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Artificial neural network based temporal processing of waveforms to detect military impulse noise

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ABSTRACT

Civilian noise complaints and damage claims have created the need for stations to monitor military impulse noise. However, the stations currently in service suffer from numerous false positive detections (due to wind noise) of impulse events and often miss many events of interest. To improve the accuracy of military impulse noise monitoring and in a continuation of previous efforts, an algorithm based upon an artificial neural network classifier with inputs of temporal characteristics of collected waveforms is proposed. To train and evaluate the noise classifier approximately 1,000 waveforms were field collected. In addition to evaluating the performance of such a classification method, networks constructed of both conventional sigmoidal activation function neurons and saturating linear neurons were evaluated. The use of linear saturating neurons may provide a more computationally efficient method of classification in an actual DSP implementation of this algorithm. The proposed classifiers performed to accuracies of up to 100% on the testing and validation data.

1. INTRODUCTION

In the interest of maintaining a good relationship with surrounding communities, monitoring the levels of high amplitude impulse noise produced at military installations has become of great interest in recent years[1]. Monitoring combined with analysis of the collected data allows military officials to better schedule training exercises likely to disturb the surrounding communities to times and conditions where community annoyance can be minimized. Monitoring also allows officials to validate or refute noise complaints and damage claims that may occur in the surrounding areas[2].

Several noise monitoring programs have been in service since the mid-1980's[3]. However, the main problem with all of the systems has been false event detections due to wind noise passing over the measurement microphones and the inability of the monitoring stations to detect events, particularly those with comparatively lower peak sound pressure level values (<119dB). Several noise monitoring efforts utilizing multiple microphones have produced detection methods with a significant degree of accuracy. However, many military impulse noise monitoring systems currently in service utilize only one measurement microphone. These stations rely on an incoming waveform complying with a specific set of temporal conditions. In

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the interest of cost savings, it is proposed that a new impulse detection/non-impulse rejection algorithm could be developed to retrofit these older monitoring stations without major hardware upgrades. In previous efforts, great success has been achieved with artificial neural network and Bayesian classifiers using a combination of traditional acoustic metrics and custom spectral-based metrics as inputs[4-6]. The waveforms that these classifiers were trained and evaluated on comprised a data library consisting of military impulse noise (various weapons observed from several ranges under multiple conditions) and commonly encountered non-impulse sources (wind and aircraft noise). Upon visual examination of the waveforms in this library, it became apparent that, after viewing the plotted waveform of a few examples of each type of noise source, an observer could easily identify which class of noise a waveform belonged to based on the shape of the waveform. It was then hypothesized that if this task could be easily carried out by a human operator with little training, an algorithm based on the same principles could be developed. Thus the aim of this effort is to develop an algorithm to identify military impulse noise based purely on the shape of the observed waveform.

2. TEMPORAL PROCESSING OF WAVEFORMS

A. Data Collection

As described in the previous body of work[4-6], approximately 1,000 usable waveforms were field collected to train and evaluate classifiers. Within the data set, there were 330 waveforms of military impulse noise, 560 waveforms of wind, and 110 waveforms of aircraft noise. Of the 330 recordings of military impulse noise, 66 contained more than one impulse event within the 2.1 to 2.5 second recording. The military impulse noise recordings consisted of 155mm Howitzers, 81mm mortars, 60mm rockets, M67 hand grenades, and Bangalore Torpedoes (strings of 3, (27lbs HE)). The military impulse noise records had L_{pk} values ranging from 80 to 138dB. The non-impulse noise records were wind noise and aircraft noise (F-16, A-10, C-130). The military impulse noise recordings were made at ranges between 1.5 km and 6 km from the noise sources and military aircraft noise recordings were made at distances of approximately 0.5 to 8 km. Although most of the energy of the noise sources to be measured is within the 0 to 100 Hz bandwidth[7,8], the data were sampled at 10 kHz to verify that no key features in the higher frequency range were being neglected, primarily with the non-impulse noise. Data were also measured at a variety of different locations and under a variety of different conditions in attempt to witness the largest array of factors that may affect the data.

B. Observation and generalizations from collected waveforms

Figures 1 through 3 show typical examples of military impulse noise, wind noise, and aircraft noise. Casual observation of a few examples of each type of would most likely yield highly accurate classification of any additional waveforms presented to a human observer. While this classification is a simple task for humans to perform, development of a set of rules for a classification algorithm to abide by may not be quite so trivial. A human observer does not rely specifically on each data point within a waveform to produce a judgment. Alternatively they make a generalization based on the approximate distribution of data points. It is hypothesized that an artificial neural network can be taught to do the same.

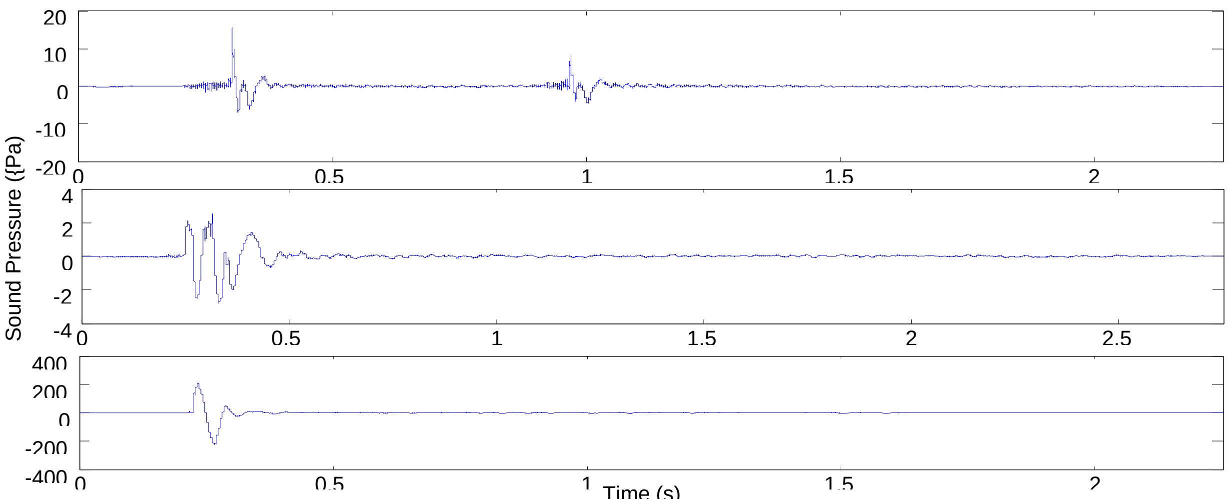

Figure 1: (top) 2 81mm detonations at 2km, (middle) 155mm high explosive round detonation at 6 km, (bottom) 3 Bangalore torpedoes at 2.5 km

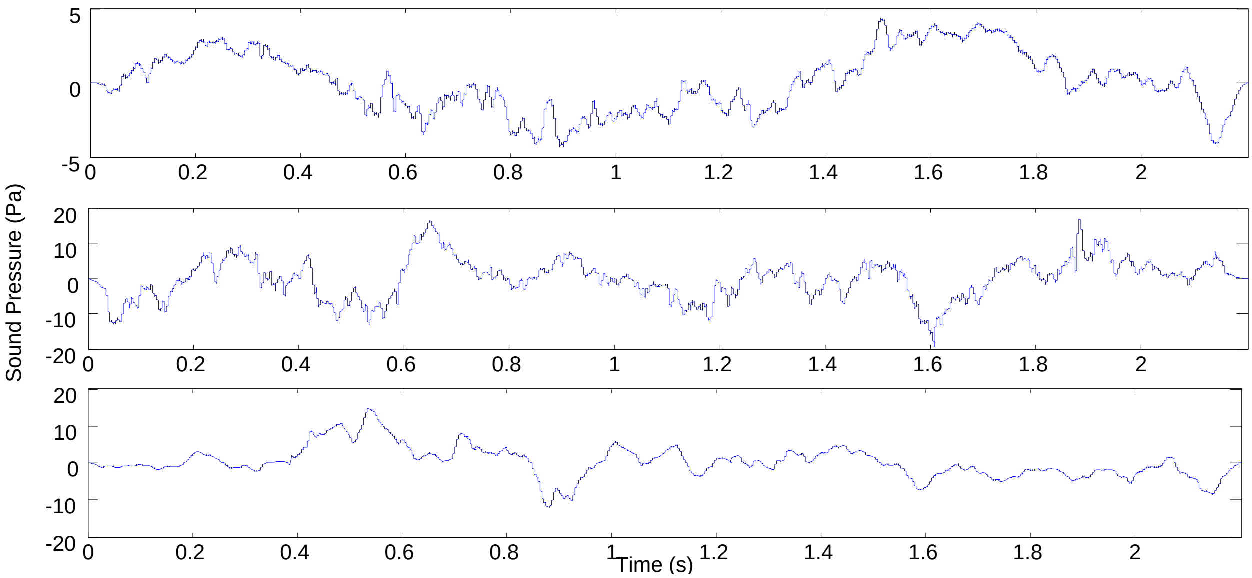

Figure 2: 3 recordings of wind noise

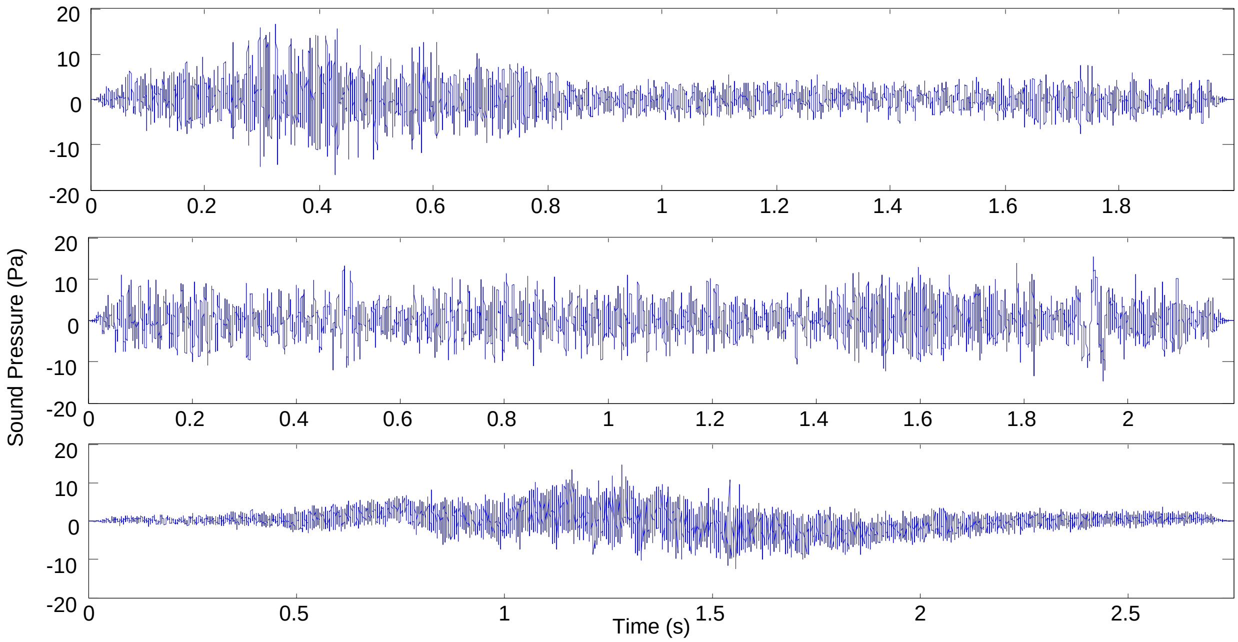

Figure 3: (top) F-16 flyover, (middle) F-16 flyover, (bottom) A-10 flyover

C. Data Pre-Processing

As previously mentioned the data were sampled at 10kHz to verify that no features within the higher frequencies were being passed over. The waveforms were then decimated by a factor of 10 to simplify processing while retaining the shape of the waveform. When a waveform is decimated from 10kHz to 1kHz the Nyquist frequency is moved from 5kHz to 0.5kHz. To verify the assumption that most of the signal features would be retained in the decimation process, the amount of signal energy retained after decimation was estimated using equation 1. Figures 4 shows the un-decimated and decimated waveforms of a typical recording of military impulse noise. The decimated and un-decimated plots are virtually indistinguishable thus, there is no perceptible difference in waveforms after executing this operation. In addition to simplifying the processing of the collected waveforms, the current monitoring stations sample data at 1 kHz, indicating that the current hardware has sufficient fidelity for these algorithms.

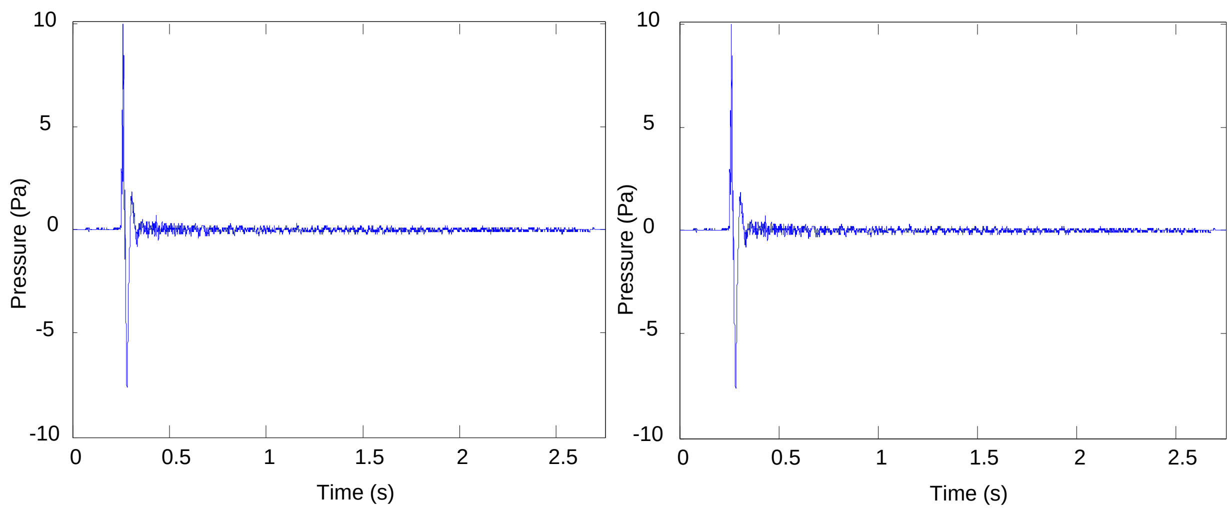

Figure 4: (Left) Recording of 155mm Howitzer at 1km sampled at 10kHz, (right) Recording of 155mm Howitzer at 1km sampled at 10kHz and decimated to 1 kHz

Temporal processing of the data set involves processing the input waveforms as an image. The first step is to normalize the image. This is done by finding the point in the waveform with maximum magnitude of sound pressure level and dividing values of the rest of the points in the waveform by this magnitude. This yields an image with a possible maximum value of 1 and possible minimum value of -1. This gives the classifier the ability to generalize waveforms of arbitrary peak level values. The final step is to discretize the normalized waveform into 100 bin grid placed over the waveform. The bin grid is 10 by 10 in structure and has equal widths in the horizontal and vertical directions (height of each bin is the scaled value of 0.2 and the width is 0.2 seconds). The feature set to be input to the artificial neural network is the number of data points that have mapped to each bin for a particular waveform. Figure 5 shows the computation of the feature set for a typical recording of military impulse noise.

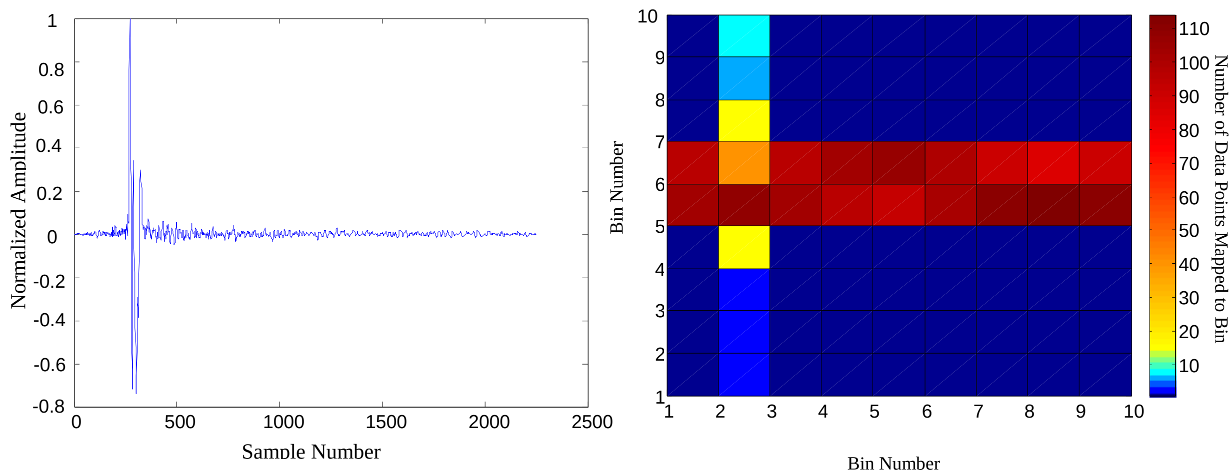

Figure 5: Computation of feature set for 81mm mortar recording

To control the number of inputs to the neural network structure and provide consistency across the slightly varying lengths of the recordings, only the first 2 seconds of each recording were considered for processing. Most considered events included a 0.25 second pretrigger thus, the effective lengths of the processed recordings were 1.75 seconds. This time length scale is deemed sufficient since most all military impulse events are completed within 2 seconds[9]. There is a possibility that the ends of some extremely large events could be missed by this method but, no such events existed in the library of recordings that were collected and the shape of the event that occurs within the set time window may already be sufficient to make a correct classification. In future efforts the time window may be extended.

D. Artificial Neural Network Processing

This classification problem is most likened to a static image processing type of problem, such as the printed character recognition problem[10,11]. This problem has been addressed in a variety of methods with a variety of different networks. In the case of this problem the type of network used is the feed-forward multi-layer perceptron trained with the back-propagation algorithm[12-14]. This network is most simple type of network and is deemed to be a good starting point for the investigation. Networks constructed of sigmoidal and saturating linear activation functions are investigated[12]. The reasoning behind the use of saturating linear neurons was that if a successful network could be constructed with sigmoidal neurons then, it may be possible to construct a network with saturating linear neurons. In an actual DSP implementation of this algorithm, saturating linear neurons may prove to be more computationally efficient than sigmoidal neurons.

Both networks consisted of 100 inputs, 2 hidden layers of 100 neurons each, and 1 output neuron. The 1000 input patterns were divided into a stratified random sample where half of the data were used to train the network, ¼ were used as validation data, and the remaining ¼ were used as testing data. The targets for the network consisted of values of 1 for records containing military impulse noise and values of -1 for records of non-impulse noise (wind and aircraft). In the case of both classifiers the decision threshold is set to zero. In an actual implementation of this algorithm, the decision threshold could be increased to make the classifier less susceptible to false positives, with the cost of more missed events, or the decision could be decreased to make the classifier more sensitive to military impulse noise, with the cost of more false positive detections. Both networks were trained for 2000 epochs using the gradient descent with momentum and adaptive back-propagation algorithm[14]. Table 1 shows the accuracy of the two configurations of artificial neural networks on the training, validation and testing datasets. It is noticeable that both networks performed extremely well on all three datasets. This indicates that the proposed classifier is capable of making accurate generalization about the origin of an acoustic waveform and has also not been over-fit to the set of training data. It is also seen that the sigmoidal neuron neural network and the saturating linear neuron neural network performed to approximately the same degree of accuracy. Thus the use of a saturating linear neuron neural network provides a comparable and possibly more computationally-efficient solution to this classification problem.

Table 1: Accuracy of artificial neural network classifiers with decision threshold set to zero

Neuron Type	**Training Accuracy**	**Validation Accuracy**	**Testing Accuracy**
Sigmoidal	100%	99.6%	99.6%
Saturating Linear	100%	98.8%	100%

Figures 6 through 11 show the activation of the output neuron of each network for each of the training, validation, and testing datasets. Training patterns containing military impulse noise are denoted by x and those training patterns of non-impulse noise are represented by o. In all cases a noticeable division of data types is seen. The greatest degree of separation of data types is seen in the training data sets. This is expected as the weights of the network are adjusted to minimize the error witnessed in this dataset specifically. The division of data types is still seen in the validation and testing datasets. This indicates that the networks are capable of making generalizations based on input patterns that are different than those used to train the networks.

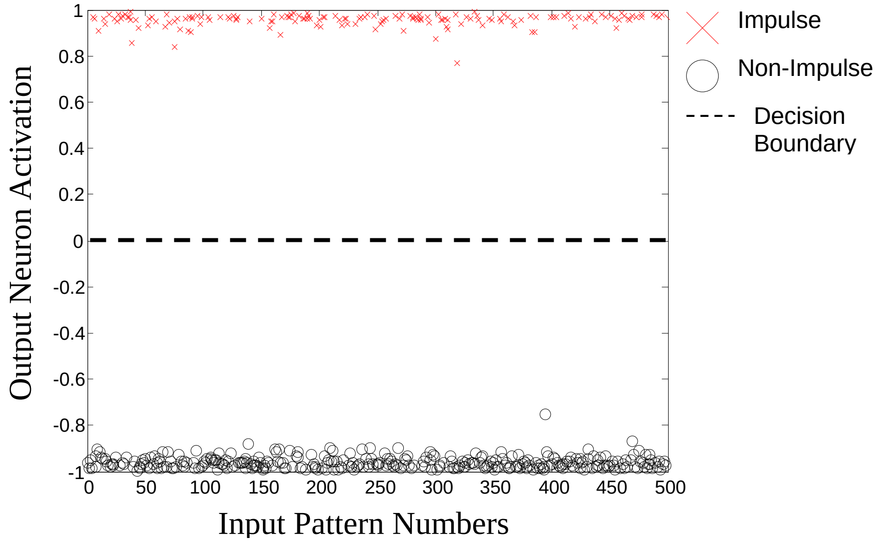

Figure 6: Output training patterns presented to sigmoidal neuron ANN

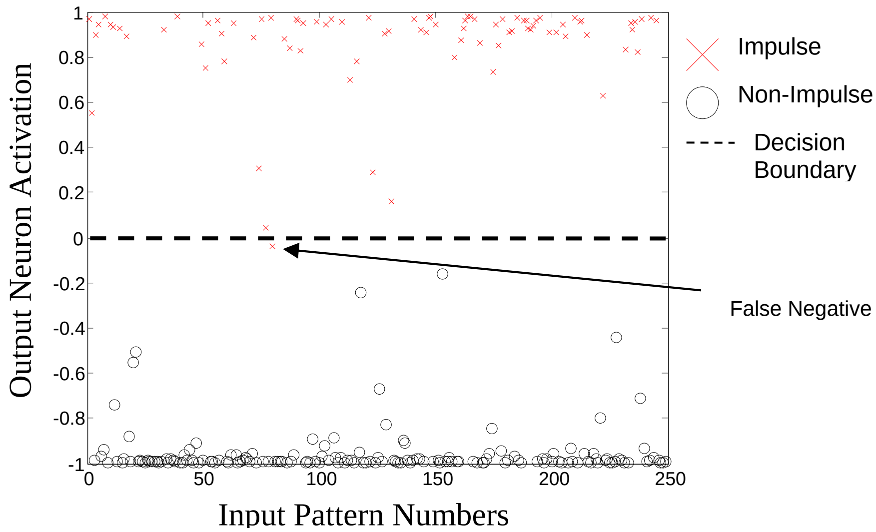

Figure 7: Output validation patterns presented to sigmoidal neuron ANN

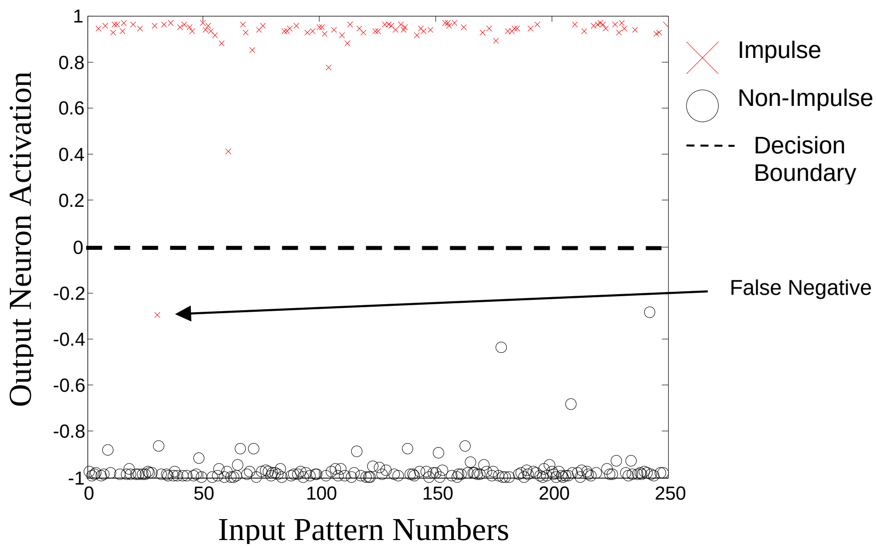

Figure 8: Output test patterns presented to sigmoidal neuron ANN

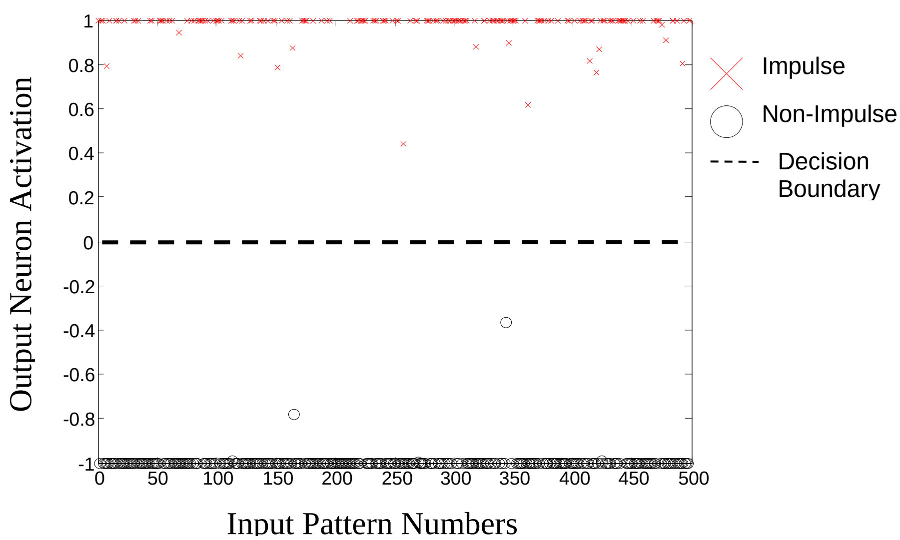

Figure 9: Output training patterns presented to saturating linear neuron ANN

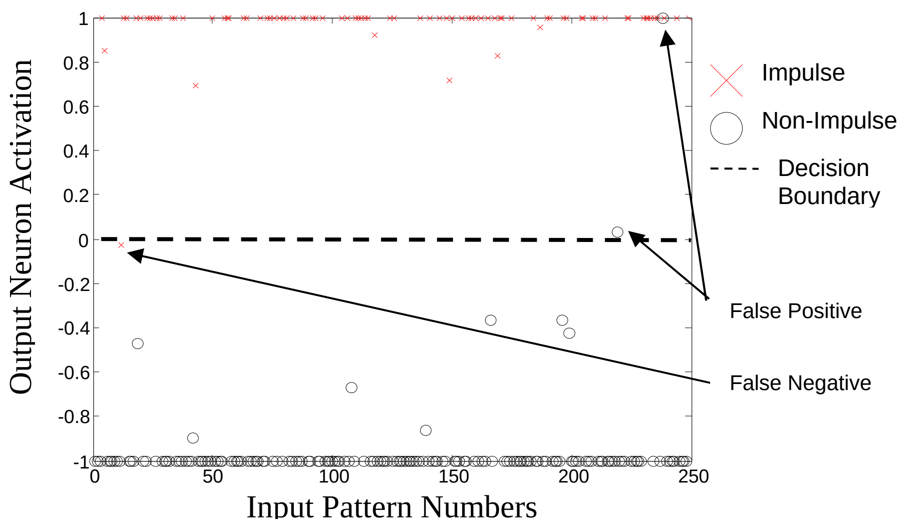

Figure 10: Output validation patterns presented to saturating linear neuron ANN

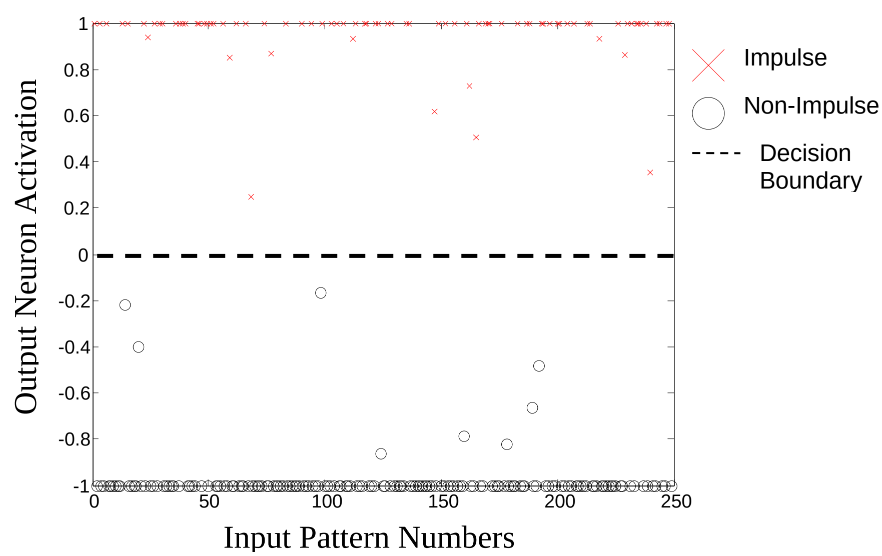

Figure 11: Output test patterns presented to saturating linear neuron ANN

3. CONCLUSION

To aid in the monitoring of the production of high amplitude military impulse noise around military installations an algorithm has been developed to identify military impulse noise from other noise sources. This algorithm has been developed to operate off of a single acoustic measurement location. In a continuation of previous work based on computed statistical and spectral metrics, a new artificial neural network based algorithm has been designed to operate from the temporal characteristics of collected waveforms. The artificial neural network is capable of making generalizations about the origin of a waveform based on the approximate shape of the waveform. In addition to evaluating the performance of a network constructed of sigmoidal activation function neurons and the performance of a possibly more computationally efficient saturating linear neuron neural network was compared to the former network. It was found that both networks are capable of producing near 100% accuracy on training, validation, and test datasets.

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