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A Study on Detection and Classification of Underwater Mines Using Neural Networks

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***Abstract*— Mine detection and classification using side scan sonar imagery is a challenging problem. As opposed to the majority of techniques, several Neural-network-based methods for the detection and classification of mines and mine like objects have been proposed. Detection and classification of underwater objects in sonar imagery is a complicated problem, due to various factors such as variations in operating and environmental conditions, presence of spatially varying clutter, variations in target shapes, compositions and orientation. Moreover, bottom features such as coral reefs, sand formations, and the attenuation of the sonar signal in the water column can totally obscure a mine-like object. Side scan sonar is a proven tool for detection of underwater objects. In order to overcome such complicated problems detection and classification system is needed. This method is able to extrapolate beyond the training data and successfully classify mine-like objects (MLOs). Five basic components of detection and classification techniques are considered namely data preprocessing, segmentation, feature extraction, detection and classification. In this paper nearly fifteen research papers of neural network techniques have been reviewed.**

***Index Terms* - Segmentation, Feature extraction, Side scans sonar, Image classification, Underwater mine detection, Neural networks.**

I. INTRODUCTION

An underwater mine is a self-contained explosive device placed in water to destroy ships or submarines. Ocean mines have been a major threat to the safety of vessels and human lives for many years. Identification of mine-like objects is a pressing need for military, and other ocean meets. In mine, countermeasures operations, side scan sonar are used to detect and classify mine- like objects if their sonar signatures are similar to known signatures of mines.

The detection and classification of underwater mines is an important task, with strong implications for the safety and security of ports, harbors and the open sea. Mine warfare, including the detection and classification of undersea mines, has become extremely important to the U.S. Navy.

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Sophisticated sea mines can be deployed at a relatively insignificant cost to cause huge problems for a battle group because of the difficulties associated with their detection and classification.Moreover, in certain scenarios, mine countermeasures operations must be performed rapidly to allow naval platforms to reach their destinations in a timely manner. Although the task of finding mine like objects has received recent attention, little has been published on the problem of discriminating between mine-like objects (MLO) and non-mine objects of similar size and shape.

This paper is structured into a number of sections. Section 2 presents the system overview, Section 3 explain about side scan sonar images, Section 4 is about Data preprocessing, Section 5 contains the segmentation, Section 6 describes the feature extraction, and Section 7 presents detection, Section 8 summarize the classification and Section 9 concludes the paper.

II. SYSTEM OVERVIEW

The main emphasis of the study was to examining Neural Network techniques tailored for side scan sonar imagery. The classification systems consider in this task can be grouped into five categories as given in Fig-1:

The first stage of classification system is **Data preprocessing** before applying any of the built-in functions for training, it is important to check that the data is "reasonable." Neural network cannot expect to obtain good models from poor or insufficient data.Neural Network learns faster and give better performance, if the input variables are pre-processed before being used to train the network. Exactly the same pre-processing should be done to the test set, to avoid peculiar answers from the network. The next stage is **Segmentation** which segments the side scan sonar images into ”sub-frames” on which each frame is threshold to identify the target structure.

The third stage is the **Extraction of representative features** from the sides scan imagery is analyzed, and the performance of several commonly used texture measures are compared in terms of classification. A number of static features are computed that describe the shape and size properties of the object. Over a consecutive scans, the feature measures for each object are computed. For any particular object, another set of temporal features is determined. These temporal features describe the changes in the static features over time.

The fourth stage is the **Detection** subsystem must isolate the parts of a return that contain possible objects, where an object is defined as the detection subsystem, to properly detect the targets of interest as well as other bottom objects. During **Classification**, information passes through the network in one direction from input layer, through hidden layer(s), to output layer. Each node actually performs two functions, collecting the activation from nodes of the previous layer and setting output activation. An exception is the input layer where nodes are directly activated by the input data.

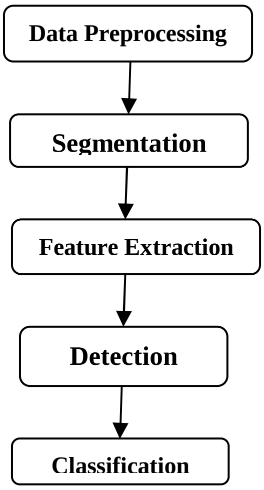

Fig.1 Flow diagram of a Classification System.

The above grouping is only a rough guide to classification system, as a great deal of overlap is often found, and some techniques defy being grouped in this way. The following sections describe about the above classification systems.

III. SIDE SCAN SONAR (SSS)

Side scan sonar has been an important tool for seafloor survey over the past few decades. Due to the highly textured appearance of sonar images, texture analysis techniques become natural choices for side scan sonar image analysis.

- Side-scan sonar (sss) is a category of sonar system that is used to efficiently create an image of large areas of the sea floor.
- Sides can sonar system is used to search a target area for detection of mines and Mine- like objects in the underwater environment

For robust feature extraction, sonar images are symbolized by partitioning the data sets based on the information generated from the ground truth.

IV. DATA PREPROCESSING

Data pre-processing is a fundamental key to successfully construct an artificial neural network. In this stage data should be analysed and treated in order, not only to select the proper inputs and outputs of the network, but also to build consistent training and test data sets.

M. Neumann, C. Knauer, B. Nolte, W. Jans and A. Ebert, (2008) examined about preprocessing. Side scan sonar images may be quite dark and may show only low contrast. To overcome the above problem the processing steps a nonlinear logarithmic spreading was suggested as a standard technique to enhance the contrast. By this type of filter the pixel values in darker image areas are stretched more in comparison to the pixel values in bright image areas, so that a good contrast enhancement is achieved. But, also other techniques to enhance the contrast are in use for the processing of side scan sonar (SSS) images [16].

W. Kenneth Stewart, Min Jiang, and Martin Marra examined the 120-kHz data are preprocessed using standard techniques. Individual ping records are corrected for average system and ambient noise (by incoherent subtraction) then gains is adjusted to compensate for transmission losses, beam patterns, and scattering strength as a function of average grazing angle. The data are slant-range corrected using a flat bottom assumption, and then down-sampled using a simple triangular filter to map a scale. Finally, along-track records are velocity corrected by simple averaging. [5].

The pre-processing block contains pre-normalization, clipping and data decimation blocks. Normalization reduces data non-homogeneity. A combination of feed-forward and backward normalizer was employed, which computes water column information and was developed by Gerry Dobeck in 2000 [15].

V. SEGMENTATION

Segmentation techniques that have the potential to classify individual pixels as belonging to background reverberation, clutter, highlights or shadows. This type of processing is usually not concerned with whether each pixel belongs to a mine-like object or not, but is often performed as a prelude to more advanced detection and classification techniques. For side-scan sonar images, segmentation is often used to separately classify pixels as belonging to highlights, background, or shadow regions before higher level techniques are used to search for mine-like objects. After each pixel has been classified into one of the three choices, the pixels are often clustered together with their neighbors to remove incorrectly classified pixels. There exists a large variety of image processing techniques for segmentation and many of these have been applied to this problem.

W. Kenneth Stewart, Min Jiang, and Martin Marra examined the automated segmentation method in the year 1994. Segmentation of side scans imagery and presented practical examples of unsupervised classification of lava flow in the Lima Basin, on the basis of texture analysis and evaluation with gray-level Co-occurrence matrices. An axial-valley segment shows the general characterizations of all sonar data. [5]

Anthony R.Castelleno Brain C.Gray (2011) proposed a thresholding segments. The thresholding segments that return into target, shadow, and background regions. The use of overlapping windows and thresholding the center portion allows the system to track background changes over the length of the return although the thresholding correctly detects targets and shadows; it also produces spurious detections because of variance in the background. These spurious detections are impulsive in nature. In order to reduce false detections without eliminating true detections, the output of the thresholding is followed by a two dimensional CxD Recursive median filter, where C is the along-track size in returns and D is the across-track size in sample points. It has been shown that a median filter eliminates impulse noise with minimal distortion of large objects and hard edges. [1]

F. Langner, C. Knauer, W. Jans and A. Ebert (2011) examined the k-means and statistics based segmentation. K-means based segmentation or higher order statistic based segmentation. Having the Region of interest (ROI) detected in the SSS image, the number of false alarms is reduced by currently applying one out of four or the combination of all four false alarm reduction algorithms. So far a single snake algorithm for the combined highlight and shadow area, a coupled snake algorithm with different coupled polygons for the highlight and the shadow area, a 2d-cross correlation with object templates and an algorithm using an iterative fuzzy segmentation followed by a classification process utilizing the existence of parallel lines for the object shadow contour have been implemented. [7]

An iterative fuzzy segmentation to extract a more precise shadow contour for a noisy image. This process starts with a segmented image based on threshold segmentation. Then, during an iteration step a membership function for the contour shadow pixels is applied by evaluating two combined fuzzy functions. One function estimates the pixel brightness and one the connectivity depending on a pixel's direct neighborhood. Determining the shadow contour is followed by a classification process. This process utilizes the shadow area and the existence of parallel shadow edges in the segmented region of interest (ROI). [7]

F. Langner, C. Knauer, W. Jans, W. Middelmann (2007), proposed a threshold and neighborhood segmentation. Normally objects in side scan sonar (SSS) image appear as highlight - shadow pairs. These highlight - shadow pairs can be extracted automatically by segmentation. For the segmentation simple approaches like threshold segmentation perform image histogram. This leads to a poor robustness against speckle and other noise. However, SSS images are typically noisy. A modified k-means based algorithm and a segmentation algorithm using neighborhood information. The iterative k-means based screening algorithm uses block processing. [8]

The segmentation algorithm puts in the beginning the center of the object highlight in the middle of the left half and the center of the shadow in the middle of the right half of the block. The second recently implemented algorithm is a segmentation algorithm using neighborhood information and for the classification started as a first approach with two simple classifiers a Probabilistic Neural Network (PNN) and K-nearest neighbor (KNN) classification. This is done by performing threshold segmentation based on a higher order histogram. Each new dimension in such a histogram represents an additional neighbor pixel.

VI. FEATURE EXTRACTION

Feature extraction has been always mutually studied for exploratory data projection and for Classification. Feature extraction for exploratory data projection aims for data visualization by a Projection of a high-dimensional space.

Onto two or three-dimensional space, while feature extraction for classification generally requires more than two or three features. Therefore, feature Extraction paradigms for exploratory data projections are not commonly employed for classification and vice versa. For robust feature extraction, sonar images are symbolized by partitioning the data sets based on the information generated from the ground truth.

James D. Tucker, Mahmood R. Azimi-Sadjadi, and Gerry J. Dobeck (2007) examined Canonical Correlation Analysis (CCA) based feature extraction. Canonical coordinate decomposition allows quantify the changes between the returns from the bottom and any target activity in sonar images and at the same time extracting useful features for subsequent classification without the need to perform separate detection and feature extraction several features are extracted based on the size, shape, and strength of the target signature. A stepwise feature selection process is then used to determine the subset of features that optimizes the probability of detection and classification. [4]

Bryan Thompson, Jered Cartmill, Mahmood R. Azimi-Sadjadi, and Steven G. Schock (2006) proposed Multichannel Canonical Correlation Analysis (MCCA).Multichannel Canonical Correlation Analysis (MCCA) is used in this paper for feature extraction from multiple sonar returns off buried underwater objects using data collected by the new generation Buried Object Scanning Sonar (BOSS) system. Comparisons are made between the classification results of features extracted by the proposed algorithm and those extracted by the two-channel Canonical Correlation Analysis (CCA) algorithm. This study compares Different feature extraction and classification algorithms [10]

W. Kenneth Stewart, Min Jiang, and Martin Marra (1994).Examined textural features extracted from gridded acoustic imagery or neighborhood features. Feature selection is an important component of pattern recognition, but there is no general rule for determining the best features for a given problem. It is currently accepted that feature extraction is an application based and depends on the researcher's knowledge, understanding, and experience with the process under study.

Anthony R. Castellano Brian C. Gray (2011) proposed Feature Vector. The feature extraction subsystem correlates a shadow with a target, if the shadow's along track dimension is equal to the targets along track dimension, and the shadow's cross track position is greater than the target's cross track position. In order to correctly determine a target's size, the relationships of a target and its shadow, must be utilized. The feature extraction subsystem was developed to extract features in slant-range space. The target's shadow is only used to determine if a target lies on the bottom or in the water column. If a shadow has been correlated with a target and it is disjoint from the target then the target is in the water column [1].

The feature extraction method to the wideband ARL-UT data set uses the extracted features for classifying mine-like objects from nonmine-like objects. Ali Pezeshki, Mahmood R. Azimi-Sadjadi, and Louis L. Scharf (2007) proposed Canonical correlation-based Feature Extraction. Canonical correlation analysis may be used to extract a set of features that capture common target attributes among two consecutive sonar returns, with certain aspect separation. The feature vectors extracted from the rest of the aspect angles of the smooth bottom data (270 aspect angles) are kept to validate the trained classifier. This validation data set is primarily used to select the best trained classifier. To see how well the trained classifier generalizes, the feature vectors extracted from the backscattered signals in the rough bottom condition has been used as a testing data set. [7]

Vinod Chandran, Steve Elgar, and Anthony Nguyen (2002) proposed higher order spectra (HOS) based feature selection. The strengths, sizes, and shapes of the prominent positive and Negative peaks in the threshold image contain information useful for deciding whether or not a block contains a mine. However, the energy output of a matched filter and most geometric-based classification techniques are sensitive to changes in size (e.g., amplification or reduction from zooming in or out), location (e.g., the position within the image is not fixed), and orientation (e.g., arbitrary rotation) of the object. Consequently, detection is improved by the use of features that are invariant to changes in target size, position, and rotation. It also is desirable to have features that are robust to noise and clutter. These properties are satisfied by a set of features based on bisector and trispectra of the image [12].

Changjing Shang and Keith Brown (1993) examined Principal feature extraction network (PEN). Feature generator is to generate a set of feature images from the given target image by following the co-occurrence maxi technique reviewed. In particular, the implemented generator produces 20 co-occurrence features. To enable the utilization of other subsystems of the classifier, the grey level of such feature images is normalized to take values from the interval. Given the resulting features which are usually highly correlated with each other, the Principal feature extraction network (PEN) implements principal feature extraction. This network is designed so that the number of nodes within the input layer and that within the output layer are the same as the number of the feature images returned by the feature generator and the number of the principal features of importance, respectively. Finally, the PCN sub-system accomplishes the feature pattern classification by mapping the principal features onto their corresponding underlying texture classes.

VII. DETECTION

Mine detection problem is to simply assign a threshold to the mapped features, based on the premise that the object should be brighter (i.e., have a stronger reflected signal) than the background of a sonar image. This approach works well for a relatively featureless background, however a textured background may encounter many false positive mine locations. Recent mine detection methods have made use of advanced signal processing techniques.

James D. Tucker, Mahmood R. Azimi-Sadjadi, and Gerry J. Dobeck (2007) proposed an optimum Neyman Pearson detector method. A new coherent-based detection and classification method for high-resolution sonar imagery is developed using CCA as an optimal Neyman-Pearson detection scheme and a feature extraction process. In both cases, the canonical correlations are formed from region of interests (ROI) within the sonar image. From these canonical correlations, coherence (or incoherence) can be measured and used to determine if a features can then be used to classify the detected ROI's target is present in the processed ROI and then the extracted. Following the detection, all the canonical correlations extracted from each ROI are used to classify target and non-target ROI's using a back propagation neural network (BPNN) classifier. [4]

F. Langner, C. Knauer, W. Jans and A. Ebert (2009) proposed automatic object detection Automatic object detection and classification under development at FWG with the assistance of FU-Berlin and FGAN-FOM is presented. Afterwards false detections of ROIs without objects of interest are eliminated by applying a single snake algorithm for the entire highlight and shadow area, a coupled snake algorithms for the highlight area and for the shadow area, a 2d-cross correlation with reference images of MLOs and an iterative segmentation, all combined with robust and fast classifiers. [7]

Payam Saisan, Shubha Kadambe examined a Binary detection using likelihood Ratio in the year 2008. The mine detection paradigm proposed had several elements to it, 1. Shape normalization. 2. Projection onto a shape normalized Mine image subspace. 3. Mine similarity score measuring the distance of a novel mine image to mine subspace and a decision theoretic analysis of the mine similarity scores using likelihood ratios for a final binary mine detection decision.

Final mine detection decisions given by the decision likelihood tests carried out on the final mine-ness measures. The mine-ness measure is defined as the distance to geometrically shape registered mine subspace as described in previous two sections. The lighter yellow patches represent those identified as likely mine patches and the blue patches are those identified as non-mine patches [3].

F. Langner, C. Knauer, W. Jans, W. Middelmann (2007). Proposed K-means based screening detection. The detection rate of the k-means based screening algorithm is significantly lower than the detection rate of the other algorithms. This could be a result of the Fact that this algorithm process the image block wise. By a block wise processing, an unfavorable location of the object in terms of the dividing process could lead to segmentation failure. A sliding window approach would solve this problem. [8]

Vinod Chandran, Steve Elgar, and Anthony Nguyen (2002) proposed AMDAC Algorithm and higher order spectra (HOS) were used to prevent detection. The detection of mines in sonar imagery is challenging because the images contain spatially varying clutter and noise, and target signatures are not consistent in shape, strength, or size. Although most signatures exhibit separated high- (highlight) and low-valued (shadow) regions, sonar returns from some mines show little highlight and others have weak shadows. Consequently, approaches to mine detection have compromised on the design of a matched filter, which often is an approximation of a segment of an ideal target signature [12].

VIII. CLASSIFICATION

The challenging problem for the classifier is to identify features that will eliminate the false targets that have target strengths similar to the mine. The classifier provides excellent classification results based upon only the data of single aspect of the sonar. The threshold for the decision making is the one which makes the correct classification rate **(P_{cc}) =1**, false alarm rate (**P_{fa}**), i.e., the point where misclassification rate is equal to the false-alarm rate.

A classification procedure is required to determine whether the detected object is a false alarm or not. While many systems define classification as simply determining whether an object is mine or not-mine, geometric analysis can be used in the classification stage to determine the shape of the object. Mines can often be described by simple objects such as cylinders, spheres, and truncated cones, therefore ensuring that, if the MLO can be classified as one of these objects, it can be identified as a mine with a high degree of confidence. Bryan Thompson, Jered Cartmill, Mahmood R. Azimi-Sadjadi, and Steven G. Schock (2006) examined CCA-based decision-level fusion classifiers. The classification results will indicate the robustness of the extracted CCA/MCCA features as well as the generalization ability of the classifiers. Next, classification systems able to classify objects based on individual feature vectors produced via both the CCA and MCCA feature extraction methods are developed. Two classifiers are created, one is trained using individual CCA feature vectors, and the other using feature vectors produced via the MCCA method [10].

W. Kenneth Stewart, Min Jiang, and Martin Marra (1994) proposed a Back propagation neural network Classification. During classification, information passes through the network in one direction from input layer, through hidden layer(s), to output layer. Each node actually performs two functions, collecting the activation from nodes of the previous layer and setting output activation. An exception is the input layer where nodes are directly activated by the input data.

Side scan-imagery classification using a network-based classifier adopt a feed Forward network with the back propagation learning algorithm. Classification begin with a brief review of BP networks, then discuss the issues associated with network configuration and training. This is probably due to the subtle sensitivity of the spectral features to geometric variation in texture among the different seafloor images. [5]

Anthony R. Castellano Brian C. Gray proposed a The Back Propagation NN (BPN) and the Probabilistic (PNN) have been used for classification, 2011. The Classification subsystem must classify the target, represented by the given feature vector. Neural networks have been shown to be effective classifiers. Specifically, the Back Propagation Neural Network (BPN) and the Probabilistic Neural Network (PNN) have both been used for classification tasks.

The distributed architecture of these neural network algorithms allows them to be implemented on a parallel processor in order to realize their real-time capabilities. Currently, the Probabilistic neural network (PNN) is used in the classification subsystem because of the training data.

The PNN is a Multi-layer feed-forward network which uses sums of gaussian distributions to estimate the probability density function (PDF) for a training set. This trained network can then be used to classify new data sets based on the learned PDF, and further, to provide a probability factor associated with each class [1].

Rebecca T. Quintal, John E. Kiernan, John Shannon Byrne, Paul S. Dysart (2010) proposed a Multilayer perceptron Network Classification. The classification method employed by the program is a multilayer perceptron network that makes use of statistical confidence metrics to manage the high number of false alarms. When using neural network Classification methods, which are based on error-minimization techniques, it is necessary to ensure that the chosen classifier is not a memorization of the data but is truly a model of the data. [14].

Vinod Chandran, Steve Elgar, and Anthony Nguyen (2002) suggested a K-Nearest Neighbor statistical classifier, Threshold classifier, and Minimum distance classifier. Classification accuracy is improved by combining features based on geometrical properties of the filter output with features based on high order spectra (HOS). The highest accuracy is obtained by fusing classification based on bispectral features with classification based on trispectra features. [12].

TABLE 1. Observation and Analysis on Existing System

Probabilistic Neural Network	F. Langner, C. Knauer, W. Jans and A. Ebert	2009	Considerations about the required resolution for the detection, Classification and identification process of objects in side scan Sonar images.	K-Means and statistics based segmentation	Statistical Features within a sliding window	Automatic Object detection	Support Vector Machine (SVM) based classifier	-.
	F. Langner, C. Knauer, W. Jans, W. Middelmann	2007	Recent and planned activities in the area of computer aided detection and classification (CAD / CAC) of mine like objects (MLOs)	Threshold and neighborhood segmentation	Statistical Features within a sliding window	K-means based screening detection	K-Nearest Neighbor and Probabilistic Neural Network Classifier	90%
Multi layer feed forward neural network	C. Shang and K. Brown	1992	A texture classification system for side-scan sonar images by using a trained multilayer feed forward neural network (MFNN) is presented.	-	Principle feature Transformer	-	The pattern classification network (PCN)	99%
	Changjing Shang and Keith Brown	1993	A texture classifier for side-scan sonar image classification using two cascaded trained MFNNs	-	Principal feature extraction network (PEN)	-	The pattern Classification network (PCN)	-
K-Nearest Neighbor based artificial neural network	Vinod Chandran, Steve Elgar, and Anthony Nguyen	2002	Features based on geometrical properties and HOS can be used to detect mines in cluttered acoustic images	-	HOS based feature selection and (PCA) is used	AMDAC Algorithm and HOS is used to prevent detection	A K-Nearest Neighbor statistical classifier, Threshold classifier, Minimum distance -classifier	90%
Bayesian Neural Network	Payam Saisan, Shubha Kadambe	2008	Detect and localize, in 2D sonar imagery, mine and mine looking objects automatically	Preset segmentation	Predermined feature Extraction-	Binary detection using likelihood Ratio -	Bayesian classification	91.3%
Multi layer perceptron Network	Rebecca T. Quintal, John E. Kiernan, John Shannon Byrne, Paul S. Dysart	2010	Rapid and accurate processing of side-scan sonar data for hydrographic surveys, this technology has wide applications in areas such as home land security, munitions detection, and search and locate	-	Detect the features of Interest	Automatic contact detection	Multilayer perceptron Network Classification	94%

NN	Authors Names	Year	Objectives	Methods				Results
				Segmentation	Feature selection	Detection	Classification	
Back propagation Neural network (BPNN)	James D. Tucker , Mahmood R. Azimi-Sadjadi, and Gerry J. Dobeck	2007	To solve a new coherent-based detection and classification method for high-resolution sonar imagery is developed using CCA as an optimal Neyman-Pearson detection scheme and a feature extraction process	Partitioning of overlapping ROI	Canonical Correlation Analysis (CCA) feature extracted	An optimum Neyman Pearson detector Method	A back propagation Neural network (BPNN) classifier.	90%
	Bryan Thompson, Jered Cartmill, Mahmood R. Azimi-Sadjadi, and Steven G. Schock	2006	Canonical Correlation analysis is extended for multi-ping feature extraction in real sonar data.	Windowing and channel correlation and Blocking	CCA and Multichannel Canonical Correlation Analysis(MCCA)	-	CCA-based decision-level fusion classifiers	85%
	W. Kenneth Stewart, Min Jiang, and Martin Marra	1994	A neural-network approach to classification of Side scan-sonar imagery is tested on data from three distinct Geo acoustic provinces of a mid ocean-ridge spreading center	Automated Segmentation	Textural Features Extracted From Gridded Acoustic Imagery or Neighborhood features	Shadow Detection	Back propagation neural network Classification	91.2%
	Anthony R. Castellano Brian C. Gray	2011	A new design, which includes the use of a neural network classifier, for the automated Processing of SSS returns.	Thresholding Segments	Feature Vector	Object Accumulator	The Back Propagation NN (BPN) and the Probabilistic (PNN) have been used for classification	-
	Ali Pezeshki, Mahmood R. Azimi-Sadjadi, and Louis L. Scharf,	2007	Canonical correlation analysis was exploited to develop a multiaspect feature extraction method for underwater target classification from a wideband sonar data set	-	Canonical correlation-based feature Extraction	Multiaspect Detection	BPNN Classifier	99.1%

Table I illustrates the type of methods which had been used in the various stages of Neural Network in the existing systems and shows that the detection and classification finding rate of the methods ranges from 85% to 99.1%.

IX. CONCLUSION

This paper has examined various neural network techniques which have the potential to aid the detection and classification of mine-like objects in side scan sonar imagery. In side scan sonar-imaging applications, five components of the detection and classification system were examined. These components are Data preprocessing, Segmentation, Feature extraction, Detection and Classification. For each of these components, neural network techniques is used to improve the performance of underwater mine, and side scan sonar systems where discussed. Examples of successful or instructive methods from the literature were given. Finally, some general neural network considerations common to each imaging methodology were given. Table 1 present the selected overview of neural network techniques among the existing systems and also display the finding rate of mine detection and classification. The need of human element of the mine hunting system is emphasized.

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