minimum: \( \mu(V(i)) = \min_{I(x,y)} I(x,y) \)

(10)

Sum: \( \mu(V(i)) = \sum_{I(x,y)} I(x,y) \)

(11)

where \( V(i) \) is a set of all nonzero pixels within a measure domain and \( I(x,y) \) is a gray-scale intensity at point \((x,y)\). After this step, an \( \alpha \) image is obtained in such a way that each \( \alpha \) value presents the local singularity of a corresponding pixel in the initial grayscale image.

The multifractal dimension \( f(\alpha) \) is subsequently calculated to represent the global singularity of the image based on the \( \alpha \)
values. First, maximal value $\alpha_{\text{max}}$ and minimal value $\alpha_{\text{min}}$ were determined from the $\alpha$ image. Next, $\alpha$ was obtained by dividing $\alpha$ into different values according to a constant value, $R$, within $[\alpha_{\text{min}}, \alpha_{\text{max}}]$:

$$\alpha_r = \alpha_{\text{min}} + (r-1)\Delta\alpha, \quad r = 1, 2, ..., R$$

$$\Delta\alpha_r = \Delta\alpha = (\alpha_{\text{max}} - \alpha_{\text{min}}) / R$$

where $r$ is defined as an index to determine the sub-range of $\alpha$. If the $\alpha$ value falls in a sub-range indicated by $r$, the value will be replaced by $\alpha_r$. Therefore, the $\alpha$ image will be covered by a regular grid of boxes with integer box sizes $j = 1, 2, ...$. The number of boxes containing at least one $\alpha_r$ value is represented by $N_j(\alpha_r)$. The Hausdorff dimension is consequently calculated as follows:

$$f_j(\alpha) = -\frac{\log N_j(\alpha)}{\log(j)}, \quad j = 1, 2, ...$$

From a set of discrete points in bi-logarithmic diagram of $\log N_j(\alpha)$ vs. $-\log(j)$, the multifractal spectrum $f_j(\alpha)$ is estimated from linear regression, in a similar manner as in the case of estimation of $\alpha$.

### III. EXPERIMENTS AND RESULTS

Our experiments were performed based on the deep-sea submersible Jiaolong while survey mission under 1500m deep of the South China Sea. And the images of seabed are captured by CCD camera mounted in front of submersible, moving at an almost constant height over seabed. Considering efficiency of computation resource, the images of seabed types are recorded on a sensor with $320 \times 240$ pixels. Multifractal analysis is developed based on the Fraclab library (http://fraclab.saclay.inrf.fr) under Matlab 2011a.

Four kinds of deep seabed types shown as Fig. 1 are selected to evaluate performance of the strategy based on the multifractal spectrum proposed in this paper. And the flow chart of the strategy is illuminated in Fig. 2.

![Flow chart of the strategy proposed in this study.](image)

The Hölder exponent and Hausdorff dimension of multifractal analysis are measured, and the multifractal spectrum for four deep seabed types are illuminated as Fig. 3.

![Multifractal spectrum for deep seabed types.](image)

Although spectra of various kinds of seabed types are similar, the spectrums $f(\alpha)$ of them have maximums at different $\alpha$ values. Therefore, the seabed type can be recognized autonomously by analyzing the multifractal spectrums of captured image sequence while survey mission underwater.

### IV. CONCLUSIONS

The experimental results demonstrate that the method based on multifractal spectrum can classify the deep seabed types by analyzing their textures. The significance of the multifractal approach is that extract information directly from the singularities, which different from other classical approaches by extracting irregularities, as contour and region. Therefore, the strategy proposed in this paper is robust at unpredictable and complex underwater environment.

### ACKNOWLEDGMENT

This work of this article is supported by a self-sponsored project of the State Key Laboratory of Robotics at Shenyang Institute of Automation under grant 2013-Z13.

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