Wavelet-Based Hybrid Neurosystem for Feature Extractions, Characterizations and Signal Classifications

Chung T. Nguyen  Sherry E. Hammel  Kai F. Gong
Naval Undersea Warfare Center Division Newport
Newport, Rhode Island 08241

Abstract

This paper presents an efficient method for signal classification from a system of multiple artificial neural networks (ANN) using wavelets. The method performs feature extraction via the wavelet transform of the underlying signal and presents the resulting coefficients to a hybrid neural network for classification. The hybrid network consists of three single neural networks; two of the networks are provided with magnitude and location information of the coefficients, and are trained with self-organizing rules. Their outputs are then presented to the third network for pattern recognition and classification. Experimental results illustrating concept feasibility for acoustic signal classifications are included in this paper.

1: Introduction

Signal classification involves the extraction and partition of feature of targets of interest. In many situations, the problem is complicated by the uncertainty of the signal origin, fluctuations in the presence of noise, the degree of correlation of multi-sensor data, and the interference of nonlinearities in the environment. Research and studies in the past have focused on developing robust and efficient methods for signal classification, many of which have been developed from traditional signal processing techniques [Oppenheim, 1978] and artificial neural network technology [Minsky, 1969], [Duda and Hart, 1973], [Lippmann, 1987]. In recent years, wavelets and their applications in classification problems have been explored and their results have shown significant advantages over these aforementioned alternatives [Huynh and Greene, 1993].

Inspired by the works on signal classification using wavelets performed by Huynh and Greene (1993), in this paper, a wavelet-based hybrid neurosystem is designed and introduced. Wavelet techniques are very suitable for signal analysis such as feature extraction and compression because of their good localization properties both in time and frequency. In addition to utilizing wavelets for feature extraction, a self-organizing feature map is employed as a basic building block in the information-processing infrastructure of the neural system. The self-organizing system provides a topographic map of the input patterns to the main neural network for classification. With a new architecture model, this hybrid neurosystem significantly enhances the performance of pattern recognition and classification. The system's architecture is presented in the next section.

2: Wavelet-Based Hybrid Neurosystem Architecture

2.1 System Architecture Overview

Depicted in Figure 1 is the layout of the wavelet-based hybrid neurosystem for signal classification. Here, the system receives and segments sensory data generated by some source of information. Then a set of features characterizing the sensory data via its wavelet transformation is extracted. Based on the characteristics of the underlying signal, different kernel functions in the wavelet library can be selected for obtaining the optimal wavelet transform. With the aid of coefficient selection algorithm, principal component analysis is then performed on the wavelet coefficients to compress the size of input patterns, thus reducing the computational complexity for the neural network classifier [Nguyen et al, 1995]. The principal components, i.e., magnitudes and locations in the time-frequency domain, are presented as inputs to the hybrid neurosystem. This consists of a parallel array of hybrid neural networks to classify the features into multiple distinct categories, which are then put into a global context for an end user. Each hybrid network consists of three separate ANN's, two of which are self-organizing to characterize the topographic map formation of the wavelet coefficients' magnitudes and locations, and the other uses back-propagation training algorithm to classify these features into different categories.
2.2 Discrete Wavelet Transform and Principal Component Analysis

A wavelet is a bandpass filter with the additional time (or space) localization capability [Chui et al, 1994]. The bandwidth and center frequency of this filter, as well as the width of its time (or space) localization-window are adjusted by changing the values of the dilation parameter. Wavelet decomposition of a function $f_M(x)$ can be expressed as:

$$f_M(x) = \sum_{jk} c_{jk} \psi_{jk}(x)$$  \hspace{1cm} (1)

where $c_{jk}$ is the wavelet coefficients and $\psi_{jk}(x)$ is the wavelet function. Indices correspond to frequency and location are $j$ and $k$, respectively. Depicted in Figure 2 is an illustration of the wavelet transform of a signal $f_M(x)$ using Daubechies orthogonal wavelet function. With this operation, the information of the function $f_M(x)$ at a given location and time is contained in the wavelet function $\psi_{jk}(x)$. However, with the Fourier transform, information of the time location is lost (see Figure 2). Furthermore, because the information content of the function $f_M(x)$ is approximated in the finite sequence of the coefficients $c_{jk}$, principal component analysis can be performed for dimensionality reduction by using wavelet coefficient selection algorithms [Nguyen et al, 1995]. The number of features needed for effective data representation is selected by discarding those wavelet coefficients that are insignificant (small or zero magnitude) and retain only those with significant magnitude. The threshold level for selecting such coefficients can be global (i.e., one threshold for all wavelet decomposition levels), or local (i.e., multiple thresholds, one for each decomposition level) depends upon the nature and characteristics of the underlying signal, and the requirement of the neural network architecture.

Figure 1 - An overview of wavelet-based hybrid neurosystem for signal classification

Figure 2 - Wavelet transform of signal $f_M(x)$ versus its Fourier transform (in term of energy)
2.3 Hybrid Neurosystem Architecture

The cornerstone of the entire system is the hybrid neurosystem classifier. As mentioned in the previous section, the hybrid system consists of three separate ANN's, namely, the magnitude network, the location network, and the classification network. The configuration of the hybrid system is depicted in Figure 2.

![Network configuration of a hybrid neural network](image)

Figure 3- Network configuration of a hybrid neural network

2.3.1 Feature Extraction Networks

Here, both magnitude and location ANN's are used in the first stage of the hybrid neurosystem. Principal components of the signal, i.e., magnitudes and time-frequency locations, will be presented to the magnitude and location networks, respectively. These networks, known as self-organizing systems, are one-layer networks based on unsupervised and competitive learning. The purpose of the algorithm for self-organizing learning is to discover significant pattern or features in the input data, and to do the discovery without a teacher [Kohonen, 1982]. There are three basis elements to a competitive learning rule (Rumelhart and Zipser, 1985), (Haykin, 1994):

- A set of neurons that are all the same except for some randomly distributed synaptic weights, and which therefore respond differently to a given set of input patterns.
- A limit imposed on the "strength" of each neuron.
- A mechanism that permits the neurons to compete for the right to respond to a given subset of inputs, such that only one output neuron per group is active.

Let $w_{ji}$ denote the synaptic weight connecting input neuron $i$ to neuron $j$. Each neuron is allotted fixed amount of synaptic weight (all synaptic weight are positive), which is distributed among its input neurons, that is

$$\sum_{i} w_{ji} = 1 \quad \forall j$$  \hspace{1cm} (2)

The standard competitive learning rule, the change of $\Delta w_{ji}$ applied to synaptic weight $w_{ji}$ is defined by

$$\Delta w_{ji} = \begin{cases} \eta(x_i - w_{ji}) & \text{if neuron } j \text{ wins} \\ 0 & \text{if neuron } j \text{ loses} \end{cases}$$  \hspace{1cm} (3)

where $\eta$ is the learning-rate parameter. This rule has the overall effect of moving the synaptic weight vector $W_j$ of winning neuron $j$ toward input pattern $x$.

The structure of the self-organizing systems in this paper consist of an input layer and an output layer with feedforward connections from input to output and lateral connections between neurons in the output layer. Both of the magnitude and location networks are trained by competitive learning; the output neurons of the network compete among themselves to be activated or fired, with the result that only one output neuron is on at any one time. They will adaptively transform an incoming signal into a discrete map in a topological ordered fashion (sometimes is referred as computational map), thus characterizing the wavelet coefficients. When used in this manner, the spatial locations of the neurons in the lattice layer correspond to intrinsic features of the input patterns. The outputs of these self-organizing systems will then be applied to the classification ANN.

2.3.2 Classification Network

The classification ANN is a standard two-layer, fully connected feed forward network and is trained with the back-propagation algorithm. Inputs to this network are the computational map outputs from the magnitude and location networks. To extract progressively more meaningful features from the input patterns without increasing the computational expense, the hidden layer in this network is designed to have 20 to 25 neurons. The classification network is supervised training with back-propagation algorithm to recognize one particular type of the interested signals. At the end of its training, the net performs a binary classification on each given input pattern. The outputs are designated as '1' and '0' for matched signal or no-match signal, respectively.

2.3.3 Parallel Array Processing

In order for multi-type signal classification, an array of multiple binary classification networks is designed and operated in parallel processing fashion. The input signal is presented to each and every hybrid network at once. By examining the output vector and its largest element, one can determine the type of the underlying signal. However, in some infrequent cases when the differences between the elements in the output vector are not so distinct, additional decision making algorithm may be needed for discrimination. This operation scheme allows the system to be readily expandable to reflect any additional contact signals that may be considered in the
future. Experimental results on a limited set of signals are shown in the following section.

3: Experimental Results And Discussions

Computer experiments were performed with data from three different contact signals recorded in open ocean sites. From each signal, nine hundred 8192-point segments are selected. Discrete wavelet transform using Daubechies wavelet is performed on each segment. In the wavelet transform domain, each segment of the input signal gives 8192 wavelet coefficients. Those coefficients then undergo a dimensionality reduction process via principal component analysis so that only 50 coefficients are selected per input pattern. The magnitudes and locations of those fifty selected wavelet coefficients in the transform domain are utilized as input information to the magnitude and location networks, respectively. The magnitude and location networks are constructed in a similar configuration. Each network has an input layer and an output layer with 50 nodes in each layer. Once the data is presented to these two networks, unsupervised and competitive training is executed. The outputs for each input pattern of the networks are in the form of self-organizing feature map and are forwarded to the classification network. Depicted in Figure 4 are an example of input pattern set, the distribution of the completely trained weights of the self-organizing network, and the computational map output. The classification network consists of a 100-neuron input layer, a 20-neuron hidden layer and a single neuron output. Supervised with back-propagation training is performed on the latter ANN. Training and testing sets of 1800 and 900 patterns, respectively, are generated and presented to the wavelet-based hybrid neurosystem. The classification results are surprisingly impressive. Of all 900 testing patterns, there is no misclassification result with 100% accuracy for classification. Substantial testing with sufficiently large quantity is ongoing for verification of the performance of the system. Summary of the performance of the hybrid system for in experiments is shown in Table 1.

![Figure 4](image)

Figure 4 - (a) Set of input patterns to a feature extraction net, (b) Distribution of the completely trained weights (c) Topological ordered computational map output
Table 1: Signal Classification Performance

| CLASSIFICATION | HYBRID NEUROSYSTEM | DEGREE OF ACCURACY |
|----------------|--------------------|--------------------|
| A: 1 0 0       | ANN 1              | 300 [300]          | 0 (0) | 0 (0) | 0 (0) | 100% |
| B: 0 1 0       | ANN 2              | 0 (0) | 0 (0) | 0 (0) | 300 (300) | 0 (0) | 100% |
| C: 0 0 1       | ANN 3              | 0 (0) | 0 (0) | 300 (300) | 0 (0) | 100% |

LEGEND:

(Bold face) - Number of corrected classifications
(Plain text) - Total testing samples

4: Conclusions

A hybrid neurosystem for signal classification under uncertainty is presented. The combination of wavelet and wavelet transform, hybrid neural network architecture, and advanced training algorithms in the design makes the system unique and provides high classification performance. In particular, signal transformation with wavelets, and principal component analysis for selecting wavelet coefficients provide efficiency in feature extraction with relatively less computational expenses. Further, hybrid neural network with self-organizing feature map produces a high classification accuracy. In self-organizing systems, the use of computational maps offer the following advantages:

- **Efficient Information Processing.** The hybrid neurosystem is required to analyze and classify complex signals arising in a dynamic environment on a continuous basis. This, in turn, requires the use of processing strategies that permit the rapid handling of large amount of information. Computational maps provided by the self-organizing systems are ideally suited for this task. In particular, computational maps represent the results obtained from complex stimuli in a simple and systematic form.

- **Simplicity of Access to Processed Information.** The use of computational maps simplifies the schemes of connectivity required to utilize the information by the classification network.

- **Common Form of Representation.** A common, mapped representation to the results of different kinds of computations permits the classification network to employ a single strategy for pattern recognition.

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