International Journal of Current Trends in Engineering & Technology
www.ijctet.org, ISSN: 2395-3152
Volume: 04, Issue: 04 (July - August, 2018)

Underwater Mine Detection and Analysis

Ashish Kumar, Dr. Shilpi Sharma
Department of Electronics & Communication
BIT College Bhopal
+91, 7000321328

Abstract- *The contributions concentrate on feature selection and object classification. The design of a single classification system, which was optimized in two fundamental aspects: the choice of the classification system and the selection of the optimal feature subset. First, the segmentation process was shortly described. A collection of features was designed enforcing the insensibility of the features values to poor segmentation scenarios. Then, a resembling algorithm that provides a quantitative measure of classifier performance independently of any specific feature subset was presented. By the sonar image features extraction of image and classifies the type of mines.*

Keywords- Mines classification, sonar image, Linear Discriminated analyzer.

Objectives

Sonar Image converted into binary image. Feature Extraction by segmentation. Classification of mines to evaluate the effectiveness of proposed work.

Literature Review

Adaptive multi view target classification in synthetic aperture sonar images using a partially observable markov decision process. In this paper proposed the problem of classifying targets in sonar images from multiple views is modeled as a partially observable Markov decision process (POMDP). This model allows one to adaptively determine which additional views of an object would be most beneficial in reducing the classification uncertainty. Acquiring these additional views is made possible by employing an autonomous underwater vehicle (AUV) equipped with aside-looking imaging sonar. The components of the multi-view target classification POMDP are specified. The observation model for a target is specified by the degree of similarity between the image under consideration and a number of pre computed templates. The POMDP is validated using real synthetic aperture sonar (SAS) data gathered during experiments at sea carried out by the NATO Undersea Research Centre, and results show that the accuracy of the proposed method outperforms an approach using a number of predetermined view aspects. The approach provides an elegant way to fully exploit multi view information and AUV maneuverability in a methodical manner.

Problem Formulation

Parameters used

Real-time underwater object detection based on electrically scanned high-resolution sonar. Synthetic Aperture Sonar: A Review of Current Status

Proposed Algorithm

Modules Used

Segmentation	It's by Markovian representation method.
Feature extraction	It's by SIFT (Scale Invariant Feature Transform).
Feature selection algorithm	It's by D-SFFS (sequential forward floating selection)
Classification	It's by linear discriminate analysis classifier (LDA)

Segmentation

The image is partitioned into three regions: the highlight of the objects, their shadows, and the background. The man-made objects, physical features of the terrain, such as rocks and sand ripples may also be segmented. Markovian method takes as input from the Region of Interest (ROI) output. Analysis the output and applies the Markovian process. The process separates the background and shadows as 0's and the object as 1's (mines).The Marko process segments the object (1's) and forward this output to the next process feature extraction. Segmentation can be done using different techniques.

Threshold: All values above some threshold are set to 1 and those below the threshold are set to 0 or vice versa. An MRF model for image segmentation is a popular approach for many applications, such as synthetic aperture radar. The context of seabed reconstruction from raw sonar data. MRF models for side scan sonar image segmentation were introduced and later used and, they were combined with the iterative conditional estimation (ICE) algorithm to achieve an unsupervised implementation. The first time that MRF based segmentation is applied to SAS images.

Feature Extraction

Each object (highlight and associated shadow) is characterized by a set of features. The SIFT (Scale Invariant Feature Transform) method is used in feature extraction process. The different features that are extracted for each segmented object are described. The selection of a meaningful feature subset, Provides the best system performance, by the feature selection methods. Traditionally, the description of sonar objects focused on the shadow shape, including, e.g., Fourier descriptors and normalized central moments. The statistical properties of the image have also been considered .The set of features presented in has been extended. A combination of statistical and geometrical features for both the highlight and shadow regions is considered. A unified ADAC system, the segmentation algorithm is introduced and the feature set is extended, in an attempt to minimize the influence that poor segmentation has on the feature values. The selection of the optimal classifier and the selection of the optimal subset of features. Indeed, they are interdependent. The classification systems are compared; typically the same feature subset is used for all of them. A different feature subset might produce a different ranking. A resampling algorithm for quality assessment of classifier performance, which is unconstrained to any specific feature subset, is proposed. The utilize it to choose the optimal classification system.

Classification Process

Each object is classified to the comparison of its feature vector and those of a training set. The physical features of the terrain are classified as clutter and the man-made objects as mines. They constitute false alarms and missed detections, respectively. It takes the input from the feature selection process as a small quantity and apply the LDA algorithm to classify the selected mine. The process of LDA is to apply the scale values, threshold value to classify the mines. The mines obtained as like cylindrical mine, truncated mine and cone like mines and stones. The design of feature based ADAC systems, and applied to the mine hunting for two different databases of SAS images. The feature-based mine hunting fuse several simple non optimal systems, to improve the performance. The design of a single classification system, which was optimized in two fundamental aspects: the choice of the classification system and the selection of the optimal feature subset.

Block Diagram

Figure 1 Proposed Modal

Numerous classification systems exist in the literature, such as, Mahalanobis' classifier, k-Nearest Neighbor (k-NN), neural networks, support vector machines, etc. The overall optimal classifier and the superiority of one over another are application-dependent. The selection of a classifier is determined by external constraints, such as limited computational power. The system designer is free to select a classification system, requires a quantitative measure in order to compare the performance of several classifier candidates.

Synthetic-Aperture Sonar

The principle of synthetic aperture sonar is to move sonar along a line and illuminate the same spot on the seafloor with several pings, produces a synthetic array equal to the distance travelled. Coherent reorganization of the data from all the pings, a synthetic aperture image is produced with improved along-track resolution. SAS processing have the potential to improve the resolution by one order of magnitude compared to conventional side scan sonar's. The sonar antenna comprises an axially symmetric acoustic surface having the cross-sectional form of a generally U-shaped curve of non-constant curvature. The curve is shaped to allow continuous coherent personification such that the power in the echo returned from a uniform flat sea floor is substantially constant. This equipment is used for underwater echo sounding and uses hydro acoustic transducers to personify the water and receive echoes.

Absorption and Scattering

The amount absorbed depends on sea state. Absorption is high when winds produce whitecaps that cause a concentration of bubbles in the surface layer. In areas of wakes and strong currents, such as riptides, the loss of sound energy is greater. Absorption is greater at higher frequencies

Reflection

When sound beam hits an object (100% reflection) called Echo Mediums of different density. In water less than 600 feet deep, sound may be reflected off the bottom. The factors being equal, transmission loss will be least over a smooth sandy bottom and greatest over soft mud

Preprocessing

The region of interest has to convert the original image or color into gray image. The color image consists of dimensions of (M*N*3). The long to process with this image. The gray image consists of dimensions (M*N).To reduce the difficulty to handle with this image type. For the reason have to convert the original image into gray image.

RGB Image

It is another format for color images. It represents an image with three matrices of sizes matching the image format. Each matrix corresponds to one of the colors red, green or blue and gives an instruction of how much of each of these colors a certain pixel should use. The gray scale images but once have learned to work with a gray scale image the principle to work with color images. An indexed image stores an image as two matrices. The first matrix has the same size as the image and one number for each pixel. The second matrix is called the color map and its size may be different from the image. The numbers in the first matrix is an instruction of what number to use in the color map matrix.

Gray image

The process of converting RGB to GRAY the images like a black and white image, called as gray image. The gray image values ranges from 0 to 255.The objects in the image look's wider.

Binary image

The gray image process we have to convert the image into binary. The value '1' for objects and take value '0 'for shadows. The image format also stores an image as a matrix but can only color a pixel black or white and nothing in between. The value assigns a 0 for black and a 1 for white, apply histogram to get image as high intensity, apply Threshold to extract the object.

Region of Interest (ROI)

The MLO (Mine like Objects) detection, which is usually realized by a template-matching technique. The scans the sonar image for the regions possibly containing MLOs. These regions are called regions of interest (ROIs). The ROIs are extracted and forwarded to the subsequent steps, the image segmentation and the feature extraction. Image Segmentation. The image is partitioned into three regions: the highlight of the objects, their shadows, and the background. The man-made objects, physical features of the terrain, such as rocks and sand ripples may also be segmented. Markovian method takes as input from the Region of Interest (ROI) output. Analysis the output and applies the Markovian process. The process separates the background and shadows as 0's and the object as 1's (mines).The Marko process segments the object (1's) and forward this output to the next process feature extraction. Segmentation can be done using different techniques. Here are ones of the simplest Thresholding. All values above some threshold are set to 1 and those below the threshold are set to 0 or vice versa. Segmentation is the process of partitioning an image into several regions. In our application, three different regions occur: the highlights of the objects in the scene, their shadows and the seabed or background.

Result & analysis

Binary image

The binary image is obtained by the preprocessing method. The preprocessing method consists of converting original image into gray image, and the gray image into binary image. This binary image is obtained in the figure.

Intensity image (gray scale image)

The value 0 corresponds to black and the value 1 corresponds to white. The other class is called uint8 which assigns an integer between 0 and 255 to represent the brightness of a pixel. The value 0 corresponds to black and 255 to white. The class uint8 only requires roughly 1/8 of the storage compared to the class double. On many mathematical functions can only be applied to the double class.

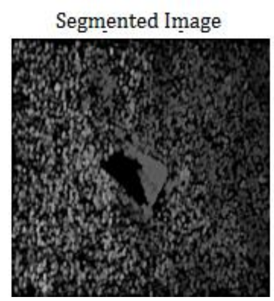

Figure 2 Segmented images:

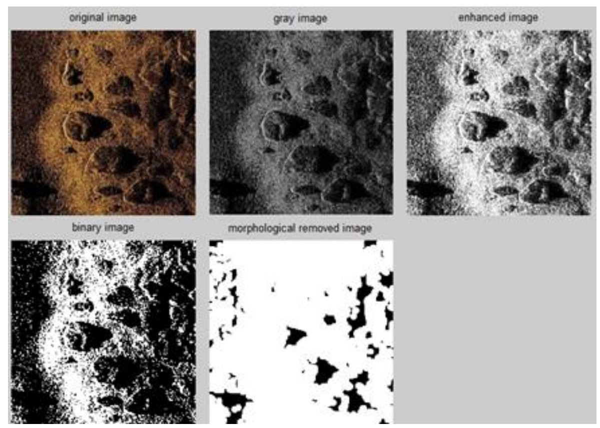

Figure 3 Binary Image

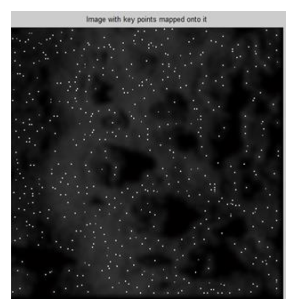

Figure 4 Dotted Images

Binary image

This image format also stores an image as a matrix but can only color a pixel black or white (and nothing in between). It assigns a 0 for black and a 1 for white. After finding Region of Interest from the binary image we have to give forward this image to segmentation process. The image is partitioned into three regions: the highlight of the objects, their shadows, and the background. Besides man-made objects, physical features of the terrain, such as rocks and sand ripples may also be segmented.

Extracted image

International Journal of Current Trends in Engineering & Technology
www.ijctet.org, ISSN: 2395-3152
Volume: 04, Issue: 04 (July - August, 2018)

The mines are extracted from the feature selection process. It classify the mine type also, as like truncated mine, cylindrical mine and cone and stones.

Figure 5 Detected object is mine

Figure 6 Mine Type is Rock-an Mineral

Conclusion

The design of feature based ADAC systems, and we applied it to the problem of mine hunting for two different databases of SAS images. Previous works on feature-based mine hunting fuse several simple non optimal systems in order to improve the performance. The design of a single classification system, which was optimized in two fundamental aspects: the choice of the classification system and the selection of the optimal feature subset. First, the segmentation process was shortly described. A collection of features was designed enforcing the insensibility of the features values to poor segmentation scenarios. Then, a re-sampling algorithm that provides a quantitative measure of classifier performance independently of any specific feature subset was presented. For the selection of features, we proposed a novel extension of two algorithms, the D-SFS and the D-SFFS, which address the limitations of the standard SFS and SFFS algorithms. Their complexity increases linearly with D. They were tested on 120 synthetic databases and on six standard data sets of the UCI repository. The D-SFS algorithm improved the figure of merit by about 20% with respect to the standard SFS algorithm for both synthetic and real data. In average, the D-SFFS algorithm outperformed the SFFS algorithm by 10% for the real data sets and by 25% for the simulated examples. The average 3-SFS algorithm is as good as the SFFS algorithm in terms of figure of merit, and is, furthermore, computationally more efficient.

References

[1]. E. Dura, J. M. Bell, and D. M. Lane, "Super ellipse fitting for the classification of mine-like shapes in side-scan sonar images," in Proc. MTS/IEEE OCEANS Conf., vol. 1. Oct. 2002, pp. 23–28.

[2]. C. M. Ciany and W. Zurawski, "Performance of fusion algorithms for Computer Aided Detection and classification of bottom mines in the shallow water environment," in Proc. MTS/IEEE OCEANS Conf., vol. 4. Oct. 2002, pp. 2164–2167.

[3]. S. W. Perry and L. Guan, "Pulse-length-tolerant features and detectors for sector-scan sonar imagery," IEEE J. Ocean. Eng., vol. 29, no. 1, pp. 138–156, Jan. 2004.

[4]. S. Reed, Y. Petillot, and J. Bell, "Automated approach to classification of mine-like objects in sides can sonar using highlight and shadow information," IEE Proc. Radar, Sonar Navigat., vol. 151, no. 1, pp. 48–56, Feb. 2004.

[5]. M. Pinto and A. Bellettini, "Shallow water synthetic aperture sonar: An enabling technology for NATO MCM forces," in Proc. Undersea Defense Technol. Conf., 2007.

[6]. A. M. Zoubir and R. Iskander, "Bootstrap methods and applications," IEEE Signal Process. Mag., vol. 24, no. 4, pp. 10–19, Apr. 2007.

[7]. J. A. Fawcett, A. Crawford, D. Hopkin, M. Couillard, V. Myers, and B. Zerr, "Computer-aided detection and classification of side scan sonar images from the citadel trial," in Proc. Inst. Acoust., vol. 29. 2007, pp. 3–10.

[8]. P. Y. Mignotte, E. Coiras, H. Rohou, Y. Petillot, J. Bell, and K. Lebart, "Adaptive fusion framework based on augmented reality training," IET Radar, Sonar Navigat., vol. 2, no. 2, pp. 146–154, Apr. 2008.

[9]. M. P. Hayes, "Synthetic aperture sonar: A review of current status, IEEE J. Ocean. Eng., vol. 34, no. 3, pp. 207–223, Jul. 2009.

[10]. R. Fandos and A. M. Zoubir, "Optimal feature set for automatic detection and classification of underwater objects in SAS images," IEEE J. Sel. Topics Signal Process. vol. 5, no. 3, pp. 454–468, Mar. 2011.

[11]. R. Paladini, M. Martorella, and F. Berizzi, "Classification of manmade targets via invariant coherency-matrix eigenvector decomposition of polarimetric SAR/ISAR images," IEEE Trans. Geosci. Remote Sens., vol. 49, no. 8, pp. 3022–3034, Aug. 2011.