Implementation of a Neural Network Classifier for Noise Sources in the Ocean

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Abstract: The paper investigates the feasibility of implementing an intelligent classifier for noise sources in the ocean, with the help of artificial neural networks, using higher order spectral features. Non-linear interactions between the component frequencies of the noise data can give rise to certain phase relations called Quadratic Phase Coupling (QPC), which cannot be characterized by power spectral analysis. However, bispectral analysis, which is a higher order estimation technique, can reveal the presence of such phase couplings and provide a measure to quantify such couplings. A feed forward neural network has been trained and validated with higher order spectral features.

Keywords: Bispectrum, Bicoherence, Quadratic Phase Coupling, Neural Networks

1. Introduction

In underwater acoustic signal processing, the noise process is generally assumed to be a linear Gaussian process. Although, the Gaussian assumption is justified in many situations, statistical experiments on marine acoustic noise data indicate that the noise characteristics may deviate significantly from Gaussianity. Thus, feature extraction techniques based on these assumptions, fail to take into account the features arising due to various non-linear interactions.

As the marine noise classification is a challenging as well as potential field, the use of non-Gaussian and non-linear feature extraction techniques that could reveal many more hidden features, has gained considerable attention from the research community. This paper presents a method for the classification of marine noise sources using higher order spectral features, which arise due to the non-linear interactions of different components in a signal.

Conventional techniques like power spectral analysis have turned out to be a widely used feature extraction technique for detection as well as classification purposes. However, being a linear method, power spectral analysis cannot fully characterize the non-linear signals and the non-linear noise generating mechanisms. It also does not preserves the phase information contained in the signal, as opposed to the higher order spectral analysis, where the phase information is not destroyed during the processing. This calls for the use of nonlinear methods like higher order spectral analysis, in order to gain a more complete understanding of signal dynamics.

The bispectrum, which is based on the third order cumulant sequence of a signal, can play a key role in analyzing the nonlinearities of the underlying signal generating mechanisms, especially those containing quadratic non-linearities [1]. Due to quadratic nonlinearity, the phase coupling between the two frequency components of a process results in generating the signal power at their sum frequency as well. Such coupling affects the third order cumulant (moment) sequence and hence the bispectrum can be used in detecting such nonlinear effects. In the proposed method, an artificial neural network (ANN) is trained with self-coupling frequencies, which corresponds to the diagonal elements of the bispectrum matrix.

ANNs can be viewed as weighted directed graphs in which artificial neurons form the nodes and directed edges (with weights) form the connections between the neuron outputs and inputs [2]. With its learning capabilities, ANNs are evolving as a potential tool for solving classification problems.

2. Bispectrum and Bicoherence

For a time series. $\{x(n)\}$, $n = 0,\ldots,N$, with zero mean, the third-order cumulant is defined as [3]

$$C_{xx}(k,l) = E\{x(n)x(n+k)x^*(n+l)\}$$

The third-order cumulant holds an important property that makes it useful for the analysis of non-gaussian signals. Accordingly, all of the third-order cumulant of a Gaussian process are always equal to zero. The third order spectrum or the bispectrum $B(f_1, f_2)$ is defined as the Fourier transform of the third order cumulant.

$$\begin{aligned} B(f_1,f_2) &= \sum_{k=-\infty}^{\infty}\sum_{l=-\infty}^{\infty} C_{xx}(k,l)\exp(-j2\pi f_1 k) \\ &\quad *\exp(-j2\pi f_2 l) \\ &= E\{X(f_1)X(f_2)X^*(f_1+f_2)\} \qquad (1) \end{aligned}$$

However, it is found that, at the bifrequency (f_1, f_2), the complex variance is proportional to the product of the power of the signals [4] at the frequencies f_1, f_2 and (f_1+f_2).

i.e, $var[B(f_1,f_2)] \;\alpha\; P(f_1)P(f_2)P(f_1+f_2)$

Thus, in order to make the bispectrum independent of the energy content at the bifrequencies, another parameter called bicoherence is used.

Bicoherence, which is a normalized form of the bispectrum, can be defined as

$$bic(f_1,f_2) = \frac{|B(f_1,f_2)|}{\sqrt{P(f_1)P(f_2)P(f_1+f_2)}} \qquad (2)$$

Since the bicoherence is independent of the energy or amplitude of the signal, it can be used as a convenient test statistics for the detection of non-Gaussian, non-linear and coupled processes.

3. Quadratic Phase Coupling

When a complex harmonic process $u(t)$ with frequencies $f_1, f_2, \ldots, f_k$ and phases ϕ_1, ϕ_2, …, ϕ_k undergoes a nonlinear transformation such as $y(t) = u(t) + \alpha u^k(t)$, at least one new component with the sum frequency $\sum_{i=1}^{k} f_i$ and the sum phase $\sum_{i=1}^{k}\phi_i$ emerges in the output [5]. Such nonlinearities give rise to the so called k^{th} order coupling phenomena and can be detected by $(k+1)^{th}$ order polyspectrum.

Considering a process with two sinusoids $x_1(n) = \cos(2\pi f_1 n + \phi_1)$ and $x_2(n) = \cos(2\pi f_2 n + \phi_2)$ being passed through a nonlinear system (with k=2), the output signal $y(n)$ is given by

$$y(n) = x_1(n) + x_2(n) + [x_1(n) + x_2(n)]^2 .$$

$$
\begin{aligned}
y(n) = {} & \cos(2\pi f_1 n + \phi_1) + \cos(2\pi f_2 n + \phi_2) + 1 + \\
& \frac{1}{2}\cos(4\pi f_1 n + 2\phi_1) + \frac{1}{2}\cos(4\pi f_2 n + 2\phi_2) + \\
& \cos[2\pi(f_1 + f_2)n + (\phi_1 + \phi_2)] + \\
& \cos(2\pi(f_1 - f_2)n + (\phi_1 - \phi_2))
\end{aligned}
$$

As given in the above equation, the output signal $y(n)$ contain the components at $2f_1$, $2f_2$, $(f_1 + f_2)$ *and* $(f_1 - f_2)$ alongwith f_1 and f_2. $y(n)$ also exhibits certain phase relations and such non-linear interactions would give rise to a quadratic phase coupling at the bifrequency (f_1, f_2). In this paper, we take into consideration the special case, where f_1 is equal to f_2 which corresponds to the diagonal elements of the bicoherence matrix.

4. Neural Networks

Artificial Neural network (ANN), inspired by biological nervous systems, are composed of simple elements operating in parallel. The connections between elements largely determine the network function. A neural network can be trained to perform a particular function or task by adjusting the values of the connections (weights) between the elements. The capability of learning, the ability of generating arbitrary nonlinear functions of input, and the highly parallel and regular structure of ANNs make them especially suitable for designing various types of classifiers [6]. ANN is also superior in situations where it is difficult to quantify the statistical properties of the phenomena as in the case of noises generated by marine species.

The multilayer feed-forward network, often referred to as multilayer perceptron (MLP) [7] has been used as the neural classifier for the signals of the type described above. The network is composed of many neurons arranged in layers.

The feature vectors are applied to the input layer and the classification results are obtained from the output layer. Between the input and output layers, there can be many layers, called hidden layers. The synaptic connections in the network exist only among the neurons of two succeeding layers and the flow of the signals is feed-forward. All neurons in the hidden and output layers are characterized by activation functions.

The net input signal u_i of i^{th} neuron in the network is the weighted sum of the signals coming to this neuron.

$$
ie, \quad u_i = \sum_j w_{ij} y_j
$$

where w_{ij} denotes the weights, associated with the links connecting the node *j* with the node *i*, and y_j denotes the output of the j^{th} node. Thus, any change in the weights will affect the activity of the neuron and thus, of the whole network. At the training stage, the network adjusts its synaptic weights, according to the learning algorithm used, for gathering the features of the object.

To efficiently achieve this, one has to adapt the weights in such a way that the error measure for all the training input-output pairs is minimized. The training procedures of the MLP, applying the gradient methods, use the so called back propagation of the error and optimization methods to minimize the error function. On completion of the training, the weights are frozen and the network is ready for use.

In the classification mode, when an input vector *x* is fed to the input layer, the network generates the output vector *y*, composed of the activities of neurons in the output layer, indicating the membership of the input feature vector to the appropriate class. The output vector *y* generally contains one element of unity value indicating the appropriate class, while the other elements are equal or close to zero.

5. Methodology

5.1. *Framing and Bicoherence*

The given data waveform is sliced in to M records, of 10K elements, with overlapping. The bicoherence of each record is computed using eqn. (2). From the Bicoherence matrix thus obtained, with a size of 128x128, the diagonal as well as anti-diagonal elements are extracted and a vector of 256 elements is formed. This acts as the feature vector, and is used for training the neural network.

5.2. *Training the Neural Network*

A feed-forward network with back propagation algorithm, consisting of four hidden layers, all with a log sigmoid activation function was used for the simulation studies. The dimension of the input layer is equal to the number of features generated and the number of output neurons was set to the number of classes under consideration. The number of hidden layers was determined by trial and error for optimal performance. An increase in the number of hidden layers results in bad generalization of the network, while very few hidden layers affected the learning process, and resulted in inefficient learning.

The neural network was trained with the feature vectors generated. Another network, with similar properties, was also trained with log of the diagonal vectors. The performances of the two networks were evaluated and compared. The whole process of feature extraction and training has been illustrated in Figure. 1.

5.3. *Classification*

After the training phase, the performance evaluation of the classifier was carried out with three types of record sets. In the first case, the network was fed with a single record of 10240 elements, and the success rate was noted. In the second case, average of the two consecutive records (of 10240 samples each) was used. The third test case is similar to the second one, except for the fact that three consecutive records were used instead of two.

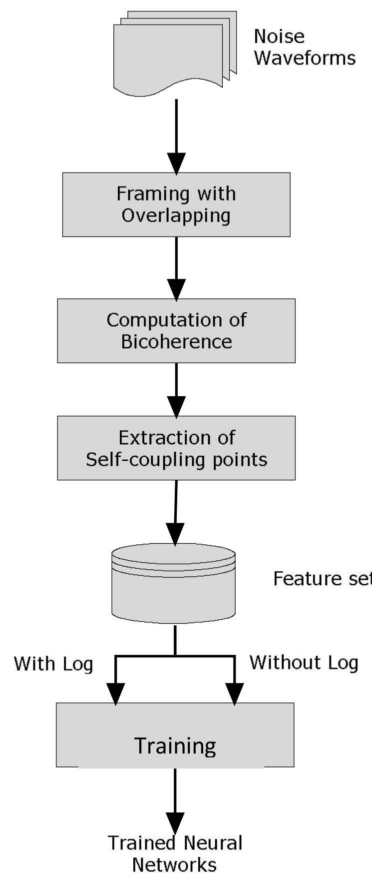

Fig. 1 Feature extraction and training

6. Results and Discussions

The noise data waveforms were sliced into overlapping records of 10240 samples each and the bicoherence matrix for each record was

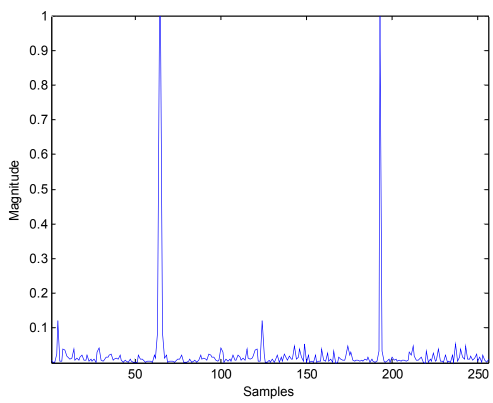

Fig. 2 (a) Plot of the diagonal and anti-diagonal elements of a record of ship noise

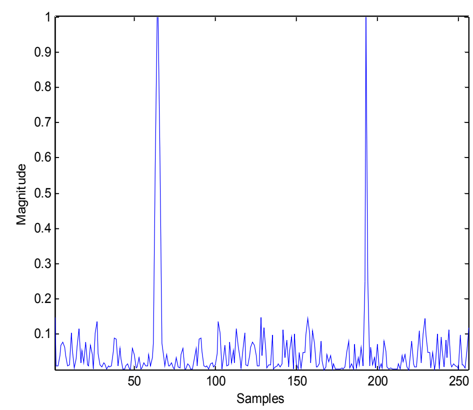

Fig. 2 (b) Plot of the diagonal and anti-diagonal elements of a another record of ship noise

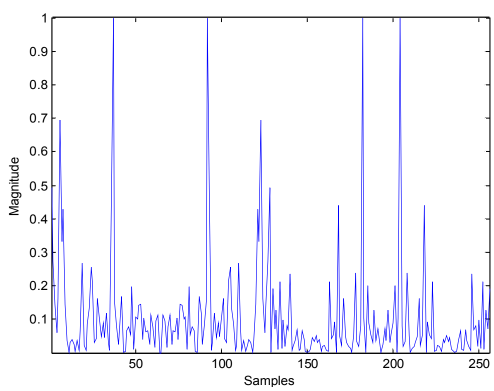

Fig. 3 (a) Plot of the diagonal and anti-diagonal elements of a record of boat noise

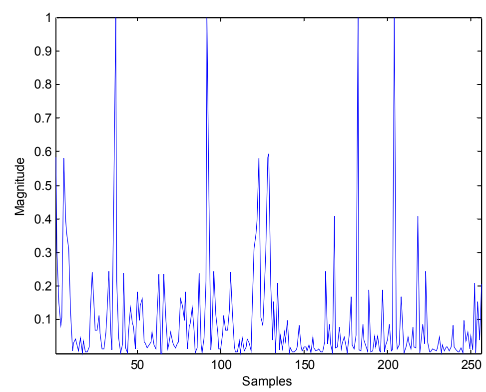

Fig. 4 (b) Plot of the diagonal and anti-diagonal elements of another record of boat noise

computed. The diagonal as well as anti-diagonal elements were extracted for gathering the self coupling components, which together constitute the feature set. Figures 2 (a) and 2 (b) show the typical plots of the diagonal and anti-diagonal elements of the bicoherence matrix computed from two different records of a ship noise, while Figures 3(a) and 3(b) show the plots for two records of boat noise.

Initially, the network was trained by considering only half the elements of the feature vectors, which corresponds to the diagonal elements only, ignoring the anti-diagonal elements. Performance of the network was evaluated and the average success rate was found to be less than 60%. Hence for improving the success rate of the system, the complete feature set was made use of, for the rest of the simulation studies.

Table 1. Performance comparison (in percentage)

	With single record	Mean of 2 consecutive records	Mean of 3 consecutive records
Without Log			
Consecutive training set	60.98	65.66	66.00
Random training set	69.23	78.31	78.00
With Log			
Consecutive training set	61.53	71.08	77.33
Random training set	78.00	84.00	83.33

The neural network was trained with two types of data. The first set of data pertains to the one with the original feature sets while the second one pertains to the log of the feature sets. In each case, the network was trained separately using two different sets of features, viz, one with 10 consecutive records and the other with 7 random records. The ten consecutive records for training was generated from the initial segments of noise data waveforms, while the 7 random records generated could span the whole wave form.

Performances of both the networks were evaluated with the three test cases, and the results are tabulated in Table 1, for a total of 16 targets. The three test cases corresponds to a single record of 10K samples, average of two consecutive records of 10K samples each and the average of 3 consecutive records of 10K samples each. It has been observed that, the performance has improved when the log of the feature set was applied. It was also noted that, when trained with random records, the network exhibits better performance. This may be justified, since the random training set can encompass more variations in the signal, when compared to consecutive training sets.

7. Conclusions

Bicoherence, a normalized form of bispectrum whose variance is independent of the energy content of the signal can play a key role in the analysis of acoustic noise sources. A properly trained neural network, with diagonal and anti-diagonal elements, can have acceptable success rates for classifying noise sources in the ocean.

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