OPTIMIZATION OF CODED SINGALS BASED ON WAVELET NEURAL NETWORK

MUSTAFA SAMI AHMED

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Faculty of Electrical and Electronic Engineering
Universiti Tun Hussein Onn Malaysia

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ABSTRACT

Pulse compression technique is used in many modern radar signal processing systems to achieve the range accuracy and resolution of a narrow pulse while retaining the detection capability of a long pulse. It is important for improving range resolution for target. Matched filtering of binary phase coded radar signals create undesirable sidelobes, which may mask important information. The application of neural networks for pulse compression has been explored in the past. Nonetheless, there is still need for improvement in pulse compression to improve the range resolution for target. A novel approach for pulse compression using Feed-forward Wavelet Neural Network (WNN) was proposed, using one input layer and output layer and one hidden layer that consists three neurons. Each hidden layer uses Morlet function as activation function. WNN is a new class of network that combines the classic sigmoid neural network and wavelet analysis. We performed a simulation to evaluate the effectiveness of the proposed method. The simulation results demonstrated great approximation ability of WNN and its ability in prediction and system modeling. We performed evaluation using 13-bit, 35-bit and 69-bit Barker codes as signal codes to WNN. When compared with other existing methods, WNN yields better PSR, low Mean Square Error (MSE), less noise, range resolution ability and Doppler shift performance than the previous and some traditional algorithms like auto correlation function (ACF) algorithm.

ABSTRAK

Teknik pemampatan denyut digunakan dalam banyak sistem pemprosesan isyarat radar moden untuk mencapai julat ketepatan dan resolusi denyut yang pendek disamping mengekalkan keupayaan pengesanan denyut yang panjang. Adalah penting untuk meningkatkan resolusi julat denyut bagi target. Penapisan isyarat radar berkod binari yang telah dipadankan menghasilkan isyarat sampingan yang tidak diingini, yang boleh menyembunyikan maklumat penting. Aplikasi rangkaian neural untuk pemampatan denyut telah diterokai pada masa lalu. Walau bagaimanapun, masih terdapat keperluan penambahbaikan dalam mampatan denyut untuk meningkatkan julat resolusi bagi target. Pendekatan baru untuk pemampatan denyut menggunakan teknik pincang hadapan Wavelet Neural Network (WNN) telah digunakan, menggunakan satu lapisan input dan output serta satu lapisan tersembunyi yang mengandungi tiga neuron. Setiap lapisan tersembunyi menggunakan fungsi Morlet sebagai fungsi pengaktifan. WNN perupakan satu kelas baru rangkaian yang menggabungkan rangkaian neural sigmoid klasik dan analisis wavelet. Simulasi telah dilakukan untuk menilai keberkesanan kaedah yang dicadangkan ini. Keputusan simulasi menunjukkan keupayaan penganggaran yang tinggi oleh WNN dan keupayaannya dalam membuat ramalan dan pemodelan sistem. Kami melakukan penilaian menggunakan 13-bit, 35-bit dan 69-bit kod Barker sebagai kod isyarat kepada WNN. Berbanding dengan kaedah-kaedah lain yang sedia ada, WNN menghasilkan PSR lebih baik, Ralat Kuasa Dua (MSE) yang lebih rendah, kurang gangguan, keupayaan julat resolusi dan prestasi anjakan Doppler yang lebih baik daripada sebelumnya dan beberapa algoritma tradisional seperti fungsi algoritma auto korelasi (ACF).

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LIST OF SYMBOLS AND ABBREVIATIONS

NN	Neural Network
ANN	Artificial Neural Network
SNR	signal-to-noise ratio
T	Transmitted Pulse Width
E_t	Single-Pulse Transmit Energy
P_t	Transmitted Power
MLNN	Multi-layer Neural Network
LP	Linear programming
SCNFN	Self-Constructing Neural Fuzzy Network
RBFN	Radial Base Function Network
RRBF	Recurrent Radial Basis Function
DWT	Discrete Wavelet Transform
CWT	Continues Wavelet Transform
RF	Radial Function
RLS	Recursive Least Squares
FFNN	Feed Forward Neural Network
MLPNN	Multi-Layer Perceptron Neural Network
MF	Matched Filter
SSR	Signal –to-Side lobe Ratio
RNN	Recurrent Neural Network
GA	Genetic Algorithm
LFM	Linear Frequency Modulation
MBPCC	Multilevel Biphase Pulse Compression Codes
PSL	Peak Side Lobe
PSO	Particle Swarm Optimization
NLFM	Non-Linear Frequency Modulation
MSE	Mean Square Error
N_s	subpulse
B	Bandwidth

ACFs	Autocorrelation Functions
N	sequence
MF	Matched Filter
BPNN	Back-Propagation Neural Network
BPFFNN	Back-Propagation Feed Forward Neural Network
L	Number of layers
LMS	Least Mean Square
a	scale or dilation parameter
b	shift or translation parameter
n	number of node in the hidden
w	weight
u_i	input training vector
y_k	output of the network
$\star$	Convolution
ψ	Mother Wavelet
φ	Father Wavelet
R	The target range
C	The velocity of signal propagation
IIR	infinite-duration impulse response
ISL	Integrated Sidelobe Level
FIR	finite-duration impulse response
FT	Fourier Transform
WF	Wiener Filter
WA	Wavelet Analysis
WT	Wavelet Transform
WFT	Windowed Fourier Transform
WNN	Wavelet Neural Network

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CHAPTER 1

INTRODUCTION

1.1 Background

Radar is an electromagnetic system for the detection and location of objects. Radar stands for Radio Detection And Ranging [1]. It operates by transmitting a particular type of waveform, a pulse-modulated sine wave for example, and detects the nature of the echo signal. Radar is used to extend the capability of one's senses for observing the environment, especially the sense of vision. The value of radar lies not in being a substitute for the eye, but in doing what the eye cannot do-Radar cannot resolve detail as well the eye, nor is it capable of recognizing the "color" of objects to the degree of sophistication which the eye is capable. However, radar can be designed to see through those conditions impervious to normal human vision, such as darkness, haze, fog, rain, and snow. In addition, radar has the advantage of being able to measure the distance or range to the object. This is probably its most important attribute.

An elementary form of radar consists of a transmitting antenna emitting electromagnetic radiation generated by an oscillator of some sort, a receiving antenna, and an energy-detecting device or receiver. A portion of the transmitted signal is intercepted by a reflecting object (target) and is reradiated in all directions. It is the energy reradiated in the back direction that is of prime interest to the radar. The receiving antenna collects the returned energy and delivers it to a receiver, where it is processed to detect the presence of the target and to extract its location and relative velocity. The distance to the target is determined by measuring the time taken for the radar signal to travel to the target and back. The direction, or angular position, of the target may be determined from the direction of arrival of the reflected wave (echo) front. The usual method of measuring the direction of arrival is with narrow antenna beams. If relative motion exists between target and radar, the shift in the carrier frequency of the reflected wave (Doppler Effect) is a measure of the target's relative (radial) velocity and may be used to distinguish moving targets from stationary objects. In radars which continuously track the movement of a target, a continuous indication of the rate of change of target position is also available [2].

The most common radar signal or waveform, is a series of short duration, somewhat rectangular-shaped pulses modulating a sine wave carrier [3] . Short pulses are better for range resolution, but contradict with energy, long range detection, carrier frequency and SNR. Long pulses are better for signal reception, but contradict with range resolution and minimum range. At the transmitter, the signal has relatively small amplitude for ease to generate and is large in time to ensure enough energy in the signal as shown in Figure 1.1. At the receiver, the signal has very high amplitude to be detected and is small in time [4].

A very long pulse is needed for some long-range radar to achieve sufficient energy to detect small targets at long range. But long pulse has poor resolution in the range dimension.

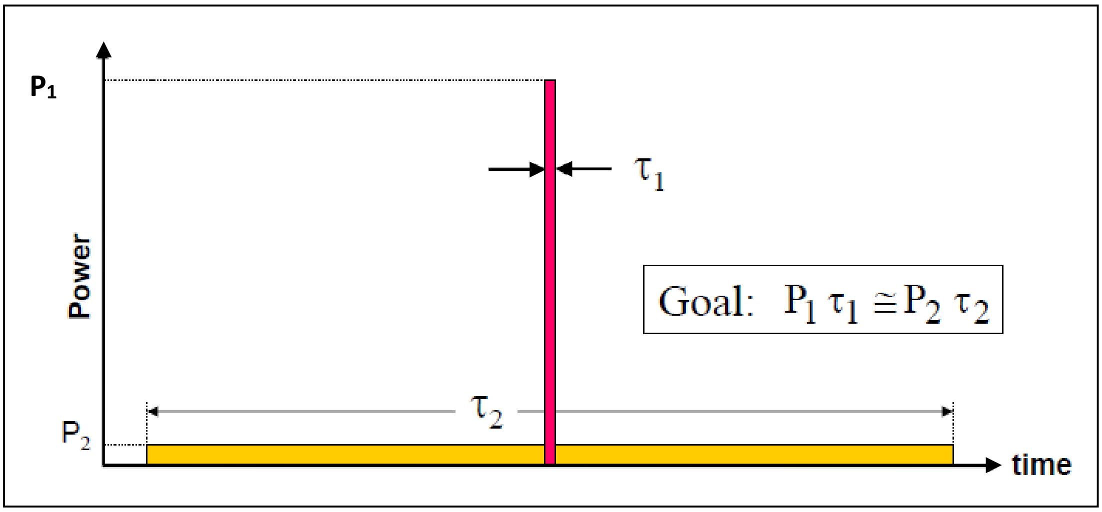

Figure 1.1: Transmitter and receiver ultimate signals

Frequency or phase modulation can be used to increase the spectral width of a long pulse to obtain the resolution of a short pulse. This is called “pulse compression”.

1.2 Problem Statements

The sidelobe which is as a result of reflection affects the signal causing wastage of energy needed for wide range. It is often essential that the time (range) sidelobes of the autocorrelation function of the binary phase-coded pulses be reduced to as low level as possible, particularly in multiple-target environments that large undesired reflectors (point clutter) or in distributed clutter are available, else the time sidelobes of one large target may appear as a smaller target at another range, or the integrated sidelobes from extended targets or clutter may mask all the interesting structure in a scene [3] . Several pulse compression techniques has been proposed by various researchers and are used in many modern radar signal processing systems to reducing the effects of sidelobe by improving the accuracy of narrow pulse and retaining the capability of long pulse detection [5, 6].

Techniques like Matched filter (MF) [7] is still used for pulse compression operation for a narrow pulse. However, the output response of the MF contains high range sidelobes which at times leads to false target detection [8]. Also, the linear frequency modulated (LFM) which was introduced in the 50s is still used widely today to reduce sidelobe as it has the ability to increase the bandwidth of the radar pulse. However, there is also a significant drawback in the approach as, it have the existence of large near-sidelobes, which block nearby targets and blur radar images [9]. Therefore reduction of the sidelobes as much as possible will save much energy and increase the main lobe to have a better signal with a wide range and better performance.

1.3 Objectives of Project

The major objective of this project is to study the characterization of Radar signal measurable objectives are as follows:

1. To design pulse compression biphase codes of various length for Radar signal having lower peak sidelobes.

2. To develop sidelobe reduction method using wavelet neural networks to improve the performance of radar.

3. To compare the proposed method Wavelet neural Network (WNN) with the existing methods.

1.4 Scopes of Project

- Generate various lengths for the Phase-Coded Pulse signal in Barker code form using code.
- Artificial Neural Network (ANN) will be used to evaluate the sidelobe reduction.
- The MATLAB Version (R2013a) program will be used to simulate the study in this project.

1.5 Research Structure

I. Chapter 1 gives an overview of the project design. It covers the introduction to Radar and, problem statement, objectives, significant and the scope of work in this project.

II. Chapter 2 gives explanation on the pulse compression, its applications, its advantages and disadvantages. This chapter also discuss neural network and how it been constructed. Finally this chapter shows the previous studies that related to neural network.

III. Chapter 3 discussed the procedure of generating the signal and the procedure of constructing feedforward neural network (FFNN) and wavelet neural network (WNN). This chapter also explains the way of implementation of wavelet neural network to separate sidelobe.

IV. Chapter 4 presents the results obtained from the simulation process and compares these results with the results of previous studies. In this chapter, the analyzing of the results to evaluate the performance has been done.

V. Chapter 5. The concluding remarks for all the chapters are presented in this chapter. It also contains some future research area that requires attention and further investigation.

CHAPTER 2

LITERATURE REVIEW

In radar signal transmission, pulse compression causes sidelobes. It is unwanted by-products of the pulse compression process. Sidelobe reduction techniques continue to be of interest, particularly in the case of relatively short binary codes which have the comparatively high level of sidelobes [8]. This chapter presents a review of works that deals with Pulse Compression, and sidelobe reduction using Artificial Neural Network (ANN) method as well as adaptive filters.

2.1 Pulse Compression

Pulse compression is important for improving range resolution. The application of neural networks for pulse compression has been well explored in the past. Two important factors to be considered for radar waveform design are range resolution and maximum range detection. Range resolution is the capability of the radar to separate closely spaced targets and it is related to the pulse width of the waveform, maximum range detection which is the ability of the radar to detect the farthest target and it is related to the transmitted energy. The narrower the pulse width the better is the range resolution. However, if the pulse width is reduced, the amount of energy in the pulse is reduced and hence maximum range detection gets decreases. To overcome this issue, pulse compression mechanism is utilized in the radar systems [10].

So, pulse compression permits radar to get the resolution of a short pulse and simultaneously using long waveforms so as to obtain high energy and that can be achieved by internal modulation of the long pulse [11]. The transmitted pulse is modified by using frequency modulation or phase modulation.

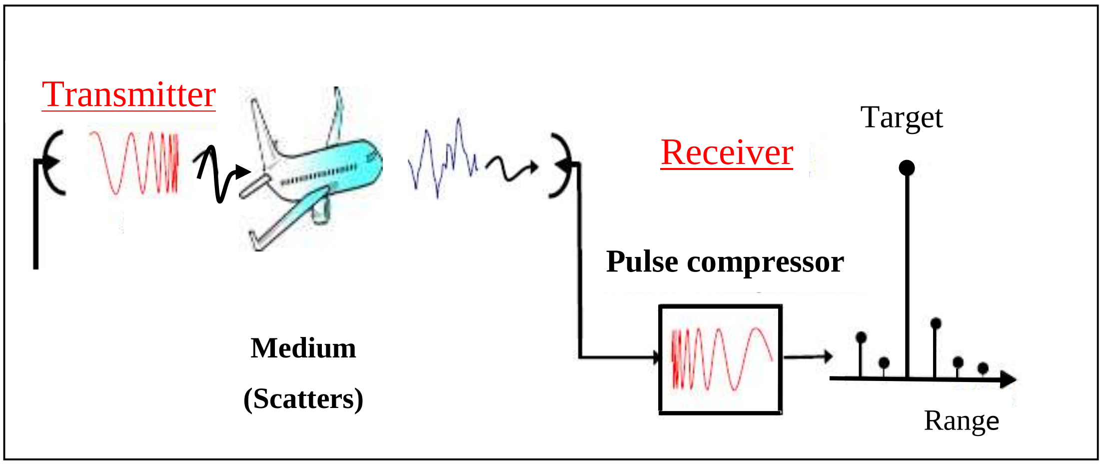

Figure 2.1: Concept of Pulse Compression

Then, upon receiving an echo, the received signal is compressed through a filter and the output signal will look like the one. It consists of a peak component and some side lobes. Figure 2.1 demonstrates the idea in simple way. The approaches by Rihaczek and Golden [12] and Baghel and Panda [8] have obtained high level of sidelobe reduction using pulse compression filter. However, this increases a computational burden and limits real time possibilities of the hardware filter applications. Pulse compression systems require advanced and expensive technology for production.

2.1.1 Advantages and Limitations of Pulse Compression

To make good range resolution and accuracy compatible with a high detection capability while maintaining the low average transmitted power, pulse compression processing giving low-range sidelobes is necessary.

According to Melvin and Scheer [10] the principle advantages of pulse compression are as follows:

1. Increasing system resolving-capability both in range and velocity.
2. Improving signal-to-noise ratio.
3. To get a pulse–hiding transmission and thereby making the condition more difficult to the enemy to detect the "code" pulse and know whether there is a radar transmission illuminating the enemy's receiver.
4. More efficient use of the average power available at the radar transmitter and in some cases avoidance of peak power problems in the high power sections of the transmitter.
5. Extraction of information from the signals presents at the receiver input to obtain an estimation of important parameters associated with the individual signals, such as range, velocity, and possibly acceleration.
6. Increased system accuracy in measuring range and velocity.
7. Reducing clutter effects by improving the signal-to-noise ratio.
8. Increased immunity to certain types of interfering signals that do not have the same properties as the coded pulse compression waveform.

2.1.2 Pulse Compression Modulation Techniques

Pulse compression can be accomplished by utilizing Frequency or Phase modulation to broaden the signal bandwidth such as in Figure 2.2. Amplitude modulation is also probable but is seldom used. The transmitted pulse width (T) is chosen to achieve the single-pulse transmit energy (E_t) which is required for target detection or tracking [13].

$$E_t = P_t\, T \tag{2.1}$$

where P_t is the transmitted power.

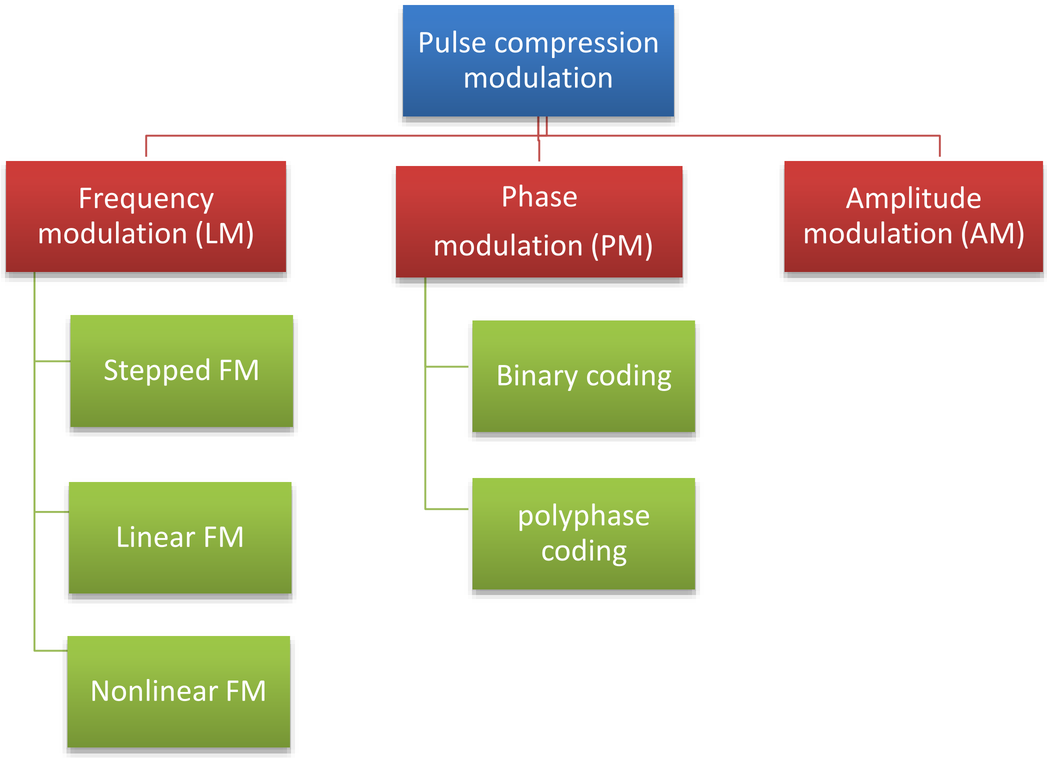

Figure 2.2: Pulse compression modulation

2.1.3 Pulse Compression Effects

The major drawback to the pulse compression is the appearance of range sidelobes around the main signal peak which leads to smearing of the return signals in range and introduces range ambiguities [14]. The existence of a small target may not be inferred from the matched filter output when there are a small target and a large target whose power is 10 dB larger than the small one. Although the small target is noticeable when it is the only present target in the environment, in the existence of the large target the small target is masked by the range sidelobes of the large target Figure 2.3 shows Matched filter output.

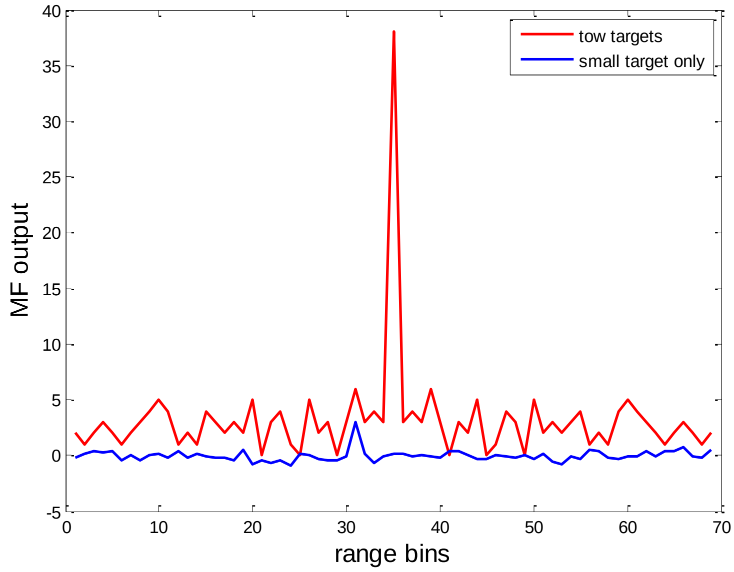

Figure 2.3: Matched filter output of received radar signal

It is possible that large sidelobes can result in detecting spurious targets that are sidelobes can be mistaken as real targets. Since high sidelobes of the bigger targets can mask nearby smaller targets, suppression of range sidelobes is critical, especially in applications with multiple target systems. This effect is tried to be minimized by using carefully chosen pairs of codes or by amplitude weighting the long pulse over its duration. In general, it is not very easy to design codes with very low sidelobes. Moreover, it may not be efficient to use amplitude weighting in respect of power efficiency.

2.2 Correlation

Correlation can be defined as similar operation of the convolution. It involves sliding one function past the other and finding the area under the resulting product [15]. Unlike convolution, however, no folding is performed. The correlation $r_{xx}(t)$ of two identical functions $x(t)$ or The convolution $x(t)\star x(-t)$ is called autocorrelation. For two different functions $x(t)$ and $y(t)$, the correlation $r_{xy}(t)$ or $r_{yx}(t)$ is referred to as cross-correlation.

Using the symbol $\star\star$ to denote correlation, we define the two operations as

$$r_{xx}(t) = x(t) \star\star \mathrm{x(t)} = \int_{-\infty}^{\infty} x(\lambda)x(\lambda - t)\, d\lambda \qquad (2.2)$$

$$r_{xy}(t) = x(t) \star\star \mathrm{y(t)} = \int_{-\infty}^{\infty} x(\lambda)y(\lambda - t)\, d\lambda \qquad (2.3)$$

$$r_{yx}(t) = x(t) \star\star \mathrm{x(t)} = \int_{-\infty}^{\infty} y(\lambda)x(\lambda - t)\, d\lambda \qquad (2.4)$$

The variable t is often referred to as the lag. The definitions of cross- correlation are not standard, and some authors prefer to switch the definitions of $r_{xy}(t)$ and $r_{yx}(t)$.

2.2.1 Properties of Correlation

Correlations of sequences Correlation is a measure of similarity between different functions and, operation used in many applications in digital signal processing. It is a measure of the degree to which two sequences are similar [16]. Given two real-valued sequences $x(n)$ and $y(n)$ of finite energy, the cross-correlation of $x(n)$ and $y(n)$ is a sequence $r_{xy}(l)$ defined as

$$r_{x,y}(l) = \sum_{n=-\infty}^{\infty} x(n)y(n - l)$$

The index $l$is called the shift or lag parameter. The special case of (2.3).

- **Correlation as Convolution**

The absence of folding actually implies that the correlation of $x(t)$ and $y(t)$ is equivalent to the convolution of $x(t)$ with the folded version $y(-t)$, and we have $r_{xy}(t) = x(t) \star\star \mathrm{y(t)} = x(t) \star \mathrm{y(-t)}$.

- **Area and Duration**

Since folding does not affect the area or duration, the area and duration properties for convolution also apply to correlation. The starting and ending time for the cross-correlation $r_{xy}(t)$ may be found by using the starting and ending times of $x(t)$ and the folded signal $y(t)$.

- **Commutation**

The absence of folding means that the correlation depends on which function is shifted and, in general, $x(t) \star\star \mathrm{y(t)} \neq y(t) \star \mathrm{x(t)}$. Since shifting one function to the right is actually equivalent to shifting the other function to the left by an equal amount, the correlation $r_{xy}(t)$ is related to $r_{yx}(t)$ by $r_{xy}(t) = r_{yx}(-t)$. correlation is the convolution of one signal with a folded version of the other

$$\begin{aligned} r_{xh}(t) &= x(t) \star\star h(t) = x(t) \star h(-t) \\ r_{hx}(t) &= h(t) \star\star x(t) = h(t) \star x(-t) \end{aligned} \tag{2.5}$$

Periodic Correlation

The correlation of two periodic signals or power signals is defined in the same sense as periodic convolution:

$$r_{xy}(t) = \frac{1}{T}\int_T x(\lambda)y(\lambda - t)d\lambda \quad r_{xy}(t) = \lim_{T_0\to\infty}\frac{1}{T_0}\int_{T_0} x(\lambda)y(\lambda - t)d\lambda \tag{2.6}$$

The first form defines the correlation of periodic signals with identical periods *T*, which is also periodic with the same period *T*. The second form is reserved for no periodic power signals or random signals.

2.2.2 Autocorrelation

The autocorrelation operation involves identical functions. It can thus be performed in any order and represents a commutative operation. Autocorrelation may be viewed as a measure of similarity, or coherence, between a function $x(t)$ and its shifted version. Clearly, under no shift, the two functions "match" and result in a maximum for the autocorrelation. But with increasing shift, it would be natural to expect the similarity and hence the correlation between $x(t)$ and its shifted version to decrease. As the shift approaches infinity, all traces of similarity vanish, and the autocorrelation decays to zero.

- **Symmetry**

Since $r_{xy}(t) = r_{yx}(-t)$ we have $r_{xx}(t) = r_{xx}(-t)$. This means that the autocorrelation of a real function is even. The autocorrelation of an even function $x(t)$ also equals the convolution of $x(t)$ with itself, because the folding operation leaves an even function unchanged.

- **Maximum Value**

It turns out that autocorrelation function is symmetric about the origin where it attains its maximum value. It thus satisfies

$$r_{xx}(t) \leq r_{xx}(0) \quad (2.7)$$

It follows that the autocorrelation $r_{xx}(t)$ is finite and nonnegative for all *t*.

- **Periodic Autocorrelation**

For periodic signals, we define periodic autocorrelation in much the same way as periodic convolution. If we shift a periodic signal with period T past itself, the two line up after every period, and the periodic autocorrelation also has period T.

2.2.3 Matched Filters

Correlation forms the basis for many methods of signal detection and delay estimation (usually in the presence of noise). An example is target ranging by radar, illustrated in Figure 2.4, where the objective is to estimate the target distance (or range) R.

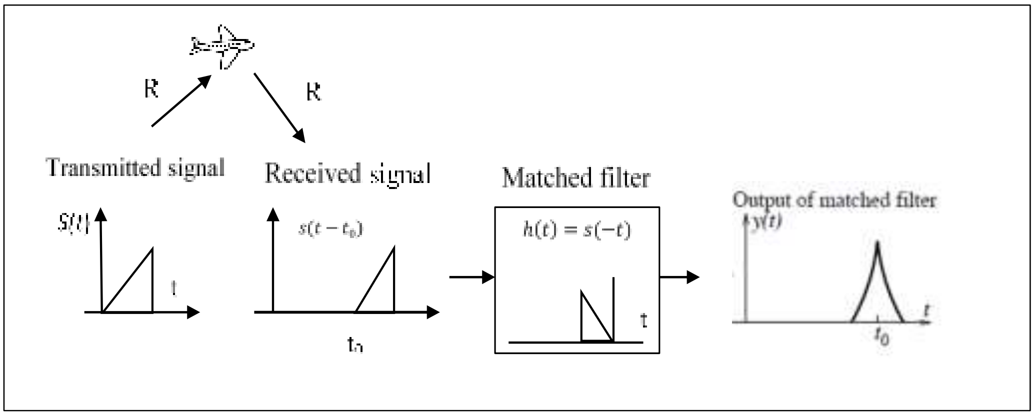

Figure 2.4: Illustrating the concept of matched filtering

A transmitter sends out an interrogating signal $s(t)$, and the reflected and delayed signal (the echo) $s(t - t_0)$ is processed by a correlation receiver, or matched filter, whose impulse response is matched to the signal to obtain the target range. In fact, its impulse response is chosen as $h(t) = s(-t)$, a folded version of the transmitted signal, in order to maximize the signal-to-noise ratio. The response $y(t)$ of the matched filter is the convolution of the received echo and the folded signal $h(t) = s(-t)$ or the correlation of $s(t-t_0)$ (the echo) and $s(t)$ (the signal). This response attains a maximum at $t = t_0$, which represents the time taken to cover the round-trip distance $2R$. The target range R is then given by

$$R = \frac{ct_0}{2} \tag{2.8}$$

where c is the velocity of signal propagation.

The received signal cannot be used directly to estimate the delay. This is due to the fact that we may not be able to detect the presence (let alone the exact onset) of the received signal because it is usually much weaker than the transmitted signal and contaminated by additive noise. However, if the noise is uncorrelated with the original signal (as it usually is), their cross-correlation is very small (ideally zero), and the cross-correlation of the original signal with the noisy echo yields a peak (at $t = t_0$) that stands out and is much easier to detect. Ideally, of course, we would like to transmit narrow pulses (approximating impulses) whose autocorrelation attains a sharp peak [15].

2.3 Neural Network

The neural network is defined by [17] as a massively parallel distributed processor made up of simple processing units, which has a natural propensity for storing experiential knowledge and making it available for use. The system emulates the brain in two ways as described below.

i. Knowledge is acquired by the network from its environment through a learning process.
ii. Interneuron connection strengths, known as synaptic weights, are used to store the acquired knowledge.

2.3.1 Biological Neuron Model

The human brain consists of more than billions of neural cells that process information. Each cell works like a simple processor. The massive interaction between all cells and their parallel processing only makes the brain's abilities possible.

The Biological Neuron as shown in Figure 2.5 consists of the following:

Dendrites: are branching fibers that extend from the cell body or soma. Soma or cell body of a neuron contains the nucleus and other structures, support chemical processing and production of neurotransmitters.

Axon: It is a singular fiber carries information away from the soma to the synaptic sites of other neurons (dendrites and somas), muscles, or glands. Axon hillock is the site of summation information. At any for incoming moment, the collective influence of all neurons that conduct impulses to a given neuron will determine whether or not an action potential will be initiated at the axon hillock and propagated along the axon.

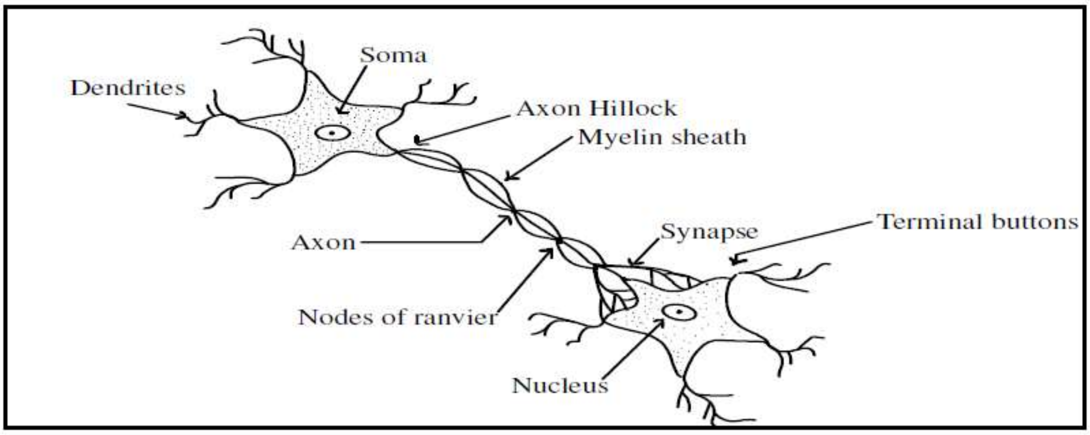

Figure 2.5**:** Structure of Biological Neuron [18]

Myelin Sheath: consists of fat-containing cells that insulate the axon from the electrical activity. This insulation acts to increase the rate of transmission of signals. A gap exists between each myelin sheath cell along the axon. Since fat inhibits the propagation of electricity, the signals jump from one gap to the next.

Nodes of Ranvier: are the gaps (about 1μm) between myelin sheath cells long axons are since fat serves as a good insulator, the myelin sheaths speed the rate of transmission of an electrical impulse along the axon.

Synapse: is the point of connection between two neurons or a neuron and a muscle or a gland. Electrochemical communication between neurons takes place at these junctions. Terminal Buttons: of a neuron are the small knobs at the end of an axon that release chemicals called neurotransmitters [18].

2.3.2 Artificial Neural Network

An Artificial Neural Network (ANN) is an information-processing paradigm that is inspired, by the way, the biological nervous system such as brain process information [19, 20]. The first artificial neuron was developed in 1943 by the neurophysiologist Warren McCulloch and the logician Walter Pits. But the technology available at that time did not allow them to proceed further. In past few decades, the ANN has emerged as a powerful learning tool to perform complex tasks in the highly nonlinear dynamic environment. The ANN is capable of performing nonlinear mapping between the input and output space due to its large parallel interconnection between different layers and the nonlinear processing characteristic. Therefore, the ANN is used extensively in the field of communication, some control systems, instrumentation and forecasting [21, 22]. ANN technique is also used for classification, modeling and optimization problems [23].

An artificial neuron basically consists of a computing element that performs the weighted sum of the input signal and the connecting weight. The sum is added with the bias or threshold and the resultant signal is then passed through an activation function of the sigmoid or hyperbolic tangent type. Each neuron is associated with three parameters whose learning can be adjusted. These are the connecting weights, the bias and the slope of the nonlinear function. For the structural point of view, a neural network (NN) may be a single layer or it may be multilayer. In Multi-layer Perceptron MLP, there is a number of layers and each layer contains one or many artificial neurons. Each neuron of the one layer is connected to each and every neuron of the next layer. A trained neural network can be thought of as an “expert” in the category of information it has been given to analyze. The advantages of ANN are:

a) Adaptive learning: It is the ability of the network to learn how to do tasks based on the data given for training or initial experience.

b) Self-organization: An ANN can create its own organization or representation of the information as it receives during learning time.

c) Real-time operation: The ANN computations may be carried out in parallel, and special hardware devices are being designed and manufactured which take advantage of this capability.

d) Fault tolerance via redundant information coding: Partial destruction of a network leads to the corresponding degradation in performance. However, some network capabilities may be retained even with major network damage.

The structure of ANN is described as follow:

I. Single Neuron Structure

A neuron is an information processing unit for the operation of a neural network. The operation in a single neuron involves the computation of the weighted sum of inputs and threshold [23]. The resultant signal is then passed through activation function. The activation functions can be defined as a limiting the amplitude of the output of the neuron and it is also called a squashing function in that it squashes (limits) the permissible amplitude range of the output signal to the some finite value. The neuronal model also includes an externally applied bias, expressed by bi, the bias bi has the effect of increasing or lowering the net input of the activation function, depending on whether it is positive or negative, respectively. The basic structure of a single neuron is shown in Figure 2.6.

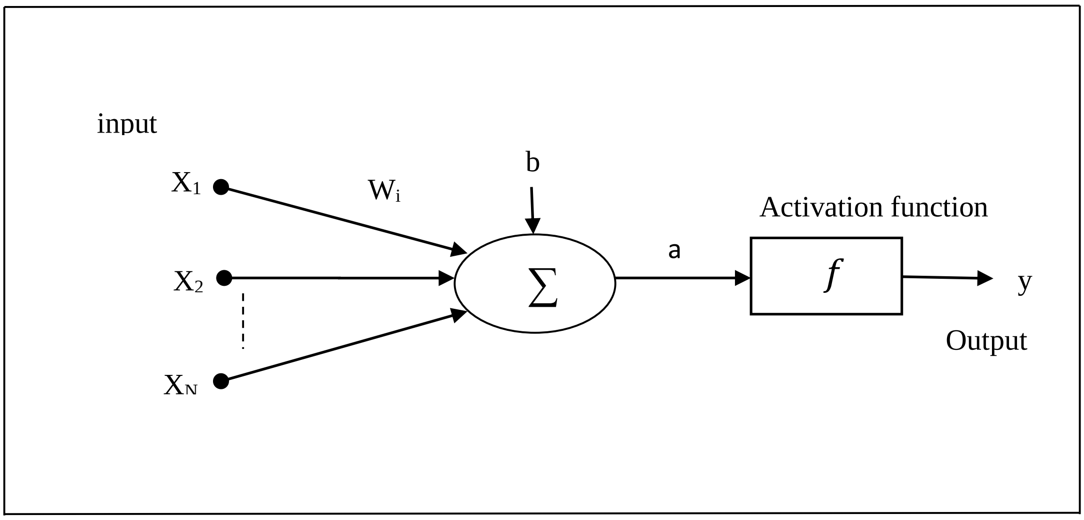

Figure 2.6: Single neuron structure

In mathematical terms, we may describe a neuron K by writing the following pair of equations:

$$a_k = \sum_{j=1}^{N} W_{kj} X_j \qquad (2.10)$$

The output associated with the neuron is computed as

$$\mathrm{Y} = f\left[\sum_{i=1}^{N} \quad a_i + \mathrm{b}\right] \qquad (2.11)$$

Where x_i, i = 1, 2...N, are inputs to the neuron; w_i is the synaptic weights of the i^{th} input; b is the bias; f is the activation function for each neuron; and y is the output signal of the neuron. The use of bias (b) has the effect of applying an affine transformation to the output (a). The most common types of activation function are discussed below [23].

- Log-sigmoid function

This transfer function takes the input and squashes the output into the range of 0 to 1, according to expression given below:

$$f(x) = \frac{1}{1+e^{-x}} \qquad (2.12)$$

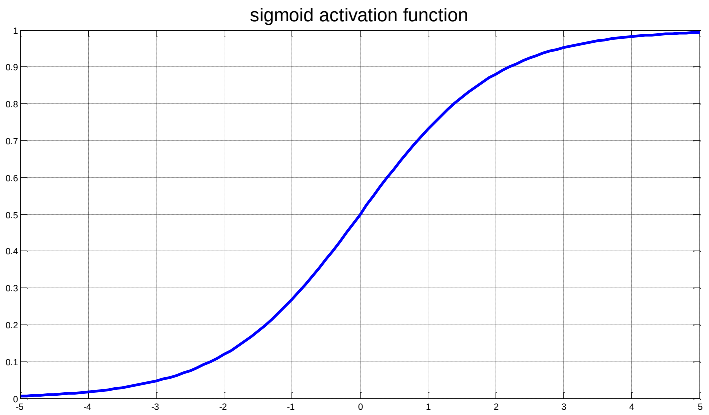

Figure 2.7: The sigmoid activation function

- Hyperbolic tangent Sigmoid:

This function is expressed in equation 2.13

$$f(x) = \tanh(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}} \qquad (2.13)$$

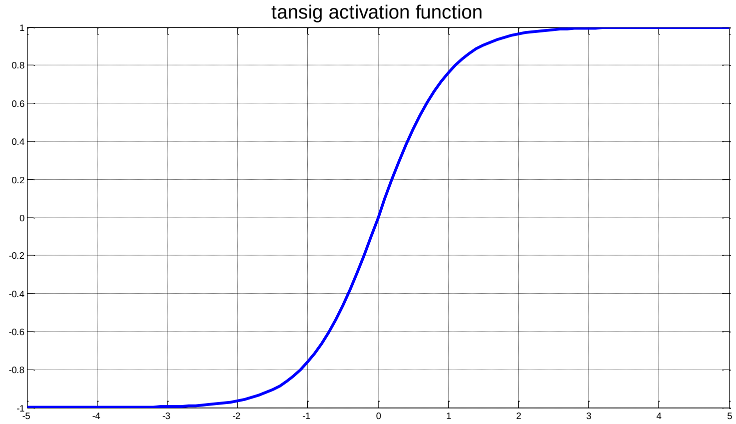

Figure 2.8: Tansig activation function

- Signum Function:

The expression for this activation function is given by

$$f(x) = \begin{cases} 1 & \text{if} \quad x > 1 \\ 0 & \text{if} \quad x = 0 \\ -1 & \text{if} \quad x < 0 \end{cases} \qquad (2.14)$$

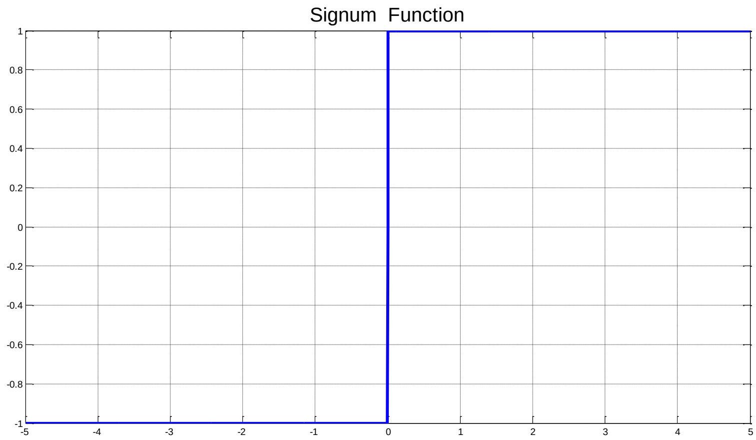

Figure 2.9: Signum activation Function

- Threshold function

This function is given by the expression

$$f(x) = \begin{cases} 1 & \text{if} \quad x \geq 1 \\ 0 & \text{if} \quad x < 0 \end{cases} \tag{2.15}$$

- Piecewise linear function

This function is represented as

$$f(x) = \begin{cases} 1 & \text{if} \quad x > 0.5 \\ x & \text{if} \quad -0.5 \leq x \leq 0.5 \\ -1 & \text{if} \quad x < 0.5 \end{cases} \tag{2.16}$$

II. ANN learning

Learning rules mean the procedure by which modifying the weights and biases of ANN, this procedure may also be referred to as training algorithm, the purpose of learning rule is to train the network to perform some special tasks. There are many types of NNs learning rules; they fall into three basic categories: supervised learning, unsupervised learning, and reinforcement learning [24].

In supervised learning, the learning rules are provided with a set of examples (training set) of proper network behavior. Supervised learning rewards accurate classifications or associations and punishes those which yield inaccurate responses. The teacher estimates the negative error gradient direction and reduces the error accordingly [24].

In unsupervised learning, the weights and biases are modified in response to the network inputs only. There is no target output available. At first glance, this might seem to be impractical. This learning is based on clustering of input data. No, a priori knowledge is assumed to be available regarding an input's membership in a particular class [25]. There are several issues involved in designing and training a multilayer neural network [26], which are:

(a) The Selecting appropriate number of hidden layers in the network.

(b) Selecting the number of neurons to be used in each hidden layer.

(c) Finding a globally optimal solution, that avoids local minima.

(d) Converging to an optimal solution in a reasonable period of time.

(e) Validating the neural network to test for over-fitting.

Depending on the architecture in which the individual neurons are connected and the choice of the error minimization procedure, there can be several possible ANN configurations.

2.4 Wavelet Analysis

Wavelet analysis is a mathematical tool used in various areas of research. Recently, wavelets have been used especially to analyze time series, data, and images. Time series are represented by local information such as frequency, duration, intensity, and time position, and by global information such as the mean states over different time periods [27]. Both global and local information is needed for the correct analysis of a signal. The Wavelet Transform (WT) is a generalization of the Fourier Transform (FT) and the Windowed Fourier Transform (WFT).

A wavelet ψ is a waveform of effectively limited duration that has an average value of zero. The Wavelet Analysis (WA) procedure adopts a particular wavelet function called a mother wavelet. A wavelet family is a set of orthogonal basis functions generated by dilation and translation of a compactly supported scaling function φ (or father wavelet), and a wavelet function ψ (or mother wavelet). The father wavelets φ and mother wavelets ψ satisfy

$$\int \varphi(t)\, dt = 1$$

$$\int \psi(t) dt = 0$$

The wavelet family consists of wavelet children which are dilated and translated forms of a mother wavelet:

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a_j}}\,\psi\left(\frac{t-b}{a}\right) \tag{2.17}$$

where a is the scale or dilation parameter and b is the shift or translation parameter. The value of the scale parameter determines the level of stretch or compression of the wavelet. The term $1/\sqrt{a}$ normalizes$\|\psi_{a,b}(t)\| = 1$.

In general, wavelets can be separated in orthogonal and nonorthogonal wavelets. The term wavelet function is used generically to refer to either orthogonal or nonorthogonal wavelets. An orthogonal set of wavelets is called a wavelet basis, and a set of nonorthogonal wavelets is termed a wavelet frame. The use of an orthogonal basis implies the use of the Discrete Wavelet Transform (DWT), whereas frames can be used with either the discrete or the continuous transform.

Over the years a substantial number of wavelet functions have been proposed in the literature. The Gaussian, the Morlet, and the Mexican hat wavelets are crude wavelets that can be used only in continuous decomposition. The wavelets in the Meyer wavelet family are infinitely regular wavelets that can be used in both Continues Wavelet Transform (CWT) and DWT. The equations that represent the Gaussian, Morlet, Shannon, Meyer and Mexican hat wavelet families are presented In the next sections [27].

2.5 Wavelet Neural Network

Wavelet networks are a new class of networks that combine the classic sigmoid neural networks and wavelet analysis. Wavelet networks were proposed by Zhang and Benveniste [28] as an alternative to feedforward neural networks which would alleviate the weaknesses associated with wavelet analysis and neural networks while preserving the advantages of each method.

Recently, wavelet networks have gained a lot of attention and have been used with great success in a wide range of applications, ranging from engineering; control; financial modeling; short-term load forecasting; time-series prediction; signal classification and compression; signal denoising; static, dynamic, and nonlinear modeling; to nonlinear static function approximation [27].

Wavelet networks are hidden layer networks that use a wavelet for activation instead of the classic sigmoidal family. It is important to mention here that multidimensional wavelets preserve the "universal approximation" property that characterizes neural networks. The nodes (or wavelons) of wavelet networks are wavelet coefficients of the function expansion that have a significant value. Bernard, Mallat [29], various reasons were presented for why wavelets should be used instead of other transfer functions as illustrated in points below:

1. wavelets have high compression abilities.
2. computing the value at a single point or updating a function estimate from a new local measure involves only a small subset of coefficients.

2.5.1 Single Wavelet Neuron Structure

The structure of the single wavelet neuron is the same as the neural network structure. neural network is one with a single input and a single output. The hidden layer of neurons consist of hidden layer (wavelons), whose input parameters (possibly fixed) include the wavelet dilation and translation coefficients. These wavelons produce a non-zero output when the input lies within a small area of the input domain. The output of a wavelet neural network is a linear weighted combination of the wavelet activation functions. Figure 2.10 shows the single Wavelet Neuron Structure.

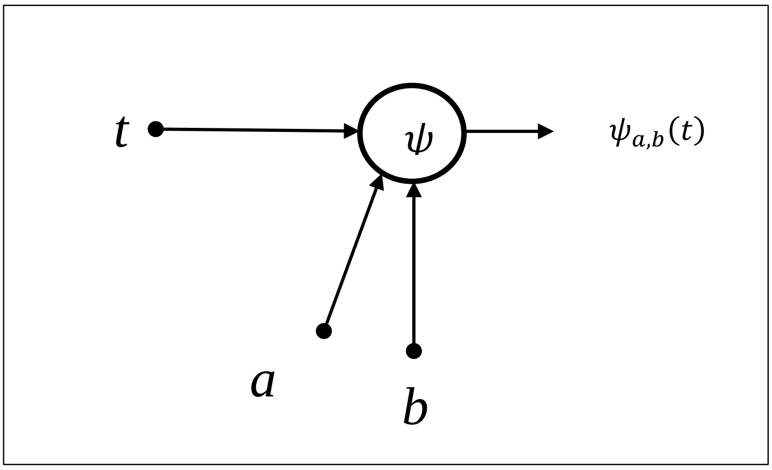

Figure 2.10: Single Wavelet Neuron Structure

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