SONAR Image Classifier using Discrete Wavelet Transform and Support Vector Machine

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Abstract—**Accurate classification of seabed or riverbed is important in many more applications like dradging, study of marine biology, coastal engineering, hydrography etc. Numerous methods have already been proposed for seabed classification. In this paper, we presented a method to classify a given side scan SONAR images depending on type of sediment such as sand, mud, rock etc.In this study, we first employed discrete wavelet transform for extracting the features from side scan sonar images followed by applying principal component analysis (PCA) to reduce the dimensions of features. These reduced features then applied to support vector machine (SVM) for classification. We evaluated our proposed methodswith four different kernels as linear, quadratic, polynomial, GRB and found that the GRB kernel achieves the highest classification accuracy as 99.67%. The result shows that DWT+PCA+SVM achieve best accurate classification results.**

Keywords—*SONAR, Side Scan SONAR, discrete wavelet transform, principal component analysis, support vector machine.*

I. INTRODUCTION

In most of the applications it is also important to know sediment composition of bottom.Over a few decades ago, hydrographer uses measurement methods like chronometers,sextant fixes and lead lines for seabed classification. Basically acoustic systems were designed and developed for measurements of ocean depths and also for obstacle detection. These acoustics systems were called as SONAR (Sound Navigation and Ranging). SONAR is an active system, which is capable of emitting and recording of the acoustic signal[1]. These systems are more accurate and there are three types are available such as, single beam echo sounder (SBES), side scan SONAR (SSS) and the multi-beam echo sounder (MBES).

In this study, side scan SONAR image database is used to determine the texture type of seabed.Side-scan sonar uses a device that emits conical or fan-shaped pulses down toward the seafloor across a wide angle perpendicular to the path of the sensor through the water, which may be towed from a surface vessel. The intensity of the acoustic reflections from the seafloor of this fan-shaped beam is recorded in a series of cross-track slices. Together along the direction of motion, these slices form an image of the sea bottom within the swath (coverage width) of the beam. The sound frequencies used in side-scan sonar usually range from 100 to 500 kHz, higher frequencies gives better resolution but less range. SONAR image analysis is carried out with texture analysis techniques due to highly textured form of sonar images [2].This is an active area in the fields of computer vision and pattern recognition and has many potential applications. In sonar images tone corresponds to amount of energy backscattered by each point in the image and gray levels express it. Textural properties correspond to the spatial organizationof the gray levels within neighborhood.Acoustic techniques can potentially provide efficientand cost effective underwater domain awareness for the planning of long-term utilization in irrigation, power generation, industry, and urban power supply and flood moderation[1]. Thus, higher research efforts are required to meet the challenges. This paper will be helpful in thestudy of underwater geology, detection of underwater mines, oil and gas exploration. Automatic recognition and classification of sonar images regarding seabed types are among the key issues.

The paper is organized into 4 sections. First section is introduction describing need for sediment classification and basics of Sidescan Sonar. Section two describes proposed methodology for sediment classification. Thirdsection reports the results of algorithm implemented. Final section is a concluding remark on project work.

II. METHODOLOGY

Wavelet transform allows analysis of images at variouslevels of resolution due to its multi-resolution analytic property so this is an effective tool for feature extraction from images. But this technique requires large storage capacity and computationally expensive.In order to reduce the feature vector dimensions, the principal component analysis (PCA) was used. To classify input data, there are two categories available one is supervised classification and other is unsupervised classification.Among supervised classification methods, the SVM is a classification methods based on machine learning theory [3].SVMs have significant advantagesof high accuracy, elegant mathematical tractability, and directgeometric interpretation as compared with ANN, decision tree and Bayesian network. Besides, it does not need a large number of training samples to avoid over fitting. This method is divided into three stages as preprocessing (includes feature extraction and reduction), training SVM, apply new

sonar image to trained SVM and predict the output. Figure (1) shows the methodology of proposed algorithm. Preprocessing step involves feature extraction and feature reduction process.
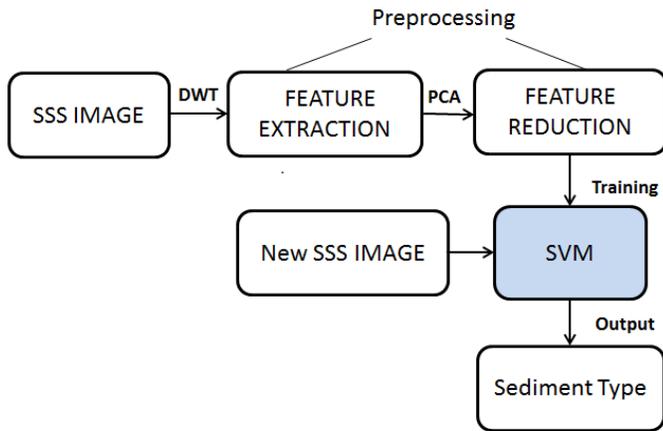

Figure 1- Schematic block diagram for sediment classification

- *Feature extraction*

Wavelet Transform (WT) is a windowing technique with variable window size and this will be helpful to preserve both time and frequency information of the signal. Another advantage of WT is that, it adopts 'time scale' view of the data instead of 'time frequency'[4]. The discrete wavelet transform (DWT) is a powerful implementation ofthe WT using the dyadic scales and positions. The fundamentals of DWT is that, suppose x(t) is a square integral function then the continuous WT of x(t) relative to a given waveletφ(t) is defined as-

$$W\varphi(a,b) = \int_{-\infty}^{\infty} x(t)\, \varphi_{a,b}(t)dt.$$

Where,

$$\varphi_{(a,b)}(t) = \frac{1}{\sqrt{a}}\, \varphi\, \frac{(t-a)}{b}$$

Here, the wavelet $\varphi_{(a,b)}(t)$ is calculated from the mother wavelet $\varphi(t)$ by translation and dilation,a is the dilation factor and b the translation parameter (both real positive numbers). In this study, Harr wavelet is used for wavelet analysis, which is the simplest one and often the preferredwavelet in a lot of applications. Above equation discretized by restraining a and b to a discretelattice ($a = 2^b \& a > 0$) to give the DWT, which can be expressed as follows.

$$ca_{(j,k)}(n) = DS\left[\sum_n x(n)g_j^*(n - 2^j k)\right]$$

and

$$cd_{(j,k)}(n) = DS\left[\sum_n x(n)h_j^*(n - 2^j k)\right]$$

$ca_{(j,k)}$ and $cd_{(j,k)}$ represents coefficients of approximation and detail components , g(n) & h(n) represents LPF and HPF respectively, j and k denotes wavelet scale and translation factor respectively. DS operator means down sampling.

- *Feature Reduction*

DWT generates excessive feature set which will increase computation times and storage memory. This will make classification more complicated so it is required to reduce the number of features. To reduce the dimension of a data set PCA is effective tool which consist of a large number of interrelated variables while retaining most of the variations. It is achieved by transforming the data set to a new set of ordered variables according to their variances or importance.

- *Classification*

Classifiers are broadly classified into two categories as: Supervised including SVM and KNN and unsupervised classifiers includes self-organization feature map (SOFM) and fuzzy *c*-means. In this paper supervised classifiers are used because it performs better in terms of classification accuracy (success classification rate) as compared with unsupervised classifier [5]. The goal of this paper is to find more accurate method for sediment classification. Also in this paper we introduced kernel SVM (KSVM) which extends linear SVMsnonlinear SVM classifiers by applying the kernel function to replacethe dot product form in the original SVMs.

III.   RESULTS

- *Database Description*

This project work uses The Edge Tech DF1000 side scan sonar image data, a part of projectREBENT, IFREMER (Location: France).This database contains 240 images of six classes of sediment textures namely Mud, Sandy Mud, Gravely Sand, Clearly Sand, Rock, Mixed Sediment. Figure 2 shows sample images for each class from database. This database was used to survey coastal benthic habitats and evaluate biodiversity changes in a 200 km sq. Area in the Bay of Concarneau on the South Brittany, France.
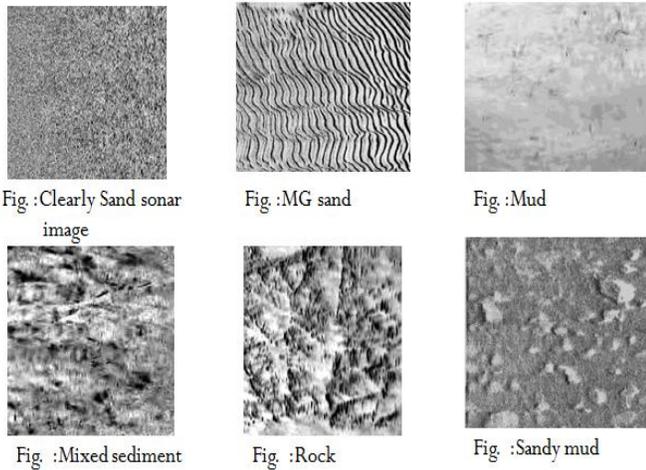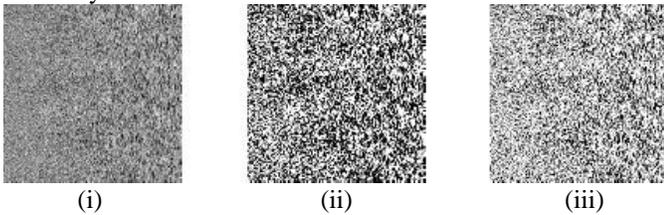
Fig. :Clearly Sand sonar image

Fig. :MG sand

Fig. :Mud

Fig. :Mixed sediment

Fig. :Rock

Fig. :Sandy mud
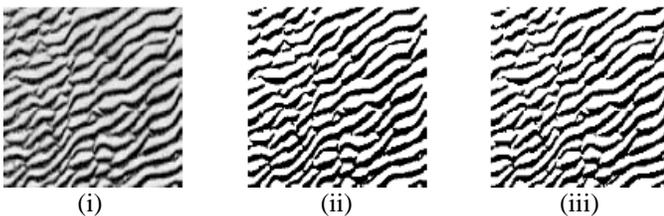
Figure 2- Sample SONAR Images from each class

- ***Feature Extraction***

In this study, features extracted from side scan sonar images using DWT and feature set is reduced to minimize the computational efforts using PCA. The reduced feature set consists of 13 features as: Contrast,Correlation,Energy, Homogeneity, Mean, Standard Deviation, Entropy, RMS, Variance, Smoothness, Kurtosis, Skewness, IDM.Suppose a test image from one of the six classes is taken and passed through DWT+PCA algorithm then following figures shows simulated results for all sediment types (i)Original SSS image, (ii) Threshold Image,(iii) Segmented Image.
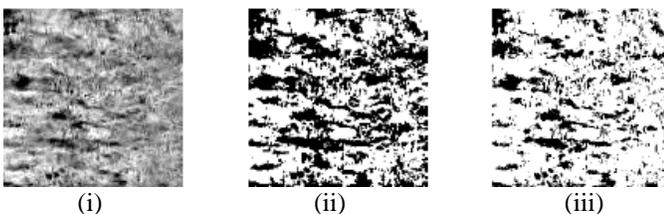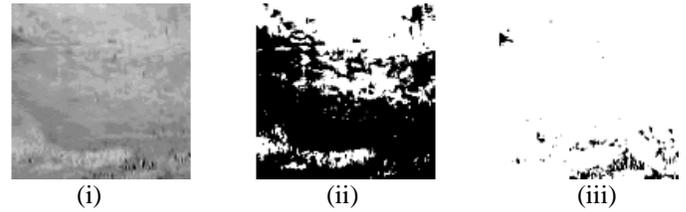
1.Clearly sand

(i) (ii) (iii)
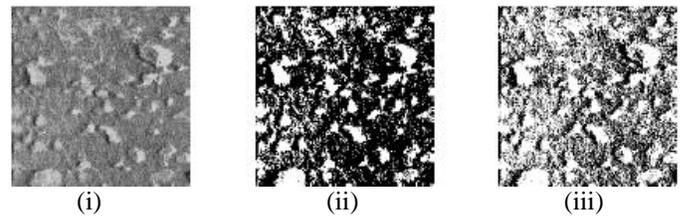
2. MG sand

(i) (ii) (iii)

3. Mixed sediment

(i) (ii) (iii)

4. Mud

(i) (ii) (iii)

5. Sandy mud

(i) (ii) (iii)

IV.   CONCLUSION

Given the textural features, an application to sonar texture classification is addressed, i.e. anunknown texture sample is assigned to one of a set of known texture classes using a SVM classifier.In this study, SVM classifier classify image correctly amongst six different classes. Using DWT+PCA+SVM classifier with Linear, Polynomial and GRB kernel function. From observed results we conclude that, polynomial kernel function shows worst accuracy for all sediment types, whereas linear kernel performs better but shows lower accuracy for mixed sediment types. But with GRB kernel function we got average accuracy of sediment classification is 99.67percent. From the wholeFeature vector applied to the classier, 75 percent is for Training and 25 percent for testing.

V.   REFERENCES

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