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European Journal of Advances in Engineering and Technology, 2015, 2(5): 91-96

Research Article **ISSN: 2394 - 658X**

Signal Classification Using Adaptive Boosting Technique in Underwater Scenario

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ABSTRACT

Detection and classification of underwater objects in sonar is a complicated problem, due to various factors such as variations in operating and environmental conditions and the attenuation of the sonar signal in the water column can totally obscure a target-like object. In order to overcome such complicated problems detection and classification system is needed. Among them classification plays a major role in detection. Adaptive Boosting Technique (AdaBoost) is one of the best classifier for classification of the things with minimum error. The aim of the project is to implement AdaBoost technique to classify the given inputs depending on the features that are given to the training data. Using this technique, the signal de-noising is achieved. So this signal de-noising application will be very useful in the underwater target detections where the noise dominance is more.

Key words: AdaBoost, classification, detection, de-noising, minimum error, underwater

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INTRODUCTION

The motivation of the paper is to classify a signal from the noise for a better target detection. Generally when compared to the places on the earth more noise involvement is there in the underwater scenario. The noise involvement is due to various factors such as variations in operating and environmental conditions, presence of spatially varying clutter, variations in target shapes, compositions and orientation [1]. Moreover, bottom features such as coral reefs, sand formations, and the attenuation of the sonar signal in the water column can totally obscure a target-like object. So in order to classify the signal from the noise a better classification technique has been used to which was called as an AdaBoost Classification technique. The main aim of this project is to de-noise a signal using this technique which will be helpful in target detection in underwater scenario.

ADAPTIVE BOOSTING TECHNIQUE

The Adaptive Boosting algorithm also known as AdaBoost was introduced in 1995 by Freund and Schapire [2]. It solved many of the practical difficulties of the earlier boosting algorithms. The algorithm takes as input a training set $\{x_1, y_1\},\ldots\ldots,\{x_m, y_m\}$ where each x_i belongs to some domain or instance space X, and each label y_i is in some label set Y. We assume $Y = \{-1,+1\}$ for binary classification. Adaptive Boosting Technique calls a given weak or base learning algorithm repeatedly in a series of round $t = 1,........,T$. One of the main ideas of the algorithm is to maintain a distribution or set of weights over the training set. The weight of this distribution on training example I on round t is denoted D_t (i). Initially, all weights are set equally, but on each round, the weights of incorrectly classified examples are increased so that the weak learner is forced to focus on the hard examples in the training set. The weak learner's job is to find a weak hypothesis $h_t : X \rightarrow \{-1,+1\}$ appropriate for the distribution D_t. The goodness of weak hypothesis is measured by its error.

It is notice that the error is measured with respect to the distribution D_t on which the weak learner was trained. Once the weak hypothesis h_t has been received, AdaBoost chooses a parameter α_t. Intuitively, α_t measures the importance that is assigned to h_t. Note that $\alpha_t \geq 0$ if $\varepsilon_t \geq 1/2$ (which we can assume without loss of generality), and that α_t gets larger as ε_t gets smaller. The distribution D_t is next updated. The effect of this rule is to increase the weight of examples misclassified by h_t, and to decrease the weight of correctly classified examples. Thus, the weight tends to concentrate on "hard" examples. The final hypothesis H is a weighted majority vote of the T weak hypotheses where α_t is the weight assigned to h_t.

Pseudo Code for AdaBoost Algorithm

The AdaBoost algorithm mathematical steps are as shown is below:

Given: $(x_1, y_1),\ldots\ldots,(x_m, y_m)$ where $x_i \in X, y_i \in Y = \{-1,+1\}$

Initialize $D_1(i) = 1/m$ For $t = 1,\ldots\ldots, T$;

Train weak learner using distribution D_t.

Get weak hypothesis $h_t : X \rightarrow \{-1,+1\}$ with error $\varepsilon_t = \Pr_{i \sim D_t}[H_t(x_i) \neq y_i]$.

Choose $\alpha_t = \frac{1}{2}\ln\left(\frac{1-\varepsilon_t}{\varepsilon_t}\right)$.

Update: $D_{i+1}(i) = \frac{D_t(i)}{Z_t} \times \begin{cases} e^{-\alpha_t} & if\ h_t(x_i) = y_i \\ e^{\alpha_t} & if\ h_t(x_i) \neq y_i \end{cases} = \frac{D_t(i)\exp(-\alpha_t y_i h_t(x_i))}{Z_t}$

where Z_t is a normalization factor (chosen so that D_{t+1} will be a distribution).

Output the final hypothesis: $H(x) = sign\left(\sum_{t=1}^{T} \alpha_t h_t(x)\right)$

Here t = 1, 2. . . T represents the number of iterations to be carried out in the AdaBoost algorithm to achieve strong hypothesis. The description of AdaBoost technique in the form of a flow diagram is shown Fig. 1.

Signal de-noising is achieved by Adaptive Boosting Technique. Here a binary classification is considered.The proposed method is described briefly below. Firstly two signals are taken where one is a clean signal and other is a noisy one. To these signal some features are calculated and are given as input to the training phase of the classifier [5].The input features calculated are mean, variance, skewness, kurtosis in both time domain and frequency domain, PSD, geometric meanand the ratio of geometric mean to the mean in frequency domain. After giving the datafeatures to the training phase a trained data is obtained. A test signal (noisy corrupted) which is to be classified is taken and datafeatures are calculated for it. These datafeatures are given along with the trained data to the testing phase of the classifier. Thus by using the algorithm the test data is classified.thus signal de-noising is achieved. Here we have used various signal combinations. We took sine, square,chirp, ping and AWGN noise signal. With the above signals different combinations are taken and are tested for classification.

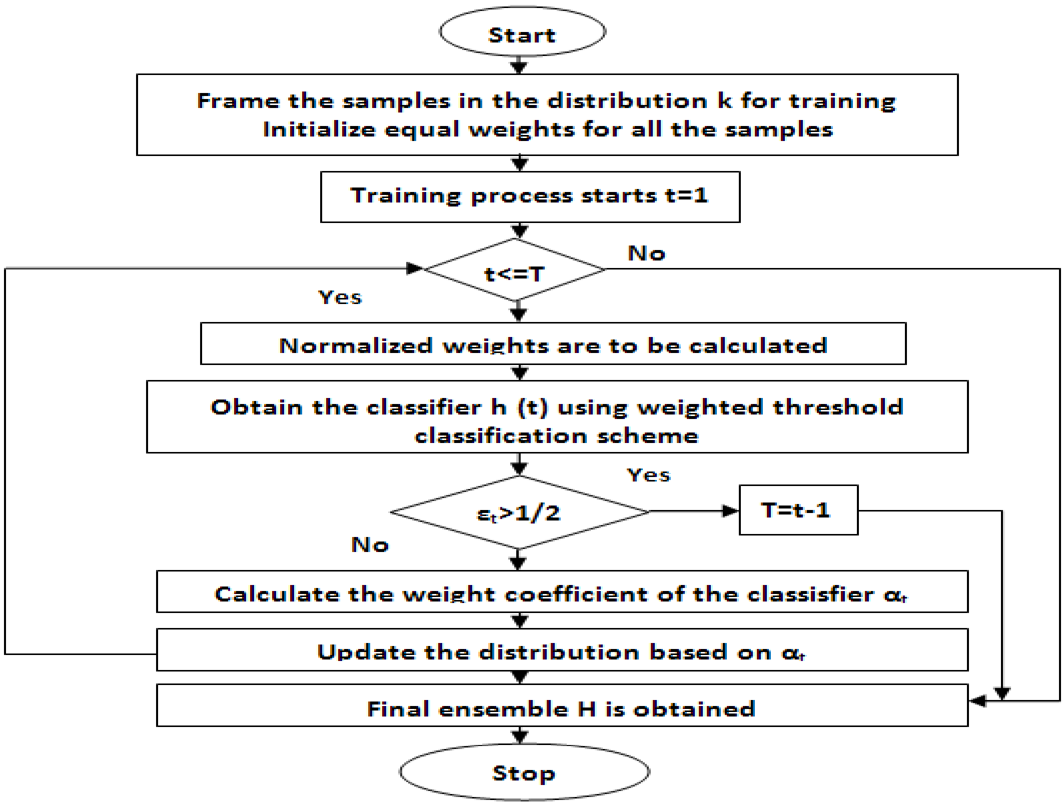


Fig. 1 Adaptive boosting algorithm flow chart

SIGNAL CLASSIFICATION USING ADABOOST

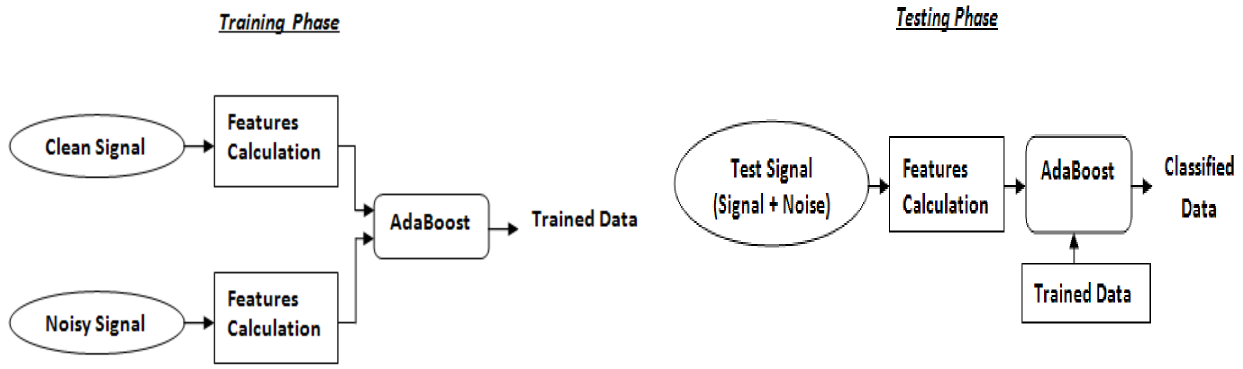
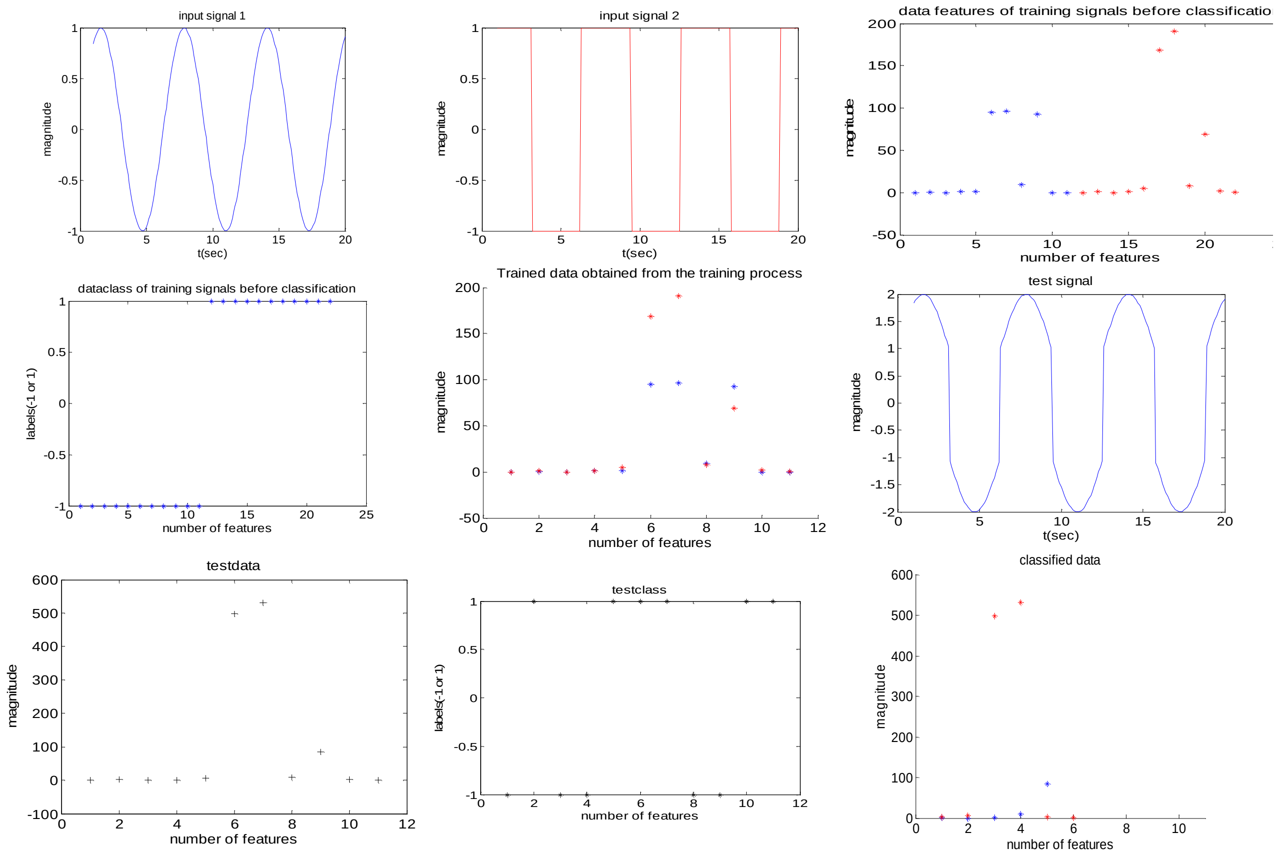


Fig. 2 Block diagram of signal classification

SIMULATION RESULTS

Sine and Square

Plot 3 represents the datafeatures and the dataclass of both input signals. These datafeatures are given to the training phase of the classifier. Plot 4 represents the trained data which is used in the classification process in the testing phase. Plot 6,7,8 represents the test signal, its data features and the data class. Plot 10 represents the error vs iteartions. As the number of iterations increases the error decreases. The stopping criteria for the number of iterations is that when the classification is done it just stops. Plot 11 represents the comparision of input features before and after classification. Similarly for the remaining combination of signals the same process is done. So the overall results are shown for the next combination of signals. Here the following plots in each Fig. represents the two input signals given to the training phase, the test signal and the comparision of input features before and after classification. The test signals taken here is a clean signal mixed with a noisy signal. The features of the test signal get classified based on the trained data features.



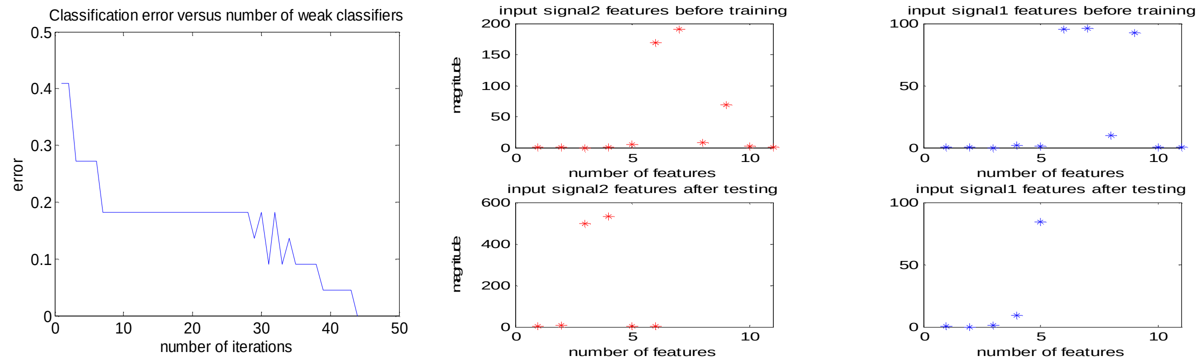
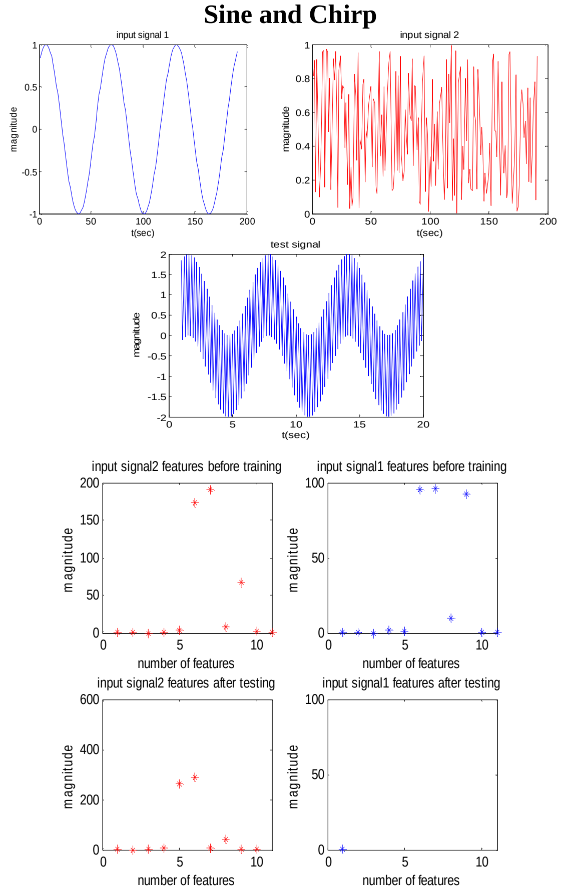


Fig. 3 Simulation results of sine and square

Sine and Chirp



Sine mixed with AWGN at SNR 3dB

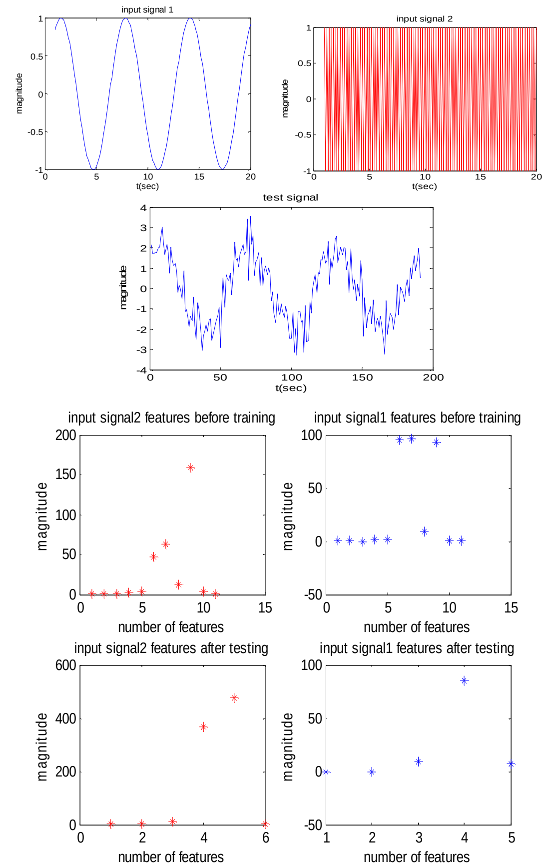
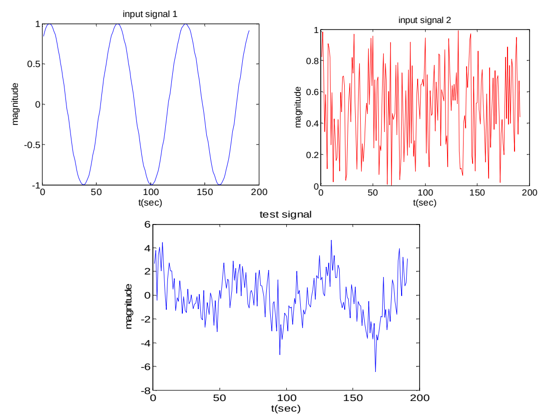


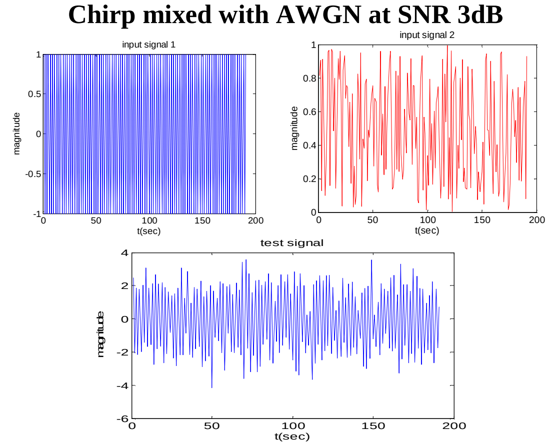
Fig. 4 Simulation results of Sine and Chirp

Fig. 5 Simulation results of Sine mixed with AWGN

Sine mixed with AWGN at SNR -3dB



Chirp mixed with AWGN at SNR 3dB



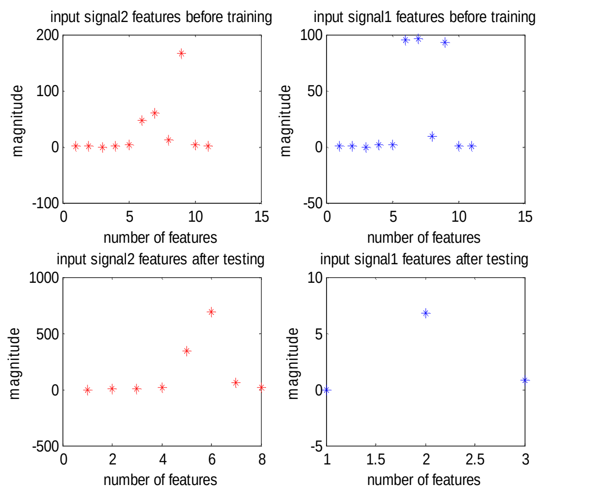


Fig. 6 Simulation results of sine signal mixed with AWGN at SNR 3dB

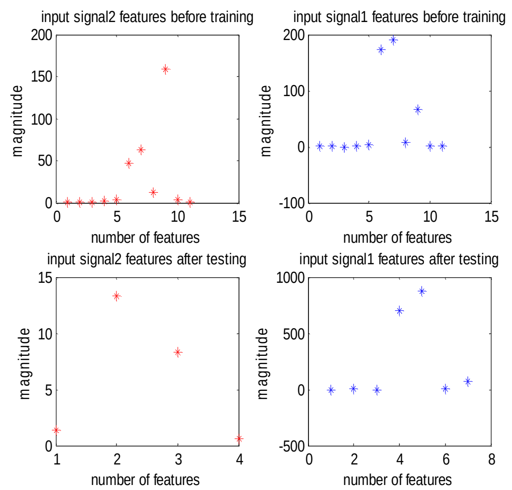


Fig. 7 Simulation results of Chirp mixed with AWGN at SNR 3dB

Chirp signal mixed with AWGN at SNR 3dB

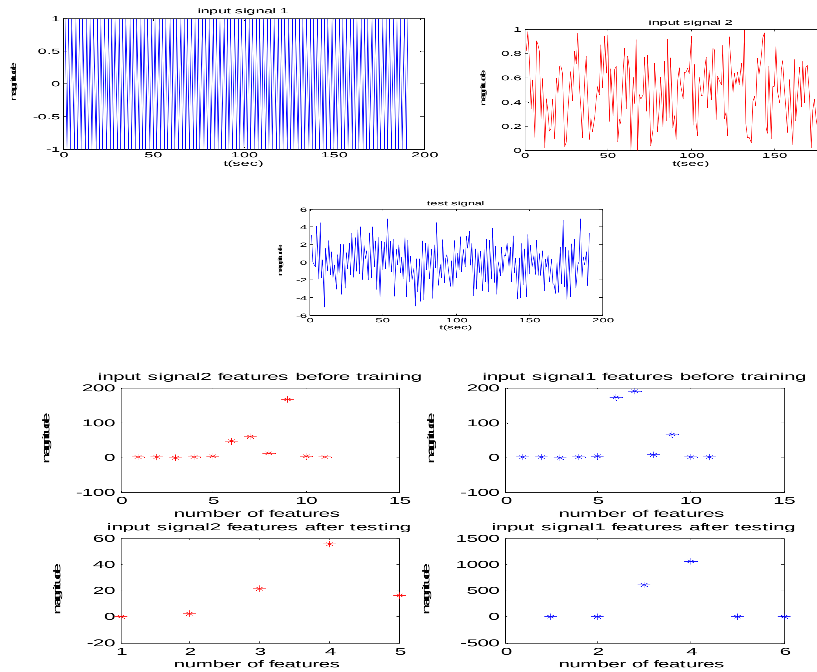
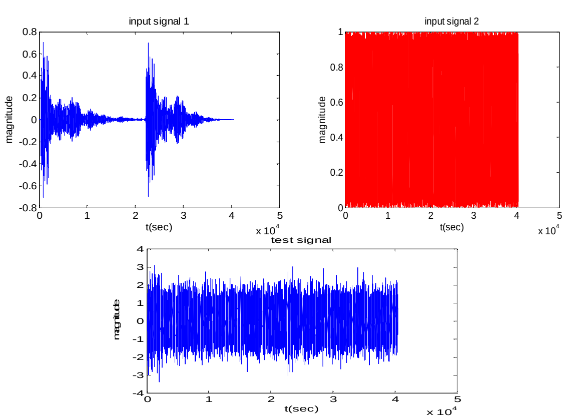
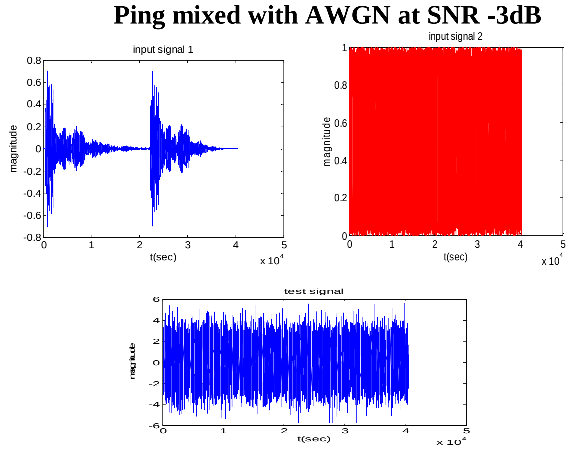


Fig. 8 Simulation results of Chirp signal mixed with AWGN at SNR 3dB

Ping mixed with AWGN at SNR 3dB



Ping mixed with AWGN at SNR -3dB



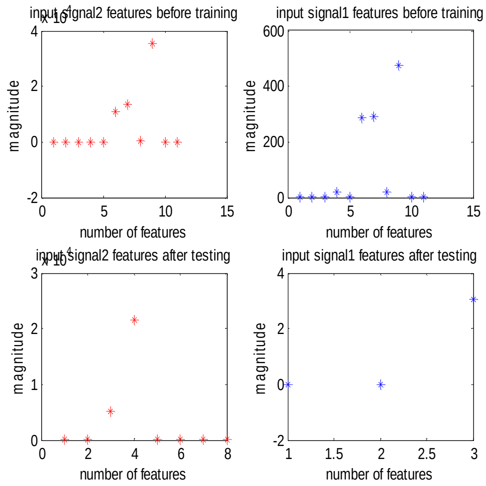


Fig. 9 Simulation results of Ping signal mixed with AWGN at SNR 3dB

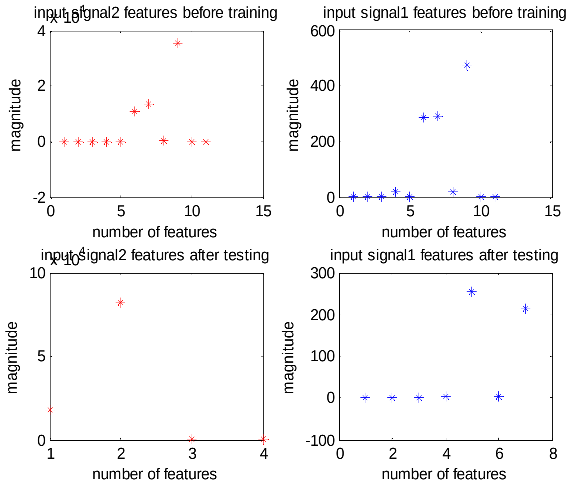


Fig. 10 Simulation results of Ping signal mixed with AWGN at SNR -3dB

CONCLUSION

In target detection, classification plays a major role. As a classifier Adaptive Boosting algorithm is of robust in nature and simple to construct. So an attempt is made that by using this classifier, the problem of de-noising is achieved through this AdaBoost classifier.

The simulation results of various mixed signals which are used in different scenarios are given as input to the classifier and the results are shown. We have separated the signal and noise features by using this classifier. By this, Adaptive Boosting Technique can also be used in signal de-noising.

This Adaptive Boosting Technique can be used in conjunction with other algorithms to improve the performance. This technique is used in the applications such as face detection, character recognition, data mining, license plate detection, text detection, and in classification of signal.

REFERENCES

[1] Kusma Kumari Cheepurupalli and Raja Rajeswari Konduri, *Noisy Reverberation Suppression Using AdaBoost Based EMD in Underwater Scenario* (Thesis), Department of ECE, College of Engineering, Andhra University, Visakhapatnam, India, International Journal of Oceanography, **2014**, Article ID 563780.
[2] Yoav Freund and Robert E Schapire, *A Short Introduction to Boosting*, AT&T Labs Research, Shannon Laboratory, 180 Park Avenue Florham Park, NJ 07932, USA, **1988**.
[3] LG Valiant, A Theory of the Learnable, *Communications of the ACM*, **1984,** 27(11), 1134.1142.
[4] Michael Kearns and Leslie G Valiant, *Learning Boolean Formulae or Nite Automata is as Hard as Factoring*, Technical Report TR-14-88, Harvard University Aiken Computation Laboratory, **1988.**
[5] Anurag Kumar, Parul Agarwal, Pranay Dighe, Subhali Subhechha Bhiksha Raj and Kishore Prahallad, *Speech Emotion Recognition by AdaBoost Algorithm and Feature Selection for Support Vector Machines*, **2015**, *http://www.academia.edu/2899315.*