

Classifying Acoustic Transient Signals Using Artificial Intelligence

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Abstract

Submarines need to identify hazardous projectiles with speed and accuracy. One method of identifying possible dangers is the process of using passive sonar. Passive sonar is the practice of listening for abnormal anomalies. This paper describes multiple Artificial Intelligent methods of classifying acoustic transients. In addition, we address localization of transients (i.e., determining the location of signal within a dataset).

Purpose

This paper presents results of research on Acoustics Transient Signals (ATC). Specifically efforts to detect, localize and classify exemplar analog signals are discussed.

The signals used in this research consist of three classes of Acoustic Transients generated using Eq. 1, 2, and 3 [1].

$$\text{Class 1} = c1(\alpha_1, \kappa) = \exp(-\alpha_1 * |\kappa - 64|) * \cos(100\kappa) \quad (1)$$

$$\text{Class 2} = c2(\alpha_2, \kappa) = \exp(-\alpha_2 * |\kappa - 64|) * \cos(150\kappa) \quad (2)$$

$$\text{Class 3} = c3(\alpha_3, \kappa) = \exp(-\alpha_3 * |\kappa - 64|) * \cos(180\kappa - \pi/8) \quad (3)$$

where κ is an integral value in the range $\kappa = [0, 127]$ and $\alpha_1 \in (0.23, 0.27)$, $\alpha_2 \in (0.13, 0.17)$, and $\alpha_3 \in (0.08, 0.12)$.

In an attempt to better achieve “real world” conditions Gaussian white noise (GWN) was added to each of the signals. The GWN was computed using Eq. 4.

$$\text{GWN} = \cos(2\pi R) * \sqrt{-2 * \ln(R)} \quad (4)$$

where R is a random number in the range $[0, 1]$.

Examples of the raw and noisy signals are shown in Figures 1, 2, and 3.

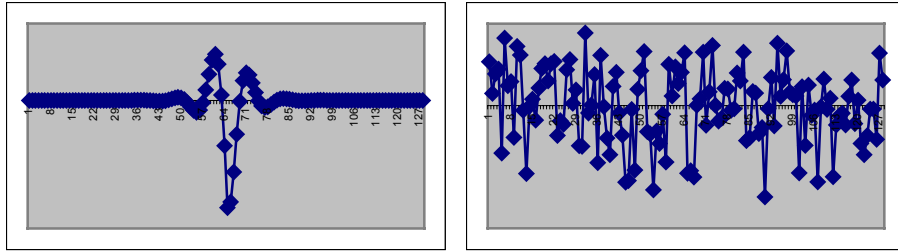


Figure 1. Class 1 Raw and Noisy Signal.

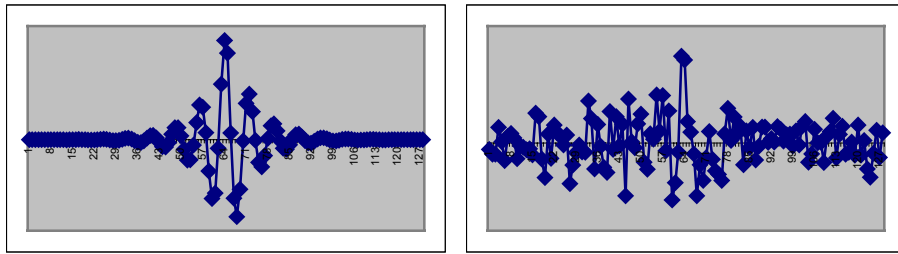


Figure 2. Class 2 Raw and Noisy Signal

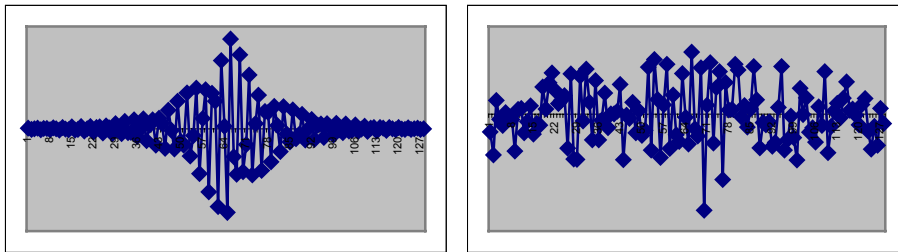


Figure 3. Class 3 Raw and Noisy Signal

Signal localization, determination of the signal location within a set of data, was achieved through the use of a mathematical convolution operation within the process illustrated in Figure 4.

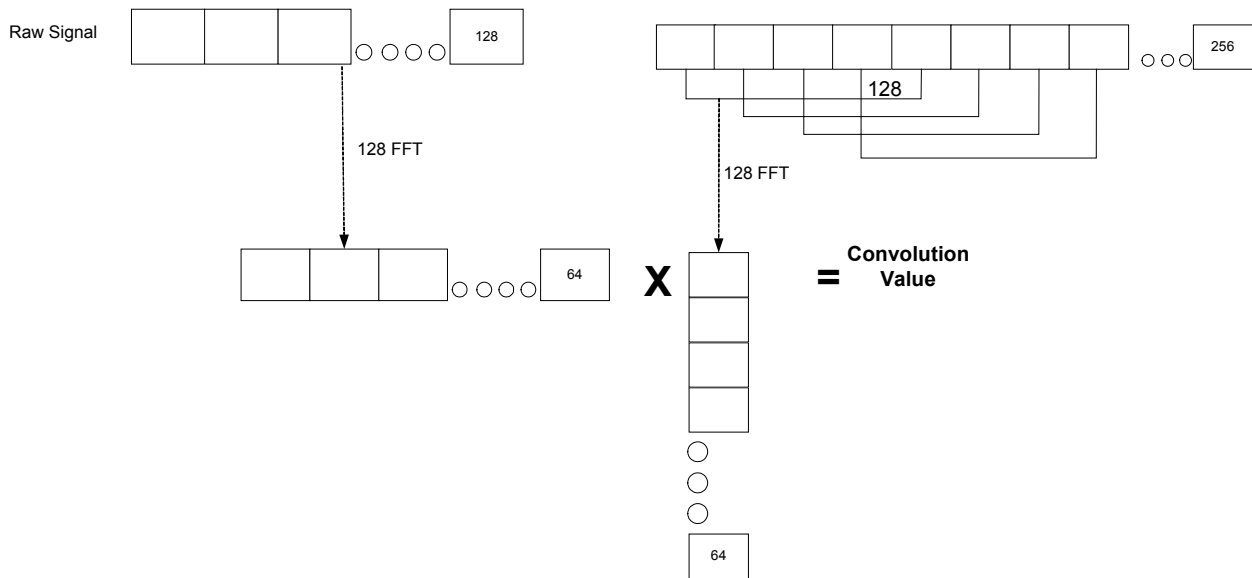


Figure 4. Signal Localization

The process compares Fast Fourier Transform (FFT) [3] data generated for a known signal class with that of the unknown data set. To do this a virtual “window”, or subset of data, of length n (the size of the known signal) is extracted from the unknown signal data set. FFT data is generated for the unknown signal data and the product (i.e., convolution) of the known signal vector and the unknown signal vector is calculated resulting in a signal value. The process is repeated using the next “windowed” set of data from the unknown signal until the data set is exhausted. The “windowed” section resulting in the highest value is considered to be the area in which the signal is most likely present.

For classification purposes a measure of total power was chosen as the feature for which each signal would be evaluated. The feature extraction process for each signal is illustrated in Figure 5.

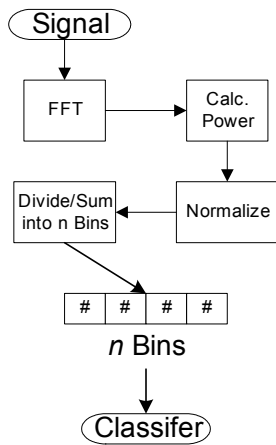


Figure 5. Feature Extraction

A Fast Fourier Transform was applied to each signal taking the signal from the time domain to the frequency domain. From the transformed data, power values were calculated according to Eq. 5.

$$power = real^2 + imaginary^2 \quad (5)$$

The power values were normalized and compressed into a total power vector. The total power vector was calculated by dividing the normalized data into n sections where each section is represented as a bin value in the total power vector. The bin values are calculated according to Eq. 6.

$$bin[j] = \sum_i^n power[i] \quad (6)$$

The total power vector generated for each signal is used as input to the classifiers.

Methods

Bayesian Neural Network

Bayesian decision theory is a fundamental statistical approach to the problem of pattern classification. It approaches the problem of classification from the probabilistic standpoint and the cost associated with each decision. This approach assumes that some a priori probability about each class is known [2].

For each known class there exists a corresponding discriminant function shown in Eq. 7.

$$g_i(x) = -\frac{1}{2}(x - \mu_i)^t \Sigma_i^{-1} (x - \mu_i) - \frac{1}{2} \ln |\Sigma_i| + \ln P(\omega_i) \quad (7)$$

where x is the unknown class vector, μ is the class mean vector, Σ is the covariance matrix, $|\Sigma|$ is the determinant of Σ , and $P(\omega)$ is the class a priori probability.

Classification of unknown classes involves several steps. First, exemplars for each known class are collected. Second, a priori probabilities are determined for each class. Third, using this data a set of discriminant functions is created. Finally, the unknown class vector is feed to each discriminant function. The class of the function resulting in the highest value is assigned as the class of the unknown.

Feed Forward Neural Network with Back Propagation

The feed forward neural network with back propagation uses the normalized calculated mean vector for inputs. The network is configured using the number of bins as the total number of inputs, one hidden layer with two nodes, and three output nodes as shown in Fig. 6. Each input corresponds to a bin of the total power vector and the output layer nodes correspond to a Class

Signal. The bias for all hidden nodes and output nodes is set to be equal to 1 and every edge in the network has a respective weight.

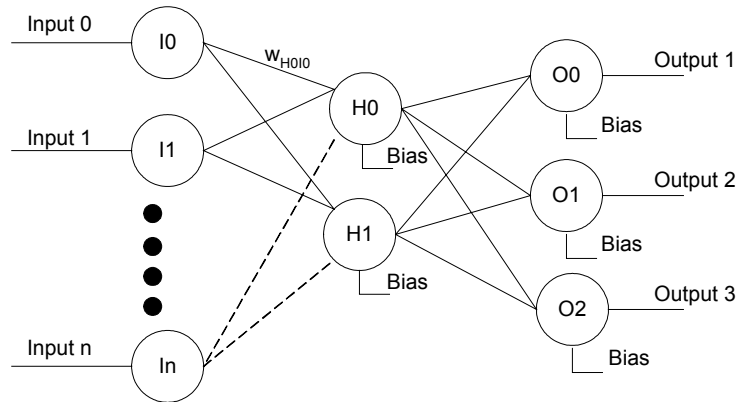


Figure 6. Feed Forward Neural Network

The Feed Forward Neural Network (FFNE) is trained using the five alpha values for every signal to equate to a total of twenty-five known noisy signals. The process for training the network follows the flow in Figure 7. The output nodes are trained to $o = 0.1$ for a losing node and $o = 0.9$ for a winning node. The completion of training is determined once the Root Mean Squared Error (RMSE) has surpassed the appropriate threshold. This implementation was optimized with the threshold equal to 0.79.

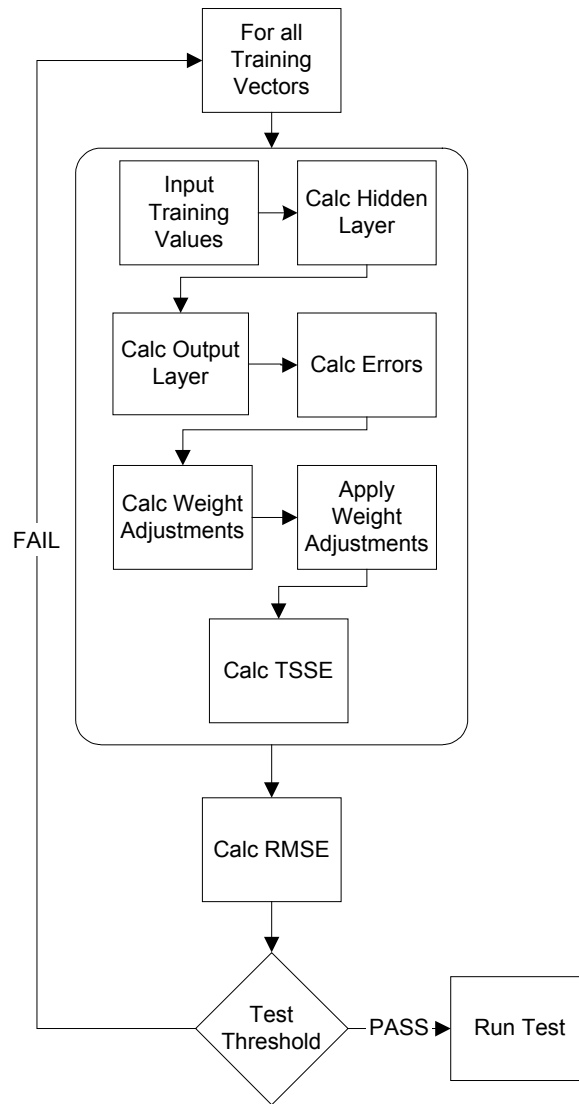


Figure 7. Feed Forward Network Process Flow.

Once the FFNE has completed training, noisy test signals of known classes are tested on the network. The number of test signals is configurable, and the class definition can be either random or defined. The winning decision is determined as the class whose corresponding output node equals $o = 0.9$. The network classifies each signal and provides a percent accuracy for signals correctly identified.

Kohonen Neural Network

The Kohonen network is an unsupervised approach of classification. The network consists of inputs and a network map as shown in Figure 8. Each input corresponds to a bin of the total power vector and the output layer nodes correspond to a class signal. The network map comprises of three class neurons. A class neuron is said to be either the single winning neuron of the map or a losing neuron.

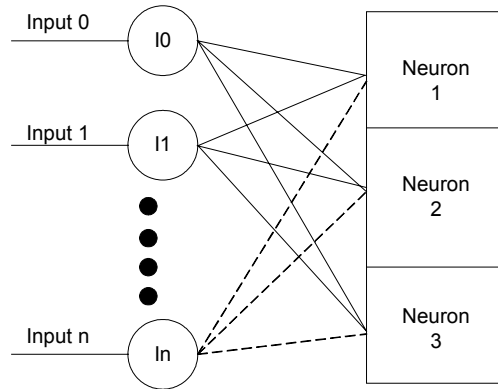


Figure 8. Kohonen Network configuration

The input vectors are normalized to the range of $[-1, 1]$. The network is trained using a known training set consisting of the five alpha values for every signal to equate to a total of twenty-five known noisy signals. The network is considered trained once either the error rate has been achieved or the change in error has changed by an insignificantly small amount. If the change in error is insignificantly small then the network is aborted and the weights are randomly reassigned and training begins again. This implementation used a learning rate equal to $\alpha = 0.2$ and max number of retries equal to 10,000. The process used for training is shown in Figure 9.

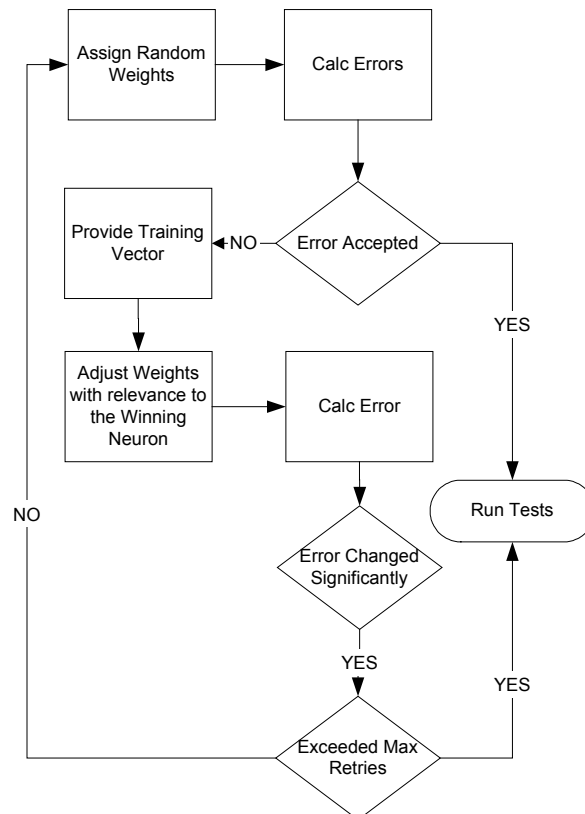


Figure 9. Kohonen Network Training Process Flow

Once the Kohonen Network has successfully completed training, noisy test signals of signals of known classes are tested on the network. The number of test used in this implementation is $n = 10,000$. The number of test signals is configurable, and the class definition can be either random or defined. The resulting neuron map produces an ON or OFF value for each neuron in the map, with the neurons set to ON not to exceed $n = 1$. The network classifies each signal and provides a percent accuracy for signals correctly identified.

Adaptive Resonance Theory 2 (ART2)

An ART2 network is a neural network approach of classification [4]. This class of neural networks is a self-organizing pattern recognition code that responds to a random sequence of analog inputs. The network consists of inputs, in this case bins of the total power vector described above, and a network map as shown in Figure 10. An ART2 network is comprised of 2 subsystems: the F1 or STM (short-term memory) and F2 or LTM (long-term memory).

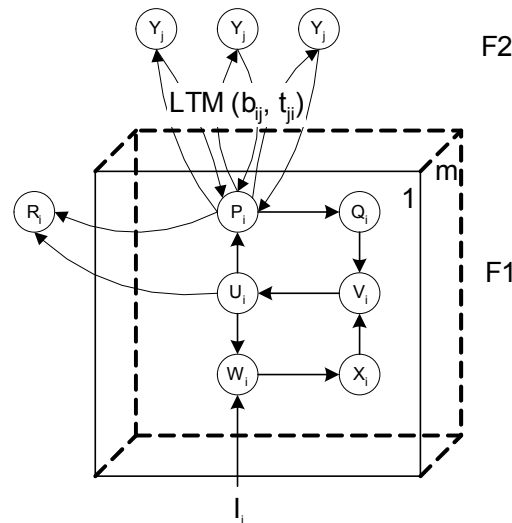


Figure 10. Example ART2 Network

The F1 layer is made up of m number of neurons where m is the dimension of the input vector. Each neuron of the F1 layer consists of 6 units (W , X , U , V , P , and Q). The primary function of the F1 layer is normalization of the input signal. To accomplish this function noise is filtered from the input through accentuation of the salient portions of the input and suppression of the noise. Once the input is normalized it is compared with learned patterns in the F2 layer using weights in the LTM.

The F2 layer is made up of n number of neurons where n is the number of learned patterns and a set of weights (bottom-up and top-down) connecting each F1 layer neuron to each F2 layer neuron. It serves as a competitive F2 layer whereby the winning pattern is chosen by the F2 neuron with the highest activation calculated using the LTM weights. A vigilance parameter ρ and the unit R are utilized to enforce a level of similarity between learned patterns.

Results

Testing was performed on all four pattern recognition classifiers including: Bayesian, Feedforward Neural Network with Back Propagation, Kohonen Neural Network, and Adaptive Resonance Theory 2 (ART2). The results are summarized in Table 1.

Classifier	Nominal Accuracy (%)
Bayesian	70
Feedforward Neural Network (1 Hidden Layer, 2 Nodes/Layer, 3 Outputs)	70
Kohonen Neural Network	65
ART2	85

Table 1. Classifier Performance

Conclusions

Evaluation of the data shows that of the classifiers tested the ART2 methodology performed the best with a nominal accuracy of 85%. In addition to greater accuracy, ART2 is more flexible in terms of adaptability given that additional classes can be introduced to the network without the need to completely retrain. This capability is not afforded to the other classifiers. Future work will focus on extraction of additional transient features to improve the accuracy of the classifiers. Such features may include data obtain through the use of Wavelet transforms. Additionally, the present Feed Forward Network was implemented using one hidden layer with two nodes per hidden layer. The effect of adding additional nodes will be investigated. An evaluation of Principal Component Analysis will also be conducted.

Reference

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