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An SVM based Underwater Target Classifier utilizing Unsupervised Neural Networks for Performance Enhancement and Novelty Detection

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Abstract: *For an underwater target recognition system operated in complex oceanic ambience, the observations may become corrupted by several noise sources and channel modulations. Additionally, the classifier can be trained only with the available limited instances of different ship and submarine emanations but in real conditions, the classifier may encounter corrupted versions of the trained instances as well as novel or entirely unknown occurrences. The state-of-the-art target classifier assigns observed target data to the best matching class in its repertoire, thereby possibly misclassifying a novel target as an existing class, which can lead to situations of strategic issues and security risks. This paper investigates the novel class detection capability of a target classifier utilizing a Self-Organizing Map (SOM) provided with representative features, in order to detect such situations so that effective countermeasures can be undertaken. The codebook generated from SOM is used to train a Support Vector Machine (SVM) classifier, a well-established supervised classifier with good generalization capability. The performance of the SVM classifier trained directly with the features extracted from the target signals as well as from the SOM codebook has been compared and their classification accuracies have been evaluated for various intensity levels of ambient noise and reverberation.*
Keywords –*Ambient Noise,Novelty Detection, Reverberation, Self-Organizing Map,Support Vector Machine*

I. INTRODUCTION

The fundamental problem associated withan underwater target recognition system is to detect and recognize objects of interest i.e. targets, in complex acoustic ambience of the ocean with several interfering noise sources. Inconsistencies in the signature of targets, similarities between the signatures of different targets, limited training and testingdata, camouflaged targets and non-repeatability of target signatures make the task of automated classification of underwater signals observed by passive sonarextremely challenging.

One of the significant issues associated with underwater classification approaches is to deal with target classes that have not been presented during the training phase and is commonly referred to as novelty detection. Many approaches for novelty detection have been discussed in [1], of which Self-Organizing Map, an unsupervised approach, proposed by Tuevo Kohonen, has been utilized in this paper for novel target detection. Appropriate features that could best represent the salient characteristics of a signal must be extracted from the raw target signalsbefore training the SOM and the output space of SOM is clustered using*k*-means clustering. The resulting clusters can be analyzed to detect the presence of a novel target.

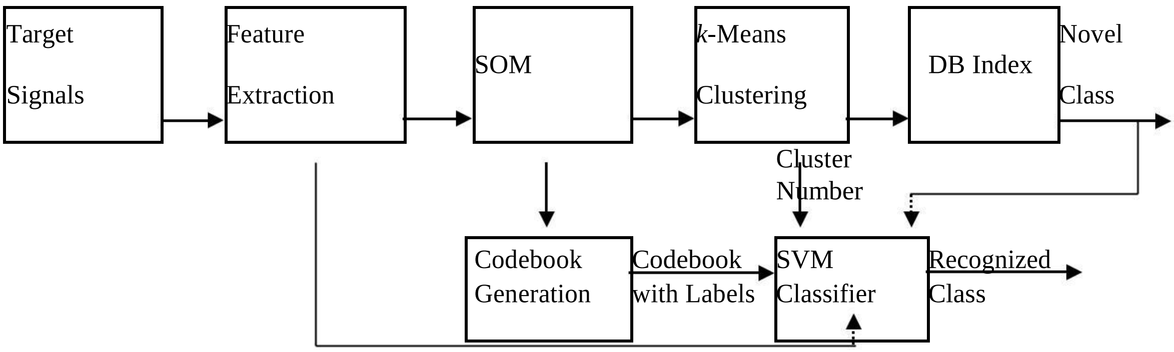
The core essence in classification is to minimize theprobability of errorin using the trainedclassifier, which is often referred to as the structural risk; and sonar is no exception. SVM, proposed by Vapnik*et al.*,is capable of minimizingthe structuralrisk by finding a unique hyper-planewith maximum margin to separate instancesfrom two classes [2].Problems of any dimensionare easily solvable with SVM keeping the model complexity relatively low and its model capacity matches the training data complexity, which resolves problems like over-fitting as well as under-fitting [3]. SVMclassifiers, therefore provide extremely goodgeneralization ability on unseen data compared with theother classifiers and hence, has been chosen for this work.

This paper investigates the combined ability of SOM and SVM for underwater target classification and novelty detection purposes. SOM, with its ability to detect novel targets, can be used to train an SVM classifier using its codebook, labels and clusters. An attempt has been made to recreate original oceanic ambience with sufficient levels of ambient noise and reverberation, so as to test the classifier performance in a real target recognition scenario. The underwater targets considered for training include seven classes of ships. For testingpurpose, several other instances from these classes of ships along with various unknown targets such as other classes of ships as well as marine mammal vocalizations have been utilized.

II. METHODOLOGY

The block diagram of the proposed system is depicted in Fig. 1. The acoustic target signals are pre-processed and relevant features are extracted from these signals. These features are then presented to SOM, whichforms a large set of prototypes, often interpreted as protoclusters [4]. These prototypes may be much larger than the expected number of clusters and hence needs another step of clustering using *k*-means algorithm to form the actual clusters. This reduces the computational cost since it is convenient to cluster a set of prototypes and they are also less sensitive to random variations than the original target signal. The Davies-Bouldin (DB) index, a measure to evaluate *k*-means clustering, is then used to detect the presence of a novel class.

The various target classes will be represented by their corresponding clusters in the cluster map generated after *k*-means clustering. If a test signal comes within any of these clusters, it can be correctly classified into its respective class whereas the formation of a new cluster confirms novelty i.e. the signal corresponds to a previously unknown class of target. The codebook with target labels generated from SOM and the cluster number obtained after *k*-means clustering are utilized to train an SVM classifier. An SVM classifier trained directly from the feature set is denoted as Direct SVM in Fig. 1. A target belonging to an unknown class, detected as novel class using DB index, can be used for evaluating the SVM classifier. The classifier is then tested with various target instances in order to evaluate its classification accuracy in diverse conditions.



Direct SVM

Fig. 1. Block diagram of the proposed system

2.1 Feature Extraction

In order to yield better classification results, a representative set of features that are unique for each class of the target has to be identified. The features are then normalized to bring their values to a uniform scale.The features that have been selected to best represent the corresponding classes of targets include Zero Crossing Rate, Pitch (estimated from harmonic product spectrum as well as zero crossing distance), Spectral features such as Roll-off, Flatness, Centroid and Mel Frequency Cepstral Coefficients (first 13 coefficients), thereby constituting a 19 dimensional feature set. [5].

2.2 Self-Organizing Map

The Self-Organizing Map transforms the incoming feature patterns adaptively in a topologically ordered fashion into a two dimensional discrete map. SOM is set up by placing artificial neurons at the nodes of a two dimensional lattice. The neurons become selectively tuned to various feature patterns and they use a neighborhood function to preserve the topological properties of the input space. Since batch training has been implemented in SOM, the weights of Best Matching Unit (BMU) and its neighbors are updated according to (1).

$$(\ + 1) = \frac{\sum_{=1} (\ )}{\sum_{=1} (\ )} \quad (1)$$

where is the time, is the BMU for the training pattern and ( ) is a neighborhood kernel centered on . The unified distance matrix (U-matrix) is a representation of SOM that visualizes the distances
between the neurons, where the distance between the adjacent neurons is calculated and presented with different colorings, while the cluster map clearly displays the various clusters with different colors.

2.3 Clustering of SOM
The clustering of SOM is accomplished by *k*-means clustering algorithm, an unsupervised learning algorithm, which classifies a given data set through a certain number of clusters (*k*) fixed *a priori* [6].

2.4 Novelty Detection from DB Index
DB index is used to evaluate *k*-means clustering [7]. If is the scatter within cluster and , is the separation between clusters and , then DB is given as in (2).For each value of *k*, DB is calculated and the value of *k* for which DB is minimum, is selected as the number of clusters since it indicates the best clustering scheme. If the number of clusters for the test signal exceeds that formed by the available repertoire, the presence of an unknown target is confirmed.

= / , (2)

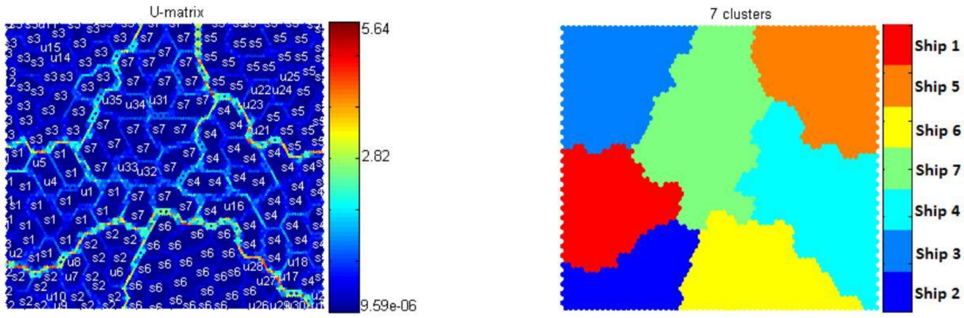
2.5 Support Vector Machines
Support vector machines, is basically a two-class classification method introduced in the context of statisticallearning theory and structural risk minimization[8]. A linear SVM may not be sufficient in an Under water target classification scenario, where the extracted features among various target classes may not be linearly separable. Hence nonlinear support vector machines have been utilized to makeclassificationsby creating a plane in a space, by mapping data to that higherdimensional input spaceusing a kernel that satisfies Mercer's theorem.Although many kernels like *linear*, *quadratic*, *rbf*, *polynomial* and *mlp* are available, Gaussian (RBF) kernel has been found to provide better separation in the higher dimensional space for the target feature set.In order to implement multi-class target classification, one-against-all approach has been utilized.

III. SOM OUTPUT SPACE
The output space of SOM is a 2-dimensional grid of neurons, which contains the following information.
Topology
Neighborhood function Codebook
Labels

The SOM typically uses rectangular and hexagonal types of topology [9]. A hexagonal topology has been preferredsinceit produces smoother maps.A neighborhood function is a radial function with a maximum at the centre, monotonically decreasing up to a radius *r*and is zero from there onwards. Although several functions like *bubble*, *gaussian*, *cutgauss* and *epanechicov* are available, Gaussian neighborhood function has been utilized since it improves the granularity of the resulting mapping. Each neuron of the SOM has an associated -dimensional prototype (i.e. weight, reference, codebook or model) vector = [1 2 …], where is equal to the dimension of the input vectors. Since a 19 dimensional feature set is provided to a 60×60 SOM, the codebook matrix consists of 3600×19 elements, where 3600 is the number of neurons.

A labelled version of the U-matrix is displayed in Fig. 2 (a). The labels on the map correspond to the neurons on to which the target sounds belonging to their respective classes are mapped. The known seven classes of ships are labelled as s1, s2, s3, s4, s5, s6 and s7 respectively whereas the test instances belonging to these classes are labelled from u1 to u35. The *k*-means clustering of the labelled map returns the cluster associated with each neuron and thereby the clusters associated with all the labels in the map, as shown in Fig. 2

(b). When there are only seven target classes and the evaluation of the SOM is done with the test instances belonging to these classes alone, only 7 clusters will be formed. The various clusters are represented using different color codes to distinguish between the various classes of ships.In order to have a better understanding of the labelling and clustering of the map, some of the neuron numbers, their associated labels and the corresponding clusters are provided in Table 1.



(a) (b)

Fig. 2. SOM Visualization(a).Labelled U-matrix&(b).Cluster Map showing 7 clusters

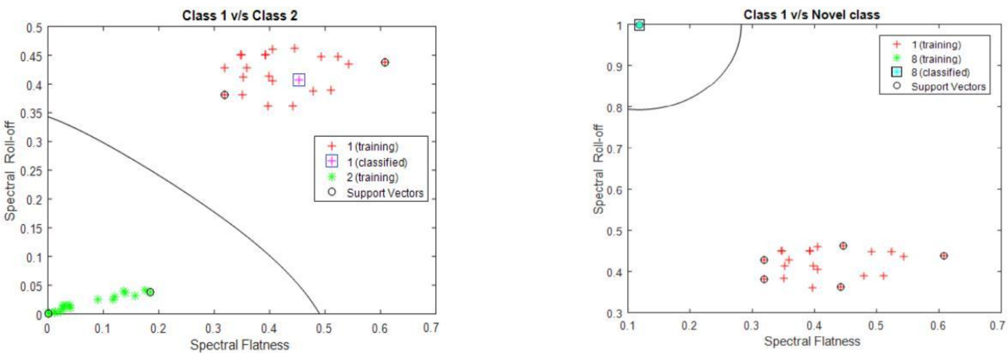
Table 1. Labeling and Clustering of SOM Neuron

Neuron No.	Label	Cluster No.	Neuron No.	Label	Cluster No.	Neuron No.	Label	Cluster No.
29	s1	1	301	s3	4	3192	u25	7
148	s1	1	781	s3	4	1496	s6	3
286	s1	1	13	u12	4	2100	s6	3
628	s1	1	2134	s4	6	2505	s6	3
936	u1	1	2673	s4	6	3120	u29	3
53	s2	2	3278	s4	6	987	s7	5
416	s2	2	3351	u18	6	1564	s7	5
1258	s2	2	2284	s5	7	1984	s7	5
1313	u6	2	2950	s5	7	2113	s7	5
1	s3	4	3443	s5	7	1217	u35	5

If a completely unknown target appears, a separate cluster will be formed, identifying the target as a novel class. The codebook, labels of the map as well as the clusters resulting from *k*-means clustering has been used to train the SVM.

IV. INTEGRATING SOM WITH SVM

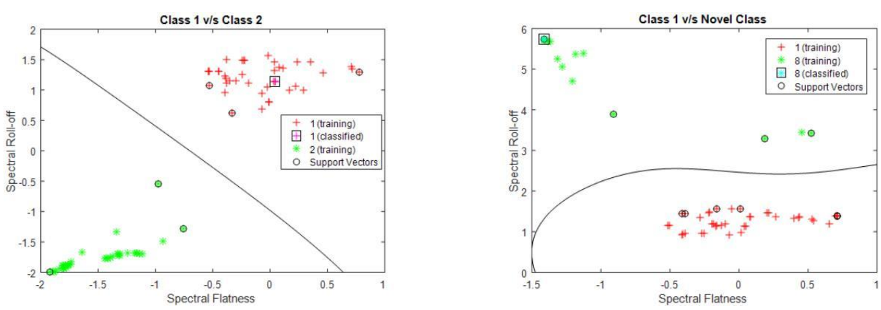
Instead of training the SVM directly using the feature setextracted from the various classes of ships, the repertoire is drawn from the SOM codebook based on the ship labels and clusters corresponding to the labels.
The SVM trained directly withthe feature set(Direct SVM), when tested with asignal belonging to ship class 1 and a novel target are plotted in Fig. 3 (a) & (b) respectively. RBF kernel has been used to map the dataset into a higher dimensional space to provide better class separation.The feature Spectral Flatness has been plotted against Spectral Roll-off in order to visualize the separating hyperplane between different classes of targets.The data point highlighted in square is the classified test signal while the remaining data points represent the training instancesand support vectors.



(a) **(b)**

Fig. 3. DirectSVM Classification for: (a). Test Sample from Class 1 &(b).Novel Target

The SVM trained using SOM codebook (SOM-SVM) evaluated for a test instance belonging to Class 1 and a novel target are shown in Fig. 4 (a) & (b) respectively. It is seen that the dataset provided via SOM is much denser due to the large number of neurons available for creating SOM. The expected out-of-sample error for SOM-SVM is found to be very much less compared to that in Direct SVM due to the large number of training examples, thereby improvingthe generalization ability of SVM.



(a) **(b)**

Fig. 4. SOM-SVM Classification for: **(a).** Test Sample from Class 1 &**(b).**Novel Target

V. EFFECT OF REVERBERATION AND AMBIENT NOISE

The success rates of most of the state-of-the-art underwater target classifiers degrade rapidly when they aretested with instances in the presence of reverberation and background noise. In the vast ambience of the ocean, both these effects are unavoidable. In order to evaluate the classifier performance in a real target recognition scenario, models of reverberation and ambient noise need to be constructed.

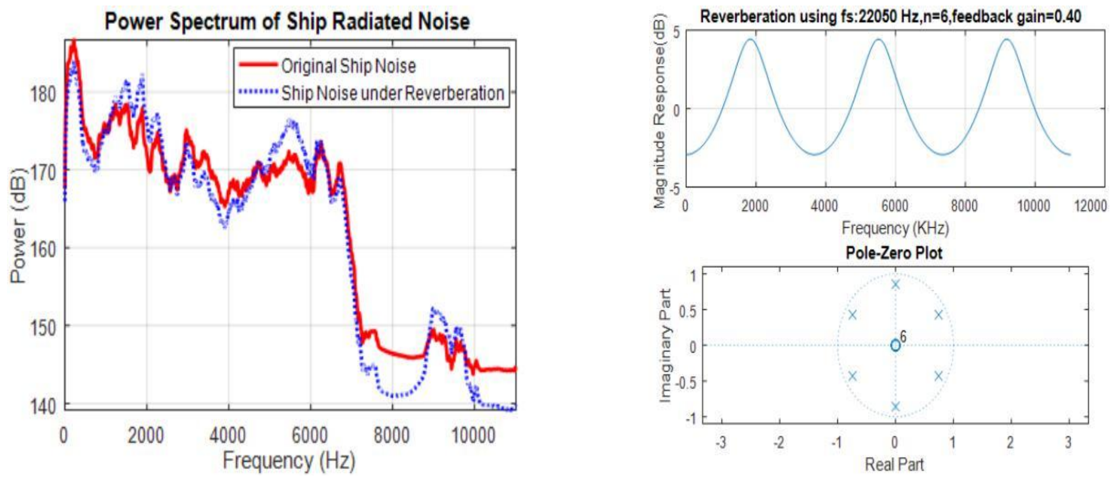
5.1 Classifier Performance under Reverberation

Reverberation consists of early reflections and late reverberation, characterized by a dense collection of echoes, produced by a very large number of reflected waves, travelling in all directions.For effective detection and classification of the target, the classifier must be least sensitive to the transformation encountered to the signal due to reverberation.In order to modellate reverberation, algorithms based on efficient infinite impulse response (IIR) filters can be utilized [10]. A discrete-time filter,due to its presence of feedback in the topology,can create an IIR response. The transfer function of an IIR filter can be expressed as a function of as in (3).

$$(\ ) = \frac{\sum_{=0} {}^{-}}{1 + \sum_{=1} {}^{-}} \qquad (3)$$

Reverberation with different intensity levels can be obtained by varying the number of elements (*n*) in the feed-forward and feedback part as well as by changing the gain on every node.

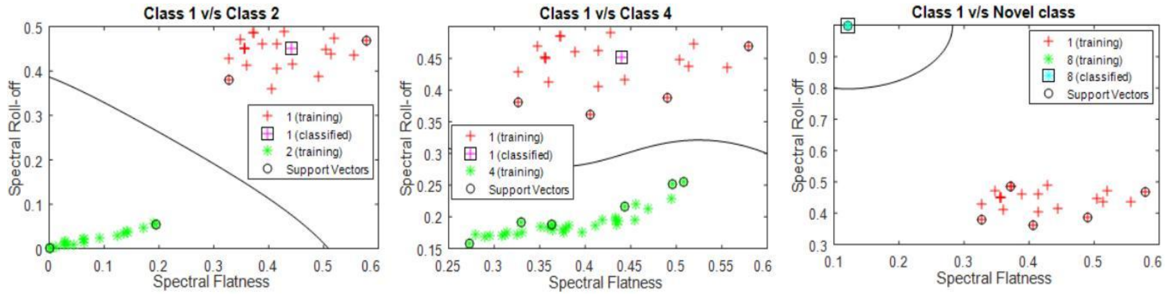
In order to evaluate the classifier performance in a real oceanic ambience, reverberation has been introduced into the target samples. Now, the training set consists of instances from both the direct sound as well as those with reverberation. Since reverberation is modelled using an IIR filter, *n* and gain have been varied to reflect the various levels of reverberation. Four different cases investigated for this purpose include n=1, 2, 6 and 24 with gain varied from 0.1 to 0.9. A sample case for n=6 and gain=0.4 is shown in Fig. 5 to understand itstransformationeffect on a ship radiated noise.



(a) **(b)**

Fig. 5. Reverberation for n=6 & gain=0.4: (a). Effect on Ship Noise& (b). Response and Z-plane plot

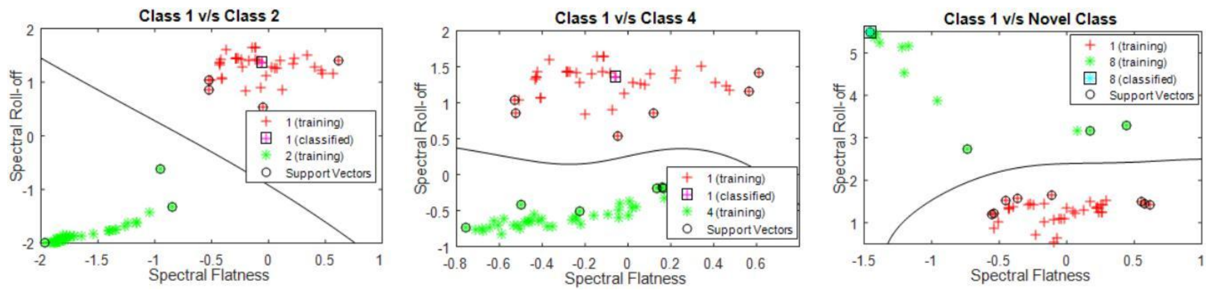
The ability of a Direct SVM classifier to discriminate between various ship classes in the presence of reverberation has been analyzed using a multi-class SVM employing one-against-all approach. Fig. 6 (a) &(b) show the ability of SVM to correctly classify a test instance (highlighted in square) belonging to Class 1 whereas Fig. 6 (c) indicates that a novel target has also been precisely classified.



(a) **(b)** **(c)**

Fig. 6. Direct SVM Classification in presence of Reverberation (n=2 & gain=0.2) for: **(a), (b).** Test Sample belonging to Class 1 &**(c).**Novel Target

AnSOM-SVMclassifierperformance has been evaluated in the presence of reverberation,as shown in Fig. 7.As discussed earlier, the dataset in SOM-SVM is seen much denser compared to that in a Direct SVM. The proper classification of a test signal belonging to Class 1 isillustrated in Fig. 7 (a) & (b), while Fig. 7 (c) is an evidenceof the classifier's ability to detect a novel target.



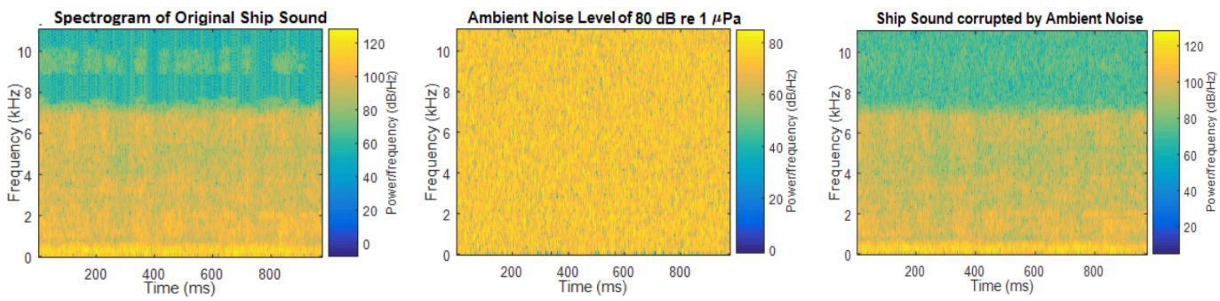
(a) **(b)** **(c)**

Fig. 7.SOM-SVM Classification in presence of Reverberation (n=2 & gain=0.2) for: **(a), (b).** Test Sample from Class 1 &**(c).**Novel Target

5.2 Classifier Performance in Ambient Noise

The target signals may be corrupted by the underwater ambient noise field, which in turn results in the misclassification of the observed target data. The main contributors of ambient noise include thermal agitation, hydrodynamic sources, oceanic traffic, seismic and biological sources [11]. These noise spectrum levels mostly span the range near 20 dB to excess of 80 dB re 1 µPa for different frequencies.In order to model ambient noise, Gaussian noise has been considered since it is a statistical noise that has a probability density function equal to that of the normal distribution [12] and is constructed using pseudorandom values drawn from the standard normal distribution.

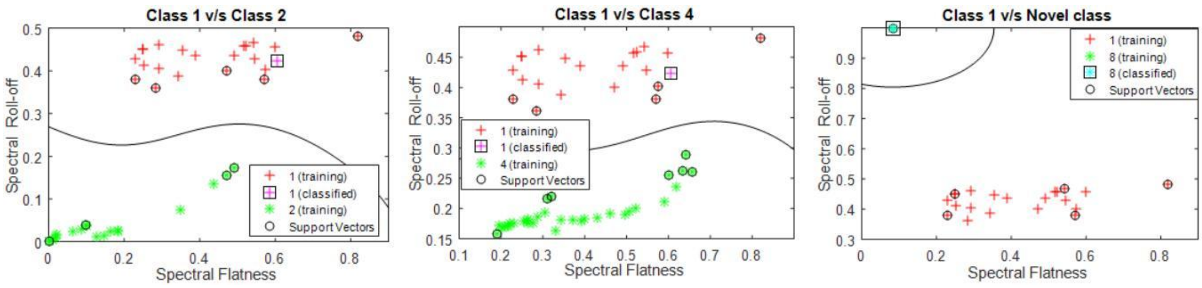
The spectral levels of the target emanations utilized in this work vary from 120 dB to 160 dB re 1 µPa since these emanations have been measured at various distances from the source. A sample case of ship emanation corrupted by an ambient noise of 80 dB is illustrated in Fig.8.



(a) **(b)** **(c)**

Fig. 8 (a). Near field Ship Sound Spectrogram**(b).**Noise level of 80 dB re 1 µPa**(c).**Corrupted Ship Sound

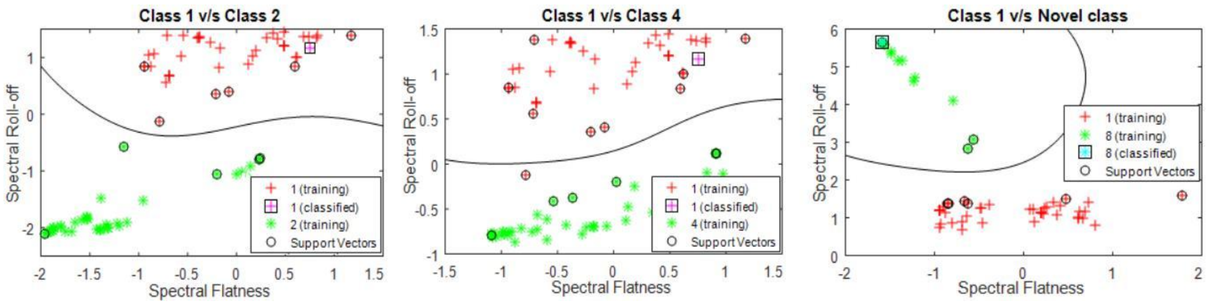
The effect of various levels of ambient noise on the classification ability of a Direct SVM classifier has been evaluated. The performance of the classifier for a test sample belonging to Class 1, when subjected to an ambient noise of 60 dB, is demonstrated in Fig. 9. A test sample from Class 1 has been correctly assigned to its class, as shown in Fig. 9 (a) & (b), while a target belonging to an entirely unknown class has been correctly identified as novel, as seen in Fig. 9 (c).



(a) **(b)** **(c)**

Fig. 9.SVM Classification in presence of Ambient Noise level of 60 dB re 1 µPa for: **(a), (b).** Test Sample from Class 1 &**(c).**Novel Target

The better discriminating ability of an SOM-SVM classifier, in the presence of ambient noise, is clearly visible from Fig. 10. As mentioned earlier, the bunch of data available for training the SVM in the presence of SOM, is much higher compared to that in a Direct SVM. This helps in improved success rates of the classifierfor test signals, such as those shown in Fig. 10 (a) &(b), where the test instance belongs to Class 1, while in Fig. 10 (c), a novel target has been properly classified.



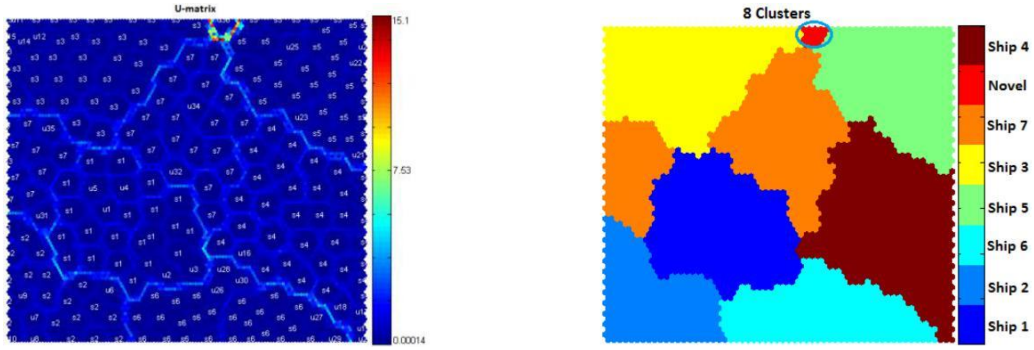
(a) **(b)** **(c)**

Fig. 10.SOM-SVM Classification in presence of Ambient Noise level of 60 dB re 1 µPa for: **(a), (b).** Test Sample from Class 1 &**(c).**Novel Target

VI. RESULTS AND DISCUSSIONS

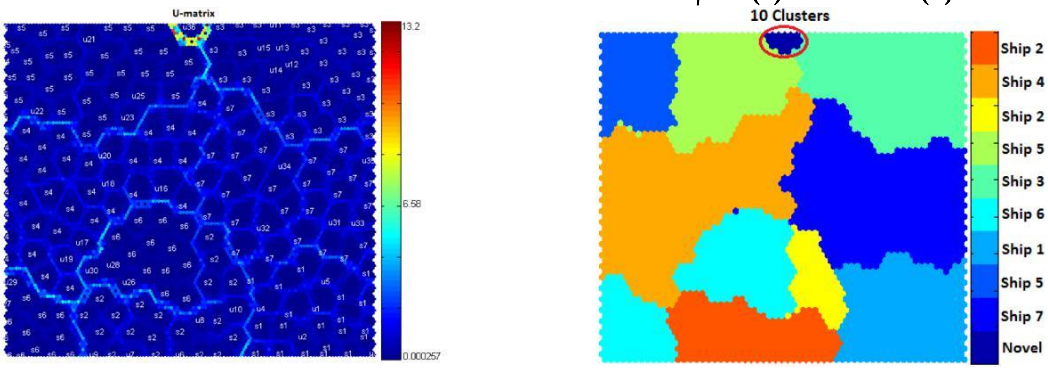
The experiment has been conducted on a 60×60 SOM with rectangular lattice and hexagonal topology. The number of epochs has been chosen to be five with learning rate function *inverse*and neighborhood function *gaussian*. After extracting the features required for batch training the SOM, the integration of SOM into SVM has been implemented using the codebook and labels obtained from the SOM output map as well as the clusters resulting from the *k*-means clustering of the map.SOM has been trained with different instances from seven classes of ships labelled as s1, s2, s3, s4, s5, s6 and s7 respectively. The codebook generated by SOM has been used for training the SVM and a performance evaluation in terms of classification accuracy has been done for Direct SVM as well as SOM-SVM. In order to replicate a real oceanic ambience, reverberation and ambient noise have been introduced into the signals of interest and the classifier performance in such a scenario has been analyzed.

SOM has been trained directly with the features extracted from the target signals,both in the presence as well as absence of reverberation and ambient noise. The U-matrix, along with its corresponding cluster map has been createdin order to visualize the mapping of target emanations belonging to known as well as unknown class. It has been observed that exact number of clusters has been formed for ambient noise levels up to the range close to 80 dB as well as for reverberation in the presence of up to 4 delay elements. Fig. 11(a) & (b) representthe U-matrix and cluster map respectively for an ambient noise level of 60 dB. The larger distance between the clusters is clearly visible from the U-matrix while the number of clusters formed after *k*-means clustering is evident from the cluster map. The map displays eight clusters, of which the cluster formed by the novel class is encircled. For a noise level of 90 dB, incorrect number of clusters (10 instead of 8) has been formed, as shown in Fig. 12. The classifier's performance is observed to degrade for noise levels above 80 dB.



(a) (b)

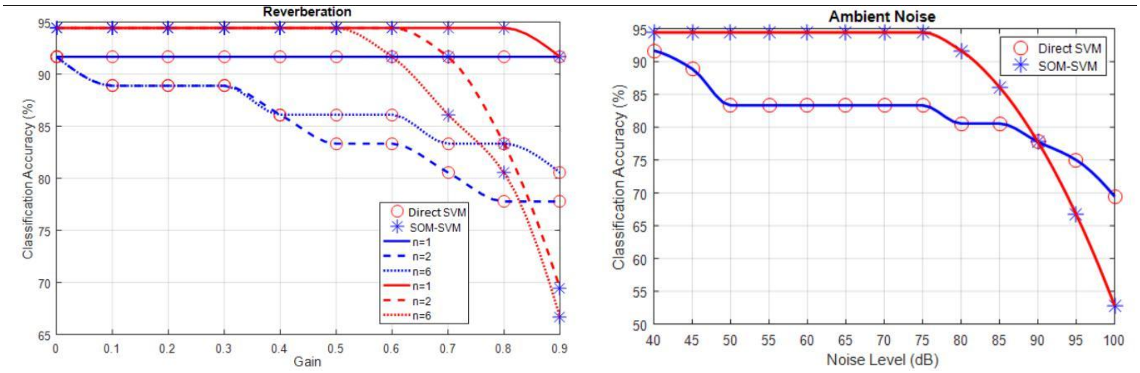
Fig. 11. SOM Visualization for an Ambient Noise level of 60 dB re 1 µPa: **(a).** U-matrix &**(b).** Cluster Map



(a) (b)

Fig. 12. SOM Visualization for an Ambient Noise level of 90 dB re 1 µPa: **(a).** U-matrix &**(b).** Cluster Map

The classification accuracy of Direct SVMas well as SOM-SVMhas been compared for various intensity levels of reverberation and ambient noise. Fig. 13(a) shows the variation of classification accuracy for different levels of reverberation (n=1, 2 and 6 with gain varied from 0.1 to 0.9) while Fig. 13(b) is a plot of the accuracy variation for various intensities of ambient noise. It is evident from the graph that an SOM-SVM classifier outperforms Direct SVM classifier in terms of classification accuracy for most of the intensity levels of reverberation and ambient noise. In an SOM-SVM classifier, the feature set is mapped into a 60×60 SOM resulting in 3600 neurons and hence the cluster belonging to a particular ship class formed by the SOM output space will consist of more number of neurons than the original data points obtained after direct feature extraction of the same class. Thus, compared to a Direct SVM classifier, the generalization capability of an SVM classifier trained using SOM codebook increases, which results in its better classification accuracy for a wide range of test instances.



(a) (b)

Fig. 13. Classification Accuracy comparison:- Direct SVM v/s SOM-SVM for: **(a).** Reverberation **(**n=1, 2 & 6 with gain=0 to 0.9)**(b).** Ambient Noise with level 40 to 100 dB re 1 µPa

VII. CONCLUSION

Constituting one of the most important subset of observations with indeterminate meaning, the unexpected or novel occurrences can often confuse the discriminating ability of a classifier having prior knowledge only for situations of determinate significance. This evokes the necessity of integrating novel class detection into existing underwater target classifiers. The novel class detection scheme has been proposed by a clustering approach on an unsupervised neural network based SOM provided with appropriate features.Novel class detection has been carried out by determining the value of k for which Davies-Bouldin index, a measure to evaluate k-means clustering, is minimum. After detecting a novel target, an SVM classifier has been trained with the help of codebook, labels and clusters obtained from the SOM, so as to evaluate the classifier's performance for test instances belonging to known as well as unknown target classes. In addition, the classification ability of the classifier has been tested in the presence of various intensity levels of reverberation as well as ambient noise and the results confirm the supremacy of the SOM-SVM classifier over a Direct SVM classifier. The future work aims to improve the classification as well as novel class detection accuracy by extracting more significant features from the target signals and selecting a suitable map size that could best represent the target classes. The behavior of the proposed system should also be studied by training the classifier utilizing a large number of acoustic emanations belonging to a wide variety of targets as well as acoustic signals from a large number of interfering noise sources.

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REFERENCES

[1] Markos Markou and Sameer Singh., Novelty detection: a review-part 2: neural network based approaches,*Signal processing, 83(12),* 2003, 2499-2521.

[2] Yang, Z. R., Biological applications of support vector machines, *Briefings in bioinformatics, 5(4),*2004, 328-338.

[3] Sherin B. M., Supriya M. H.,& P. R. Saseendran Pillai, Underwater Acoustic Target Classification System using SVM, *International Journal of Electronics and Communication Engineering, 2(5),* 2013, 73-80.

[4] Vesanto, J., &Alhoniemi, E., Clustering of the self-organizing map, *IEEE Transactions on neural networks, 11(3),* 2000, 586-600.

[5] SatheeshChandran C., Suraj Kamal, A. Mujeeb&Supriya, M. H., Novel class detection of underwater targets using Self-Organizing neural networks, *2015 IEEE Underwater Technology (UT),* Chennai, 2015, 1-5.

[6] Khaled Alsabti, Sanjay Ranka and Vineet Singh, An Efficient K-Means Clustering Algorithm, *Electrical Engineering and Computer Science,* 1997, Paper 43.

[7] James C. Bezdek and Nikhil R. Pal, Some new indexes of cluster validity, *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics) 28(3),* 1998, 301-315.

[8] ErsoyÖzand Hüseyin Kaya, Support vector machines for quality control of DNA sequencing, *Journal of Inequalities and Applications, 2013(1),* 2013: 85.

[9] E. A. Uriarte&F. D. Martín, Topology preservation in SOM, *International journal of applied mathematics and computer sciences, 1(1),*2005, 19-22.

[10] Costantini, G., and A. Uncini, Real-time room acoustic response simulation by IIR adaptive filter, *Electronics Letters, 39(3),* (2003), 330-332.

[11] Gordon M. Wenz, Acoustic ambient noise in the ocean: Spectra and sources, *The Journal of the Acoustical Society of America, 34(12),* 1962, 1936-1956.

[12] Gordon M. Wenz, Review of underwater acoustics research: Noise, *The Journal of the Acoustical Society of America, 51(3B),* 1972, 1010-1024.