SIGNAL CLASSIFICATION THROUGH MULTIFRACTAL ANALYSIS AND NEURAL NETWORKS

by

Kevin Cannons
Vincent Cheung

A Thesis submitted to the University of Manitoba in Partial Fulfillment of the Requirements for the Degree of

BACHELOR OF SCIENCE

Department of Electrical and Computer Engineering
University of Manitoba
Winnipeg, Manitoba, Canada

Thesis Advisor: W. Kinsner, Ph. D., P. Eng.

March 2003

SIGNAL CLASSIFICATION THROUGH MULTIFRACTAL ANALYSIS AND NEURAL NETWORKS

by

Kevin Cannons
Vincent Cheung

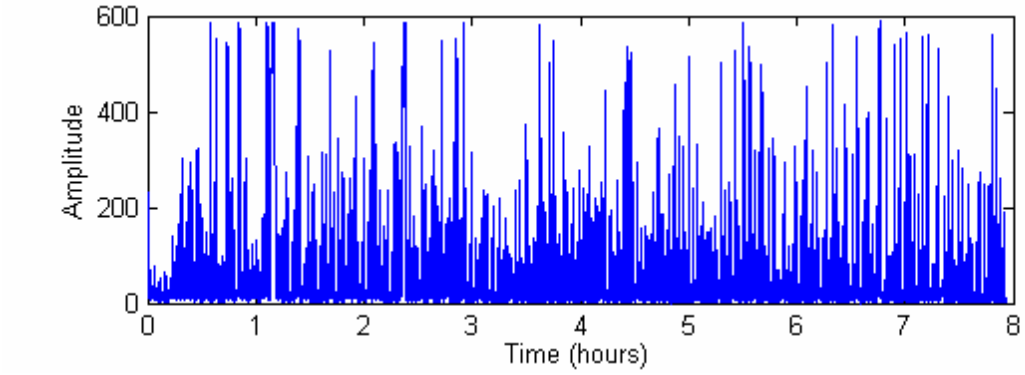
A Thesis submitted to the University of Manitoba in Partial Fulfillment of
the Requirements for the Degree of

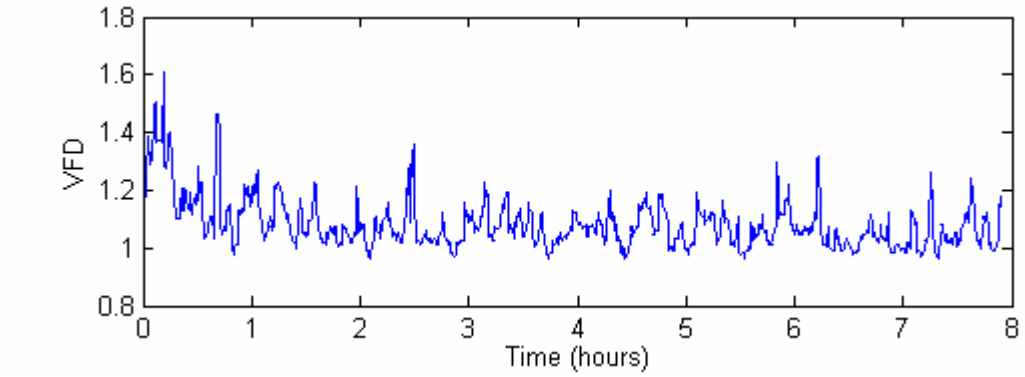
BACHELOR OF SCIENCE

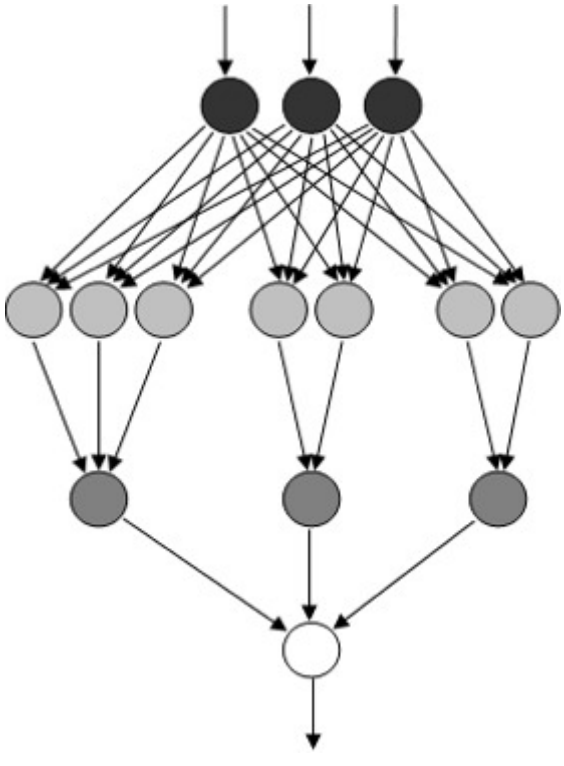
Department of Electrical and Computer Engineering
University of Manitoba
Winnipeg, Manitoba, Canada

Thesis Advisor: W. Kinsner, Ph. D., P. Eng.

(vii + 89 + A-4 + B-5 + C-1) = 106 pp.


600
400
200
0
Amplitude
0
1
2
3
4
5
6
7
8
Time (hours)


1.8
1.6
1.4
1.2
1
0.8
VFD
0
1
2
3
4
5
6
7
8
Time (hours)



ABSTRACT

This thesis proposes a method of classifying stochastic, non-stationary, self-similar signals which originate from non-linear systems and may be comprised of multiple signals, using a multifractal analysis and neural networks.

The first stage of the signal classification process entails the extraction of the most important features of the signal. To perform this feature extraction, the signal is first transformed into the fractal dimension domain by calculating its variance fractal dimension trajectory (VFDT). This transformation emphasizes the underlying multifractal characteristics of the signal, and more importantly for classification, it produces a normalized signal. The resulting VFDT can be used directly for classification. Alternatively, the most important features of the VFDT can be obtained through the use of Kohonen self-organizing feature maps (SOFMs) and the classification can then be based upon these features. Configurations with and without the SOFMs are examined in this thesis.

The second stage of the classification process involves the use of neural networks to determine the particular class of a signal based on its extracted features. This thesis employs several advanced neural networks, including probabilistic neural networks (PNNs) and complex domain neural networks (CNNs). While the use of PNN has been sparse in previous research, it has significant advantages over traditional neural networks, including faster training times and classification accuracies that are asymptotically Bayes optimal. Similarly, CNNs have not been used extensively, but research in the area has shown that they often generalize more effectively than real domain networks. Additionally, these networks are able to take advantage of the strong correlation between multiple signals that constitute an entire signal.

The classification system implemented in this thesis is verified using spatio-temporal recordings of a Siamese fighting fish when presented with various stimuli during dishabituation experiments in a fish tank. The experiments performed in this thesis show that the proposed classification systems are capable of classifying non-stationary, self-similar signals, such as the fish trajectory signal, with accuracies up to 90%. Additionally, the experiments verified that the use of multiple signal components of the fish trajectory signal yield better results than when only a single component is used.

ACKNOWLEDGEMENTS

We would like to thank Dr. Kinsner for his continued support and encouragement while working on our thesis. Additionally, we would further like to thank Dr. Kinsner for introducing us to our thesis topic, through which we have broadened and enriched our knowledge base well beyond what we would have otherwise achieved in our undergraduate studies.

We would also like to thank the members of the Delta Research Group, especially Robert Barry, Kalen Brunham, Stephen Dueck, Hakim El-Boustani, Aram Faghfouri, Neil Gadhok, Bin Huang, Michael Potter, Leila Safavian, and Sharjeel Siddiqui, as well as our families and friends for all their helpful suggestions and words of encouragement.

Many thanks must also be expressed to Dr. Pear and his research group for supplying us with the fish trajectory signals for use in this thesis.

Finally, we would like to express our sincere gratitude to the Natural Sciences and Engineering Research Council of Canada and the University of Manitoba for their financial support of the research performed for this thesis.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1
INTRODUCTION

1.1 Purpose

The goal of this thesis is to develop a software system that is capable of classifying stochastic, self-similar, non-stationary signals which originate from non-linear systems. Complicated signals such as these are often composed of multiple signals, and the system for this thesis will have the ability to take these multiple signals into account during the classification process.

This thesis is unique because of the particular techniques that that are chosen to perform the classification. Specifically, a rarely used transformation is used to represent a signal by its variance fractal dimensions. This translation emphasizes the underlying multifractal characteristics of the signal, and more importantly for classification, it has a normalizing effect. Once the most significant features are extracted through the multifractal analysis, two advanced neural networks are explored to perform the actual classification. One of the neural networks utilized in this thesis is the probabilistic neural network. While the use of this network has been sparse in previous research, it has significant advantages over traditional multilayer feedforward neural networks including faster training times and classification accuracies that are asymptotically Bayes optimal. The second neural network used for classification is the complex domain neural network. This network has yet to be used extensively in research or practice, but it is often able to generalize more effectively than real domain neural networks and is able to take full advantage of the multiple signals that constitute an overall signal.

1.2 Problem

Signal classification is the analysis of a signal whereby the signal is determined to belong to a particular class based on certain characteristic features. The membership to a particular class usually signifies something about the physical process or system from whence the signal originated. The classification and analysis of stochastic, non-stationary, self-similar signals produced by non-linear systems is important because many real world processes have been shown to generate signals of this type. The nature of these signals makes them very challenging to

analyze because traditional techniques, such as the Fourier transform, which often depend on the stationarity of a signal and the linearity of the analyzed system, cannot be applied. In addition to belonging to the class of stochastic, self-similar signals, non-stationary signals, many signals that are produced in the real world consist of multiple signals that are required to completely define the overall signal. For example, multichannel audio signals and multiple lead electroencephalograms and electrocardiograms all consist of many signals, all of which are required to provide a complete description of the physical process from which they were created.

Since traditional techniques cannot effectively be applied to these types of complex signals, more advanced methods are sought. The first task that is usually undertaken in an attempt to classify these complex signals is to extract the most important characteristics, or features from the signal. In general, the fewest number of features that are capable of representing the different classes of signals are desired. Once the most important features have been extracted from the signal, they are used to determine the class membership of the signal. The function that maps these input features to an output class is often unknown and very complex. As a result, sophisticated classification methods are required to determine to what class the signal belongs based on its given features.

1.3 Scope

This paper will limit the feature extraction to utilizing a multifractal characterization through the computation of the variance fractal dimension trajectory in addition to Kohonen self-organizing feature maps. The classifiers used to perform the classification based on these features are restricted to probabilistic and complex domain neural networks. The differing degrees of success of the various configurations of the system will be measured through the use of fish trajectory signals in which only two components of the signal are considered.

1.4 Thesis Organization

This paper is divided into seven distinct chapters. Chapter 1 provides a general introduction to the thesis and outlines its motivation and objectives. Chapter 2 gives background information on the different techniques that are used in the thesis. The third and fourth chapters describe the design and implementation of the classification system. The fifth chapter details the testing and verification methods used to ensure that the software components operate as expected.

Chapter 6 explains the experiments performed to gauge the performance of the classification system and thoroughly discuss their results and implications. Chapter 7 concludes the thesis and suggests future work that can extend the work done in this thesis to improve the performance of the system. Appendices A and B provide a description of the fish trajectory signals used to verify the classification system and the clustering technique used to derive the training and testing sets for classification. The source code and documentation for the classification system are contained in Appendix C.

CHAPTER 2
BACKGROUND

2.1 Signal Classification and Terminology

This section provides a general description of the overall idea of signal classification and introduces the terms used to describe the types of signals used in this thesis.

Before proceeding any further into this thesis, the concept of signal classification must first be concretely defined. Signal classification means to analyze different characteristics of a signal, and based on those characteristics, decide to which grouping or class the signal belongs. The resulting classification decision can be mapped back into the physical world to reveal information about the physical process that created the signal. Often, when signal classification is performed, it is not the goal to determine to which class an entire signal belongs. Instead, a signal is usually provided where it is known that a variety of different classes exist at different points throughout the signal. For example, if the signal under analysis is represented in the time domain, the purpose of classification might be to determine that the first 15 minutes of the signal belong to class B, while the next fifteen minutes belong to class A, and so on. In this case, all the principles behind classification remain the same as when the entire signal is classified, but instead of classifying the whole signal, only a segment of the signal is classified.

In order to perform classification upon signals, several analysis techniques are typically performed. First, the characteristics or features upon which the signal is to be classified must be defined. There are an infinite number of features that could be extracted from the signal for the purpose of classification, including the mean of the signal, its Fourier coefficients, and its wavelet coefficients [Mall98]. Based on the selected signal features, a classifier will determine to which class the signal belongs. The output of the classification system, in which the class membership of the input signal is determined, can then be used to infer what event in the real world process occurred to produce the input signal. In this thesis, multifractal analysis and Kohonen self-organizing feature maps (SOFMs) are used to extract the critical features from signals, while neural networks are the tools used to perform the classification.

It may seem like overkill to use complicated techniques such as multifractal analysis and SOFMs to extract the important features from the signals when much simpler metrics such as the

mean and Fourier coefficients of the signal could be used. However, these complex feature extraction and classification tools are required for this thesis because of the nature of the signals being classified. Specifically, the signals under analysis in this thesis are non-stationary, stochastic, self-similar signals that originate from non-linear systems. These terms describe very complex signals and may not commonly be known, hence they will each be briefly defined.

The term non-stationary, in the general sense, means that the statistical properties of a signal change over time. More specifically, properties such as the signal's mean, variance, kurtosis, and skewness do not remain constant over the entire duration of the signal, but rather, change from one point in the signal to the next. A standard sine wave, for example, would be considered a stationary signal as its statistics remain constant. The statistics for other signals, such as those produced by speech, clearly do not remain constant, making them non-stationary. Although an overall signal may not be stationary, usually smaller windows, or parts of those signals will exhibit stationarity. For example, there is a maximum speed at which the vocal chords of a human's voice box can change the sound which they are producing. As a result, a voice signal is stationary for that small amount of time during which it is physically impossible for the vocal chords to change sounds. Knowledge of the period over which a particular type of signal remains stationary is very valuable during signal analysis.

Stochastic refers to signals where the events in the signal occur in a random fashion and self-similar, at the simplest level means that if a portion of a signal is magnified, the magnified signal will look the same and have the same statistical properties as the original signal.

Linear systems are systems that abide by the principle of superposition. Most systems in the real world are decisively non-linear meaning that superposition does not apply. For example, humans are non-linear systems. Consider a situation where a person is told to perform a chore and then correspondingly does so. If that same person was yelled at twice as loud to carry out that same duty, he or she would not necessarily complete the task twice as fast.

Non-stationary, stochastic, self-similar signals originating from non-linear systems are challenging to analyze, but what makes matters even more complicated is that these signals are often composed of multiple different recordings, each of which contribute to the information content of the overall physical phenomena which created the signal. Examples of such signals include multichannel audio signals and multiple lead electroencephalograms and electrocardiograms. A classification system can choose to ignore the fact that multiple recordings

are required to completely define such signals and merely perform classification using the recording which is deemed the most important. On the other hand, a classification system, such as the one developed in this thesis, can make use of the information held within the different recordings in an attempt to achieve superior results.

The goal of this thesis is not the analysis of a particular signal, rather it is the development of a general classification system which can be used to perform analysis upon non-stationary, stochastic, self-similar signals originating from non-linear processes. However, in order to verify the operation of the classification system and gauge its performance, fish trajectory signals are used. These signals are the result of tracking the three-dimensional position of a fish in a fish tank when presented with various stimuli over an eight hour period. The fish signals exhibit the desired stochastic, self-similar, non-stationary properties and originate from a non-linear system – a fish. The fish trajectory signals also are composed of multiple recordings, one for each of the Cartesian co-ordinate axes so that the effects of utilizing multiple recordings during classification can be studied. Sample plots of these signals are shown in Fig. A.2 in Appendix A. The details of the experiment that generated these signals and a discussion of these plots are also provided in Appendix A.

2.2 Fractals

This section introduces some of the fundamental concepts behind fractals, and explains how a specific fractal dimension, the variance fractal dimension, is calculated. By computing the variance fractal dimension in a sliding-window fashion over an entire signal, a multifractal analysis is performed whereby a variance fractal dimension trajectory (VFDT) for that signal can be created. It is the samples in this signal representing the fractal dimensions of the original signal which is used as the features from which to perform classification. The use of the VFDT technique has been fairly limited thus far; however, the benefits of its use are significant. The VFDT representation of the signal can assist in revealing the underlying characteristics of a signal which may not have been apparent when analyzing the original signal, while simultaneously compressing the signal into a more compact representation. Being able to reduce the number of points needed to represent a signal is an invaluable procedure as it makes the classification process for a classifier much more practical. Most importantly, the resulting VFDT representation of a signal is normalized, which is essential for the classification based on these extracted features.

2.2.1 Introduction

The first notion that must be understood in regards to fractals is that in the simplest sense, fractals are self-similar entities. As previously defined, self-similarity means that no matter what magnification is used when viewing an object, its statistical properties, structure, and complexity remain constant [Mand82]. For example, consider the Koch curve, which is displayed in Fig. 2.1.

The lower of the two images shown is the standard Koch curve. If the upper portion of the Koch curve is magnified, the resulting image looks identical to the original Koch curve itself, as can be seen in the upper image of the figure. Mathematically, even if a portion of the Koch curve is repeatedly magnified, it will still look identical to the original, unmagnified curve.

The idea of an object looking the same regardless of what magnification it is viewed under is quite a contrast to the way most shapes and objects appear when magnified. For example, if the upper portion of a hexagon is magnified, as shown in Fig. 2.2, the magnified portion does not look similar to the original, unmagnified hexagon. Typically, as a portion of a non-fractal object is magnified repeatedly, its complexity will decrease to the point where the magnified portion will merely appear as a straight line. With fractal objects, this is not the case. For example, the appearance and complexity of the Koch curve remains constant no matter the level of magnification used for viewing.

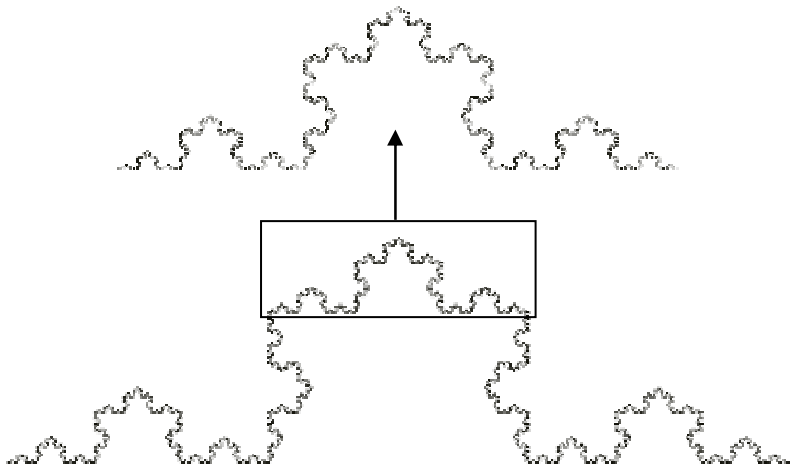


Fig. 2.1: The Koch curve fractal at various magnifications.[1]

[1] Adapted from http://www.jimloy.com/fractals/koch.htm last checked March 6, 2003

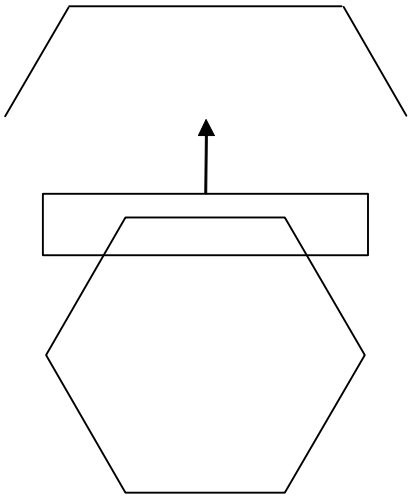


Fig. 2.2: A hexagon viewed at different magnifications.

Another important concept to be cognizant of when studying fractals is that of fractal dimensions. Typically, when individuals speak about dimensions, they are referring to the standard Euclidean dimensions which are discrete, integral numbers. For instance, a line is considered a one dimensional object, a square is a two dimensional object, and a cube is a three dimensional object. These integral dimensions can proceed to higher and higher arbitrary values, but objects with a dimension higher than the third dimension become difficult to visualize. However, it is also possible for objects to exhibit fractional dimensions. In fact, the term fractals was coined to describe objects that have a dimension that is non-integral. The Koch curve in Fig. 2.1 is a fractal curve with a dimension of approximately 1.2619 [PeJS92], meaning that it has a greater complexity than a straight line, but is not quite a two dimensional object.

The importance of the dimensionality of an object is that it provides information regarding that object. For example, if one is told that a particular drawing is displayed in two-dimensional space, then even before that drawing is seen, an individual knows some of the characteristics of that drawing. In particular, it is known that the drawing does not display a third dimension, but rather, stays within the flat bounds of two dimensions. Likewise, dimensionality can be used to extract particular characteristics from a signal that is under analysis. If the signal happens to exhibit self-similar characteristics, then fractal dimensions can be employed. Regardless of whether or not the dimension calculated is integral or non-integral, the dimension provides valuable information about the properties of the signal. This thesis exploits the underlying fractal dimension of signals for the purpose of feature extraction and the ultimate goal of signal classification.

2.2.2 Variance Fractal Dimension

To further consider the ideas that dimensions need not be integral and that fractal objects typically possess non-integral dimensions, the process of calculating the dimensionality of an entity must be explained. Complicating matters is the fact that there are many different types of dimension. These include topological dimension, box-counting dimension, as well as many others [PeJS92]. In certain cases the different types of dimensionality, when calculated, yield the same result for the same object. However, at other times, the computation of the different dimensions provides different numerical values. For the purposes of this paper, only one form of fractal dimension, the variance fractal dimension [Kins94], is utilized.

As the name suggests, the variance fractal dimension is based on calculations involving the variance of the amplitude increments of a signal. The first concept required to calculate the variance dimension is to understand that the amplitude increments of a signal over a time interval Δt follow a power law relationship as shown in Eq. (2.1), where *x(t)* represents the signal and *H* is the Hurst exponent.

$$Var[x(t_2) - x(t_1)] \sim |t_2 - t_1|^{2H} \tag{2.1}$$

Intuitively this formula seems reasonable because it indicates that differences between points that are very close to each other in a signal will have a small variance. For example, consider a situation where a 1 Hz sine wave is being analyzed. If the signal is sampled such that the samples are only separated by 0.001 seconds, then the variance of the differences between all of these samples is not very high because the signal changes very little in that short period of time. On the other hand, if the samples are separated by 0.25 seconds, the variance is significantly larger. Thus, as Eq. (2.1) suggests, as the time interval increases, so too does the variance.

The value of the variance fractal dimension is actually just the Hurst exponent, *H*, modified by two factors. Because (2.1) is a power law relationship, it is easier to view when plotted on a log-log plot. If a signal adheres to the relationship in (2.1), then when it is plotted on a log-log plot, it should yield a straight line. The slope of that straight line divided by a factor of two is the Hurst exponent. In mathematical terms, if $\Delta t = |t_2 - t_1|$ and $(\Delta x)_{\Delta t} = x(t_2) - x(t_1)$, then the Hurst exponent can be calculated via a log-log plot using Eq. (2.2).

$$H = \lim_{\Delta t \to 0} \frac{1}{2} \frac{\log[Var(\Delta x)_{\Delta t}]}{\log(\Delta t)} \tag{2.2}$$

As mentioned previously, the variance fractal dimension is merely the Hurst exponent modified by two factors, which is shown in Eq. (2.3), where D_σ is the variance fractal dimension, and E is the Euclidean dimension.

$$D_\sigma = E + 1 - H \tag{2.3}$$

The Euclidean dimension is equal to the number of independent variables in the signal. Thus, since this thesis concentrates solely upon Euclidean one-dimensional signals, E can be set to 1. Equation (2.3) then reduces to:

$$D_\sigma = 2 - H \tag{2.4}$$

The variance fractal dimension can be calculated repeatedly over the duration of a signal to compute the variance fractal dimension trajectory of the signal. The process of calculating the VFDT of a signal essentially involves breaking up the entire signal into numerous sub-signals, or windows, and calculating the variance fractal dimension for each of these windows. The concatenation of all these fractal dimensions to form a signal is the signal's VFDT.

A multifractal signal is a signal whose fractal dimension changes over time. Conversely, a simple fractal signal's fractal dimension remains constant. The process of computing a signal's VFDT is a multifractal characterization as it will expose if a signal contains multiple fractal dimensions. Should the VFDT be computed upon a simple fractal signal, then the resulting VFDT is simply constant. There are several benefits in representing a signal in the fractal domain including dimensionality reduction, underlying feature exemplification, and normalization.

Keeping in mind that the VFDT merely involves taking a signal and transforming it so that it is represented in the multifractal domain, the following steps [Kins94] outline the procedure used to calculate the variance fractal dimension trajectory of a signal:

1. Select values for the window size, N_T, and window displacement, d. The window size is the number of points that are held in each of the smaller sub-signals for which the variance fractal dimension is calculated. The size of the window should be selected based on the stationarity of the signal under analysis. The displacement indicates how far the window shifts following each variance fractal dimension calculation, and determines the resolution of the resulting VFDT. Both the window and displacement parameters have an effect on the number of points in the VFDT. A high resolution is usually desired, indicating a smaller displacement should be used. However, the displacement should not be given an extremely small value since this would result in significant windowing artifacts because of the excessive correlation between windows.
2. Next, the change in magnitude, Δx , is required in order to calculate the Hurst exponent, as seen in Eq. (2.2). Additionally, as the equation indicates, the time period over which Δx is being calculated must be specified. In (2.2) the difference in time was indicated by Δt . However, when implementing the VFDT algorithm, the signal being worked with is digitized and hence the separation should be presented by the number of samples rather than time. Hence, the number of samples separating two points for which Δx is calculated is called n_k, and is set as follows:

$$n_k = 2^k, k > 1 \tag{2.5}$$

   The base of 2 in Eq. (2.5) can be any integer number greater than zero. For this thesis only a value of 2 is considered. Thus, n_k will take on the values of 2, 4, 8, 16, and so on as k is incremented.
3. Determine the maximum allowable separation, n_{Khi}, between two points for which Δx can be calculated by using the following formula:

$$K_{hi} = \left\lfloor \frac{\log N_T}{\log 2} \right\rfloor - \left\lceil \frac{\log 30}{\log 2} \right\rceil \tag{2.6}$$

   The first factor in Eq. (2.6) ensures that the two points remain within the bounds of the current window. However, if the first factor were left by itself, then the two maximally separated points for which Δx is calculated would cover almost the entire window. Thus, in order to remain statistically valid, there must be room in the window for at least 30 non-overlapping, distinct Δx intervals. The subtraction factor in (2.6) ensures that the

maximum allowable separation of the two points involved in the Δx calculations stays small enough so that at least 30 Δx calculations can be performed within the window.

4. Determine the minimum allowable separation between two points, K_{low}, for which Δx is calculated. In order to ensure that the correlation between adjacent values is not too strong, K_{low} must be a value greater than 1.
5. Create a pointer indicating the beginning of the current window.
6. Position the pointer to the beginning of the signal.
7. Let the first N_T points following the position pointer be considered the current window.
8. Cycle a variable, k, from K_{low} to K_{hi}.
    a. For each value of k, calculate the variance of Δx for samples separated by n_k points using the following formula

$$Var(\Delta x)_k = \frac{1}{N_k - 1}\sum_{j=1}^{N_k}\left[(\Delta x)_j - \overline{(\Delta x)}\right]^2 \tag{2.7}$$

where

$$\begin{aligned} N_k &= \left\lfloor \frac{N_T}{n_k} \right\rfloor, \\ (\Delta x)_j &= x(jn_k - 1) - x\left((j-1)n_k\right), \text{ and} \\ \overline{\Delta x} &= \frac{1}{N_k}\sum_{j=1}^{N_k}(\Delta x)_j \end{aligned} \tag{2.8}$$

    b. For each value of k, calculate $X_k = \log[n_k]$ and $Y_k = \log[\,Var(\Delta x)_k\,]$ and store the results in preparation for calculating the slope of the log-log plot.

9. Calculate the slope of the log-log plot, s, using the following formula, where $K = K_{hi} - K_{low} + 1$

$$s = \frac{\sum_{i=1}^{K}(X_i - \overline{X})(Y_i - \overline{Y})}{\sum_{i=1}^{K}(X_i - \overline{X})^2} \tag{2.9}$$

10. Compute the Hurst exponent using $H = \frac{1}{2}s$.
11. Calculate the variance fractal dimension using Eq. (2.4).

12. Move the window pointer farther down the signal. The distance to move the pointer is equal to the displacement specified in step 1.
13. Repeat steps 7 through 12 for each window until the end of the signal is reached.

When the above algorithm is implemented, the resulting program will process a signal and calculate its VFDT. With these fractal dimension features extracted from the signal, the actual classification of the signals can be pursued.

2.3 Neural Networks

2.3.1 Introduction

Artificial neural networks constitute a vast field of study, largely because they are tools that have been proven to be useful in many different applications in a variety of fields. Additionally, the field of neural networks is very extensive because there are so many different types and configurations that are open to investigation. Neural networks, in general, have been studied and utilized for several decades. Different types of neural networks have played a role in numerous research projects ranging from speech recognition to stock market predictions. New types of neural networks are still under investigation, and older configurations continue to be refined and modified, indicating that the neural network paradigm is still thriving.

A neural network, in the most generic sense, is a function approximator. A simple neural network that implements an inverter, an and-gate, or a sine function can be implemented, but there is little practical purpose for doing so because these functions can be programmed directly. Neural networks are more often put to use in applications involving classification, noise reduction, or prediction; situations in which the function mapping between the inputs and outputs is complex and unknown.

Signal classification is the major focus of this paper, hence this section of the report will explore the use of neural networks as classifiers. Neural networks are by no means the only technique that is available for classification purposes. For example, rather than implementing a neural network, one could use an expert system [WeKu91] to perform classification. However, there are many advantages to using neural networks rather than other techniques. One of the main advantages of neural networks is that they have the ability to learn, adapt and generalize. In contrast, expert systems merely emulate the decisions of a human expert. An expert system does

not have the ability to adapt or learn, and as a result, its performance is limited by the knowledge of the expert who designs it. Since a neural network can learn and generalize, it can surpass the abilities of the experts who created it, and potentially, uncover information that eluded the experts.

The information presented in this thesis will introduce the basic global concepts behind the general class of multilayer feedforward neural networks. Once these broad concepts have been introduced, the main types of neural networks considered in this thesis, namely backpropagation, complex domain, and probabilistic neural networks, as well as Kohonen self-organizing feature maps, will be highlighted and explained.

2.3.2 Basic Concepts

The first concept to be mentioned is the general topology of multilayer feedforward neural networks. Neural networks consist of two main components: neurons and synapses, as can be seen in Fig. 2.3.

The neurons of a neural network are the units responsible for performing the calculations. Although the calculations performed by each neuron are relatively simple, when combined with the calculations of all the other neurons, the neural network as a whole can solve very sophisticated and complex problems. Neural networks accomplish their goal by passing messages from neuron to neuron through synapses. The synapses are simply the connections between neurons and typically have weights associated with them. These weights are adjusted so that the neural network computes the function that it is supposed to approximate. However, the inclusion of weights on the synapses is not mandatory. Some neural networks, such as the

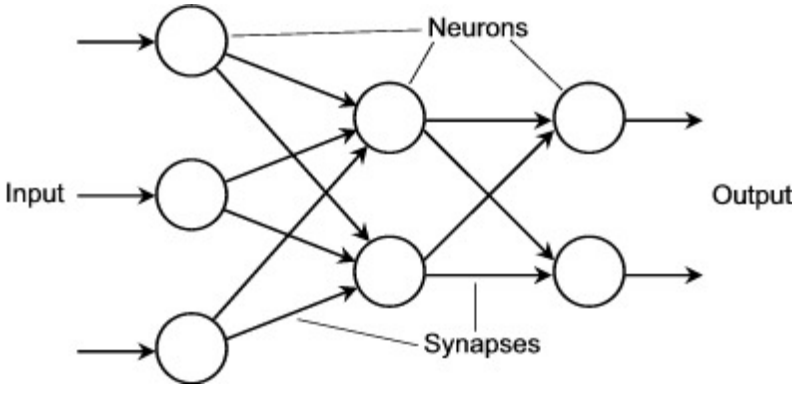


Fig. 2.3: A multilayer feedforward neural network.

probabilistic neural network, define their functionality using other methods which will be discussed later in this report. Fig. 2.3 further demonstrates that neural networks have inputs and outputs to interact with the outside world.

An additional observation concerning the neural network shown in the above figure is that it is organized into several layers of neurons. This aspect of grouping neurons into one or more layers is a main characteristic of multilayer feedforward neural networks. Multilayer feedforward neural networks have three or more layers: an input layer, an output layer, and one or more hidden layers. Typically, the neurons in each layer have different jobs to perform. In Fig. 2.3, the three neurons on the extreme left make up the first layer, the input layer, of the neural network. The two neurons in the middle of the diagram form the second layer of the neural network, the hidden layer. Finally, the remaining two neurons, located on the extreme right, constitute the output layer. It should also be noted that information in the network progressively flows from one neuron layer to the next, meaning that the output synapses from neurons in a particular layer do not connect to neurons in the same or previous layers.

Given the general characteristics and architecture of a multilayer feedforward neural network, the first operational detail that will be addressed is the manner in which the neurons operate. The following description applies primarily to the multilayer feedforward class of neural networks, and it is not applicable to some more specialized types of neural networks, such as probabilistic neural networks. Despite the lack of universality with the following description, it will provide insight into the specifics as to how the neurons in a multilayered feedforward neural network operate. The operational details of the neurons in other neural networks are not significantly different from the ideas presented here.

The operation of the input neurons is quite simple. The input neurons are merely used for distribution purposes as their task is to take the inputs that are supplied to the neural network and distribute them to each of the hidden neurons.

As can be seen from Fig. 2.3, the hidden neurons have one or more input and output synapses. Fig. 2.4 shows how a hidden neuron processes the signals it receives via its input synapses, and the procedure through which it generates an output. In the figure, x_i represents an input value along a synapse and w_i is the corresponding synaptic weight. The neuron first multiplies each input by the weight of the synapse on which it is traveling and then sums these weighted inputs. It should be noted that Fig. 2.4 includes an additional bias input for the neuron.

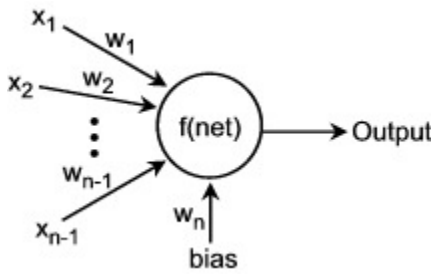


Fig. 2.4: The basic operation of a neuron.

Unlike the other synapses, which connect the neurons together, the bias input does not originate from another neuron. The bias input is simply an additional input to the neuron that always has an input value of one. The bias input behaves just like any other input in that the weight of the synapse, w_n, multiplied by the input value for that synapse, one, is added to the sum. This weighted net sum is abbreviated in the equation as net. The f(net) located inside the neuron of Fig. 2.4 is the neuron's activation function, which is used to transform the multiple inputs into the neuron into a single output. The output of the neuron is simply the result of the activation function upon the net sum:

$$Output = f(net) = f(\sum_{i=1}^{n} x_i w_i + w_n) \tag{2.10}$$

The activation function used by the hidden neurons depends on the application, but most neural networks use a sigmoid activation function. Sigmoid activation functions are smooth, continuous, monotonically increasing, and are "S-shaped". There are a variety of different sigmoid activation functions that can be used with a neural network, but the particular function chosen typically has little effect on the overall performance of the network. A common sigmoid function to use is the logistic function, which has the following formula:

$$f(x) = \frac{1}{1+e^{-x}} \tag{2.11}$$

Other common sigmoid activation functions include the hyperbolic tangent and arctangent functions [Mast93].

Usually the output neurons of the multilayer feedforward neural network are designed to behave in exactly the same fashion as the hidden neurons, but this is not a requirement.

Up to this point, a description of the topology of multilayer feedforward neural networks has been presented, and the general operation of the different types of neurons explained. However, the matter of how the overall neural network is configured to achieve its overall desired function has not been addressed, and such an explanation is now in order.

One of the main advantages of neural networks, as mentioned previously, is that they have the ability to learn and generalize. The operational description of the different neurons certainly has not substantiated these claims. The reason that neural networks have looked so bland up until this point is that only the execution of a multilayer feedforward network has been described. That is, the only events that have been detailed so far are the steps involved in generating an output when a trained network is presented with an input. The real learning involved with neural networks does not take place when the network is executed, but rather when the network is trained.

There are two main categories of algorithms that can be used to train a neural network: supervised and unsupervised training algorithms. With supervised training, the neural network is provided with both input values as well as the desired output that is associated with each input. In contrast, unsupervised neural network training involves providing the neural network with just a set of inputs, but not outputs. In both supervised and unsupervised learning, the basic concept of training involves optimizing a particular parameter, or set of parameters, throughout the neural network. For example, in the general multilayer feedforward neural network, training involves finding an acceptable set of synapse weights so that the neural network can produce the correct output for any given input.

When training a multilayer feedforward neural network, whether it be supervised or unsupervised, sample inputs are provided to the neural network After analyzing the outputs that are produced by the neural network, the parameters being optimized are updated. Each repetition of presenting the neural network with one or more inputs and adjusting the parameters is known as an epoch. The number of input presentations that are used to train the network during each epoch is known as the epoch size. There are some heuristics [Mast93] which outline the epoch size and the number of epochs that a neural network requires in order to be trained, but the general idea is to repeat the training process until the error reaches an acceptable level. The exact manner in which the various parameters are updated during an epoch is different for each type of

neural network, and thus will be discussed as the different types of neural networks are introduced.

When solving any practical problem, it is not feasible to train the neural network with every possible input combination. In fact, in most instances, the entire set of all possible inputs is not known. Instead, the designer has a set of sample inputs for which he or she knows the correct output. This set of samples is known as the training set. Choosing an effective training set is often a challenging problem, as one wants the training set be representative of the entire set of possible inputs, but the number of known samples from which to select the training set is often not very large.

Once a neural network is trained, it is almost always necessary to monitor how well the network performs. In order to gauge the performance of the neural network, a second set of inputs, known as a testing set, must be selected from the sample inputs. The testing set is presented to the neural network after it has been completely trained, and the performance of the neural network is measured by calculating the percentage of the testing set for which the neural network provides the correct output.

As seen in Fig. 2.5, the testing and training sets must not overlap. The reason for having testing and training sets completely separated involves the notions of memorization and generalization. It is relatively easy to train a neural network that is capable of memorizing the correct responses for each input in the training set. If a neural network is evaluated by using a testing set that is identical to the training set, it should perform with 100% accuracy. However, this "test" does not prove anything except the fact that that the neural network was able to

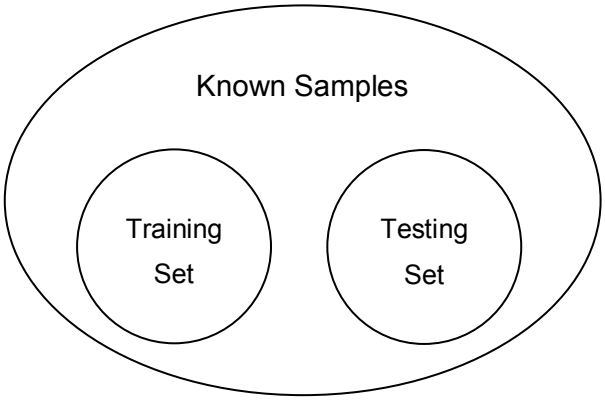


Fig. 2.5: Mutually exclusive training and testing sets.

memorize the training set. This performance gauge provides no real indication as to how the neural network will react if it is presented with an input that it has never seen previously. In any practical application, the neural network must be able to generalize so that it can produce correct outputs for inputs that have not been introduced to it during training. Thus, in order to achieve an accurate measure of generalization and a true unbiased gauge of performance, the testing and training sets must be mutually exclusive of one another.

This concludes the introduction to the fundamental ideas behind neural networks. Although the main concepts behind multilayer feedforward neural networks were explained, there are still many other details that have to be dealt with when designing a neural network. The answers to these design problems are not trivial and vary from application to application. Even decisions such as selecting the number of hidden neurons and the number of hidden layers [Mast93] can be difficult. There are numerous heuristics that can be used in order to determine near-optimal values for these parameters, but these heuristics are many and varied. Their intricacies will not be further elaborated upon at this time, but the reasons for making all design decisions and the ramifications of these decisions will be detailed later in the thesis.

2.3.3 Backpropagation

The backpropagation algorithm is the most common and basic method of training the general class of multilayer feedforward neural networks. One of the reasons the backpropagation algorithm is used so frequently is that it is fairly simple. The downside to the backpropagation training algorithm's simplicity is that it is slow. Another disadvantage of backpropagation is that it often has problems dealing with local minima. Despite these shortcomings, the backpropagation training algorithm has a proven record of providing decent results in practice, and as such, is taken into consideration in this thesis. Furthermore, the backpropagation algorithm provides the foundation for training the more advanced complex domain neural networks, described later in this thesis. This section will provide the concepts and formulas required for understanding the operation of the backpropagation training algorithm. Full derivations of the mathematics behind the backpropagation training algorithm can be found in many neural network texts [Hayk99].

The backpropagation algorithm is a supervised form of training that is used to determine acceptable values for the synapse weights in a multilayer feedforward neural network. The basic premise behind backpropagation is as follows. First, the neural network calculates the output for

an input training vector. Since backpropagation uses supervised training, the output produced by the network can be compared against the output that is desired for that particular training vector. More often than not, the desired response and the actual response will not be identical. In other words, there is an error associated with the output produced by the neural network. One common method for measuring the size of the error is to calculate the mean square error using formula (2.12), where t is the correct or target output and o is the output that is actually produced by the particular output neuron.

$$E = (t - o)^2 \tag{2.12}$$

The goal of adjusting each of the synapse weights is to attempt to make the error as small as possible. The backpropagation training algorithm is a gradient descent algorithm, and as such, it makes use of gradients in an attempt to minimize the error function. The gradient of a function indicates the direction of maximum increase of the function, thus the direction completely opposite to the gradient is the direction of maximum decrease. Hence, the backpropagation algorithm calculates the gradients of the error function and then adjusts the weights to move slightly in the opposite direction in an attempt to decrease the error as much as possible.

Mathematically, the gradients are the partial derivatives of the error function with respect to each synapse weight. The formulas for calculating the gradients vary depending on whether the gradient is being calculated for an output or hidden neuron. The backpropagation algorithm first starts by calculating the gradients for the output neurons using the formula given in Eq. (2.13), where o_i denotes the output of the i^{th} hidden layer neuron, f is the output neuron's activation function, t_j is the target output for the j^{th} output neuron, o_j is the actual output produced by the j^{th} output neuron, and net_j is the sum of the weighted inputs to the j^{th} output neuron.

$$\frac{\partial E}{\partial w_{ji}} = -o_i f'(net_j)(t_j - o_j) \tag{2.13}$$

Often this equation is broken down into two equations as follows:

$$\begin{aligned} \delta_j &= f'(net_j)(t_j - o_j) \\ \frac{\partial E}{\partial w_{ji}} &= -o_i \delta_j \end{aligned} \tag{2.14}$$

The gradient equations for hidden neurons is slightly different from those of the output neurons because, unlike the output neurons, hidden neurons don't have any "correct" output that they are supposed to match. Instead, the hidden neurons make use of the δ values that were previously calculated for the output neurons. Thus, the gradients for the hidden neurons are calculated using the formulas in (2.15), where the index k denotes a particular neuron in the adjacent layer closest to the output of the network, index i indicates an individual neuron in the adjacent layer closest to the input of the network, and index j indicates the current hidden neuron whose weights are being updated.

$$\begin{aligned} \delta_j &= f'(net_j)\sum_k(\delta_k w_{kj}) \\ \frac{\partial E}{\partial w_{ji}} &= -o_i\delta_j \end{aligned} \tag{2.15}$$

As (2.14) and (2.15) demonstrate, the calculation of the partial derivatives begins at the output layer, and then continues layer by layer until the input layer is finally reached. It is this propagation backwards through the network where the backpropagation algorithm gets its name. However, simply calculating the partial derivatives does not improve the neural network in any way; the gradients need to be used to adjust the weights of the neural network. This weight adjustment is achieved by using (2.16), where w_{new} is the new weight value, w_{old} is the old value of the weight, and α is the learning rate.

$$w_{new} = w_{old} - \alpha\frac{\partial E}{\partial w_{old}} \tag{2.16}$$

The learning rate is a very important parameter in the backpropagation algorithm as it determines the amount by which the weights are modified during each epoch. If the learning rate selected proves to be too small, then the backpropagation algorithm will take a long time to converge to a set of acceptable synapse weights. On the other hand, if the learning rate selected is too large, then the weights may vary so much from epoch to epoch that the weights do not converge at all.

The backpropagation training algorithm, in its most basic form, merely calculates the gradients and updates the weights using (2.14), (2.15), and (2.16) over a number of epochs. However, some of the above formulas are rather inefficient when used in the backpropagation algorithm, and a few minor modifications can be implemented to improve performance. As

mentioned previously, the weights of the neural network are adjusted in the direction which will result in the maximum decrease in error. This approach is reasonable, but at times it can cause large oscillations in the descent to the minimum, thus slowing convergence. To circumvent the oscillation problem, a momentum factor is often included in the weight update calculations as seen in Eq. (2.17), where β is the momentum coefficient and Δ_{old} is just Δ_{new} from the immediately preceding epoch.

$$\begin{aligned} \Delta_{new} &= \beta \Delta_{old} - \alpha \frac{\partial E}{\partial w_{old}} \\ w_{new} &= w_{old} + \Delta_{new} \end{aligned} \tag{2.17}$$

By incorporating the momentum factor, the amount that the weights are changed is smoothed so that rapid fluctuations are reduced.

One other issue regarding the backpropagation algorithm relates to the values that were initially assigned to the synapse weights. All of the above formulas assumed that there was always some previous weight value to adjust. The typical way to set the initial weights for the first epoch is to set all the weights to random numbers.

2.3.4 Complex Domain Neural Networks

Neural networks that work with real valued inputs are sufficient for most situations, but when the inputs to the neural network are naturally represented as complex numbers, it is advantageous to use a neural network that takes this representation into account. Complex valued data can be provided to a real domain neural network by separating the components of the complex values and providing them separately as inputs; however, the strong correlation between the components is lost. While in theory, real valued neural networks have the same ability as complex domain neural networks, in practise, the training of complex domain neural networks is typically faster and they often generalize better, especially when only a sparse training set is available.

There are many examples where the data is naturally represented as complex numbers. One such example is the frequency spectrum resulting from a Fourier transform, where each frequency value is represented by both a magnitude and phase. Other examples include multiple simultaneous signal recordings, where each signal contains different information, such as multichannel audio signals and multiple lead electroencephalograms and electrocardiograms.

The fish trajectory signals used in this thesis, consists of a three dimensional trajectory of a fish, whereby each sample in the signal can be considered as consisting of three values, one for each of the Cartesian co-ordinate axes. By restricting the classification to a single plane, complex valued signals can be obtained by utilizing the samples from one of the axes as the real part of the samples and the samples from the other axis as the imaginary part.

The architecture of the complex domain neural network is identical to that of its real valued counterpart. The actual operation of the complex domain neural network works in an analogous manner to that of real valued networks except that each input value and synapse weight is a complex number consisting of both a real and imaginary part. Consequently, the computation of the net input to the neuron, as shown in Fig. 2.4, requires complex multiplication. The activation function used in this thesis for the complex domain neurons is a scaled version of the hyperbolic tangent function, tanh(1.5x) [KaKw92], which is applied to the magnitude of the complex valued input and then multiplied by the unit vector of the input so that the output of the activation function maintains the same direction as the input [Mast94]. Since the purpose of using this neural network in this thesis is for classification, which usually results in binary decisions for the inclusion or exclusion of an input to a particular class, it is inefficient to employ complex-valued outputs as it does not aid in making the classification decision. Rather, for classification purposes, the imaginary part of the output of the output neurons is discarded and the decisions are based solely upon the real part of the output.

The extension of the neural network architecture into the complex domain is rather straightforward, but training is made more challenging because the error derivates, which are required for most training algorithms, demand complex analysis in order to compute them. Thus, in order to minimize the complexity of this neural network, this thesis employs the backpropagation training algorithm in order to optimize the synapse weights. The idea behind the backpropagation algorithm in the complex domain remains the same as that in the real domain, whereby the error gradient is used to indicate the direction with which to modify the weights. The difference in the complex domain is that both the real and imaginary parts of the weights must be updated and the derivatives become more complicated. The extension of Eq. (2.16) to the complex domain is shown in Eq. (2.18), where the *real* and *imag* subscripts indicate the real and imaginary parts of the weights.

$$w_{new_{real}} = w_{old_{real}} - \alpha \frac{\partial E}{\partial w_{old_{real}}}$$
$$w_{new_{imag}} = w_{old_{imag}} - \alpha \frac{\partial E}{\partial w_{old_{imag}}} \tag{2.18}$$

The full derivation of the error gradients shown on the far right of (2.18) will not be developed here, but the reader is encouraged to read the full derivation in [Mast94].

2.3.5 Probabilistic Neural Networks

This section of the paper will focus on another neural network called the probabilistic neural network (PNN). Unlike multilayer feedforward networks employing the backpropagation algorithm, PNNs are based on sound mathematics. Meisel [Meis72] first introduced the basic mathematical concepts behind PNNs thirty years ago. At that time, Meisel's ideas seemed to have very little practical value because the processing of the equations he derived requires a fairly substantial amount of memory. Today, memory in computers is economic and plentiful, so the main disadvantage to Meisel's work has been removed. As a result, the use of PNNs has started to see some resurgence.

Even though interest in PNNs has recently begun to increase, it is rather surprising, given the PNN's numerous advantages, that more research and development has not been performed using PNNs. One major advantage of PNNs that should attract people's attention is the fact that the training time is very fast. In fact, PNNs are able to train several orders of magnitude more quickly than neural networks using backpropagation training [Wass93]. Another significant advantage of probabilistic neural networks is the fact that, when used as classifiers, their classification accuracy asymptotically approaches Bayes optimal [Wass93]. Furthermore, PNNs do not have nearly as many problems as other neural networks regarding local minima. One final, practical advantage of PNNs is that training samples can be added or removed without extensive retraining of the neural network. This compares very favourably to neural networks based on backpropagation training, which may require that the entire network be retrained when training samples are added or removed, a very time consuming process.

Of course, if that were all to be said about PNNs, then they would undoubtedly be the most popular form of neural network in use today. Unfortunately, there are a few disadvantages with the use of PNNs. The first drawback with PNNs is the fact that they are not as general as many other types of neural networks. PNNs are predominately designed for classification

purposes. They can be forced into performing other tasks, but the original intent of PNNs was classification. Two more difficulties with PNNs are that they are slower to execute than most other neural networks, and as previously stated, they require a large amount of memory.

The advantages of PNNs definitely appear to outweigh the disadvantages, especially when the task of the neural network is to perform classification. The potential for PNNs to approach a Bayes optimal decision indicates that very high classification rates can be attained by a PNN if it is designed properly. Because of this substantial classification potential, PNNs will be discussed thoroughly in this thesis.

As a means of introduction, the mathematical concepts behind PNNs will first be introduced, followed by a description of how these ideas can be molded into the framework of a multilayer feedforward neural network. The first concept that requires introduction is the Bayes optimal decision rule and how it pertains to classification. Consider a case in which there are a number of objects known to be derived from a number of different classes. Simply put, the goal of a classifier is to identify what class a new, unidentified object belongs to. The Bayes optimal decision rule for determining which class an unidentified object should be assigned to, is expressed as follows, in which the object is assigned to class *i* provided that:

$$h_i c_i f_i(X) > h_j c_j f_j(X), j \neq i \tag{2.19}$$

where h_n is the prior probability that new object belongs to class n, c_n is the cost of misclassifying an object that belongs to class n, and f_n is the probability density function (PDF) of class n. It must also be noted that X is the input vector that will be classified. Typically, when dealing with PNNs the prior probabilities and cost of misclassification are not known a priori and are made to be equal, hence Bayes optimal decision rule reduces to:

$$f_i(X) > f_j(X), j \neq i \tag{2.20}$$

This rule indicates that if the PDFs of the different classes are known, then the best classification decision can be made by merely making a few simple comparisons. Unfortunately, the probability distributions of the different classes are not usually known and are much too complicated to attempt to approximate with simpler distributions.

In order to circumvent the problem of unknown probability distributions, Parzen [Parz62] introduced a method for approximating the PDFs of each class by using training samples from each of the classes. Mathematically, the PDF for a single class can be approximated using Eq. (2.21), where σ is a smoothing parameter, W is the weighting function, X is the unknown input sample to be classified, X_{ik} is the k^{th} training input from the i^{th} class, n is the number of training inputs for class i, and $g_i(x)$ is the PDF estimate for class i.

$$g_i(X) = \frac{1}{n_i \sigma} \sum_{k=1}^{n_i} W\left(\frac{X - X_{ik}}{\sigma}\right) \tag{2.21}$$

As the number of sample inputs, n, for class i increases, Eq. (2.21) approaches the true PDF for class i. When all of the PDF estimations are calculated, they are used in Eq. (2.20) in place of the true PDFs and the classification decision is made.

There are still two facets of (2.21) that require further explanation: the weighting function, W, and the scaling parameter, sigma, σ. For estimating the PDFs, a weighting function is needed so that when the unknown sample to be classified is in close proximity to a particular training sample (i.e. the input to the weighting function is small), the weighting function produces a large value. In other words, when the unknown sample is quite similar to one of the training samples from a particular class, the value of the estimated PDF for that class should increase rather substantially. On the other hand, if the unknown sample and an input training vector are not very close to one another (i.e. the input to the weighting function is large), the weighting function should produce a small value. In this case, the unknown input is quite different from the training sample from the particular class, and as such, the PDF for that class should not be increased much at all. Typically, the proximity or distance between the training sample and the unknown input is measured using Euclidean distance. The weighting function often used is the Gaussian function because it exhibits the aforementioned properties and is relatively easy to calculate. By setting the weighting function to the Gaussian function, (2.21) becomes:

$$g_i(X) = \frac{1}{(2\pi)^{p/2} \sigma^p n_i} \sum_{k=1}^{n_i} e^{-\frac{\|X - X_{ik}\|^2}{2\sigma^2}} \tag{2.22}$$

where p is the length of the input vector, X.

The second aspect of the PNN formulas that still requires clarification is the role of the scaling parameter, sigma. The scaling parameter dictates how wide an area the weighting function takes into account when determining the contributions of each training sample. If sigma is selected to be too small, then only those training samples that are extremely close to the unknown input will have any major contribution to the estimated PDFs. As a result, the classification system simply breaks down to a nearest neighbour classifier. If, however, the sigma selected is too large, then even training samples that are separated by a great distance from the unknown input will have a large contribution to the estimated PDFs, causing the system to display matched filter behaviour. Hence, some effort must be put forth to find an appropriate scaling parameter for the particular classification problem. Fortunately, in most problems, there is a range of values that will yield acceptable results [Wass93][Spec88], as can be seen in Fig. 2.6. Hence, since there is typically a plateau of sigma values producing optimal results, extremely intense algorithms do not have to be utilized to find an exact, superior sigma value.

It should also be mentioned at this point that multiple sigma values can be employed when using a PNN. For example, different sigma values can be utilized for each of the different classes. Separate sigma values for each class can be useful if some classes are very tightly defined (the training samples from such classes are very similar to one another) while other classes are more loosely defined (the training samples from such classes vary over a wider range). The idea of using different sigma values for each class is considered in this thesis. The formula for calculating the PDFs for such a multi-sigma PNN is almost identical to Eq. (2.22) and is given in (2.23).

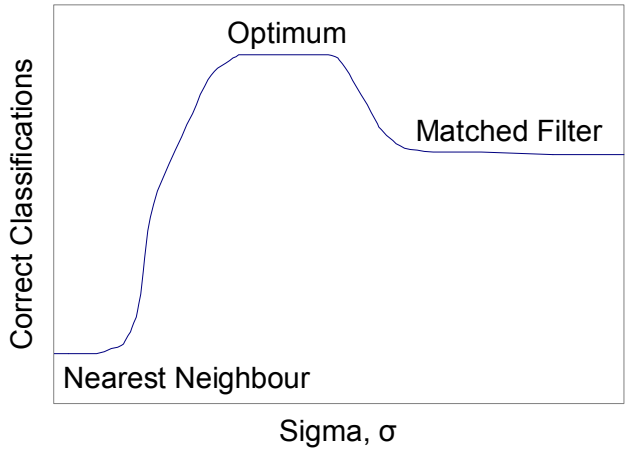


Fig. 2.6: Correct classification rate as a function of sigma,σ.

$$g_i(X) = \frac{1}{(2\pi)^{p/2}\sigma_i^p n_i} \sum_{k=1}^{n_i} e^{-\frac{\|X - X_{ik}\|^2}{2\sigma_i^2}} \tag{2.23}$$

The only difference between equations (2.22) and (2.23) is the presence of the subscript *i* for each sigma, indicating its class membership.

Now that the mathematics behind the PNN have been described, the manner in which the math is mapped to the architecture of a multilayer feedforward network, as first performed by Specht [Spec88], will briefly be explained. The architecture of a PNN is organized into four layers: the input layer, pattern layer, summation layer, and output layer, as seen in Fig. 2.7.

The role of the input layer in the PNN is virtually identical to that of the other neural networks described thus far. In essence, the input layer accepts input values from the outside world and then distributes those inputs to each of the neurons in the pattern layer. No computations are performed. Each neuron in the pattern layer corresponds to a training sample of the PNN. Notice that for Fig. 2.7, the neurons in the pattern layer have been grouped into three sets representing three different classes. The job of each pattern layer neuron is to compute the

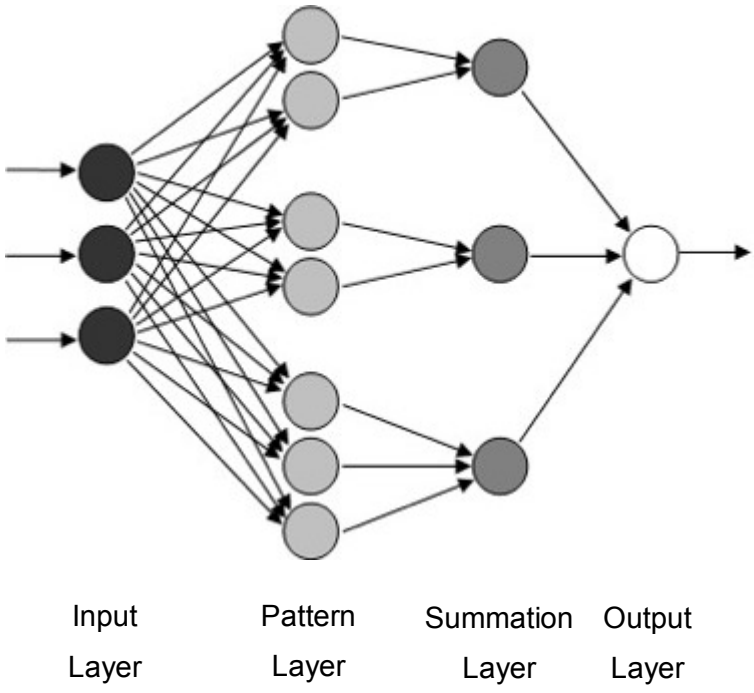


Fig. 2.7: Basic architecture of a PNN.

result of the weighting function.

The summation layer neurons have a different task to fulfill than that of the pattern layer neurons. There is a single summation layer neuron for each class. A summation layer neuron accepts the result of the weighting functions for each training vector belonging to its class, and then calculates the sum. In essence, the summation layer is performing the summation as seen in (2.22) and (2.23).

Generally, there is only one neuron in the output layer in the basic PNN. The output neuron accepts all the results from each of the summation neurons and selects the class that generates the largest sum.

2.3.5.1 Probabilistic Neural Network Training

Now that the mathematics behind PNNs and the method by which those mathematical functions are formed into a neural network architecture have been explained, the next topic that must be discussed is the process of training a PNN. As indicated earlier, the scaling parameter, sigma, must be optimized such that it matches the cluster sizes of the different classes. To perform this optimization, a two step line minimization algorithm is used [Mast95]. Specifically, the minimum must first be bounded, and then a search over the bounded interval is performed to find the actual minimum.

At its roots, single sigma optimization is merely a single variable optimization problem. Optimization problems are typically easily resolved provided the function one is attempting to optimize is known. The process of differentiating the function and setting the result to zero yields the function's minima and maxima. However, in the case of optimizing sigma, the exact description of the function is not known. As a result, other means of optimizing sigma must be used. The only way to definitively find the globally optimal sigma value is to search the entire problem space. However, this is obviously not a practical solution, as it would require an infinite amount of time.

As mentioned, the line minimization algorithm used in this thesis for optimizing sigma begins by attempting to bound the minimum. This process entails the selection of several trial sigma values within a given range, and then evaluating each trial sigma to observe how it performs. When complete, the algorithm returns three sigma values. The middle sigma produces the best results out of the trial sigma values. The first and third sigma values returned are the trial

points to the immediate left and right of the middle sigma value. Obviously the first and third values returned do not perform as well as the middle value. Hence, there must be a minimum in this interval defined by the three sigma values. The minimum in this interval may not be the absolute global minimum, but it is assumed that it will provide adequate performance.

The bounded interval defined by the three sigma values found in the first stage can be quite large, but the second step of the line minimization will usually locate the minimum after completion of a small number of trial points. The algorithm used for the second step of the line minimization process utilizes a sectioning algorithm in an attempt to minimize the number of trial sigma values required to locate the minimum. This portion of the line minimization algorithm begins with the best sigma produced in the bounding stage. The algorithm compares the distance between the current minimum sigma value and its left neighbour, as well as the current minimum sigma value and its right neighbour. The algorithm selects the larger of the two intervals in order to search for a better minimum. The value of the new trial sigma, located in the larger of the two intervals, is dictated by the particular sectioning algorithm used. In bisectioning, the most intuitive case, the trial sigma is the point in the middle of the interval; of course, the interval could be sectioned in any number of other ways. If the trial sigma produces a better result than the current best sigma, then the optimal sigma and its bounds are updated. On the other hand, if the trial sigma does not outperform the current best sigma, the optimal sigma remains the same, but the bounding points are altered to narrow the search interval. This process is repeated until it is determined that the current optimal sigma produces sufficiently accurate results, or the bounded interval gets so small that new trial sigma points are only slightly different from the current best sigma.

The above line minimization algorithm is by no means the most sophisticated method for finding a near-optimal sigma value. There are many more complex methods, such as genetic algorithms and simulated annealing, that could be utilized for this optimization step, but the two step line minimization algorithm presented here is much faster than most other algorithms, and still is very effective. As Fig. 2.6 indicates, there is usually a range of acceptable sigma values, hence this simple optimization algorithm will often produce sufficient results in a fraction of the processing time.

One matter that has yet to be mentioned is the manner by which the validity of a sigma value is determined. The procedure outlined here for evaluating the performance of a particular

sigma is called jackknifing [Mast93]. Jackknifing is a reliable method for evaluating different sigma values because it provides a very good representation of how well a particular sigma performs, while at the same time does not require an excessive number of training samples.

When training the PNN, several known input samples are used to serve as examples from each of the different classes. These known examples are the network's training set. The premise behind jackknifing is to train and test the PNN k times, where k represents the number of training data samples. During each of the k trainings sessions, one of the training sample inputs will not be included in the training process. Then, once the PNN has been trained, the single training vector that was excluded will be presented to the PNN to be classified. During each of the k training and testing sessions, should the single excluded training input be incorrectly classified, the sigma value receives a point. The lower the score a sigma receives the better, as the score indicates the total number of inputs the PNN has incorrectly classified.

The jackknifing metric provides a reasonable measure of performance for a particular sigma value when the goal is to try to optimize sigma. However, it must be stressed that jackknifing is a biased measure of performance because the testing inputs are being used to train the neural network. As a result, the true ability of the PNN should be measured once training has been completed. This measurement would be performed by attempting to classify a testing set which does not include samples that were present in the training set.

A few points should be mentioned about the manner of optimizing sigma values when a different sigma is used for each of the different classes. In this scenario, the problem has been extended to a multivariate optimization problem, and as such, is slightly more difficult. The technique utilized in this thesis to determine an acceptable set of sigma values is a conjugate gradient method. As conjugate gradient methods are standard mathematical entities, a full description will not be provided here, but there are many reference materials available that describe such algorithms in full detail [PrFTV88].

One requirement for the conjugate gradient algorithm that must be discussed is that of a continuous error function. When performing single sigma optimization, the jackknifing technique measures the performance of a particular sigma value based on a point scoring system. The fewer the number of points a sigma value receives, the better it has performed in its classification, since the points signify errors. This technique is sufficient for the single sigma optimization, but something more sophisticated must be used for multi-sigma training.

Specifically, a continuous error function must be derived whereby the goal of the conjugate gradient algorithm is to minimize the error function. There are two main reasons why a continuous error criterion is used for the conjugate gradient algorithm rather than the point scoring system. First, a continuous error function provides the jackknifing algorithm with a superior metric as to how well a set of sigma values performs. With the point scoring system described for single sigma training, tied results would occur quite frequently, whereas with a continuous error function the occurrence of ties is much more of a remote possibility. The second, more important reason for selecting the continuous error function is that the conjugate gradient algorithm uses the error function and its partial derivatives with respect to the sigma values in order to perform its optimization.

The continuous error criteria used for this project is defined in (2.24), where X is the input being classified, index i is the class to which X belongs, index k represents all of the other classes, and b_n are the Bayesian confidences.

$$e_i(X) = \left[1 - b_i(X)\right]^2 + \sum_{k \neq i} \left[b_k(X)\right]^2 \tag{2.24}$$

The Bayesian confidences, are defined in (2.25), where K is the number of classes and $g_i(X)$ is defined in (2.23).

$$b_i(X) = \frac{g_i(X)}{\sum_{k=1}^{K} g_i(X)} \tag{2.25}$$

Equation (2.24) intuitively seems reasonable because if X belongs to class i, then ideally the Bayesian confidence, b_i, will be close to 1, and b_k, $k \neq i$, will be close to 0, which will produce a small error. If b_i decreases, an indication that the PNN did not believe X belonged to class i (an incorrect result), then the error produced will be larger.

The full derivation of (2.24) and its first and second partial derivatives with respect to the sigma values will not be presented here as they become quite tedious, and are not a core component to understanding the thesis as a whole. Hence, for further information regarding the continuous error function and its derivatives that are used in conjunction with the conjugate gradient function, the reader is encouraged to refer to [Mast95].

2.3.6 Kohonen Self-Organizing Feature Maps

Kohonen self-organizing feature maps (SOFMs) are neural networks that use unsupervised competitive learning algorithms. These neural networks are referred to as topology-preserving in that the neighbourhood relations of the data are preserved and structure is imposed upon the neurons in the network [Koho84]. This clustering of the data based on their relations allows for the discovery of the underlying structure of the data. The use of SOFMs in this thesis is two-fold. First, SOFMs are incorporated for objectively determining the clusters, or classes, of the signals used to verify the classification system. The second use of the SOFMs in this thesis is for feature extraction purposes by creating a signature pattern for a given signal.

An SOFM is composed of just two layers of neurons: an input layer and an output layer. The neurons in the output layer simply output the Euclidean distance (or the square of the Euclidean distance) between its weights and the input, as shown in (2.26), where n is the number of inputs to the network.

$$out_j = \sum_{i=1}^{n} (w_{ji} - input_i)^2 \tag{2.26}$$

The neuron that has the smallest output is declared the "winner". It is this "winner" that is allowed to have its weights updated, hence the competitive nature of the learning. Training of the network is performed by modifying the weights of the "winner" neuron to make it more closely resemble the input as shown in Eq. (2.27), where w is the neuron weight, index k signifies the "winner" neuron, and index i is the input neuron.

$$\begin{gathered} w_{ki_{new}} = w_{ki_{old}} + \eta(input_i - w_{ki_{old}}) \\ k \,|\, out_k > out_j \forall j \neq k \end{gathered} \tag{2.27}$$

In addition, the surrounding neurons also have their weights updated during training, in order to encourage groupings and clusterings. It is this group learning from which the SOFM attains its power. The aim of the training is to have similar inputs activate neurons in the same area. The function that dictates which nearby neurons also learn is referred to as the neighbourhood function. There are many different neighbourhood functions that can be used, such as a constant, linearly decreasing, exponentially decreasing, or Mexican hat, which uses negative learning rates in an attempt to more distinctly isolate the groupings [EbDo90].

However, the neighbourhood function has little overall effect on the SOFM as long as enough training is permitted for the network to converge to a steady state [Fere95]. This thesis uses a constant neighbourhood function where all neurons within a designated distance, or radius, of the "winner" neuron have their weights updated at the same rate as the "winner" neuron. A heuristic is used whereby the radius of the neighbourhood function decreases along with the learning rate as the training progresses. Using this technique, the SOFM initially roughly defines the clusters when the radius and learning rate are high and then refines these clusters as training progresses and the radius and learning rate are decreased.

There are two common ways in which the neurons in the output layer can be organized. The first is simply in a one-dimensional array, and the second is in a two-dimensional matrix. The main difference between these layouts is how the neighbourhood function is defined, in that for the two-dimensional case, there are neighbouring neurons in multiple directions that may have their weights updated. This thesis does not consider this type of SOFM as the signals used in this thesis are represented as one-dimensional vectors and do not require the extra complexity of the two-dimensional SOFM.

The primary manner in which SOFMs are used in this thesis is for feature extraction of signals. The number of weights in the SOFM is typically less than the length of the signal that is used to train it. Hence, when the SOFM is presented with segments from the signal, the weights of the SOFM have to adjust such that they represent the predominant characteristics that are present in the signal. In other words, the weights are adjusted such that they represent the most prominent features in the signal. When training is complete, the set of weights contained in the SOFM are commonly referred to as the codebook, as it contains a set of codes representative of the signal. These weights, or codes, within the codebook are known as codewords and each codeword represents a specific feature that the SOFM found within the signals. In addition to the reduction in the number of features representing the signal, the use of SOFMs provides some translational robustness in that signals which are mere translations of one another result in very similar codebooks.

The second way in which SOFMs are used for this thesis is to derive the different classes from the signals by exploiting the SOFM's clustering abilities. Clustering algorithms are not the main focus of this thesis but are utilized to form the training and testing sets for the purpose of

classification since the annotations of the signals used in this thesis were not provided. A more thorough discussion of the use of SOFM for clustering can be found in Appendix B.

2.4 Summary

This section of the thesis has provided the background on signal classification and has introduced the techniques used to perform feature extraction for the purpose of classification, namely, the variance fractal dimension trajectory and Kohonen self-organizing feature maps. In addition, the probabilistic and complex domain neural networks have been presented as they are used to perform the signal classification based on these features.

CHAPTER 3
SYSTEM DESIGN

One of the primary goals of the signal classification system is a maximal independence from the signal itself. It is this requirement that drives much of the design of the architecture of the system and the components of the system.

There are three main design goals for the classification system developed for this thesis: the average correct classification rate must be greater than 90%; the time required to train the system must be less than a day; and the time required for the system to classify a given input signal must be shorter than the duration of the signal itself. The correct classification rate of 90% was selected because this success rate indicates that the system is able to correctly classify inputs with a high degree of consistency. Additionally, a rate of 90% was deemed to be a reasonable target given the time-constraints of the thesis.

The training time design constraint was selected in a less precise manner because there are no reasons in this thesis to dictate a definitive time limit for the training of the system. Thus, the training time criterion was selected so as to ensure that the system was capable of training in a time frame in the realm of reasonability. As a result, the constraint for the training time of the classification system was selected to be on the order of minutes or hours, and not days or months.

The final design criteria specifying that the execution of the classification system require less processing time than the duration of the signal itself was decided to ensure that the system could be applied to performing analysis on signals in real-time, should it be required.

3.1 System Architecture

There are many challenges for a system flexible enough to work with a variety of different signals while requiring minimal changes to the system. One of the first issues in such a system is simply reading the signal from its raw data representation since there is no universally adopted format with which to represent signals. The first component of the system is preprocessing, as shown in Fig. 3.1, and the primary function of the component is to convert the signals from their original data representation to a proprietary format developed for this thesis. The application of a different signal to the system primarily requires only a minor addition to the

preprocessing stage to perform the necessary data conversion. This common data representation provides the ground from which the rest of the system can stand upon.

The preprocessing stage is also responsible for performing any necessary filtering to reduce noise or other signal manipulations required before its analysis. For the purpose of this thesis, no filtering is performed so as to further test the robustness of the system.

The task of designing the part of the system to perform the actual classification of signals seems daunting at first because of the abundance of signal processing techniques available. The main idea behind classification is to group the signals into classes in which membership to a particular class is based solely upon a selected set of features. The entire classification of the signals is dependent upon the careful selection of the features with which to uniquely identify each class of signals. The difficulty is that there are an infinite number of features to choose, ranging from the average value of the samples, the variance of the samples, Fourier transform coefficients, wavelet coefficients [Mall98], or even the signal samples themselves. For the signals examined in this thesis, simple statistical measures are insufficient to uniquely identify the signal classes and the ubiquitous Fourier transform is not applicable because of the non-

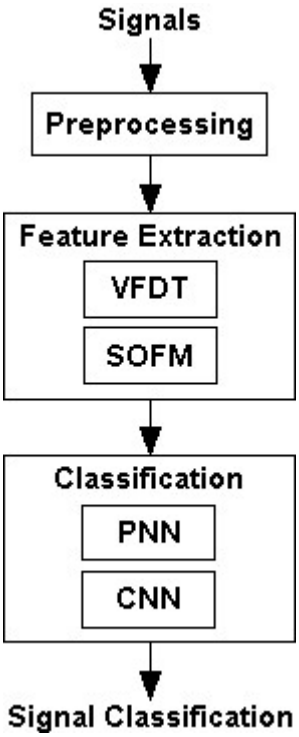


Fig. 3.1: System block diagram.

stationarity of the signal and the non-linear processes that generate these signals. It is naïve to simply use the samples from the signal to attempt to identify the classes because in most cases, this results in too many features for the classifier to base the classification upon. Furthermore, the sample domain is very sensitive to changes in amplitude, frequency, and phase. The windowed Fourier transform or wavelet transformation could however be utilized, but this thesis chooses to take advantage of the self-similarity of the signals and use a multifractal characterization with which to uniquely identify each class. The particular technique used is to represent the signal as a trajectory of its variance fractal dimension through sliding windows across the signal. The advantages of this transformation are two-fold. First, this scale-invariant transformation emphasizes the underlying complexity of the signal, which provides the unique identification for each class. Second, the transformation provides a normalizing effect since the theoretical limits of dimensionality of Euclidean one-dimensional signals is bound between one and two. Normalization is critical for the classification process, since all signals in a particular class must have similar values for the defined set of features. Without normalization, signals in the same class could potentially take on any values for the set of features and it would be impossible to perform classification because the range of acceptable values would be infinite.

Without any further feature extraction, the classification can be performed based solely upon the signal's variance fractal dimension trajectory (VFDT), and this is explored by this thesis. The difficulty is that the VFDT is actually another signal. Although it is much less sensitive than the original signal, it still suffers from translational problems. Slightly shifted VFDTs should be interpreted to be of the same class, but when compared sample by sample, they would be quite different. Feature extraction upon the VFDT itself could be performed using any of the techniques mentioned previously, but the goal is to not lose the normalization achieved or the features already extracted. The technique proposed is the use of Kohonen self-organizing feature maps (SOFMs). The goal is to extract the characteristic features of the VFDT and form a fingerprint of it. The SOFM will form a codebook that represents the VFDT and slightly sample shifted signals would then have very similar codebooks. Furthermore, this feature extraction can lead to a compression in the number of features used to represent the signal and hence, reduce the size of the classification problem

With the set of features established, the remaining task is to perform the actual classification of the signals based on these features. The classification should be automated and not be specific to the actual signal being classified. There are two main lines of thinking for

performing this task: expert systems and machine learning. Expert systems involve establishing customized predefined rules for separating the signals into classes based on their features; however, this is too rigid of a structure to be easily adaptable to different signals. Furthermore, in most cases, it is not known how to arrive at concrete rules about how to perform this classification.

Machine learning, on the other hand, entails having the computer discover its own way of performing the classification based on some examples of signals belonging to each class. Simply providing examples of each class requires much less work than specifically defining the rules needed to determine exactly how to classify the signals based on the selected features. Utilizing machine learning allows the data to speak for itself. The particular choice of machine learning used in this thesis is neural networks. Neural networks are used in this thesis for their ability as function approximators, meaning that they can learn virtually any function. Additionally, neural networks were chosen because of their generalization ability and robustness to noise, meaning that they perform well upon data they have never seen before and in situations involving abnormalities. This flexibility is important because with any classification, there will be some variability in the acceptable values of features for a given class.

Even with the decision of utilizing neural networks to perform the classification, there are a variety of neural networks to choose from. While the basic backpropagation neural network generally comes to mind, it is not the best neural network to choose for classification. The probabilistic neural network (PNN), or Bayes classifier, trains faster and is asymptotically optimal as the number of training vectors increases.

One aspect to consider is that some signals are composed of multiple recordings, each capturing different information about the physical system. In the case with two simultaneous signal recordings, the signal can be considered to consist of a single array of samples, each of which are represented as complex numbers, where the real part is a sample from one of the recordings and the imaginary part is a sample from the other recording. Extensions to hypercomplex numbers, where three or more simultaneous recordings are available, are possible, but this thesis will restrict the number of signals to being complex.

Ignoring the additional information that the multiple recordings provide could restrict the performance of the classification. The SOFMs can be modified to handle the values as complex numbers, as can the PNNs by appending the second signal to the first and creating a single real

valued signal; this technique is discussed in the corresponding component design sections. As an alternative to the PNN, this thesis also proposes to use a complex domain neural network to perform the classification upon the signals and take advantage of this additional information as well as the strong coupling between the two values that compose each complex valued sample. This extension to the complex domain adds complexity, so the basic backpropagation training algorithm is used. It is not known to what extent the inclusion of additional information with the use of complex domain neural networks will have on the classification, so comparisons will be made between probabilistic neural networks using one or both fish signal recordings and the complex domain neural networks using both fish signals simultaneously.

3.2 Component Design

Even with the components selected for use in this thesis, many design decisions must be made about the components themselves, as there are a variety of options available and several parameters to set.

3.2.1 Preprocessing

The function performed by this component is to perform data conversion from the raw data format of the signal to a proprietary format developed for this thesis. For the most part, each type of signal has its own unique file format, so the data conversion involves parsing any relevant information from the file header and translating the signal samples from their original ASCII, binary, or other encoding schemes. Further complicating matters, some raw data files contain multiple signals, which must be separated in order to facilitate the function of the other components. Thus, for a given raw data file containing n signals, the output of the preprocessing stage is n files, each containing one of the signals from the original data file in the proprietary format used in this thesis.

The format chosen for this thesis is simple but contains all the information needed to perform the analysis upon it. The processed files representing the signals have some basic header information containing the sampling rate of the signal and the number of samples in the file. This header is followed by the actual samples of the signal. All values are written in uncompressed binary, little endian format, with floating and double point values conforming to the IEEE 154 standard. This file format allows for flexibility in the data type of the sample points, since it is

inefficient to use a lowest common denominator and represent 4-bit integers as 64-bit double values. The consequence is that a matching reader object is required for each data type.

For the signals used in this thesis, noise filtering is not performed because little is known about the fish trajectory signal and the absence of filtering provides an opportunity to test the resilience of the classification process to noise.

Error correction is however, necessary for the fish trajectory signals and is performed in this component. For these signals, tracking errors occasionally occur and result in missing samples. These missing samples are corrected by using first order, or linear, interpolation and zeroth order, or nearest neighbour, extrapolation. Linear interpolation is used for its simplicity and because the tracking errors generally do not occur in large numbers of consecutive samples. Nearest neighbour extrapolation is performed in order to ensure that the extrapolated samples remain in the valid range of values. In addition, the end points are not crucial since they have little effect on the overall signal and it is sufficient to assume that the fish remains stationary at those points.

3.2.2 Variance Fractal Dimension Trajectory

While the basic VFDT algorithm remains consistent with that shown in Chapter 2, some modifications are made to improve the robustness of the algorithm. In its original form, the VFDT algorithm occasionally produces some undesired artifacts. Two such artifacts are considered here. Given a particular window, if the variance of the difference between samples is exactly zero, which occurs when the samples from the signal lie on a straight line, then the algorithm fails when forming the log-log plots, since the log of zero is undefined. One option would be to use a threshold and set any value below the threshold to some predefined small value. However, should the signal exhibit a straight line, then the variance at each scale would be exactly zero, meaning that the threshold value would be enforced for each point in the log-log plot, yielding a horizontal line in the log-log plot. The slope of such a line is zero, which gives a dimension of two, which is not theoretically correct. Straight lines have fractal dimensions of one, thus the modification made is to simply set the dimension to one should a variance of zero be produced for any of the points in the log-log plot. This situation occurs almost exclusively in fabricated cases and is very rare in real signals since signals invariably have noise making the occurrence of perfectly straight lines nearly impossible. In fact, this situation does not occur in any of the fish trajectory signals used in this thesis.

The second modification to the VFDT algorithm is slightly more involved. It was observed that in some instances, the log-log plots seemed to exhibit some peculiar behaviour whereby the first few points clearly formed a straight line, and exhibited power law behaviour, but the last point was significantly lower than what would be expected if the line were to be extended to the last point. This phenomenon is demonstrated in the top left plot in Fig. 3.2, where the individual points are plotted along with the associated linear regression. A typical log-log plot exhibiting power law behaviour is shown in the top right of the same figure. The irregularity shown in the left plot is contrary to what is expected because the variance of the difference between samples close together should be lower than the variance between samples farther apart, since closer points are more correlated than farther points. This is generally the case unless the signal is periodic with a period similar to the distance between samples used in the VFDT algorithm at the largest scale, in which case, the variance between samples would be unexpectedly small. Computing the frequency spectrum of the window, as shown below the log-log plots, corroborates this claim in that the frequency corresponding to the sampling in the largest scale, indicated by the triangle along the frequency axis, has a significantly larger presence than in cases where the log-log plots exhibit power law behaviour. The resulting artifact is that the slope of the linear regression is smaller than anticipated, which causes an increase in the

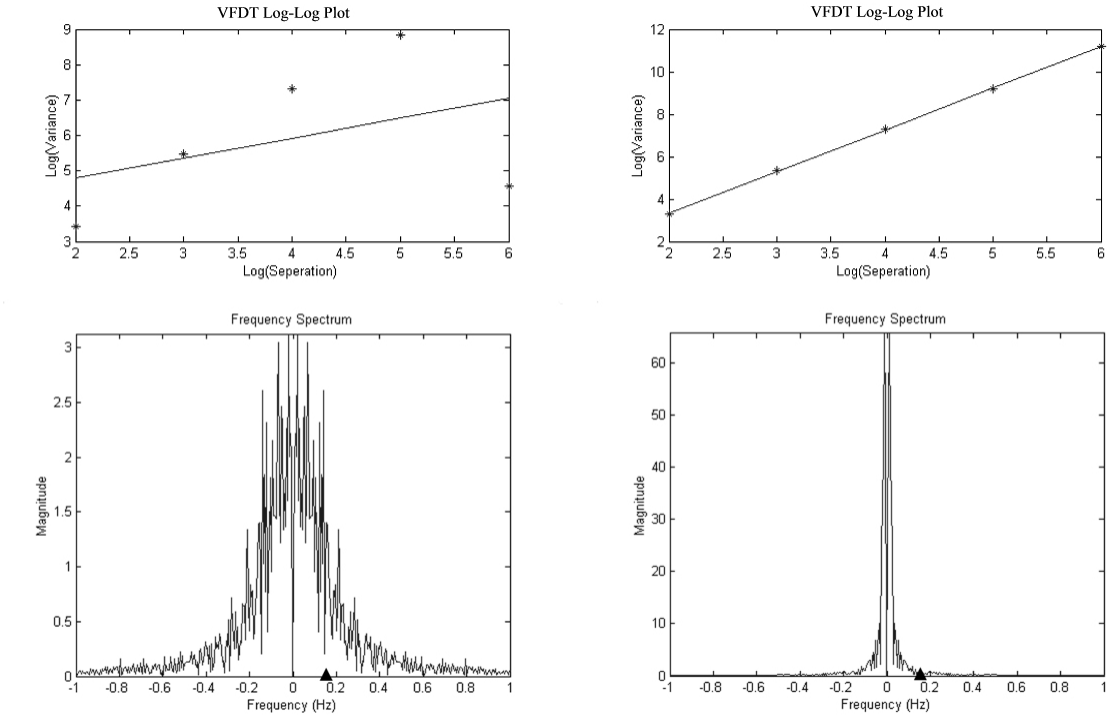


Fig. 3.2: VFDT log-log plots and frequency spectrum plots.

fractal dimension.

To remove these artifacts, the last point is discarded in log-log plots where the points are progressively increasing in value, but the last point is lower than its predecessor. By ignoring the last point in these instances, the linear regression can then capture the power law behaviour exhibited by the remaining points. Periodicities corresponding to the last point is not the only problem, since periodicities affecting the separation corresponding to the second last point would have a similar affect. In such a scenario, both the second last point and the last point would be lower than expected because the frequency corresponding to the last point is merely a harmonic of the second. More sophisticated algorithms could be used to eliminate the outliers in general, but are not explored in this thesis since it was observed that artifacts caused by these periodic situations had a low rate of occurrence.

Aside from the design modifications to the VFDT component itself, there are also design decisions to be made concerning the two free parameters involved in the algorithm. The choice of the window size is very important and unfortunately, the choice is specific to each type of signal. Generally, the window size is chosen to match the stationarity of the signal; however, since such knowledge does not exist for the fish trajectory signals used in this thesis, the window is experimentally determined. The window is chosen such that in general, the log-log plots obey a power law relation. The second parameter is the displacement of the sliding windows. The amount that the sliding window is shifted for each calculation of a variance fractal dimension determines the resolution of the VFDT. Unlike the window size, the experimental determination of the window displacement is more subjective in nature. Furthermore, these two parameters affect the size of the classification problem in that the value of the window size and displacement control the number of features to be used for classification. The actual choice of the window size and displacement used during the verification of the classification system is discussed in the experimental results and discussion in Chapter 6.

3.2.3 Kohonen Self-Organizing Feature Map

For the purpose of feature extraction and further reduction of the size of the classification problem, SOFMs are used to produce a fingerprint of the VFDT by picking out the most common characteristics from the VFDT. The fingerprint produced is simply the codebook of the SOFM trained using samples from the VFDT signal. For a given codeword length, the SOFM is trained by providing it with intervals of the VFDT with the same length as the codeword. The SOFM

then determines the most representative codewords from the VFDT and arranges them in a topological-preserving manner. The classification is then based upon these set of codewords. Because the chosen intervals of the VFDT are allowed to be shifted anywhere along the signal, the codebooks should be more robust to translational shifting than the VFDT signals. While the codeword length is important because it determines the size of the features extracted from the VFDT, the number of codewords is also an important because it determines the number of features selected. If the number of codewords is too small, then the SOFM cannot capture all the important features. Conversely, if the number of codewords is too large, then the size of the classification problem is larger than necessary and the SOFM may extract insignificant features. These parameters are determined experimentally and their choices specific to the fish trajectory signals are discussed in Chapter 6.

Another architectural design decision is the organization of the neurons in the SOFM. The most common organization represents the neurons in a two-dimensional map; however, since the signals used in this thesis are one-dimensional in the Euclidean sense, and to reduce the complexity of the SOFMs, the neurons are organized one after another in a one-dimensional array.

As it is currently presented, the SOFM is only able to form a codebook based upon a single real valued signal. In order to extend the SOFM such that it can perform feature extraction of two signals simultaneously in cases where the classification is dependent upon two separate, but correlated signals, each signal sample can be represented as a complex number, with the real part representing a sample in one signal, and the imaginary part representing a sample in the other signal. By replacing the real domain Euclidean distance between the neuron weight and the input vector in Eq. (2.26) with the more general complex domain version, and performing some straightforward manipulations, Eq. (3.1) can be obtained.

$$out_j = \sum_{i=1}^{n} \left\| w_{ji} - input_i \right\|^2$$

$$out_j = \sum_{i=1}^{n} \left(\sqrt{(w_{ji_{real}} - input_{i_{real}})^2 + (w_{ji_{imag}} - input_{i_{imag}})^2} \right)^2$$

$$out_j = \sum_{i=1}^{n} (w_{ji_{real}} - input_{i_{real}})^2 + \sum_{i=1}^{n} (w_{ji_{imag}} - input_{i_{imag}})^2 \qquad (3.1)$$

This result demonstrates that using an SOFM that accepts complex valued inputs is equivalent to a real domain SOFM where the real and imaginary parts of the input are concatenated to form a single real valued array. Thus, no architectural changes are required to have the SOFM perform feature extraction upon multiple simultaneous signals.

The input to the SOFM are intervals of VFDT signals, consequently, the values are, for the most part, normalized between one and two, and hence the weights of the SOFM need only be between one and two. Since no assumptions are made about the signal or its VFDT, the weights are initialized by simply using random numbers uniformly distributed between one and two.

The training of these initially random weights involves a number of design decisions. The epoch size is set to one, meaning that the weights are updated after each presentation of a training vector as that is the standard for this neural network. Since no a priori knowledge about the VFDT is assumed, the training vectors are randomly selected intervals from a single VFDT signal. Because the training is unsupervised, there is no right or wrong that can be assessed, so the number of training vectors presented to the SOFM is fixed and simply such that the SOFM converges to a steady state. Again, this value is determined experimentally, but in general, each training vector should be presented at least a couple of times during training. Another decision to be made is the neighbourhood function to use for training. The neighbourhood function is not that important as its primary effect is a slight alteration of the speed of convergence of the network. As such, the simplest function, the constant function, is used where all the neurons within a particular distance, or radius, of the "winner" neuron learns at the same level. The choice of the radius of the neighbourhood function and learning rate are however, quite important. Initially these parameters are set to large values in order to establish the general groupings in the map and are then decreased as the training proceeds in order to refine the clustering. The question arises as to how to decrease these parameters. Two disparate options are exponential and linear reductions of the parameter values. Through experimentation, it was discovered that exponential reduction does not produce good results because the parameters are reduced too quickly and the general clustering is not properly established before the parameters decrease to levels where refinement dominates. As a result, maps are produced where the clusters and extracted features are poorly defined. Linear reduction causes the SOFMs to converge quicker and produce better clustered codebooks representative of the training vectors. The initial radius of the neighbourhood function is set to the size of the codebook and the learning rate is set

to 0.9. Both parameters and they are reduced in a linear fashion until the radius is 0, meaning that no neighbouring neurons are affected, and the learning rate is 0.1.

3.2.4 Probabilistic Neural Network

Probabilistic neural networks (PNNs) are utilized in this thesis for their excellent classification ability. The majority of the design decisions in regard to the PNN relate to the smoothing parameter, or sigma value, used in the Gaussian functions in the pattern layer of the neural network. The first decision to be made is whether a single sigma value is to be used for each feature. A different sigma may be desired for different features if the features have different normalizations or importance. For this thesis, the features provided to the PNN are either a VFDT signal or a SOFM codebook created from a VFDT signal, thus there are no reasons to have any preference or special consideration for any particular feature, as they all represent fractal dimensions. However, when the PNN is used to classify complex valued signals consisting of samples from two separate recordings, things are slightly different. When dealing with complex valued inputs with the PNN, a transformation is performed whereby a single input to the PNN is formed by the concatenation of the two recordings, which is identical to how this situation is handled with the SOFM in Eq. (3.1). Such a transformation is valid to use in conjunction with the PNN because the pattern layer of the PNN simply uses a Euclidean distance measure, as was used in the SOFM. Since in this configuration, the input to the PNN is a combination of the features from multiple recordings, it may be desired to use different sigma values for each recording, but due to time constraints, this option is not explored in this thesis.

Multiple sigmas may be also desirable when signal classes have very different spreads, meaning that the signals in one class may have very little variability, or spread, whereas signals in another class may have a high level of variability. In such instances, larger sigmas are desired for classes with large spreads and smaller sigmas for classes with small spreads. This thesis allows the option of choosing whether or not different sigma values for classes are used. The consequence of using multiple sigma values is an increase in the complexity of the training algorithm and the training time.

Training a single sigma PNN entails deciding an appropriate sigma value. However, the problem space is infinite and the problem function is not known, so determining the globally optimal value for the sigma parameter is not guaranteed. Although the problem landscape is unknown, it is known that there is correlation between points in the landscape in that the

performance of the PNN as a function of the sigma value is a continuous function, and in most cases the function changes very slowly and there are few local minima, as shown in Fig. 2.6. Furthermore, the sigma value has a multiplicative effect with respect to the Gaussian function used to estimate the probability density functions. By taking advantage of this information, a simple training algorithm can be used to train a single sigma PNN by attempting to bound the optimal sigma value. A global line minimization is first performed whereby a variety of sigma values between some initial bounds are tested. Because of the multiplicative effect of the sigma value, a logarithmic space is used to select the sigma values between the initial bounds in order to provide for a more efficient search. Jackknifing is used to evaluate the performance of the sigma value because it is able to provide a quick estimate of the performance of the PNN for a given sigma value based entirely upon the training set. After this approximate bounding, the optimal value is refined using a sectioning algorithm. This algorithm reduces the bounds of the sigma value by cutting it in half in a geometric sense in each iteration until the optimal sigma value is found or the improvements become insignificant. Because of the way the PNN operates, the bounding of the optimal value of sigma is on the number of inputs to the neural network. It has been experimentally determined that the initial bounds of 10^{-6} and 10^{-1}, both multiplied by the number of inputs to the network, usually bounds the optimal value. Furthermore, 15 initial sigma values used in the global line minimization also seems to provide an adequate initial bounding.

When training the multi-sigma PNN created for this thesis, the goal is to derive an acceptable sigma value for each of the different classes. The multi-sigma training algorithm is slightly more complex than the single sigma training algorithm because it must optimize an unknown function of n variables, where n is the number of classes, whereas the single sigma algorithm only has to optimize a function of one variable.

The actual multivariate function that must be optimized during multi-sigma training is the continuous error function, (2.24), described in Chapter 2. There are several different techniques that can potentially be used to optimize a multivariate function. The three most popular techniques are conjugate gradient methods, quasi-Newton methods, and Newton's method. The quasi-Newton and Newton's methods were not used in this project because of their excessive requirements. The problem with quasi-Newton methods is that an approximation of the Hessian matrix must be calculated and stored. In problems involving neural networks, the amount of storage required to hold the Hessian matrix can become quite large. Newton's method also requires large amounts of memory because it must store all of the mixed partials of the

continuous error function. Additionally, computing all of the mixed partials for Newton's method can be a very time consuming process. Conjugate gradient methods, on the other hand, do not require the large storage requirements nor the large amounts of processing of quasi-Newton and Newton's method, yet, at the same time, the performance of conjugate gradient methods are almost as good as the other two methods. As a result, a conjugate gradient method is used to perform the multi-sigma optimization.

The first decision to be made with respect to the conjugate gradient algorithm is the selection of the initial sigma values. One possibility is to simply select random initial sigma values and perform the optimization from there. This is a quick and simplistic approach, but it was decided that a slightly better technique could be utilized. A logical method to obtain initial sigma values is to execute the single sigma training algorithm and use its result as the starting point for each of the sigmas in the multi-sigma set. The single sigma training algorithm provides an estimate of the average amount of variability in the classes. Often the amount of variability contained within each class is fairly similar, thus the multiple sigma values chosen will be very close to the original single sigma. In other problems, the amount of variability in each class is more pronounced, meaning that the multiple sigma values will vary more greatly from the sigma value chosen with single sigma optimization. However, in either scenario, the single sigma value chosen provides a middle ground starting point that can be increased for some classes and decreased for other classes to find an appropriate set of sigma values.

At the heart of the conjugate gradient method is the line minimization algorithm. Thus, the next decision to be made is regarding which line minimization algorithm to use. The line minimization algorithm used is merely a minor extension to the algorithm used with the single sigma optimization. More specifically, the line minimization algorithm first performs the same global line minimization, used in the single sigma case, to bound the minimum, and then refines the minimum in its second step, using the well-known Brent's line minimization. This line minimization technique is a good choice for the conjugate gradient algorithm as it provides a reasonable minimum very quickly. Since the conjugate gradient algorithm performs the line minimization step numerous times, it is imperative that it be as fast as possible.

3.2.5 Complex Domain Neural Network

This thesis explores the use of neural networks that are designed to directly handle complex valued inputs because their training is typically faster and their generalization ability is

usually superior to their real-valued counterparts. This particular component requires a number of design decisions, including some architectural in nature and some pertaining to the training of the network.

Architecturally, the main design decisions concern the number of neurons to use in the network. The number of input neurons is fixed by the number of features used for classification and is not a parameter that is specific to the complex domain neural network itself. A single output neuron is used for each class since it is an unnecessary burden to place upon the network to encode the class in a binary fashion or some other encoding. This one-hot encoding is simpler in that the network only has to activate one neuron and deactivate the others. Since each output neuron is used as a binary indication of the inclusion or exclusion of an input to a particular class, having a complex output for each neuron unnecessarily adds complexity. The network can be simplified by ignoring the imaginary part of the output and training the network to produce only real output values so that the classification decision can be based upon real output values. The network is trained to have the output neuron corresponding to the input vector's class produce a value of 0.9 and with the rest of the output neurons producing -0.9. The classification decision for a given input is then based upon which output neuron produces the highest activation.

The network is restricted to a single hidden layer since additional layers would substantially increase the complexity of the network as well as the training time, while not significantly adding to the network's ability because a three-layer neural network is sufficient in virtually all situations. The number of neurons to place in this layer has a dramatic effect on the network's ability to perform the desired operation and the speed at which it executes and trains. The heuristic which specifies that the number of hidden neurons should be set to the geometric mean of the number of input and output neurons is used in this thesis. Through experimentation, it was discovered that this heuristic provides a good balance in that there are enough neurons to learn the desired function without simply memorizing the inputs and the network is restrained to a reasonable size so that the training and execution time of the network is acceptable.

Backpropagation was chosen as the training algorithm for the complex domain neural network in order to keep the complexity of the network to a reasonable level for this thesis. The network is trained using an epoch size equal to the size of the training set so as reduce the oscillations of the values of the weights during training and thus speed up the convergence of the network. A second modification to the basic backpropagation algorithm used is the inclusion of a

momentum factor, whereby a fraction of the previous correction value for the weights is added to the present correction value. Again, the purpose of this modification is to reduce the oscillations that are typical when using backpropagation. A learning rate of 0.5 and a momentum coefficient of 0.9 are used in this thesis, as it was experimentally found that these values provided a balance between readily responding to the error derivatives while avoiding too much compensation and resulting in oscillations. The training of the network is generally stopped when the mean square error of the network is below a desired value. However, a maximum number of epochs is also imposed so that the training completes in cases where the network refuses to converge. As with the learning rate and momentum factors, these values were experimentally determined and a mean square error of 10^{-5} is sought and a maximum of 10^{5} epochs is enforced.

3.3 Summary

This section of the thesis has outlined the major design decisions made in developing a classification system able to handle non-stationary, self-similar, stochastic signals arising from non-linear processes. What remains is a discussion of the actual implementation of the system along with the method in which the system was tested and verified.

CHAPTER 4
SYSTEM IMPLEMENTATION

4.1 System

As this thesis involves the implementation of a number of different algorithms and techniques, a purely software approach is adopted for rapid development, ease of interfacing with the existing data, flexibility, and cost. The chosen programming language for use in this thesis is Java because of its object-orientated nature, platform independence, well-documented application programming interface, cost, and its built-in documentation abilities through Javadoc. The main drawback of using Java is inferior performance when compared to programs written in native compiled languages such as C or C++. However, compiling the Java bytecode to native language code significantly narrows the performance gap. The native compiler used in this thesis is Excelsior JET[2], which reduces the execution time of the programs used in this thesis by 30-50% over simply running the Java bytecode inside a Java virtual machine.

Because of the uniqueness and sophistication of the techniques used in this thesis, toolboxes and packages are insufficient for the implementation of this thesis. Consequently, the entire classification system is built specifically for this thesis, which also provides for complete control and customization over every aspect of the system.

The primary goal in implementing the classification system is flexibility. The system must be implemented in such a way that only minimal changes are necessary in order to use the system with different types of signals. This relative independence of the system from the specific signal being analyzed is achieved through the object oriented implementation of the preprocessing component as well as the common format used to represent signals in this thesis. The system must also be easily reconfigurable so that different techniques can be used for feature extraction and classification. This reconfigurability is obtained by implementing independent and decoupled components.

---

[2] Obtained from http://www.excelsior-usa.com/ last checked March 6, 2003

4.2 Component

The implementation of the system is divided up into a number of components, the details of which are discussed in this section. The component responsible for the preprocessing of the signals is presented followed by the feature extraction by the variance fractal dimension trajectory and the Kohonen self-organizing feature maps. The components for the neural network classifiers are then described. Finally, components related to the construction of input vectors for classification and the component responsible for actually performing the classification are detailed.

4.2.1 Preprocessing

The preprocessing component is implemented in such a way to allow for flexibility in the specific signal used in the classification system. A common preprocessing interface is used for all Java classes performing the preprocessing of signals, as shown in the Unified Modeling Language (UML) class diagram [Doug99] of the preprocessing component in Fig. 4.1. UML class diagrams depict the hierarchical structure and high level interactions between classes in an object-oriented program. The FishPreprocessor class performs the preprocessing logic for the fish trajectory signals. Adapting the system to operate with a different signal requires that a corresponding preprocessor class be created. These preprocessing classes perform the entire

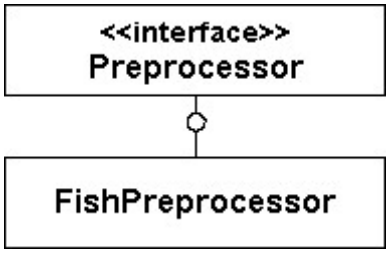


Fig. 4.1: Preprocessing UML class diagram.

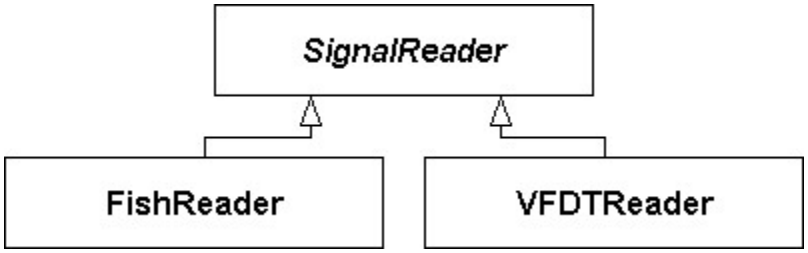


Fig. 4.2: SignalReader UML class diagram.

functionality of the preprocessing component discussed in the system design in Chapter 3. Because of the flexibility in the data type of the signal samples in the proprietary format used in this thesis, special reader classes are needed to translate the signals stored in files into Java arrays, as shown in the UML class diagram in Fig. 4.2. The SignalReader class is an abstract class, as indicated by the italics text, because it contains several assistance methods for its subclasses. An abstract class cannot be instantiated and it is used for this class because it only makes sense to create objects from specialized subclasses of this class that reads a particular type of signal. For the fish trajectory signals, the FishReader class performs the necessary conversion from the processed file to a Java array. The VFDTReader class provides the analogous conversion for VFDT signals stored in a file. This object oriented design using common interfaces and abstract super classes allows for simplification of the components in the rest of the system, since alterations in the type of signal used in the system requires only in supplying the other components with different Preprocessor and SignalReader objects.

4.2.2 Variance Fractal Dimension Trajectory

The implementation of the variance fractal dimension trajectory (VFDT) component is primarily a straightforward implementation of the VFDT algorithm presented in the background in Chapter 2 and the modifications discussed in Chapter 3. The majority of the logic is contained within the VFDT class shown in Fig. 4.3. The VFDT class contains a method that accepts an array, a window size, and window displacement and returns the corresponding variance fractal dimension trajectory. The code for performing the linear regression used in conjunction with the log-log plots is separated from the VFDT class and it provides the equation of the linear regression when provided with the Cartesian co-ordinates of the points which to perform the

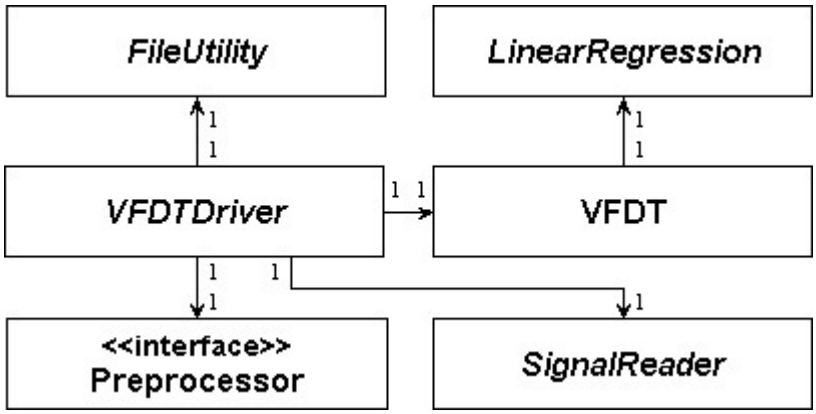


Fig. 4.3: Variance fractal dimension trajectory UML class diagram.

regression upon. The VFDTDriver abstract class connects the preprocessing and VFDT components by utilizing a Preprocessor object to perform the preprocessing upon the raw data files and to create files that can be read into an array by a SignalReader object. This array can then be supplied to the VFDT class along with a desired window size and displacement in order to obtain the VFDT. The FileUtility class is a multipurpose class used throughout this thesis to assist in writing to and reading from files. The VFDTDriver uses this class to write the VFDT to a file in the same proprietary format used by the preprocessing component, which can be later read by a VFDTReader object.

4.2.3 Kohonen Self-Organizing Feature Map

The Kohonen self-organizing feature map (SOFM) implementation is constrained to organizing its output neurons in a one dimensional configuration, as justified in the design of the SOFM component. Logically, the network is composed of a number of neurons, thus the functionality for the individual neurons are separated from the SOFM itself and is represented by the KohonenNeuron class depicted in Fig. 4.4. The Kohonen1DSOFM class acts as the interface for the SOFM, as it will construct the network out of a number of KohonenNeurons when provided with the desired number of input and output neurons.

The Kohonen1DSOFM class also contains methods for training the network. The SOFM training algorithm requires a number of different parameters, some of which are required parameters, such as the number of epochs, the initial learning rate, and the initial radius of the neighbourhood function. In order to limit the number of required parameters to a reasonable level, some of the parameters are simply given predefined values, such as the minimum learning

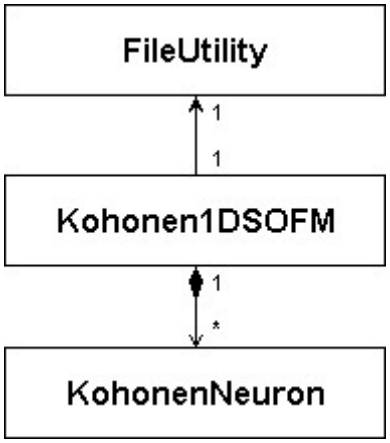


Fig. 4.4: Kohonen self-organizing feature map UML class diagram.

rate and the minimum neighbourhood radius. However, for flexibility purposes, these predefined values are public members to the class and can be overwritten by the calling class. To facilitate the functionality of the other components to the system, the Kohonen1DSOFM class allows for the weights of the network, or the SOFM codebook, to be retrieved. Additionally, the network is able to utilize the FileUtility class to write its codebook to a file and also restore the network from a file containing a codebook.

4.2.4 Probabilistic Neural Network

The implementation of the probabilistic neural network (PNN) component is the most complicated out of all the components because of the flexibility and extensibility it provides, which consequently involves a large number of classes. The structure of the classes in the PNN implementation is shown in Fig. 4.5. The PNN class acts as the class to be used by other classes when this particular neural network is desired. This class contains all the functionality of the neural network, but distributes most of the work to other classes. The behaviour of the pattern and summation layers are provided by classes which use the PatternSummationLayers interface, such as the EuclideanGaussianPSL class, which utilizes Euclidean distances in the pattern layer and Gaussian weighting functions in the summation layer. The PNN class contains a single

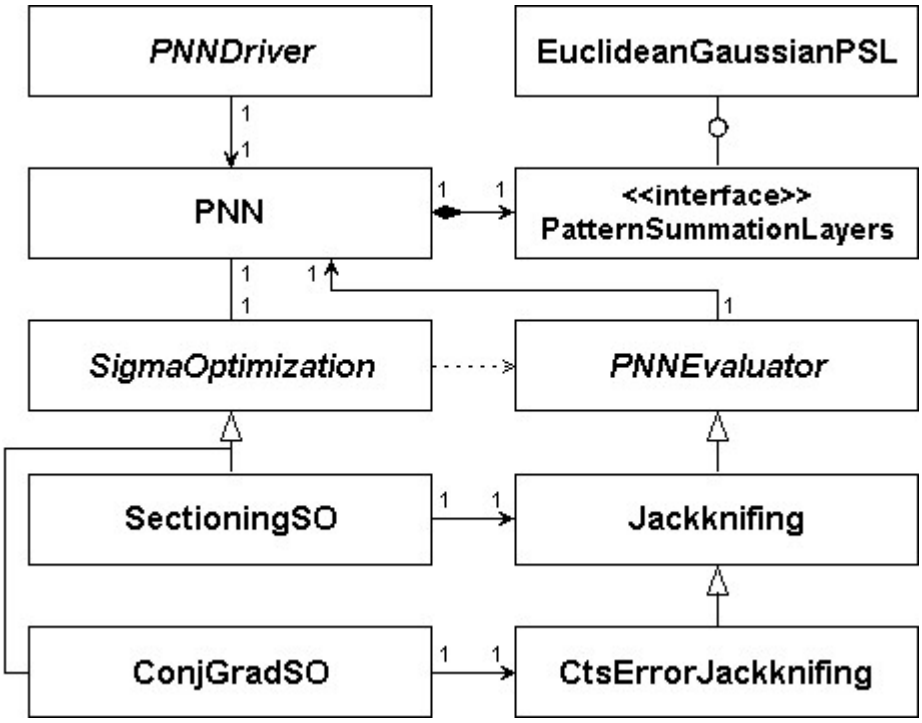


Fig. 4.5: Probabilistic neural network UML class diagram.

instance of a class with the PatternSummationLayer interface. The purpose of adding this extra complexity is that it allows for either the operation of the pattern or summation layers to be modified. By creating a class that uses the PatternSummationLayers interface and employs a different measure in the pattern layer or a different weighting function to estimate the probability distribution functions in the summation layer, the operation of the PNN can easily be modified to adopt these new pattern and summation layers by replacing the declaration of the EuclideanGaussianPSL class in the PNN class with the desired class. The PNN class itself contains the logic for interpreting the output of the summation layer and performing the actual classification of the inputs. The PNNDriver abstract class is not part of the network itself; rather, it creates an instance of the PNN class, trains it upon a given training set, evaluates the network upon a provided testing set, and reports the results to an external file. This class is used by the actual executable program, which is discussed later in this chapter, in order to reduce its complexity.

The training of the PNN is rather involved and is further complicated by the fact that two different training algorithms are explored in this thesis. The implications of these facts are that to reduce the overall complexity of the PNN class, the logic for performing the training algorithms is to be delegated to classes dedicated to the training of the network. All training algorithms are subclasses of the abstract SigmaOptimization class, so that they can be readily swapped inside the PNN class without any major modifications to the PNN class itself. The two training algorithms implemented are the sectioning algorithm for training of single sigma PNNs, represented by the SectioningSO class, and the conjugate gradient algorithm for training of multi-sigma PNNs, represented by the ConjGradSO. In both cases, the training algorithm requires access to the network itself so that the trained sigma value can be applied to the network, hence the bidirectional association between the PNN and SigmaOptimization classes.

The PNNEvaluator abstract class provides the framework for classes that can be used by the SigmaOptimization subclasses for gauging the quality of sigma values of the PNN. This relationship between the SigmaOptimization and PNNEvaluator classes is shown as a dependency on the UML class diagram. For the evaluator to calculate the performance of a particular set of sigma values, it requires access to the network itself so that the network can be executed upon test inputs. Hence, the PNNEvaluator and PNN classes are governed by an associative relationship. For this thesis, the method of evaluating the sigma values is Jackknifing. This evaluator class is directly used by the SectioningSO class; however, the ConjGradSO class

utilizes a subclass of the Jackknifing class, the CtsErrorJackknifing class. This more specific evaluator is required since the ConjGradSO class depends on the use of error gradients, or derivatives, in its optimization of the sigma values, and the discretized Jackknifing evaluation is insufficient.

The classes involved in the sectioning training algorithm are detailed in Fig. 4.6. As previously discussed, the SectioningSO class utilizes the Jackknifing class to evaluate the performance of a given sigma value. The sectioning algorithm itself utilizes two separate classes. The purpose of this separation is two-fold. First, this separation is based on functionality, which allows for substitutions of either of the components in cases where improvements to the basic algorithm are desired. Second, the separation facilitates reuse of the classes. The GlobalLineMin class performs the initial search through the problem space in an attempt to acquire a rough bound of the optimal sigma value. This rough bound is then provided to a subclass of the SectionLineMin class, for refinement. The SectionLineMin class performs the sectioning algorithm whereby the interval thought to contain the optimal sigma value is progressively reduced. The particular means in which the interval is reduced is provided by the SectionLineMin class's subclasses. The BisectionLineMin class dictates that the interval be reduced by a factor of two in each iteration by simply calling the SectionLineMin's refinement method with a parameter of two. The choice of successively reducing the interval by two is reasonable, but it should be noted that the interval can be reduced in any number of ways, some

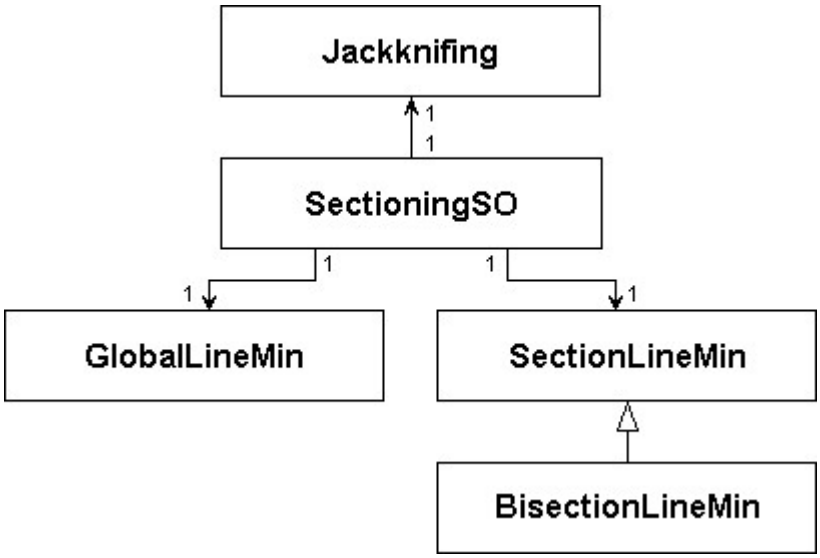


Fig. 4.6: Sectioning sigma optimization UML class diagram.

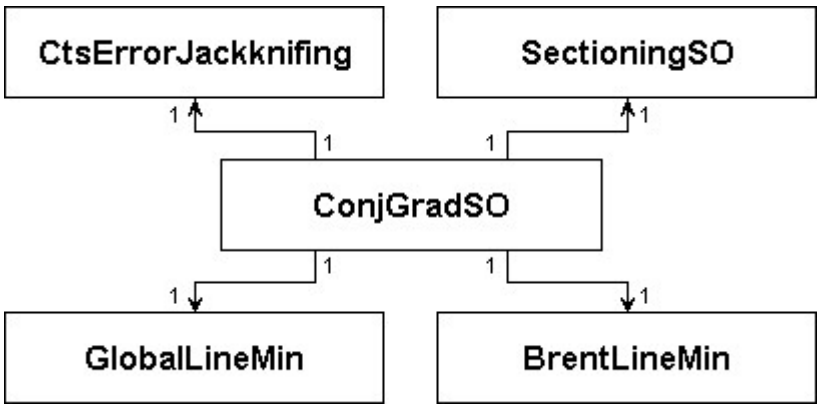


Fig. 4.7: Conjugate gradient sigma optimization UML class diagram.

of which may take advantage of the nature of the problem space. One such alternative to bisecting is utilizing the golden mean, $2 / (1 + \sqrt{5})$, for reducing the intervals, as suggested in [Mast95]. This modification was explored, but it did not produce any noticeable difference.

The conjugate gradient training component of the PNN is shown in more detail in Fig. 4.7. The ConjGradSO class utilizes the SectioningSO class in order to initiate the process by optimizing for a single sigma PNN. The sigma values are then allowed to take on different values and are optimized using a standard conjugate gradient algorithm, which is performed by the ConjGradSO class. The GlobalLineMin class is reused here by the ConjGradSO class. The BrentLineMin class, which performs Brent's line minimization is also utilized by the ConjGradSO class in executing the conjugate gradient algorithm The error derivates used in the algorithm are provided by the CtsErrorJackknifing evaluator class, as previously mentioned.

4.2.5 Complex Domain Neural Network

The second classifier neural network used in this thesis is the complex domain neural network. Complex numbers are not built into the Java language, so a ComplexNumber class is implemented to represent complex numbers, using Cartesian co-ordinates, and perform basic operations with complex numbers. This class contains a number of methods for complex number arithmetic as well as operations mixing real and complex numbers in order to facilitate the implementation of the complex domain neural network. These functions include addition, subtraction, multiplication, division, and polar co-ordinate conversions.

The network itself is represented by the CNN class shown in Fig. 4.8, which is composed of any number of neurons operating upon complex inputs. These neurons are implemented as the ComplexNeuron class. Both classes utilize the ComplexNumber class extensively. The

backpropagation algorithm and the computation of the error derivatives the algorithm utilizes are simply implemented inside the CNN class.

The CNNDriver abstract class is analogous to the PNNDriver used in conjunction with the probabilistic neural network. This class is utilized to simplify the interactions with the complex domain neural network when verifying the operation of the classification system.

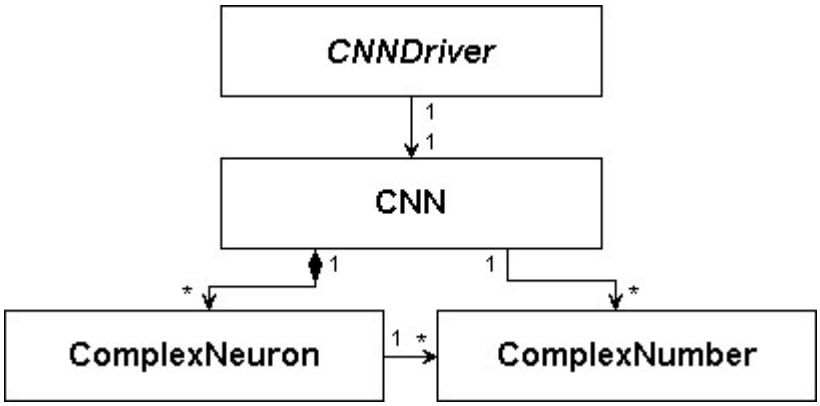


Fig. 4.8: Complex domain neural network UML class diagram.

4.2.6 Input Vector Creation

The classifying neural networks, the probabilistic and complex domain neural networks, require input vectors consisting of the set of features to base the classification upon. For this thesis, the features to be extracted from the signal arise from a multifractal characterization by computing its variance fractal dimension trajectory. Additionally, further feature extraction may be performed upon the VFDT signal via SOFMs. To facilitate this feature extraction and development of input vectors for the training and testing sets used with the classifying neural networks, a CreateInputVectors class is implemented, as shown in Fig. 4.9.

This class requires that a file be provided that lists the signals and the signal segments from which to create the input vectors Each signal may be divided into a number of smaller segments, in which the signal segments are classified rather than the entire signal. This situation arises when the behaviour of the signal changes during its duration and contains a number of segments, which belong to different classes. The CreateInputVectors class is able to handle this situation as well as cases where the entire signal is classified as a whole. In addition to the specification of the signal segments, the file must also identify the known class of each of the

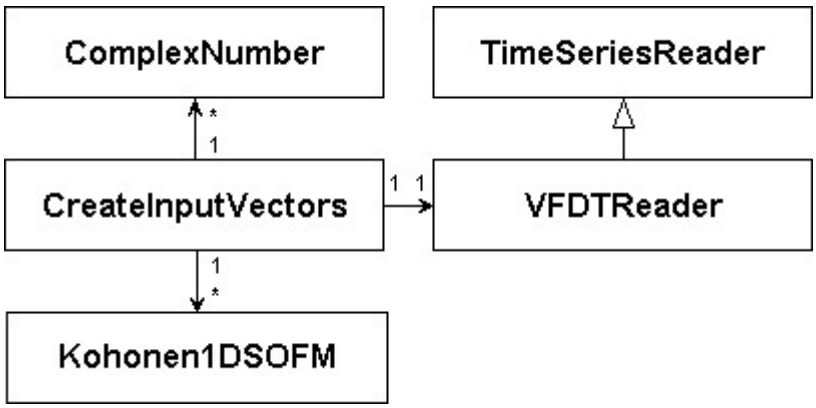


Fig. 4.9: Create input vectors UML class diagram.

signal segments, since the CreateInputVectors class is used to create training and testing sets, which require that the classes of each of the signals be known ahead of time.

The CreateInputVectors class also requires that the VFDT signals be computed ahead of time and stored in files. Once the signals to create the input vectors from are identified, their VFDTs are read from the files by using the VFDTReader class shown in the figure. Based on the specifications in the file, the portions of the VFDTs corresponding to the signal segments are extracted to form the set of features for the signal segments. The set of input vectors for classification can be formed directly from these VFDT segments since the file also specifies the classes of each of the signal segments and the input vectors can be grouped according to their designated class. The CreateInputVectors class also contains a method to use a Kohonen self-organizing feature map to perform feature extraction upon these VFDT segments, as shown by the class's association with the Kohonen1DSOFM class. The codebooks produced from the SOFMs are then used as the input vectors to the classifiers. In either case, the CreateInputVectors class returns a set of input vectors corresponding to the signal segments specified in the file and are grouped according to the class specifications in the file.

Additionally, this class is able to produce complex valued input vectors, each of which are derived from two correlated signal segments. The two signals are typically simultaneous recordings, which capture different information about its source. The extraction of VFDT features from these signals is straightforward, as the VFDTs for these signals are contained in separate files and can be independently extracted. In the case where the input vectors are directly obtained from the VFDT segments, complex numbers can be formed by using the VFDT segment corresponding to one of the signal segments as the real part and the VFDT segment corresponding to the other signal segment as the imaginary part. When SOFMs are used to

extract features from the VFDT segments, the two VFDT segments corresponding to the two signal segments are used as the training data for the SOFM. The input vectors to the SOFM consist of appended portions of the VFDT segments, as explained in the design of the SOFM component in Chapter 3. This ability of the CreateInputVectors class to produce complex valued input vectors requires the use of the ComplexNumber class, as shown in Fig. 4.9.

4.2.7 Classifier Driver

The classifier driver programs are the only executable programs in the system and they connect all the components together in order to form the various configurations of the classification system. There are separate classifier driver programs for the configurations of the system which use the probabilistic and complex domain neural networks, but they are identical except that they use different classifier neural networks. Since the interface for the two networks are very similar, their corresponding classifier driver programs differ only by a few lines.

The classifier driver for the PNN is shown in Fig. 4.10. The PNNClassifer driver is an active class, indicated by the bold lines, meaning that it is executable. This class is responsible for performing the preprocessing of the signals and computation of the VFDT signals. This work is delegated to the VFDTDriver class. The training and testing sets are then formed through the use of the CreateInputVectors class. Finally, the PNNDriver class is used to train the network with the input vectors in the training set and also to classify the testing set input vectors. The UML diagram for the classifier driver program that uses the complex domain neural network is identical to that of Fig. 4.10, except that the classifier driver is named CNNClassifierDriver and it uses the CNNDriver instead of the PNNDriver. The classifier driver programs require only that the high level parameters such as the VFDT window size and displacement, the size of the SOFM codewords, the number of codewords, and the specification of the training and testing sets be provided. The values of these parameters are passed along to the corresponding components.

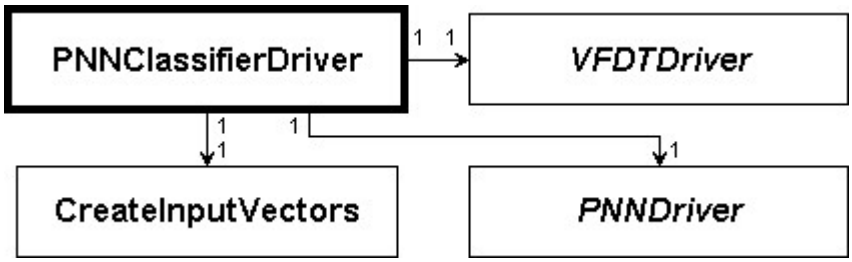


Fig. 4.10: Classifier driver UML class diagram.

The final result of the execution of the driver program is a file summarizing the performance of the classification system upon the testing set.

4.3 Summary

This section has discussed the implementation of the system and its components. While the implementation of the system is finished, the overall development of the system is not complete until it has been thoroughly tested and verified.

CHAPTER 5
SYSTEM VERIFICATION AND TESTING

The necessity of testing and verifying any design, whether it be software or hardware, is of paramount importance. Testing and verification must be performed upon a system in order to ascertain whether the results it produces are valid. The testing and verification of the software used in this thesis is subdivided into two distinct sections. First, each of the individual, distinct components of the system underwent separate tests to ensure their accuracy. Afterwards, testing and verification of the system as an integrated whole was performed to ensure that the resulting system performed as expected.

5.1 Component Verification and Testing

5.1.1 Preprocessing

The primary verification of the functionality of the preprocessing component is the confirmation that the data conversion performs without introducing any error into the signals. In order to perform this verification, a signal was read from its raw data file and then from the processed file. The values read were then compared visually by plotting the two signals side by side and numerically by comparing the signals sample by sample. Both plotted signals appeared as expected, demonstrating that the signals were read correctly and the numerical verification demonstrated that the conversion was error free.

5.1.2 Variance Fractal Dimension Trajectory

The calculations involved with the VFDT algorithm for even small signals are a computationally heavy process. Thus, it was determined that verifying the system by hand would be far too lengthy a process. As a result, other methods of verification, both subjective and objective, were selected to verify the correctness of the VFDT component.

While the VFDT algorithm itself is too involved to verify by hand, the linear regression used by the algorithm is simple and ubiquitous enough to independently confirm its correct operation. The linear regression was provided with some points in a Cartesian plane and the equation of the resulting regression was obtained. These values were then confirmed by

performing the identical operations by hand and independently verifying the values by using a mathematical program to perform the regression.

The verification of the operation of the VFDT component was performed mostly by computing the VFDT of various simulated power line transients and comparing the results to those found in [Chen01]. The plots resulting from the VFDT component developed for this thesis and those of the published plots correlated, thus providing a high level verification of the implementation of the algorithm.

Another subjective measure used to verify the VFDT component was that by visual inspection of the plots of the VFDT signals, it was observed that the signals were, for the most part, bound between the theoretical limits of one and two. Furthermore, the signal was reasonable in that it seemed to emphasize the changes in the original signal. Additionally, changes to the window size and displacement yielded expected results whereby decreasing the displacement increased the resolution of the VFDT signal and differing window sizes controlled the amount of smoothing that occurred.

Lastly, it should be noted that the artifacts caused by straight lines and certain periodicities in the sample domain signal were discovered during the testing and verification of this component and modifications were made to the component during the iterative design process to reduce the effect of these artifacts, as discussed in Chapter 3. With the modification to the VFDT algorithm, the verification of the reduction of the artifacts was observed. By comparing the individual samples of the VFDT signals before and after the modification to the algorithm, it was observed that the difference was minimal, confirming the infrequency in occurrence of these artifacts.

5.1.3 Kohonen Self-Organizing Feature Map

The Kohonen self-organizing feature map (SOFM) component was tested by tracing through the code and performing some hand calculations and verified using toy problems. Hand computations were performed first in order to ensure the operation of the neurons and the synapse weight training. After completing manual calculations, the correctness of the SOFM component was verified by training the SOFM with several groups of sinusoidal signals of varying amplitudes, frequencies, and phase, along with noise. The resulting codebook was plotted and it was visually seen that distinct clusters had formed, each of which were characteristic of the sinusoidal signal classes. Further tests were performed to verify the SOFM's ability to perform

feature extraction of signals. In once instance, the SOFM was instructed to form a representative codebook of a complicated signal. This trained codebook was used to perform learned vector quantization of the original signal. Each interval of the original signal was replaced with the best matched codeword in the codebook, producing a signal formed entirely from the codewords in the codebook. Visually, the resulting signal was very similar to the original signal, even though the number of codewords was mere a fraction of the total number of interval segments in the signal itself. By computing the mean square error between the two signals, it was noted that numerically, the signals were fairly different, but considering the amount of compression achieved, the result was acceptable. This learned vector quantization verified the feature extraction capabilities of the SOFM.

5.1.4 Probabilistic Neural Network

The probabilistic neural network component was tested using a small number of hand calculations and verified quite extensively by the use of toy problems. The hand calculations were primarily used to confirm that the mathematical calculations in layers of the network were being correctly calculated. Specifically, the program was traced so as to ensure that the neurons in the pattern layer were calculating the Euclidean distance between the input to the neural network and the training input correctly. The output of the weighting function of each of the pattern layer neurons was also verified by hand. Additionally, the calculations performed by the neurons in the summation layer were performed by hand to ensure that the scaled estimations of the PDFs generated by the neurons were correct.

The verification of the PNN was performed by evaluating its performance on toy problems. One of the main toy problems used to test the operation of the PNN was to simply create k different classes of points in n-dimensional space. The PNN was trained using various example training inputs from each of the k classes. To verify that the PNN was capable of learning and generalizing, the PNN was then tested with samples from the classes that were not present in the training set. The level of difficulty of these point-clustering toy problems ranged from very easy, when each class consisted of a single cluster of points, to more challenging, where some of the classes were multimodal and the cluster borders overlapped. The PNN performed very well on all of the toy problems, including those which involving multimodal classes, typically obtaining correct classification rates well above 90%.

The multi-sigma PNN was also tested using toy problems with classes of points in n-dimensional space. With the multi-sigma PNN, the classes of points were designed such that some of the class clusters spanned a wide area, while others were very tight and well defined. This type of toy problem demonstrated that the multi-sigma training algorithm was capable of selecting different sigma values, depending on the relative size of the class clusters. Accordingly, the sigma values selected for classes whose points spanned a wide area received larger sigma values, while the classes whose points were confined to a very tight area were assigned smaller sigma values.

5.1.4.1 Line Minimization

The verification of the line minimization algorithm used in the training of the PNN component was straightforward, as direct inspection could be performed. Specifically, the line minimization component was tested using several higher order polynomials containing a variety of local minima and maxima. The line minimization module was then configured to attempt to discover an acceptable minimum over a particular portion of these functions. Effort was made to ensure that the section used for the minimum search contained several different minima and maxima, thereby confirming the fact that the optimization problem was not trivial.

Upon running the line minimization program on several higher order polynomials, the component usually yielded the absolute minimum within the specified interval. There were however, instances in which the program did not find the global minimum, and instead, discovered a local minimum. The reason the algorithm did not always uncover the global minimum was not a flaw in the implementation of the component, but rather a problem in the algorithm itself. During the first stage of the line minimization process, the algorithm selects several trial points at which it evaluates the function. The trial point that yields the smallest result is assumed to be very close to the global minimum of the function, so the area immediately surrounding that point is searched to find the minimum. However, the assumption that the global minimum is close to the smallest result found in the first stage of the algorithm may not always be valid.

In the simple example shown in Fig. 5.1, the line minimization algorithm selects three trial points, which is an unreasonably small number, but has been chosen for explanation purposes only. As can be seen in the figure, of the selected three points indicated by the arrows, the point on the extreme left yields the smallest function value of the three. Hence, the second

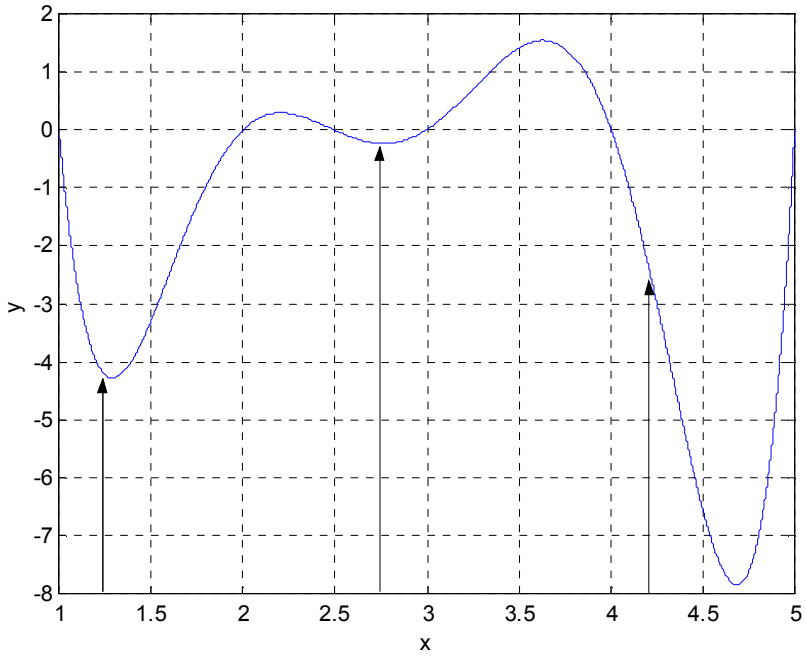


Fig. 5.1: Erroneous selection of bounded minimum.

step of the line minimization algorithm will look for the minimum in the area immediately surrounding this trial point. Of course, in doing so, the algorithm will find the local minimum between the X-axis values of 1 and 1.5. As can be seen in the figure, there is a superior minimum located between the X-axis values of 4.5 and 5 that was not identified by the algorithm.

This specific difficulty with the algorithm was recognized before the testing process was undertaken, but was not considered to be of large concern. If the number of trial points in this example were increased to a more reasonable number, such as 15, then the true global minimum would have been identified. This line minimization is being used in this thesis to optimize the smoothing parameter(s) of the PNN, which, as was noted earlier in this paper, generally tends to have a region of values which are acceptable. Hence, more importance was placed on finding a reasonable local minimum in a short period of time, as opposed to finding the absolute global minimum through a lengthier search.

Despite the fact that the algorithm was designed with the knowledge that it might not always uncover the absolute minimum within a given interval, the algorithm was shown to operate correctly through the testing and verification stage.

5.1.5 Complex Domain Neural Network

As was the case with most of the components implemented in this thesis, the testing of the complex domain neural network was difficult to perform thoroughly by virtue of the fact that its computations were so numerous. As a result, it would have been time consuming to fully verify the algorithm's calculations by hand. Nonetheless, the correctness of the neural network was verified through a combination of hand calculations and toy problems.

Initially, the complex domain neural network using the backpropagation training algorithm was verified with hand calculations. The computations were performed by hand on a simple toy problem where the neural network implemented a very simple parity checker involving only two inputs, one hidden neuron, and one output neuron. The calculations focused on ensuring that the hidden layer neurons computed the correct net sums, and that the results of the activation functions were accurate. Additionally, some of the partial derivatives used in the actual backpropagation algorithm were performed by hand to ensure that the algorithm was implemented correctly. Furthermore, updating of the synapse weights was verified by hand. The hand calculations were limited only to the first few iterations, as attempting to perform full verification through the thousands of iterations was overtly cumbersome. These limited calculations that were performed by hand did help to ensure that all the mathematical formulas had been programmed correctly.

After the hand verification of the complex neural network was completed, the next step was to confirm that it was capable of learning, generalizing, and operating correctly as a whole. To that end, a more complicated parity testing toy problem was utilized as well as a classification problem in an n-dimensional space similar to that used with the PNN. The complex neural network was able to correctly identify the parity of the various inputs in the testing set and perform the classification of points in an n-dimensional space. In both cases, the neural network correctly performed the operation on the testing set well above 90%, indicating that the component was operating overall as anticipated.

5.2 Overall System Verification and Testing

In addition to performing testing and verification of all the individual components created for this thesis, it was still necessary to verify that when all those components were interconnected, the overall system would operate correctly. The overall system operation was verified through

the use of simulated signals. By creating signals with known class memberships, such as power line transients used in [Chen01], the classification system using the PNN component was verified by performing classification of these signals using both the VFDT and SOFM components to perform feature extraction. Initially, the correct classification rates obtained by the system were not as high as expected, achieving rates only in the low 70% range. However, further examination showed that the less than spectacular results were caused because the system was consistently unable to classify signals from particular classes. In these classes, the simulated power line transients only exhibited simple transitions and were not fractal in nature, hence, according to their VFDT signals, they were all the same. By grouping these simple transients into a single class, the resulting classification results showed much improvement, correctly classifying the signals above 90% of the time.

In order to further verify the various configurations of the system, additional tests using a small subset of the fish trajectory signals and assumed classes based upon a priori knowledge of the experiment were performed. The different system configurations, including the complex domain neural network and the probabilistic neural network with complex inputs based systems, did, for the most part, successfully perform the requested classification. The results however, will not be quoted here as the classes which the classification was based upon were very limited and not known to be true.

The only problem that was encountered during system testing and verification was that the multi-sigma training algorithm was not able to operate successfully with the fish trajectory signals. During training, the error derivatives unexpectedly become zero, causing the algorithm to fail. It is suspected that the cause of the problem was the size of the classification problem and the limited precision of the floating point values used in the PNN component. Thus, due to these complications which were not resolvable within the time limits of this thesis, the PNN multi-sigma training will not be further examined.

5.3 Summary

The verification and testing of the classification system and its components were discussed in this section of the thesis. Aside from the multi-sigma PNN, no difficulties were encountered. The remaining task is to verify that the classification system indeed works well upon stochastic, self-similar, non-stationary signals arising from non-linear systems.

CHAPTER 6
EXPERIMENTAL RESULTS AND DISCUSSION

In this section, the experiments used to formally verify and compare the various configurations of the system will be presented and explained. The classification system begins with a preprocessing stage to convert the signals into the format used in this thesis. Following the preprocessing stage, a multifractal analysis is performed whereby the signal is transformed into the fractal dimension domain to produce a variance fractal dimension trajectory (VFDT). In one configuration of the system these fractal dimensions are directly used as features for the classification process. In the second, Kohonen self organizing feature maps (SOFMs) are used to extract the features from the VFDT signal in an attempt to eliminate redundancy while simultaneously reducing the size of the classification problem. To perform the classification based on the extracted features, this thesis explores two different types of neural networks: probabilistic neural networks (PNN) and complex domain neural networks (CNN). The signals used to verify the various configurations of the system consist of two recordings. The extent to which classification can be performed with a single recording is explored through the use of the PNN. Further experiments upon the system are performed by classifying the signals while taking into consideration features from both recordings via the PNN and CNN in separate experiments.

6.1 Experiment Set-Up

The particular verification signals used in this thesis are fish trajectory recordings produced from a tracking system that monitors the position of a fish in a fish tank along the X, Y and Z axes when presented with various stimuli, as explained in Appendix A. Seventeen of these recordings have been obtained and are used for the formal experiments. Of the 17 recordings, nine involve one particular fish while the remaining eight concern a different fish. Ordinarily, class specifications and examples from each of the classes would be available to construct the training and testing sets which are used to train the classification system and evaluate its performance. These specifications were not available for the fish trajectory signals. Since training and testing sets are a necessity, an objective method in deriving these sets was sought. It was decided that clustering upon the time domain signals using an SOFM would be an appropriate vehicle to arrive at the desired class specifications. A full discussion of the derivation of the training and testing sets is presented in Appendix B.

This thesis is not concerned about the classification of the fish signals per se, but rather in using them in order to verify the system. Thus, the two most important axes, X and Z, are used since the CNNs only operate on two simultaneous recordings.

Through the clustering performed upon the signals in Appendix B, it was shown that four different classes were present in each signal when they were divided into segments of 4096 samples, which corresponds to just under seven minutes. All the segments from nine of the files were dedicated to the training set, while the segments from the other eight were delegated to act as the testing set. Both the training and testing sets have approximately equal number of recordings from both of the fish. It is important to note that the training and testing sets are mutually exclusive so as to provide an unbiased performance assessment of the various configurations of the classification system.

With the training and testing sets established, the classification of the signals can actually be performed. Preprocessing is the first task that must be executed so as to put the signals into the propriety format used by the rest of the components in their analysis. The recordings along

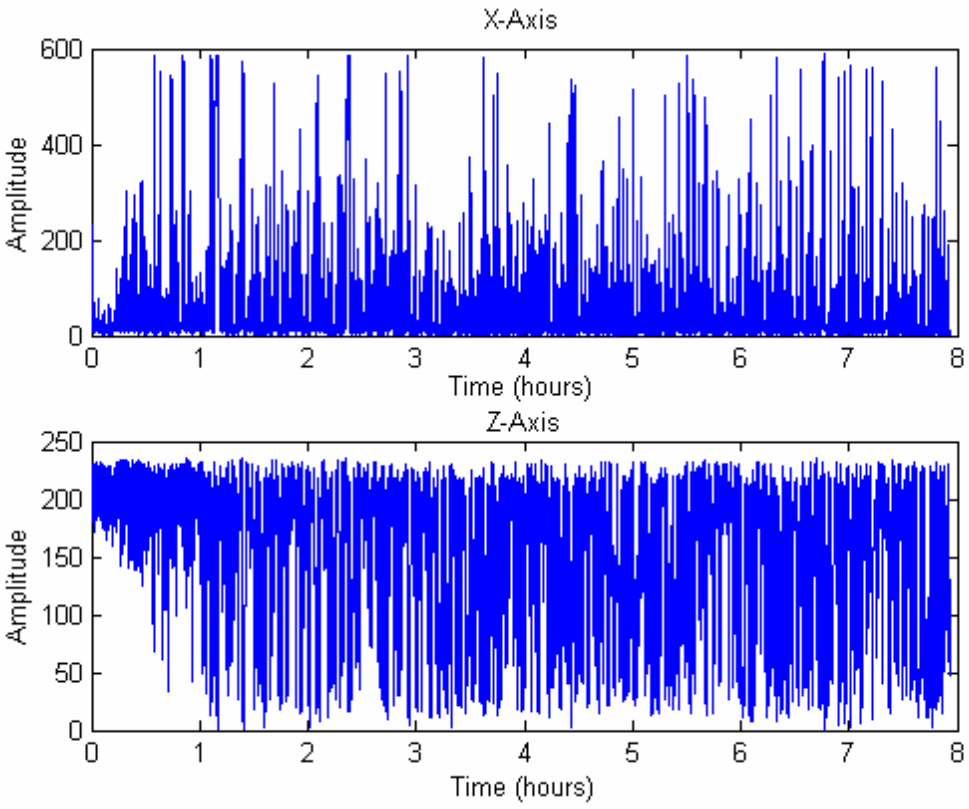


Fig. 6.1: Time domain plots of a fish trajectory signal.

the X and Z axes for a sample signal following the preprocessing stage are plotted in Fig. 6.1. The time required to perform this preprocessing for each signal is approximately four and a half minutes on a 1 GHz AMD Athlon computer.

The next stage of the classification system involves computing the VFDT of the signals for the purpose of feature extraction. There are two parameters involved in calculating the VFDT: window size and the displacement of the windows. Normally the window size would be decided upon based on the largest stationarity of the signal; however not enough is known about the fish trajectory signals, so the window size had to be determined experimentally. It was discovered that a window size of 2048 and window displacement of 256 provided the best results in that the combination yielded a good balance between an adequate resolution and substantial reduction in the problem size. Because of this displacement, 256 samples in the sample domain correspond to one sample in the VFDT, thus the 4096 samples in each segment are represented by only 16 fractal dimensions. The plots of the VFDT signals corresponding to the signals of Fig. 6.1 are shown in Fig. 6.2. The processing time required to computer these plots for each axis is

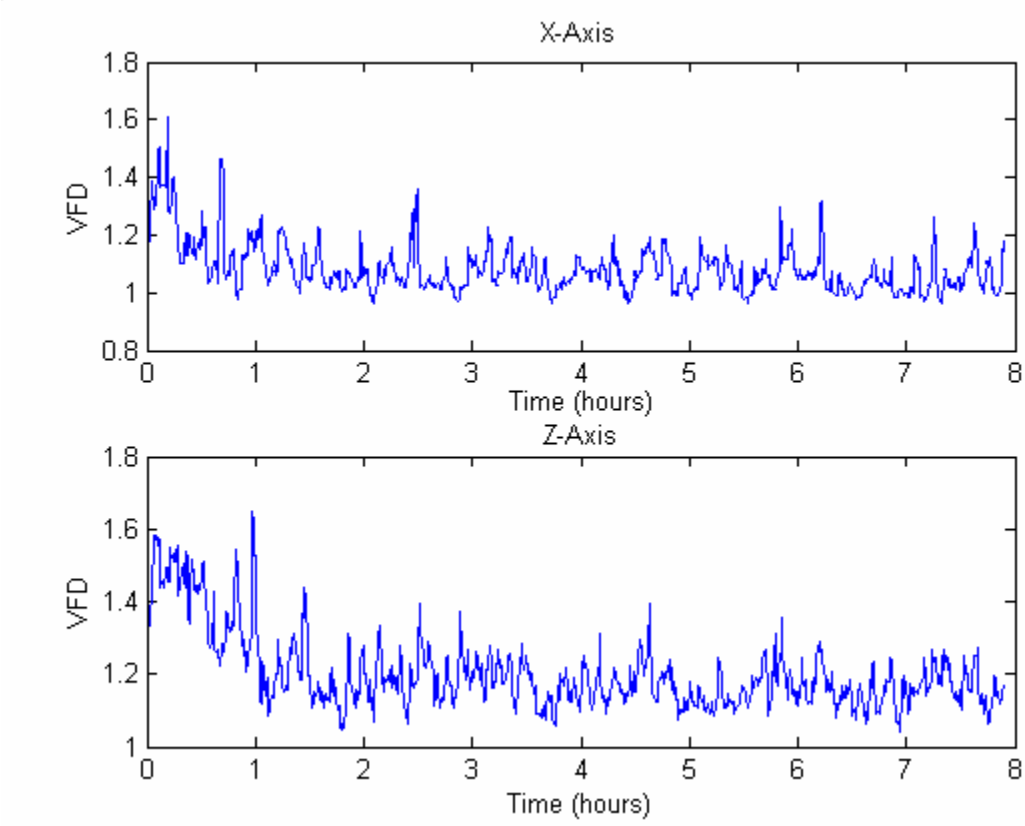


Fig. 6.2: VFDTs of a fish trajectory signal.

only a third of a second. The first thing to note about the VFDT plots is that the fractal dimension of the signals change, indicating that it is a multifractal. It can further be noted that the samples of the VFDT are normalized between dimensions of one and two, which is essential for the classification process. Additionally, the VFDT plots visually seem to correspond to the time domain plots in that they tend to emphasize some of the characteristics in the original signal; the most exemplary characteristic being the initial dramatic changes in the VFDT signals which correspond to the irregular motion of the fish as seen in the time domain plot. The VFDT plots shown are characteristic of all the fish trajectory VFDTs.

In calculating the VDFT, log-log plots were produced and linear regressions upon the points in these plots were computed as per the VFDT algorithm as presented in Chapter 2. As a means of evaluating the signal's accordance to the power law behaviour, mean square errors (MSEs) between the linear regression and the sample points in these log-log plots are tabulated in a histogram format, as shown in Fig. 6.3, which correspond to the VFDT signals in Fig. 6.2. The vast majority of the MSEs are low, which indicates that the power law behaviour is exhibited

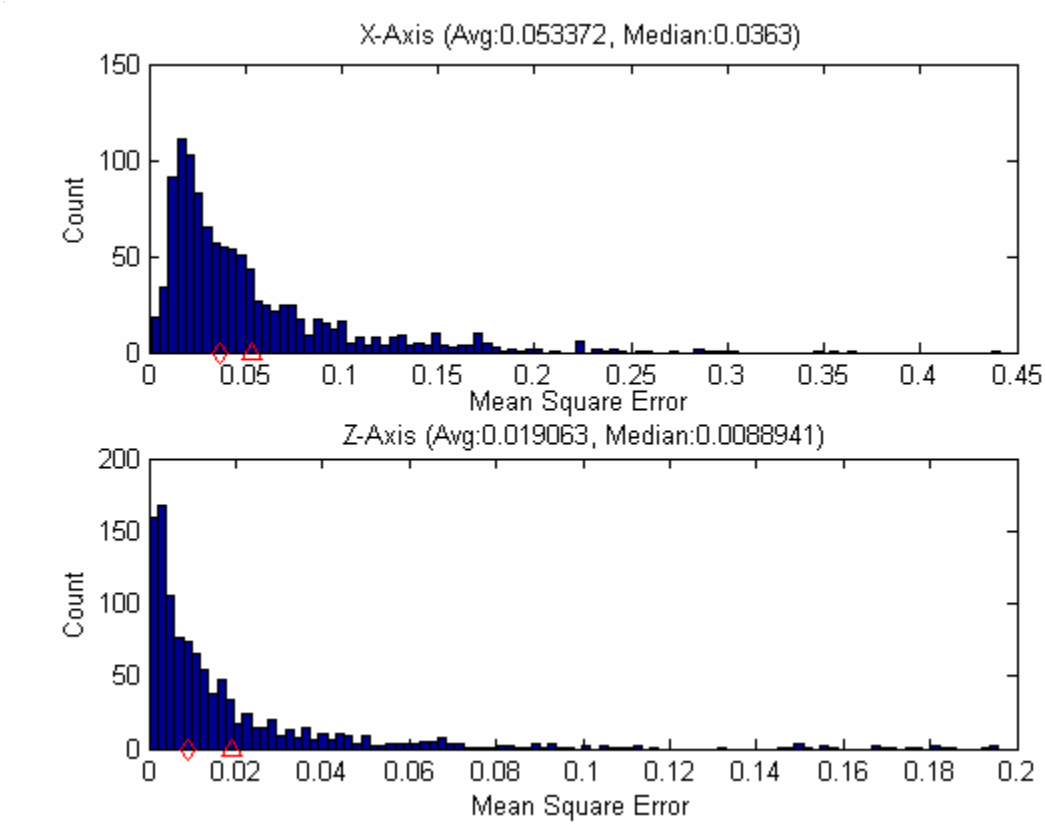


Fig. 6.3: MSE histogram of the VFDT of the fish trajectory signal.

throughout most of the signal. There are some outliers where the MSE is more substantial but their occurrence is very seldom. This adherence to the power law behaviour indicates that the particular window size is valid for the signal and furthermore, that indeed that the signal is fractal in nature.

Segmentation of the VFDT signals is performed at this stage in such a manner to correspond to the time domain segments of length 4096 as defined for the training and testing sets. These VFDT segments are the features for classification.

In the configurations of the system using the SOFM, feature extraction is performed upon these VFDT segments. The SOFMs can be used to extract features from VFDT segments which consist of a single recording or multiple recordings. In order to facilitate the extraction of features from segements involving multiple recordings, the recordings are merely appended to each other prior to being presented to the SOFM as was shown in Eq. (3.1).

For the formal experiments used to verify the different configurations of the classification system, the SOFM was configured to use three codewords, each of which had a length of four. This combination means that 12 features are extracted from each VFDT segment. The configuration of three codewords with a length of four apiece was selected as experimentally it yielded very good results. Scenarios where fewer codewords were used usually produced decent results and decreased the problem size even further. However, the overall classification accuracy decreases with fewer codewords. Since none of the systems take more than a few seconds to execute, it was decided to make use of more codewords instead of reducing the problem size as much as possible.

Figure 6.4 shows a sample segment of a VFDT and its corresponding SOFM codebook. The codebook contains the codewords most representative of the signal and it should also be noted that the classification problem size is reduced during the transition from the VFDT segment to the SOFM codebook in that the number of features used to represent the signal segment is reduced. The generation of the all the codebooks for the entire training and testing sets require no more than a third of a second, whether it be for a single recording signal or a multiple recording signal. In the configurations of the system involving the SOFM component, it is these codebooks and their codewords that are provided as inputs into the neural networks rather than the VFDT as is done when the SOFM module is not used.

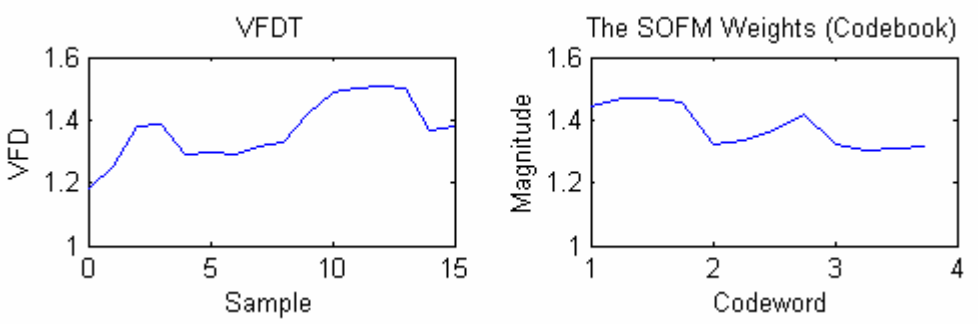


Fig. 6.4: VFDT segment and its codebook.

6.2 Results

6.2.1 Experiment 1: X-Axis with PNN

For the first experiment, the VFDT segments corresponding the X-axis were directly used to form training and testing sets for use with the PNN. It took approximately four seconds to train the PNN and less than a fifth of a second to classify the entire testing set consisting of 544 input vectors. The results of the testing set classification are summarized in the confusion matrix shown in Table 6.1. The rows of the confusion matrix indicate the expected class of a particular signal segment, as defined in the testing set, whereas the columns indicate the experimental classification result produced by the PNN. The count in any given cell is the corresponding number of signal segments from the testing set which the PNN considered to belong to that class. As a result, the entries along the diagonal indicate the number of correct classifications for a given class whereas cells off the diagonal indicate incorrect classifications where the PNN identified the signal segment as belonging to a class different than was expected. The column on

Table 6.1: X-axis PNN confusion matrix.

		Experimental				Correct Classification Rate
		1	2	3	4	
Expected	1	24	0	0	0	100.00%
	2	3	135	4	4	92.47%
	3	0	12	111	65	59.04%
	4	0	23	70	93	50.00%
Average Correct Classification Rate: 66.73%						
95% Confidence Interval: [62.77%, 70.69%]						

the extreme right indicates the percent correct classification for each of the individual classes. With respect to the first experiment, the table show that all 24 inputs from class 1 were classified correctly, yielding a classification accuracy of 100%. For the second class, three inputs were erroneously considered to belong to class one, four inputs to class three, and four inputs to class four. However, the classification system correctly identified 135 inputs as belonging to class two, which meant that class two had a correct classification rate of 92.47%. This same analysis procedure can be performed for the remaining rows of the confusion matrix.

The average classification rate, shown below the confusion matrix, is the overall performance indicator of the network and is the ratio of the number of correct classifications to the total number of signal segments presented to the network. For example, in this experiment the average classification rate is calculated by (24 + 135 + 111 + 93) / 544 * 100%. For this experiment, the average classification rate is approximately 67%. Despite the overall poor performance, the system did function quite well with respect to the first two classes. However, the network was simply not able to differentiate between the last two classes with much success. Although 67% is not a substantially high correct classification rate, if the system were to perform classification by randomly guessing to which class an input signal belongs, then the expected rate of classification would only be 25%. In that regard, 67% shows that there is confidence that the system is able to analyze the signal and is not just performing arbitrary assignments. However, a 67% correct classification rate is still far from the desired rate of 90%.

Since randomness is involved in the particular selection of the testing sets, confidence intervals are computed. These particular intervals show the range of values within which the true classification rate falls, with a confidence of 95%. The computation of the confidence intervals for the average classification rate comes from the binomial distribution, in that each input vector to the neural network is either correctly or incorrectly classified. The estimation of the standard deviation about the true mean is given by $s = \sqrt{r(1-r)/n}$, where r is the average classification rate and n is the total number of input vectors in the testing set. The 95% confidence intervals are defined by $[r - 1.96s, r + 1.96s]$. For this experiment, it can be stated that the true mean classification rate falls between 62.77% and 70.69% with a 95% confidence. This experiment did not produce a correct classification rate as high as desired, even when the confidence intervals are taken into consideration; however, this experiment only made use of the information in the X-axis recordings. The additional inclusion of the information contained in the Z-axis during the classification process should increase the classification rate.

6.2.2 Experiment 2: X-Axis with SOFM and PNN

The second experiment performed was similar to the first experiment in that only the X-axis information from the fish trajectory signals was used to perform classification. What differentiates these two experiments is the fact that the second experiment made use of the SOFM component to perform feature extraction upon the VFDT signal whereas the first experiment did not.

The inclusion of the SOFM feature extraction process did not improve the overall classification rate of the system as indicated by the average classification rate seen in Table 6.2. Making use of the SOFMs did, however, reduce the number of inputs into the PNN from 16 in experiment one to 12 in experiment two, which caused a reduction in the training and execution times of the system. Hence the SOFM stage did not improve the overall classification accuracy of the system, but it did reduce the classification problem size, which expedites the classification process. Specifically, the training time was reduced to a little less than three seconds while the execution time was closer to a tenth of a second.

One important aspect to note about the confusion matrix for experiment two is that the classification system was able to distinguish between the first three classes with a good deal of success, but was unable to perform effective classification upon the fourth class.

Overall, no conclusions can be drawn as to whether the system configuration presented in this second experiment provided superior classification accuracies than the first because the confidence intervals overlap. As with the first experiment, the performance of the classification system in this particular configuration is disappointing.

Table 6.2: X-axis SOFM PNN confusion matrix.

		Experimental				Correct Classification Rate
		1	2	3	4	
Expected	1	24	0	0	0	100.00%
	2	4	131	8	3	89.73%
	3	0	16	131	41	69.68%
	4	0	29	84	73	39.25%
Average Correct Classification Rate: 65.99%						
95% Confidence Interval: [62.01%, 69.97%]						

6.2.3 Experiment 3: Z-Axis with PNN

The third experiment has the same set-up as experiment one except for the fact that it utilizes the Z-axis fish trajectory information rather than the X-axis. Hence, the goal of the experiment was to gauge the importance of the Z-axis information as compared to the X-axis information for the fish trajectory signals and to see how the differences in importance affect the classification rate.

The confusion matrix for this experiment, as shown in Table 6.3, indicates that this configuration of the classification system was not very effective in differentiating between the first three classes. However, this configuration of the system was quite successful in classifying inputs of fourth class. It should be noted that when classification was performed upon the information in the X-axis, as was done in experiments one and two, the systems were able to classify inputs from the first two classes, but failed to perform well on the class four inputs. Hence, the information contained in the X and Z axes is somewhat complimentary in that the information in the X-axis signal can be used to identify inputs from classes one and two and the Z-axis signals can be used to identify signals of class four. Given this observation, using both the X and Z axes during classification should cause the classification rate to improve significantly.

Overall, the performance of the configuration of the system used for this experiment was inferior to that of experiment one as the average classification rate was a lower value of about 58%. This experiment also required the same amount of time to train and execute as in experiment one because the problem size remained constant. The fact that the results from experiment one were superior to those attained through this experiment seems to indicate the X-axis of the fish trajectory signals contains more important information than the Z-axis.

Table 6.3: Z-axis PNN confusion matrix.

		Experimental				Correct Classification Rate
		1	2	3	4	
Expected	1	15	3	3	3	62.50%
	2	9	43	44	50	29.45%
	3	7	51	89	41	47.34%
	4	0	5	12	169	90.86%
Average Correct Classification Rate: 58.09%						
95% Confidence Interval: [53.94%, 62.24%]						

6.2.4 Experiment 4: Z-Axis with SOFM and PNN

This experiment is analogous to experiment two in that the overall set-up of the system was the same, but rather than making use of the X-axis recordings, this experiment performs classification using the information in the Z-axis signals. This experiment is also similar to experiment three, except that for this experiment, SOFMs are used to extract the important VFDT features prior to classification.

Table 6.4 shows that the configuration of the system used for this experiment did not successfully differentiate between the first three classes. In fact, the classification accuracy of the second class was an extremely low rate of 15.75%, showing that this system was very confused as to what defined the characteristics of that class. Similar to experiment three, the configuration of the system used for this experiment was very effective in classifying inputs from class four.

The overall average classification rate for this experiment was slightly higher than those obtained in experiment three. Hence, not only did the inclusion of the SOFMs cause a reduction in the problem size, effectively shortening the training and testing speeds to the levels indicated in experiment two, they also caused an increase in the average classification rate. Even though the classification rate for this experiment is slightly higher than that achieved in experiment three, conclusions can not be drawn as to which system configuration was superior in terms of classification accuracy as the confidence intervals for the two experiments overlap.

Table 6.4: Z-axis SOFM PNN confusion matrix.

		Experimental				Correct Classification Rate
		1	2	3	4	
Expected	1	15	1	5	3	62.50%
	2	12	23	66	45	15.75%
	3	10	19	127	32	67.55%
	4	0	4	15	167	89.78%
Average Correct Classification Rate: 61.03%						
95% Confidence Interval: [56.93%, 65.13%]						

6.2.5 Experiment 5: X and Z-Axis with PNN

Building off the idea that greater classification rates may be possible if both the X and Z axes are utilized, this experiment focuses on the case where both axes are taken into consideration when performing classification with the PNN.

The system used for this experiment performed at a consistently high rate for all of the different classes. The individual classification rates for each class were all above 90% except for class three. When the X and Z axes were used independently for classification, as was the case for experiments one through four, class three consistently had a fairly low classification rate. Thus, it is not all that surprising that the when the classification system uses information from both X and Z-axis that it still has difficulties with class three.

Overall this experiment produced the highest average classification rate of any of the experiments and the results are summarized in Table 6.5. The slight drawback of this configuration of the system when compared to the systems outlined in experiments one though four is that this system takes approximately twice as long to run since the classification problem size is twice as large. However, in this case that meant that the classification system took approximately seven seconds to train and a quarter of a second to execute, which is still very fast and meets the time-based design constraints. This is also the one system that meets the design constraint of at least a 90% average correct classification rate.

Table 6.5: X and Z-axis PNN confusion matrix.

		Experimental				Correct Classification Rate
		1	2	3	4	
Expected	1	24	0	0	0	100.00%
	2	3	139	2	2	95.21%
	3	0	12	157	19	83.51%
	4	0	9	1	176	94.62%
Average Correct Classification Rate: 91.18%						
95% Confidence Interval: [88.80%, 93.56%]						

6.2.6 Experiment 6: X and Z-Axis with SOFM and PNN

This experiment is analogous to experiments two and four where the SOFMs are used in an attempt to improve classification. However, for this experiment, rather than simply using the X or Z-axis independently, this experiment considers both axes when developing the codebooks used for classification.

As with experiment seven, the system configuration used in this experiment produced very good results. Test inputs were classified quite successfully for each of the classes and the average classification rate was a respectable 87.68%, as shown in Table 6.6. From this data it cannot be determined whether the system used for this experiment was outperformed by the configuration from experiment five because the average classification rate confidence intervals overlap. However the execution time of the system used for this experiment is less than that of the system in experiment five because it only took a little more than three seconds to train and a sixth of a second to execute. Hence, the system used for this experiment yielded a classification rate almost as high, if not as high as that of experiment five's system, while requiring less training and execution time.

Table 6.6: X and Z-axis SOFM PNN confusion matrix.

		Experimental				Correct Classification Rate
		1	2	3	4	
Expected	1	23	1	0	0	95.83%
	2	2	133	5	6	91.10%
	3	0	14	161	13	85.64%
	4	0	19	7	160	86.02%
Average Correct Classification Rate: 87.68%						
95% Confidence Interval: [84.92%, 90.44%]						

6.2.7 Experiment 7: X and Z-Axis with CNN

Although experiments six and seven showed that the PNN is capable of classifying the fish trajectory signals at very high classification rates by appending information from the X and Z axes together, further experiments were performed to see how well a complex domain neural network would perform. The PNN was not designed to be used in conjunction with complex valued signals, but the complex domain neural networks were explicitly created for that purpose.

Hence it was conjectured that greater classification accuracy would be obtained through the use of the complex domain neural networks.

This experiment is very similar to experiment five except for the fact that complex valued signals are formed by representing the X-axis as the real part and the Z-axis as the imaginary part of the complex numbers. This complex number representation is in contrast to how the inputs to the PNN were simply a set of concatenated real values.

The complex domain neural network used in this experiment performed quite well in separating all of the different classes. As is the common trend throughout most of these experiments, the first class had a very high correct classification rate while the system did not produce quite as good results for class three.

As is shown in Table 6.7, the average classification rate for this experiment was about 87% which provides a high confidence in the system to perform correct classification. The confidence intervals do overlap with those in experiment five, so again, it can be confidently concluded that the system of experiment five performed any better than the complex domain neural network used here. Another factor to consider with respect to this experiment is that the complex neural network took nearly seven minutes to train but only thirty milliseconds to execute the entire testing set.

Table 6.7: X and Z-axis CNN confusion matrix.

		Experimental				Correct Classification Rate
		1	2	3	4	
Expected	1	23	0	0	1	95.83%
	2	3	127	8	8	86.99%
	3	0	11	151	26	80.32%
	4	0	13	3	170	91.40%
Average Correct Classification Rate: 86.58%						
95% Confidence Interval: [83.72%, 89.44%]						

6.2.8 Experiment 8: X and Z-Axis with SOFM and CNN

The final formal experiment is fairly similar to experiment six, only this time, the complex domain neural network was used as the classifier rather than the probabilistic neural

network. For this experiment, the codebooks are identical to those used during experiment six, except now the portions of the codebook that correspond to the X-axis are used to form the real part of a complex number while the Z-axis components fulfill the role of the imaginary part of the complex number. This complex number representation of the codebook is then used as the input into the complex domain neural network.

As the confusion matrix shown in Table 6.8 indicates, the SOFM, CNN combination performed quite well. The performance difference between the configuration of the system used in this experiment as compared to results obtained through experiment seven are insignificant as indicated through their overlapping confidence intervals. Yet, the configuration of the system presented in this experiment only required five minutes to train and twenty milliseconds to execute.

Table 6.8: X and Z-axis SOFM CNN confusion matrix.

		Experimental				Correct Classification Rate
		1	2	3	4	
Expected	1	24	0	0	0	100.00%
	2	2	129	10	5	88.36%
	3	0	13	150	25	79.79%
	4	0	16	10	160	86.02%
Average Correct Classification Rate: 85.11%						
95% Confidence Interval: [82.12%, 88.10%]						

6.3 Discussion

The formal verification experiments performed upon the various configurations of the system using the fish trajectory signals provided some valuable insight into the abilities of the different systems. First, configurations using, and the corresponding systems not incorporating SOFMs obtained average classification rates that were approximately equal. Essentially, the SOFMs were successful in removing the redundant information content contained within the signals so that less features were used in the classification process while still maintaining high classification rates. Because the SOFMs reduced the size of the classification problem, the systems that made use of the SOFMs were faster than the equivalent systems that did not use the SOFMs.

A second general observation that can be made from these experiments is that the classification systems that made use of only the X-axis information outperformed those systems which only used the Z-axis information. This indicates that the X-axis contains more important information than the Z-axis. Configurations that made use of both axes simultaneously, however, dramatically outperformed the systems that only utilized one axis. Intuitively this finding makes sense as the clustering techniques as explained in Appendix B use both axes when deriving the classes. Hence, when a classification system only makes use of one of the X or Z-axis, it is effectively only taking only half the information content of the signal into account. The systems making use of both axes used all the information in the signals when making classification decisions, which provided higher classification rates. In improving the classification rate above configurations utilizing only a single axis, the neural networks when presented with both axes, demonstrated that they were also able to differentiate between which axis information was important when making each individual classification decision. More specifically, the X-axis seemed to contain the most important information regarding classes one and two while the Z-axis seemed to provide the most information regarding class four. Both the CNN and PNN were able to use the complementary information from each of the signals in order to achieve greater classification accuracy.

A third observation to note is in regard to the training and execution times of the two neural networks used to perform classification based on the selected features. It was stated in the background that probabilistic neural networks train orders of magnitude faster than most other neural networks, and this fact is corroborated by the results of the experiments performed. When comparing the training time of experiment five to that of experiment seven, the PNN trained more than 50 times faster than the CNN. In comparing experiments six and eight, the CNN was approximately 100 times slower than the PNN. In terms of execution time, PNNs were stated to generally have slower execution times than other neural networks, and again, the experiments confirmed this fact. In the experiments performed in this thesis, once trained properly, the CNNs were able to classify input vectors more than eight times faster than the PNNs. But in the end, both networks were fully able to meet and exceed both of the time design constraints, in that the training time for the neural networks were only on the order of minutes or seconds, and the networks were both able to perform classification upon eight separate eight hour signals in less than a second; hence, based on their speed of execution, they would be applicable for use in real-time systems.

Overall, from the experiments it appears that the system used in experiment five whereby the PNN makes use of both X and Z-axis information provided the highest correct classification results. This configuration of the system attained an average classification rate of about 90% which indicates that a high degree of confidence can be placed in the results obtained by the system. However, one may wonder why the system does not obtain classification rates in the range of 95-100%, especially when both the clustering analysis and PNN techniques use Euclidean distance during their calculations. The main flaw in this logic is that the training and testing sets were derived directly from the fish trajectory time series, whereas the actual classification system based its decisions upon the multifractal characterization provided by the variance fractal dimension trajectory. Hence, the clustering analysis performed to derive the testing and training sets is very sensitive to factors such as changes in magnitude and phase shifts. Because of these shortcomings with the clustering algorithm, the training and testing sets derived and used for the formal experiments may not be optimal. These non-ideal testing and training sets would be a contributing factor in decreasing the average classification rate. Other reasons why a perfect classification rate is not practical include the fact that the signals used in this thesis contain inherent noise which was not removed during the preprocessing stage and that not enough training and testing sets were utilized.

6.4 Summary

This section presented the formal experiments conducted in verifying the classification system developed for this thesis. In performing these experiments with the fish trajectory signals, the results were mostly as expected and a number of observations were made. First, it is detrimental to the classification process to ignore information contained in the signal. Second, while the use of the SOFM was generally unsuccessful in improving the classification of the system, it was able to reduce the size of the classification problem while maintaining approximately the same level of accuracy. The PNN and CNN both performed well; however, the PNN trained orders of magnitude faster than the CNN, but the CNN executed faster than the PNN. In the end, all the design constraints for the classification system were met in the particular configuration where the PNN utilized the VFDT from both the X and Z axes as the features for classification.

CHAPTER 7
CONCLUSIONS AND RECOMMENDATIONS

7.1 Conclusions

This thesis illustrated a system capable of classifying the general group of self-similar, stochastic, non-stationary signals which originated from non-linear processes. This thesis is unique in that it uses very experimental, but powerful techniques to perform classification upon these signals, because traditional signal processing methods are insufficient. The use of the VFDT has also been shown to be effective in extracting a set of compressed features which represent the characteristics of the signal while simultaneously performing normalization. These fractal dimension features have been shown to be a sufficient metric upon which to classify these challenging signals. Furthermore, probabilistic neural networks and complex domain neural networks have been shown to be capable of performing classification based on these extracted features with a high degree of success. The system developed for this thesis is also very practical as it has been designed to adapt to a wide array of signals including those which are composed of multiple signals.

This thesis presented various different configurations of the classification system. One system was shown to meet all the specified design criteria, namely a correct classification rate of at least 90%, a system training time of less than one day, and an execution time of less than the signal duration itself. Several other configurations also met the time-based constraints, but failed to meet the correct classification rate by about 5-10%.

7.2 Recommendations

Although the classification system created for this thesis was shown to perform quite successfully in classifying non-stationary, self-similar, stochastic signals which may or may not consist of multiple recordings, there are always further improvements that could be made. One such enhancement would be to tweak the PNN training algorithm that selects a separate sigma value for each class so that it correctly functions with the fish trajectory signals. Similarly, the multi-sigma concept could be extended even further to include a separate sigma value for each variable. This could improve performance in the case where the inputs to the PNN consist of

multiple recordings as there is no guarantee that each recording has equal importance. A different sigma for each variable would take the variation of importance of each recording into account and potentially improve the performance of the PNN with such signals.

Additionally, the classification system could be extended to incorporate hypercomplex inputs. In the case of the fish trajectory signals, this addition would allow all the axes to be included in the classification process rather than just the X and Z axes. For the fish trajectory signal, this addition may not significantly improve performance as it is difficult to gauge the importance the Y-axis readings. However, other signals that consist of three or more independent recordings, each of which holds significant information content, may benefit greatly from this enhancement.

Another beneficial task that could be undertaken is comparing the results of the classification system developed for this thesis with those derived by expert psychologists studying the fish trajectory signals. This collaboration was not arranged in time for this thesis, hence the classes were derived and the system verified in a completely objective manner. Comparing the objective classification system with the subjective analysis performed by the experts would provide another metric to evaluate the performance of the system and may lead to insight as to further improvements to the system

A total of 17 different fish trajectory signals were used for the formal experiment in this thesis. Of these 17 recordings, nine were used for training while eight where used for testing the system. These signal recordings provided sufficient results for this thesis, but incorporating a larger training set should improve the performance of the system and an increased testing set would provide a better overall picture of the system's performance.

A task that could be completed to further verify the performance of the system would be to superimpose synthetic noise upon the signals in order to test the system's robustness to noise. Further, the use of additional types of signals with the system would further test the neutrality of the system with respect to the specific signal used and would show that the system can be applied to a variety of stochastic, self-similar, non-stationary signals with a high level of success.

REFERENCES

[Chen01] J. Chen, *Classification of Transients in Power Systems*. MSc Thesis, University of Manitoba, 2001.

[Doug99] B. Douglas, *Doing Hard Time: Developing Real-Time Systems with UML, Objects, Frameworks, and Patterns*. Reading, MA: Addison Wesley Longman, Inc., 1999.

[EbDo90] R. Eberhart and R. Dobbins, *Neural Network PC Tools: A Practical Guide*. San Diego, CA: Academic Press, Inc., 1990.

[Fere95] K. Ferens, *Perceptual Measures off Signal Features*. Ph.D. Thesis, University of Manitoba, 1995.

[Hayk99] S. Haykin, *Neural Networks: A Comprehensive Foundation.* Upper Saddle River, NJ: Prentice-Hall, Inc., 1999.

[KaKw92] B.L. Kalman and S.C. Kwasny, "Why tanh? Choosing a sigmoidal function", *International Joint Conference on Neural Networks*, vol. 4, pp. 578-581, June 1992.

[Kins94] W. Kinsner, "Batch and real-time computation of a fractal dimension based on variance of a time series," *Technical Report*, DEL94-6; UofM; June 15, 1994, (v+17) 22 pp.

[Koho84] T. Kohonen, *Self-Organization and Associative Memory*. Berlin: Springer-Verlag, 1984.

[Mall98] S. Mallat, *A Wavelet Tour of Signal Processing*. San Diego, CA: Academic Press, 1998.

[Mand82] B. Mandelbrot, *The Fractal Geometry of Nature.* San Francisco, CA: W. H. Freeman and Co., 1982.

[Mast93] T. Masters, *Practical Neural Network Recipes in C++*. San Diego, CA: Academic Press, Inc., 1993.

[Mast94] T. Masters, *Signal and Image Processing with Neural Networks: A C++ Sourcebook*. New York, NY: John Wiley & Sons, Inc., 1994.

[Mast95] T. Masters, *Advanced Algorithms for Neural Networks: A C++ Sourcebook*. New York, NY: John Wiley & Sons, Inc., 1995.

[Meis72] W. Meisel, *Computer-Oriented Approaches to Pattern Recognition*. New York, NY: Academic Press, 1972.

[Parz62] E. Parzen, "On estimation of a probability density function and mode", *Annals of Mathematical Statistics*, 33:3, pp. 1065-1076, 1962.

[PeJS92] H.O. Peitgen, H. Jürgens, and D. Saupe, *Chaos and Fractals: New Frontiers of Science*. New York, NY: Springer Verlag, 1992.

[PrFTV88] W. Press, B. Flannery, S. Teukolsky, and W. Vetterling, *Numerical Recipes in C*. New York, NY: Cambridge University Press, 1988.

[Spec88] D.F. Specht, "Probabilistic neural networks for classification, mapping, or associative memory", *IEEE International Conference on Neural Networks*, vol. 1, pp. 525-532, July 1988.

[Spec92] D.F. Specht, "Enhancements to probabilistic neural networks", *International Joint Conference on Neural Networks*, vol. 1, pp. 761-768, June 1992.

[Wass93] P. Wasserman, *Advanced Methods in Neural Computing*. New York, NY: Van Nostrand Reinhold, 1993.

[WeKu91] S. Weiss and C. Kulikowski, *Computer Systems that Learn: Classification and Prediction Methods from Statistics, Neural Nets, Machine Learning, and Expert Systems*. San Mateo, CA: Morgan Kaufmann Publishers, Inc., 1991.

APPENDIX A
FISH TRAJECTORY SIGNALS

The signals used for verifying the classification system developed for this thesis are fish trajectory signals obtained from Dr. Pear of the University of Manitoba's psychology department. Dr. Pear studies operant conditioning principles through dishabituation experiments, whereby the spatio-temporal agonistic behaviour of Siamese fighting fish is studied. During these experiments, one of several fish is placed inside a fish tank with a mirror at one end. A stereoscopic camera system is used to track and record the three dimensional Cartesian co-ordinates of the fish over an eight hour period, where the position of the fish is sampled ten times a second. The experiment set-up and co-ordinates of the system are shown in Fig. A.1. The X-axis is the direction normal to the mirror, the Y-axis is the lateral distance along the mirror, and the Z-axis is the direction along the height of the fish tank. The stereoscopic capability of the camera system is used to obtain the Y-axis.

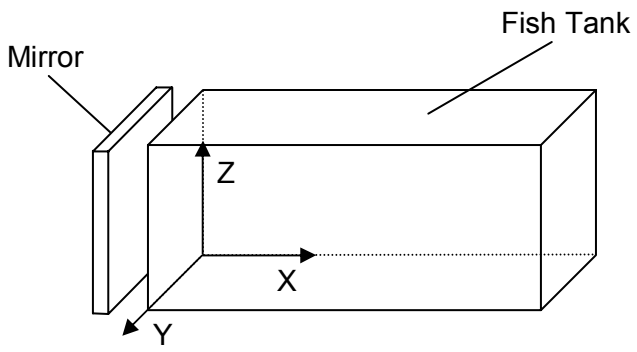


Fig. A.1: Fish trajectory signal experiment set-up and fish tank co-ordinate system.

Sample fish trajectory recordings for a particular fish are shown in Fig. A.2. This figure represents the fish's position in the tank during one of the dishabituation experiments along the X, Y, and Z axes. As can be seen in these figures the fish exhibits different behaviour patterns over the eight hours period of the dishabituation experiment. Particular attention should be drawn to approximately the first 15 minutes of the experiment. During this time frame, the fish maintains close proximity to the mirror which is indicated by the very small X-axis values. In essence, the fish is responding to its natural instinct to attack an enemy, i.e. the reflection. Additionally,

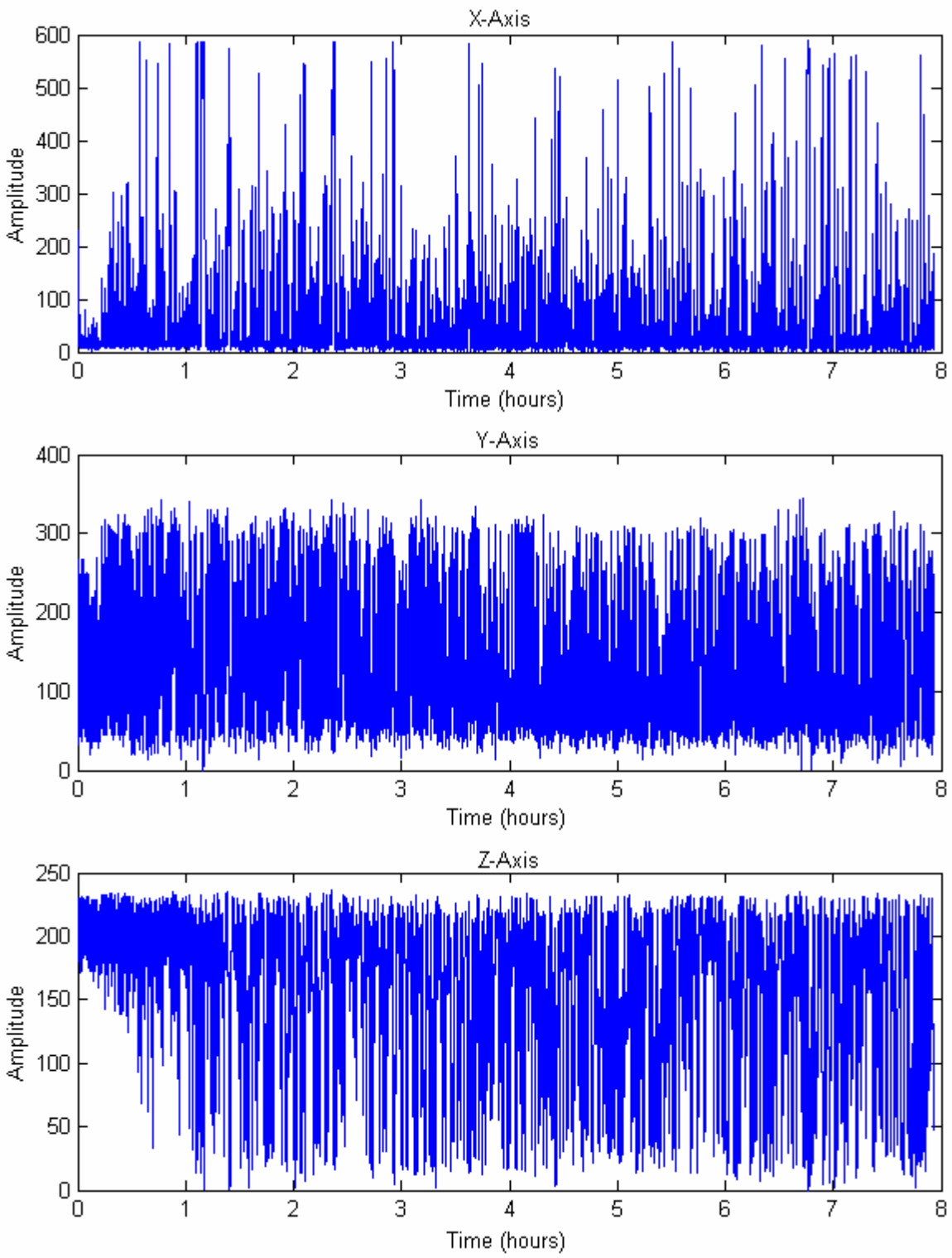


Fig. A.2: Fish trajectory signals.

during these initial 15 minutes the fish remains close to the surface of the tank, as indicated by large Z-axis values. This behaviour is exhibited because the fish breathes air and requires more air when it is excited.

Following the initial 15 minute period the fish begins to move farther away from the mirror and for longer periods of time. At seven hours into the experiment, the mirror is removed for 60 seconds and a dishabituation stimulus is presented in an attempt to have the fish revert to its initial behaviour. This dishabituation stimulus is a conspecific – another Siamese fighting fish – in a separate fish tank positioned at the side of the tank directly opposite the mirror. After 60 seconds the mirror is restored to its original position and the conspecific is removed.

As previously mentioned, the stereoscopic portion of the camera system was used to obtain the Y-axis recordings. Because of this configuration, the Y-axis is the least accurate of any of the axes. This was arranged because the Y-axis is the only direction which there is no explicit stimuli and is considered the least significant in terms of the information provided. Both the mirror and conspecific are stimuli along the X-axis and is correspondingly considered the axis that contains the most useful information. While the experiment presents no stimuli along the Z-axis, what differentiates this direction from that of the Y-axis is that the fish must periodically breathe air, and this action of rising to the surface of the water to breathe has significance in the experiment. As this thesis restricts its scope to developing a system to classify signals composed of two correlated recordings, only the X and Z axes used for the purpose of verifying the system.

As with all real signals, the tracking system is subject to noise and inaccuracies along all three axes. Furthermore, because of the set-up of the experiment, the system sometimes encounters tracking errors where the fish moves into a particular position close to the mirror that is outside the view of the camera, and results in missing samples. These non-idealities aid in testing the robustness of the signal classification system.

An important issue to consider when processing any signal is the sampling rate. Obviously the sampling rate must adhere to the Nyquist sampling theorem. The following explanation justifies the sampling rate used in the recording of the fish trajectory signals. Assume that the fish moves in a sinusoidal trajectory at the Nyquist frequency, or half of the sampling frequency. Further, assume that the amplitude of the sinusoidal is approximately the size of the fish, since this guarantees that the tracking system identifies this lateral motion. The resulting signal is given by $x = A\sin\omega t$, where A is the amplitude, 2 cm, and ω is the Nyquist frequency,

$2\pi 5$ rad/s. The corresponding velocity is given by the derivative of this sinusoidal, $v = A\omega cos\omega t$. If the fish is to travel this particular trajectory, then it must be able to move at the maximum velocity, $A\omega$. Thus, the fish must be able to reach a speed of 62.8 cm/s. However, this value is beyond the maximum speed of the fish observed during these experiments and thus, it is not possible for there to be frequencies above the Nyquist frequency, given the sampling rate of 10 Hz. Therefore, the sampling rate is valid for this signal.

The purpose of attempting signal classification upon these signals is to identify the various behaviours exhibited by the fish in an automated, quantitative manner. This quantitative assessment based on the position of the fish in the fish tank could then be compared to the psychological qualitative analysis performed by Dr. Pear and his graduate students. Because this signal emanates from a living being that is acting erratically, the system in question is non-linear. Further, the fish's reaction to the stimuli is random in nature and changes over time, hence its stochastic and non-stationary properties. The self-similarity property of a signal is difficult to intuitively identify, but it can be shown that the signal is indeed self-similar. Because of the complex nature of the signal and the properties it exhibits, this fish trajectory signal is used as the basis to verify the performance of the classification system developed for this thesis.

APPENDIX B
CLUSTERING OF FISH TRAJECTORY SIGNALS

The fish trajectory signals used for the verification of the classification system developed for this thesis were not accompanied by the specification of the classes. However, example signals from each of the different classes are required in order to establish the training and testing sets. For the purposes of this thesis, the determination of the classes is to be performed in an objective manner that is unbiased with respect to the techniques used in the thesis itself. Furthermore, this class specification is to be performed assuming nothing about the data itself, so as not to bias the results based on a priori information.

In order to determine these class specifications, it is desired to perform a clustering analysis upon the signals to discover the groupings that exist within the signal. There are numerous techniques for performing clustering, but most require that at minimum, the number of classes be known a priori; information that is unfortunately not known for the fish trajectory signals. The proposed clustering technique is Kohonen self-organizing feature maps (SOFMs), as discussed in the background in Chapter 2. This unsupervised neural network is able to perform a topology-preserving clustering with no a priori information about the data. The result of training the network is a codebook consisting of codewords representative of the input vectors to be clustered. The codewords in the codebook are grouped in the codebook based on their similarity. By visually viewing the groupings of the codewords, the underlying clustering of the signal can be inferred.

Each signal is divided up into a number of segments and it is these segments of the signals which are to be classified by the system and thus clustering is based upon these segments. By utilizing these segments of the signal as the input vectors to the SOFM, it will produce the desired codebook containing the clusters. However, it would be naïve to perform clustering only upon one axis since it would then completely ignore the information contained in the other axes. Since this thesis restricts the classification to complex valued signals composed of two separate recordings and the purpose of utilizing these fish trajectory signals is solely for the verification of the system, not the analysis of the behaviours of the fish, only the axes considered to be the most important, the X and Z-axis, are considered. In order to adapt the SOFM to perform clustering by taking both axes into account, the input vectors to the SOFM are formed by concatenating the signal segments from the X and Z-axis, as explained in Eq. (3.1).

The difficulty in performing this clustering based on both the X and Z-axis is that because of the nature of the signals, the fish exhibits more dramatic changes along the X-axis as compared to the Z-axis. This inequity causes a problem because the X-axis influences the clustering much more than the Z-axis because of its greater changes in magnitude. To circumvent this problem and to put the two axes on equal footing, a Z-score normalization is performed separately upon the axes, whereby the signal samples are normalized according to (B.1), where x is the sample, $\bar{x}$ is the sample mean of all the samples for the axis, and s is the sample standard deviation of all the samples for the axis.

$$y = \frac{x - \bar{x}}{s} \tag{B.1}$$

The axes are separately normalized such that the mean of all the samples for the axis is zero and the standard deviation is one. This normalization ensures that both axes equally influence the outcome of the clustering, as desired. This need for explicit normalization is in contrast to the actual classification system where the computed variance fractal dimension trajectory naturally produces normalized features.

The details of the operation and training of the network, as well as the design, implementation, and testing and verification of the SOFM can be found in the body of the thesis.

Once the SOFM has been trained, the codebook must then be analyzed to discover the clusters of the signal segments. It was found that segments of length 4096 samples, or approximately 6.8 minutes, produced decent clustering. Plots of the codebook using segments of the aforementioned size are shown in Fig. B.1 where the portions of the codewords corresponding to the different axes are first extracted and then appended together. Thus, in the figure, the first codeword actually consists of the segment between 0 and 1 of the X-axis codebook followed by a concatenation of the segment between 0 and 1 of the Z-axis codebook. Note that visually, the codewords are grouped together in such a manner that adjacent codewords are similar.

There is a range of segment lengths where the clustering yields similar results. It was discovered that, lengths between 2048 and 4096 samples produced similar codebooks, meaning that the classes of the signal are approximately constant over 4096 samples. Here, the segment size selected was the largest segment where the signal's class of behaviour remained constant, i.e. 4096 samples.

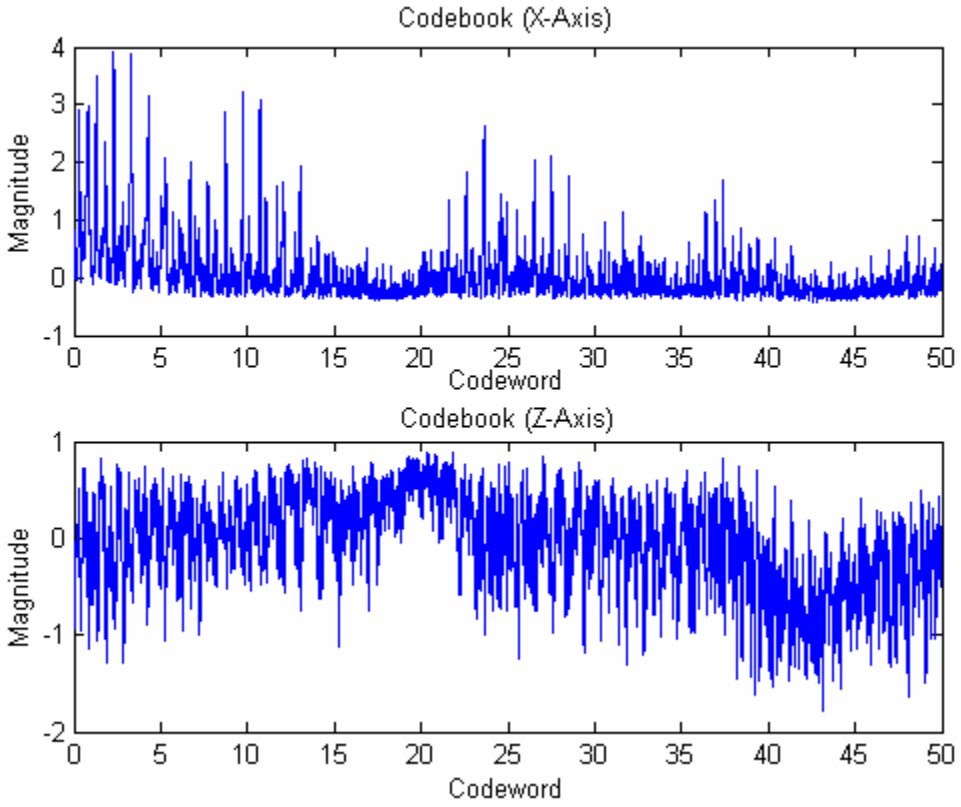


Fig. B.1: Clustering Codebook.

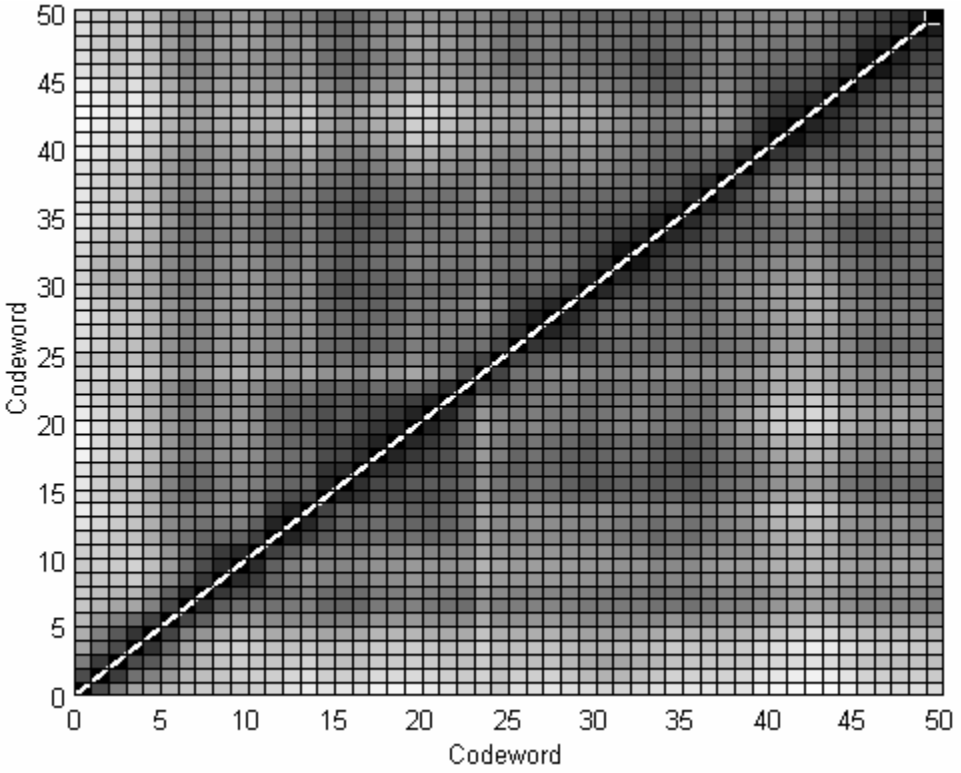


Fig. B.2: Euclidean Distance Between Codewords

Direct analysis of the clustering in this view is quite difficult. In order to better view the clustering, a plot is created to exemplify the relative similarity between the codewords. The judge of similarity between codewords is done by computing the Euclidean distance between all the combinations of codewords and plotting these results in a colour map, as seen in Fig. B.2. The number of the codewords appears along both axes and the value for a given row and column is the Euclidean distance between the two codewords. The distance between two codewords is represented in the figure as a gray scale colouring, where black corresponds to a distance of zero and white corresponds to a very high distance. Note that the values along the diagonal should always be black because the distance between a codeword and itself is zero. The fact that the diagonal appears to be white in the figure is merely an artifact of the plotting program used. The groupings can be much more easily seen in this plot because the relative similarity of the codewords is clearly shown. Dark sections are indicative of groups of codewords that can be considered to be of the same class. Ideally, if the groupings were very distinct and separable, there would be several dark areas where the intersection of the dark areas on the map are lightly coloured, meaning that none of the codewords in a particular class are similar to the codewords in any other class.

This plot shows some separability of the classes, but it is difficult to see in print. There seems to be a distinct class consisting of the codewords 0 through 5, as the Euclidean distance between all these codewords are very small, and the Euclidean distance between these codewords and others are substantially higher. The second class appears to be between 6 and 22, but are not as well formed as the first class. There appears to be a third class between the 23rd and 39th codewords, which leaves the codewords from 40 to 49 as the fourth class. Referring back to Fig. B.1, these classes seem reasonable, as the codewords defined to be of the same class visually seem similar. By identifying these clusters, the signals can be annotated by segmenting them into lengths of 4096, which corresponds to the codeword size and discovering to which codeword it corresponds. The codeword corresponding to a given signal segment is determined by the "winner" neuron in the SOFM for that given input. The class which that codeword belongs, as determined by the visual inspection, is then assigned to the signal segment in question. This procedure is repeated for every segment in each signal. These segments now act as examples for each of the classes for use in the formation of training and testing tests. With segments of size 4096 samples, there are 68 segments in each signal. The segments in nine of the files are set aside for the training set and the segments in the other eight files are set aside for the testing set.

Note that this clustering is based on the time domain, so it is sensitive to changes in such things as magnitude and phase shifts. The simple similarity of signals when compared sample to sample is not a particularly good judgement of whether the signals have the same behaviour and hence, belong to the same class, but it is an objective way of performing this clustering and is unbiased to the techniques used in this thesis.

APPENDIX C
SOURCE CODE

The source code for all of the programs written for the various configurations of the classification system developed for this thesis is provided on the attached CD. The source code can be found the "src" directory. In addition to the source code, full documentation in the form of Javadocs for all of the programs is supplied on the CD in the "doc" directory.

CONTRIBUTIONS

Thesis Report

The writing of this thesis was a combined effort between the two team members. Although the entire thesis was edited and revised by both group members, the following list indicates which individual made substantial written contributions to each section of the report.

Abstract ..... [Kevin and Vincent]

Chapter 1 Introduction ..... [Kevin and Vincent]

Chapter 2 Background

- 2.1 Signal Classification and Terminology ..... [Kevin]
- 2.2 Fractals ..... [Kevin]
  - 2.2.1 Introduction ..... [Kevin]
  - 2.2.2 Variance Fractal Dimension ..... [Kevin]
- 2.3 Neural Networks ..... [Kevin and Vincent]
  - 2.3.1 Introduction ..... [Kevin]
  - 2.3.2 Basic Concepts ..... [Kevin]
  - 2.3.3 Backpropagation ..... [Kevin]
  - 2.3.4 Complex Domain Neural Networks ..... [Vincent]
  - 2.3.5 Probabilistic Neural Networks ..... [Kevin]
  - 2.3.6 Kohonen Self-Organizing Feature Maps ..... [Vincent]

Chapter 3 System Design

- 3.1 System Architecture ..... [Vincent]
- 3.2 Component Design ..... [Vincent]
  - 3.2.1 Preprocessing ..... [Vincent]
  - 3.2.2 Variance Fractal Dimension Trajectory ..... [Vincent]
  - 3.2.3 Kohonen Self-Organizing Feature Map ..... [Vincent]
  - 3.2.4 Probabilistic Neural Network ..... [Kevin and Vincent]
  - 3.2.5 Complex Domain Neural Network ..... [Vincent]

Chapter 4 System Implementation ..... [Vincent]

Chapter 5 System Verification and Testing ..... [Kevin and Vincent]

Chapter 6 Experimental Results and Discussion ..... [Kevin and Vincent]

Chapter 7 Conclusions and Recommendations ..... [Kevin and Vincent]

Appendix A Fish Trajectory Signals ..... [Kevin and Vincent]

Appendix B Clustering of Fish Trajectory Signals ..... [Vincent]

Individual Contributions

Individual	Work Completed
Kevin Cannons	Implemented Brent's line minimization algorithm. Implemented the conjugate gradient multi-sigma training algorithm for the PNN. Extensively tested and compared the performance of the single sigma PNN and the multi-sigma PNN.
Vincent Cheung	Designed and implemented the preprocessing, variance fractal dimension trajectory, Kohonen self-organizing feature map, probabilistic neural network, and complex domain neural network components. Designed and implemented the classes to create the input vectors for classification and for performing the actual classification of the signals with the various configurations of the system. Thoroughly tested and verified each component as well as the overall system. Optimized the VFDT, SOFM, PNN, and CNN parameters. Conducted the formal verification experiments to compare the performance of the various configurations of the system with the fish trajectory signals. Performed the clustering of the fish trajectory signals using Kohonen self-organizing feature maps in order to develop the training and testing sets.

VITA

NAME:	Kevin Cannons
PLACE OF BIRTH:	Palo Alto, California, USA
YEAR OF BIRTH:	1981
SECONDARY EDUCATION:	Shaftesbury High School
HONOURS and AWARDS:	1999 • Advanced Placement and International Baccalaureate Scholarship Enhancement • APEGM Engineering Entrance Scholarship • Dr. Kwan Chi Kao Entrance Scholarship in Engineering • I.O.D.E Jon Sigurdsson Memorial Entrance Scholarship • University of Manitoba Advanced Early Admission Scholarship 2000-2002 • Dean's Honour List • UMSU Scholarship 2000 • Faculty of Engineering Second Year Scholarship • NSERC Undergraduate Student Research Award 2001 • Engineering Academic Excellence Award • Grettir Eggertson Memorial Scholarship • Technical Communication Report Prize 2002 • Grettir Eggertson Memorial Scholarship • NSERC Undergraduate Student Research Award

VITA

NAME: Vincent Cheung

PLACE OF BIRTH: Thompson, Manitoba, Canada

YEAR OF BIRTH: 1981

SECONDARY EDUCATION: Shaftesbury High School

HONOURS and AWARDS:

1999
- Governor General's Award
- Advanced Placement and International Baccalaureate Scholarship Enhancement
- APEGM Engineering Entrance Scholarship
- Challenge Math Award
- Doug Strang Memorial / Reid Crowther Scholarship
- Dr. Kwan Chi Kao Scholarship
- Johana Gudrun Skaptason Scholarship
- Manitoba Hydro Entrance Scholarship

2000-2002
- Dean's Honour List
- Dr. A.W. Hogg Undergraduate Scholarship
- Isbister Scholarship in Engineering
- MTS Pursue Your Calling Scholarship
- UMSU Scholarship

2000
- APEGM First Year Scholarship
- Dr. Kwan Chi Kao Scholarship in Elec. and Comp. Eng.
- Edward Oliver Grimsdick Memorial Prize
- EECOL Electric Inc. Scholarship
- Faculty of Engineering Second Year Scholarship

2001
- Donald George Lougheed Memorial Scholarship
- Engineering Academic Excellence Award - Comp. Eng.
- Royal Air Force Auxiliary Memorial Scholarship
- Technical Communication Report Prize

2002
- Abitibi-Consolidated Inc. Scholarship
- Dr. Kwan Chi Kao Scholarship in Computer Engineering
- NSERC Undergraduate Student Research Award