A Fast Sonar-based Benthic Object Recognition Model via Extreme Learning Machine

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***Abstract*—The fast sonar-based object recognition turns out to be one of the most challenging topics in the underwater signal analysis. In this paper, we try to develop a fast benthic object recognition model via the extreme learning machine (ELM) on the basis of the structured geometrical feature extraction. Geometrical features such as major and minor axis, eccentricity, circularity and so on are employed to construct learning samples of ELM. The classifier based on ELM is used to recognize the target objects in sonar images. It has been shown in the simulation experiments that the proposed model could keep a quite good recognition performance with a much fast speed.**

Keywords—Sonar Image; Object Recognition; Geometrical Feature Extraction; ELM;

I. INTRODUCTION

Side scan sonar has been widely used in ocean investigations, especially for the benthic surveys. Due to the large amount of acoustic noises, sonar signals are easily polluted and interfered during image collection so that the sonar images usually diverge from the true situation, or degrade the accuracy. On the other hand, because of the computational complexity in the sonar image processing, it is particularly difficult to capture the in-situ information in the real time, while both the remotely operated vehicles (ROVs) and the autonomous underwater vehicles (AUVs) need a rapid response urgently from the side scan sonar. Therefore, the fast sonar-based object recognition turns out to be one of the most challenging topics in the underwater signal analysis.

Aiming at the characteristics of sonar images such as low resolutions, high background noises and lack of useful information, people have brought forward some theories and algorithms by combining the achievements of optical image. These include: acoustic shadow techniques, texture analysis techniques, morphological methods, artificial neural network classifications, voting approaches based on template, template matching and so on [1-4]. In fact, the seabed properties and sediment erodibility in most of the benthic scenes bear seldom or no visual features, and there are only a few of typical observation spots with particularly obvious characteristics. Here a variety of the shape representation and geometrical properties have been taken for the classification in the underwater structured objects [5-7].

So far, artificial neural networks have been extensively adopted to perform object recognition due to their benefits on generalization, flexibility, nonlinearity, fault tolerance, self-organization, adaptive learning, and computation in parallel [8-10]. However, the bottlenecks in the conventional implementations may lead to issues such as over fitting, local minima, time consuming [8]. The work in [11-14] has made a great breakthrough and founded a novel learning framework called extreme learning machine (ELM) in the single-hidden layer feedforward neural net-works (SLFNs), which tends to obtain solutions straight-forward and provides with the better performance at extremely fast learning speed with inspiring abilities such that the hidden node parameters can be randomly chosen and the output weights be analytically determined.

In this paper, we try to develop a fast benthic object recognition model via extreme learning machine on the basis of the structured geometrical feature extraction. The paper is organized as follows: section II describes our sonar-based benthic object recognition model. Section III introduces the geometrical feature extraction. Section IV is about the ELM algorithm. Section V shows the experimental results and Section VI comes to the conclusions.

II. GENERAL FRAMEWORK

The fast sonar-based benthic object recognition model is specially designed to recognize the target object (we only focus on whether the target object is submarine pipeline or not in this paper) in benthic sonar images via ELM. The brief flow chart of our object recognition approach is shown as Fig. 1. After sonar image acquisition, some preprocessing is first done in advance such as the format changes, the correction, the image denoising, the expansion and corrosion, the image

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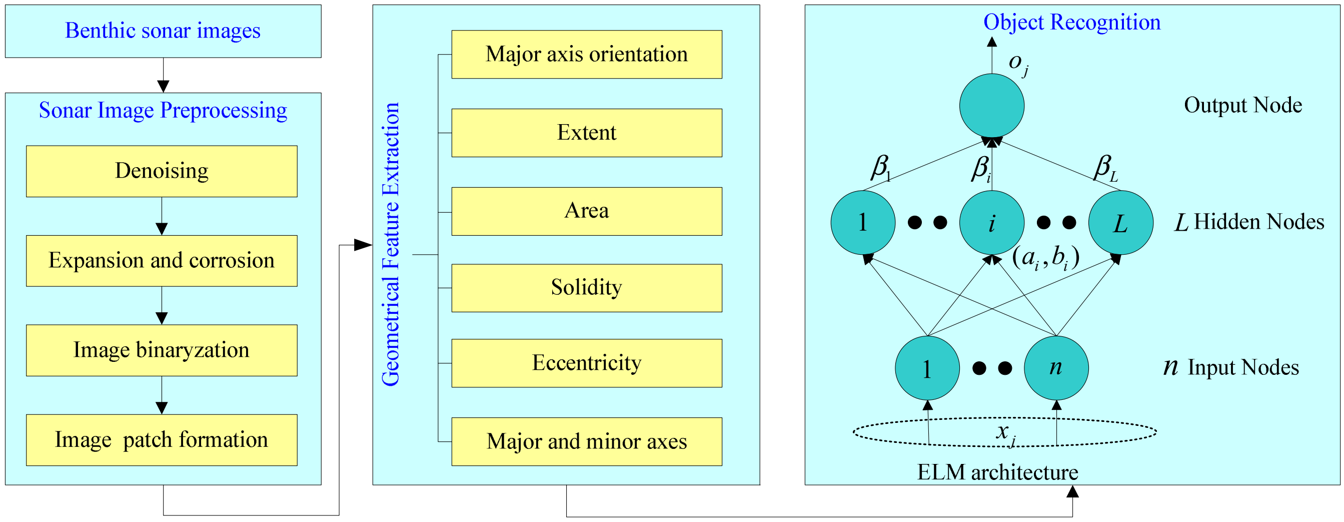

Fig. 1. The flow chart of target recognition based on ELM and geometrical features

patch formation, etc. Before classification, geometrical features of sonar image are found from its binary image. The geometrical features of sonar image consist of the major axis length, the minor axis length, the eccentricity, the solidity, the shape area, the major axis orientation, extent. These seven geometrical features would become inputs to SLFNs trained with ELM algorithm.

III. GEOMETRICAL FEATURE EXTRACTION

Before feature extraction, some preprocessing is first done in advance such as the image denoising, the expansion and corrosion, the image binaryzation, etc. All the sonar images patches will be resized as 64*64 in pixels. Feature extraction is step for finding the morphology of target objects in sonar images patches by their shape. Geometry feature is used in this research which measure certain geometrical attributes of the object, such as the following :

1. Area(A)——the actual number of pixels in the target region. It actually represents the size of the target object in the sonar images patches.
2. Major axis length(L)——the length (in pixels) of the major axis of the ellipse that has the same normalized second central moments as the target region in the sonar images patches.
3. Minor axis length(l)——the length (in pixels) of the minor axis of the ellipse that has the same normalized second central moments as the target region in the sonar images patches.
4. Major axis orientation(O)——the angle (in degrees ranging from -90 to 90 degrees) between the x-axis and the major axis of the ellipse that has the same second-moments as the target region in the sonar images patches.
5. Eccentricity(E)——the eccentricity of the ellipse that has the same second-moments as the target region in the sonar images patches. The eccentricity is the ratio of the distance between the foci of the ellipse and its major axis length. The value is between 0 and 1.
6. Solidity(S)——the proportion of the pixels in the convex hull that are also in the target region in the sonar images patches. Computed as Area/ConvexArea.
7. Extent(e)——the ratio of pixels in the target region to pixels in the total bounding box in the sonar images patches. Computed as the Area divided by the area of the bounding box.

These geometrical features were obtained by on-line inspection using the calculation functions developed in matlab code. Fig. 2 lists some example geometrical properties from different kinds of benthic sonar image patches. And the left sonar image patche shows the target object: submarine pipeline, whereas the right sonar image patche shows the other object.

IV. ELM FOR SONAR-BASED BENTHIC OBJECT RECOGNITION

A. Extreme Learning Machine

So far, Extreme Learning Machine (ELM) has been developed to work at a much faster learning speed with the higher generalization performance, both in the regression problem and in the pattern recognition [15-17]. The ELM aims at minimizing the training error and the norm of the output weights. The key point of ELM is that it needs no iteration when determining the parameters, which results in less computational time for training the SLFNs. For the given N sonar images patches $\{x_i,t_i\}_{i=1}^{N}$, where $x_i=[x_{i1},x_{i2},\cdots,x_{in}]^T$ is consist of the seven geometrical features of the sonar-based benthic object: A, L, l, O, E, S, e and $t_i=[t_{i1},t_{i2},\cdots,t_{im}]^T$ is the corresponding class labels of the sonar-based benthic object. The standard model of the ELM learning can be written as the following matrix format:

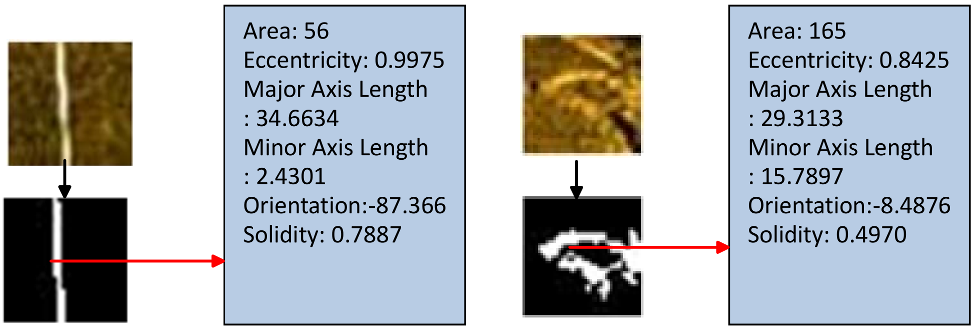

Fig. 2. Example geometrical properties

$$\begin{aligned} & H\beta = T \\ & H(x) = \begin{bmatrix} h_1 & h_2 & \cdots & h_L \end{bmatrix} \\ & = \begin{bmatrix} h_1(x_1) & \cdots & h_L(x_1) \\ \vdots & \vdots & \vdots \\ h_1(x_N) & \cdots & h_L(x_N) \end{bmatrix} \\ & = \begin{bmatrix} G(a_1,b_1,x_1)\cdots & G(a_L,b_L,x_1) \\ \vdots & \vdots \\ G(a_1,b_1,x_{N_0})\cdots & G(a_L,b_L,x_{N_0}) \end{bmatrix}_{N\times L} \\ & \beta = [\beta_1,\beta_2,\cdots,\beta_L]^T_{m\times L}, T = [t_1,t_2,\cdots,t_N]^T_{m\times N} \end{aligned} \tag{1}$$

where $a_i = [a_{i1}, a_{i2}, \cdots, a_{in}]^T$ is the weight vector connecting the i th hidden neurons and the input neurons, b_i is the bias parameter of the i th hidden neurons, $\beta_i = [\beta_{i1}, \beta_{i2}, \cdots, \beta_{im}]^T$ denotes the weight vector connecting the i th hidden neuron and the output neurons, and there are L hidden neurons with the activation function $g(x)$. All kinds of the activation functions can be chosen here, such as the Sigmoid function, the hard-limit function, the Gaussian function, the multiquadric function, and so on.

The hidden node parameters a_i and b_i of SLFNs need not be tuned during training and may simply be assigned with random values in ELM. Equation (1) then becomes a linear system and the output weight β is estimated same as

$$\hat{\beta} = H^{\dagger} T \tag{2}$$

Where $H^{\dagger}$ is the Moore-Penrose generalized inverse of the hidden layer output matrix H.

B. *Recognition*

We have trained the classification model off-line on the basis of ELM aforementioned. Tamuraet al.[18] and Huang et al.[19] pointed out that SLFNs (with N hidden nodes) with randomly chosen sigmoidal hidden nodes (with both input weights and hidden biases randomly generated) can exactly learn N distinct observations. In this paper, we set hidden nodes to 8 to get a better recognition result. We manually collect 2000 sonar image patches for training. Fig. 4 lists some example sonar image patches. We extract the geometrical properties as the feature descriptor to represent the object in the sonar image patches. Accordingly, we get a feature vector of 7 dimensions to represent the target object region. Then we train a network with 8 hidden nodes and 2 output neurons as the classifier on the basis of ELM.

V. SIMULATION EXPERTMENT

In our simulation experiments, we set up a Myring streamline AUV system with one side scan sonar on board to collect the benthic images for the underwater visual tasks, with the frequency band 100kHz-600kHz, the expd operating ranges（per side）120m-500m, the pulse length 5ms-20ms, the across track resolution 1.4cm-6.3cm, the along track resolution 0.45m-1.9m per 100m, the horizontal beam width 0.26^{o}-1.28^{o}, the Vertical beam width 50^{o}. When we applied our proposed approach to detect and recognize the submarine pipeline in our database of 2000 typical sonar image patches with 1500 training samples and 500 test samples, the recognition rate could be up to 98.46% with an average running time 0.15s. Table I lists both the recognition accuracy and recognition time by the classical Back Propagation algorithm (BP) as well as our proposed approach respectively. It has been shown that our proposed model could keep a quite good recognition performance with a much faster speed.

VI. CONCLUTION

In this paper, an effective approach for benthic object recognition is presented, on the basis of ELM and the structured geometrical feature extraction. After sonar image acquisition, some preprocessing is first done in advance. And the training set and test set are then selected from the sonar image database. We feed the geometrical descriptions of the benthic sonar image patches in the training set into the ELM architecture and the expected output consists of the corresponding class labels of the underwater objects. The simulation results have shown the excellent performance in the accuracy and efficiency of the developed approach.

For the next research, it is suggested do some appropriate image processing technique, to extract features

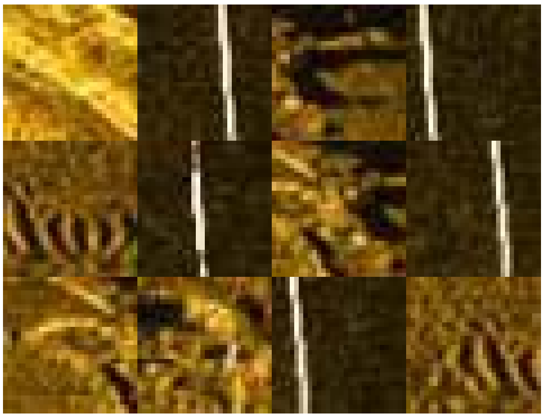

Fig. 4. Example benthic sonar image

TABLE I. COMPARISON BETWEEN ELM AND BP

Algorithms	Training Accuracy (%)	Testing Accuracy (%)	Training Time (s)	Testing Time (s)
ELM	99.41	98.46	0.1318	0.0201
BP	99.43	97.73	2.52	0.1156

before the classification. And we will focus on the object recognition with deep learning method.

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