WAVELET AND NEURAL NETWORK BASED GROUND TARGET CLASSIFICATION IN FORWARD SCATTERING RADAR

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WAVELET AND NEURAL NETWORK BASED GROUND TARGET CLASSIFICATION IN FORWARD SCATTERING RADAR

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WAVELET AND NEURAL NETWORK BASED GROUND TARGET CLASSIFICATION IN FORWARD SCATTERING RADAR

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DECLARATION

I declare that this thesis satisfies to all requirements as a thesis for the degree of Master of Science in computer science. This thesis entitled “Wavelet and neural network based ground target classification in forward scattering radar”. The thesis has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.
DEDICATION

I dedicate this work to:

Allah Almighty my creator, my strong pillar, my source of inspiration, wisdom, knowledge and understanding. The source of my strength throughout this program...

The soul of my father great (ASHRI), and the best women ever, my mother...

My dearest wife, who leads me through the valley of darkness with light of hope and support…

My beloved brother and sisters…

My little souls: Mohammed and Yousef, whom I can't force myself to stop loving...

My friends, the symbol of love and giving, who encourage and support me…

All the people in my life who touch my heart…

Ahmed Ashri
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Sincere thanks to Dr. Yassir my supervisor. His sage advice, insightful criticism and patient encouragement aided me across the research different stages in innumerable ways. I would like also to thank my colleagues Kanona, Khalafallah, Mutaz, Yassin, Abdelmalik and all others who will be forever memorized and I will be owing them a great debt. Special thanks to someone who arrives late but I will never forget the support that I found from.
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ABSTRACT

This thesis reveals the significance of de-noising techniques utilization as a pre-processing step with Neural Network (NN) in radar applications for target classification. Forward Scatter Radar (FSR) is a special type of bistatic radar under which many recent works show that FSR can be effectively used for classification using NN. The existing researches also studied the target classification under different noise levels ignoring any type of pre-processing techniques to decrease the existing noise, so there is a crucial requirement to have more detailed and precise analysis and results on target classification in FSR for ground targets by using and utilizing wavelet de-noising mechanism as a pre-processing step before implementing and using neural network as an appropriate method for detected target classification. To justify and proof this, results from FSR experiments were used to determine what and which tools that should be utilized among available ones. The target used for this experiment is a ground vehicle which is represented by typical public road transport. However, the aims of this research are to study and analyze target classification of ground targets in FSR using Wavelet de-noising algorithm before passing the de-noised signal to the neural network (NN), has been implemented and tested under different noise level to investigate and analyze noise effects in target classification. Several experiments are made to determine the best mother wavelet technique among four different techniques which are: Haar, Daubechies (db), Symlets (sym) and Meyer (dmey). Finally, we came out with that the results of those experiments is to adopt SYM as preferred mother wavelet technique for de-noising the signals. In addition to the previous outcome, the conducted experiments and analysis proved that using wavelet as a preprocessing step before classifying FSR signals under noisy environment, improve the percentage of classification accuracy of the captured target signal by 23%.
الاستخدام الموجي والشبكات العصبية في تصنيف الأهداف الأرضية للرادار المبعت للإمام

أحمد محمد عثمان أحمد

المستخلص

هذه الأطروحة تكشف أهمية استخدام تقنيات تقليل تشويش الإشارة كخطوة معالجة مسبقة مع الشبكة العصبية (NN) في تطبيقات الرادار لتصنيف الهدف. الرادار المبعت إلى الأمام (FSR) هو نوع خاص من الرادار ثنائي المسار حيث تظهر العديد من الأعمال الحديثة أنه يمكن استخدام FSR بشكل فعال للتصنيف باستخدام الشبكة العصبية. كما درست الأبحاث الحالية التصنيف المستهدف تحت مستويات تشويش مختلفة متجاهلة أي نوع من تقنيات المعالجة المسبقة لالتقسيم الضوضاء الموجودة. لذلك هناك حاجة ماسة لإجراء تحليل ونتائج أكثر تفصيلاً ودقة على التصنيف المستهدف في الأهداف الأرضية بواسطة FSR كخطوة معالجة مسبقة قبل تنفيذ واستخدام الشبكة العصبية كأسلوب مناسب لتصنيف الهدف المكتشف. لثبت ذلك تم استخدام نتائج تجارب FSR لتحديد ما هي الأدوات التي يجب استخدامها بين الأدوات المتاحة والهدف المستخدم في هذه الأطروحة هو مرتبة أرضية ممثلة بالنقل البري العام النموذجي. لذلك فإن أهداف هذا البحث هي دراسة وتحليل التصنيف المستهدف للأهداف الأرضية في FSR باستخدام خوارزمية إلغاء التشويش Wavelet قبل تميز البطر الابتسام الإشارة مع استخدام آلية وافرية ضوئية (NN) تتكون من الرادار المبعت إلى الأمام (FSR) التي تحتوي على التصنيف إلى الشبكة العصبية، تم تنفيذ ذلك واختبار تحت مستويات تشويش مختلفة دراسة وتحليل تأثيراتها المختلفة في تصنيف الهدف. تم إجراء عدة تجارب لتحديد أفضل تقنية بين الأربعة تقنيات المختلفة وهي و أخرى يمكن أن يخرج بأن نتائج تلك التجارب هي Symlets (sym) و Meyer (dme) وDaubechies (db) و Haar كدليل على استخدام تقليل التشويش والضوضاء بالإشارة، بالإضافة إلى النتيجة السابقة أثبتت التجارب والتحليلات التي أجريت أن استخدام الموجات كخطوة مسبقة قبل تصنيف إشارات FSR في بيئة متشوشتة تحسن بصورة كبيرة في دقة تصنيف إشارات الأهداف التي تم التقاطها بنسبة 23%.
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CHAPTER ONE
INTRODUCTION

1.1. BACKGROUND OF THE STUDY

RADAR is an acronym for Radio Detection and Ranging. The radar systems and radar stations are intended for detecting various objects in space and establishing their current position, as well as determining velocities and trajectories for moving objects (Nezlin et al., 2007). From the basic point of view, this is achieved by transmitting an electromagnetic (EM) wave from the transmitting antenna. If the target is present within the radar coverage area, the wave will be reflected back to the receiving antenna, and all the information collected at the receiver will then be analyzed to determine the above parameters (Abdullah, 2007). There are different types of radar systems, based on the transmitter-receiver topology shown in Figure 1.1 in the monostatic radar, the transmitter and the receiver are spatially combined. On the other hand, the multistatic radar designates single radar with one transmitter and several spatially distributed receiving stations with joint processing of received information. Multisite radar is radar which has several specially separated transmitting-receiving facilities in such a way information gathered from each target (from all sensors) can be fused and jointly processed. Bistatic radar consists of a single transmitter and single receiver which are separated specially by a distance, which is comparable to that of the maximum range of target (Nezlin et al., 2007).

Forward scattering radar (FSR) is a special case of bistatic radar (Abdullah, 2007), where it is designed to detect and track targets moving in the narrow region along the base line. The FSR offers a number of peculiarities which make the radar interesting. The most attractive features include:

The essential increase in the power budget, in the directions close to the base line, results in a significant increase in the target radar cross section, and it is stated that the RCS, at the forward scattering, is bigger than in the monostatic case by 30-40 dB, which further improves the radar system sensitivity depending on the frequency band (Chesnokov and Krutikov, 1996).

The FSR has an ability to reduce the ambiguities caused by the target fluctuations (Nezlin et al., 2007), as compared to the monostatic radar. The forward scattering RCS mainly depends on the target physical cross section and the wavelength. It is also independent on the shape of the target surface, and any radar absorbing material (RAM) coating which reduces the RCS of the target in
the traditional radar. This feature makes the FSR robust to stealth technology (Hiatt et al., 1960, Abdullah, 2007). On the other hand, the FSR presents a conservative class of systems which have a number of fundamental limitations, which include the following:

- The absence of the range resolution and operation within the narrow angles; this therefore requires the target to be very close to the transmitter-receiver baseline.
- The radar loses its ability to measure the range when the target crosses the base line.

In this work Wavelet will be used as pre-step to separate noise and try to get clean signal as much as possible before pass to Neural Network to ensure the accuracy of the classification of the ground targets.

1.2. PROBLEM STATEMENT

Despite the researches have been done on target detection, coordinate estimation and automatic classification, most studies of FSR have only been carried out in a small or specific number of scenarios specially dealing with different levels of noise and interference masking the received signal. The existing researches also did not study utilizing a pre-processing technique(s) for de-noising the captured signal, so there is a crucial requirement to have more results on target classification in FSR for ground targets.

1.3. RESEARCH OBJECTIVE

The aims of research is to enhance target recognition and classification of ground targets in FSR under noisy environments by utilizing integrating two signal processing techniques, Wavelet as a pre-processing step for de-noising signals and Neural network for ground target classification. Moreover the research will determine the best mother wavelet technique and number of breaking down levels to be implemented according to signal nature and Signal to noise ratio.

1.4. RESEARCH SCOPE

This research will implement two signal processing techniques together, wavelet and neural network to classify the ground targets using noisy signals obtained by a forward scattering radar. The below Figure 1.2 describe the research scope graphically.
Figure 1.1 Research Scope
1.5. METHODOLOGY

Signals from transmitter to receiver will be exposed to different degrees of Noise, on the receiver side the signals will be applied to a de-noising technique using wavelet and then apply to NN fitting tool to increase the accuracy level of the ground target classification to prove that using a wavelet de-noising technique leads to better results comparing with previous researches in the same area. The below Figure 1.3 shows the methodology.

*Available noise-data sample of Vehicles signals

Figure 1.2 Methodology flowchart
1.6. ORGANIZATION OF THE RESEARCH

This study organized into five parts. In chapter two, literature review and related works are explained and listed. Chapter three describes the methodology adopted and theoretical approach of the FSR in the ground target classification, by taking combi vehicle as a sample for its ground target. Similarly, neural network approach to analysis the vehicle signature after adding the noise and all parameter that used in this approach. Chapter four shows the results and discussion of the outcomes, and this is followed by the conclusions and recommendations for future work in Chapter five.
CHAPTER TWO
LITERATURE REVIEW & RELATED WORKS

2.1. INTRODUCTION

In this chapter a brief introduction to Forward Scattering Radar (FSR), that does not cover all aspects of the research. It concentrates only in certain parts which need to be very clear before reading next chapters.

2.2. RADAR TECHNOLOGY

The term RADAR is an acronym for Radio Detection and Ranging (Stimson, 1998). Radar is a system that uses electromagnetic waves to detect and locate a target of interest. Radar can identify the Range, altitude, speed and direction of targets such as aircrafts, ships, vehicles, personnel, and Terrain and weather formations. When the radar transmitter transmits an electromagnetic Wave, and the target (for example an aircraft) is present within the radar coverage area, the Wave will be scattered back to the receiving antenna and the target can be detected. The Information about the target can then be determined.

Radar configurations can be classified as monostatic, bistatic and multistatic. In monostatic radar the transmitter (TX) and receiver (RX) are collocated and often use the same antenna for transmitting and receiving a signal as shown in Figure 2.1(a). In contrast, the bistatic radar transmitter and receiver are separated by a distance comparable to the maximum range of a target. The angle between the transmitted TR and reflected RR rays is a bistatic angle, b (Figure 2.1(b)).

Monostatic and bistatic radars usually have narrow-beam TX and RX antennas to obtain a longer target detection range and better angle resolution. In a conventional bistatic radar configuration, when the bistatic angle significantly differs from 180°, the transmitted signal is not received by the RX antenna due to narrow-beam antenna patterns (Figure 2.1(b)). Radar only receives the signal scattered (reflected) by a target. Bistatic radar has been on the radar scene for decades. More than 200 types of bistatic radar have become operational since the late 1930s (Willis, 1995).
2.3. PRINCIPLES OF THE FORWARD SCATTERING RADAR (FSR)

In the bistatic radar, as in Figure 2.2 the angle which the target makes to the transmitter and receiver is one of the main factors which affects the electromagnetic (EM) field strength and the pattern at the receiver; this angle is called bistatic angle, $\beta$. When the bistatic angle is equal or near to 180° ($\beta \approx 180^\circ$), the radar system is referred to as the FSR system (Abdullah, 2007), as shown in Figure 2.1. At the forward scattering (and as it is known from the theory of electromagnetic), the presence of a target will partly block the front, known as the target shadow. This shadow is actually an EM field, being scattered by the target. This is according to the EM field theory as depicted in Figure 2.2, which is (Chernyak, 1998).

This field is a result of the primary field disturbances. The scattered field can be represented as the shadow lobe, and this lobe pattern follows the antenna pattern of a uniformly illuminated flat
antenna, in the shape of the shadow with negative illumination (180°) relative to the primary field (Abdullah, 2007).

Designating an electric component as the shadow field as Esh, the full scattered field is then determined by the sum:

\[ E_{\text{sum}} = E_s + E_{sh} \]

Where \( E_s \), the self-scattering field, the shadow field is concentrated in the narrow solid angle near 180°, and this is known as the forward scattering field. In this region, the self-scattering field is much weaker than the shadow field, and due to this fact, analyzing the scattering fields in FS region allows the effect of the current on the surface of the target to be neglected.

The shadow field polarization is similar to that of the incident wave. Although the pattern of the shadow is dependent on the silhouette of the target, it does not depend on the surface shape of the target. This characteristic indicates the reliance of the forward scatter RCS to the so-called radar absorbing material (RAM) coating, which reduces the scattered field, generated by the surface currents on the target (Nezlin et al., 2007).

Another important characteristic of the forward scattering is that the complex targets in the FSR system have reflections which are similar to those of the point targets. Furthermore, the signals in the FSR do not experience fluctuation due to the natural swinging of the target and because of the absence of the range resolution (Abdullah, 2007).

### 2.4. BRIEF HISTORY OF THE FORWARD SCATTERING RADAR

Historically the first radars were not monostatic; they became bistatic only after the invention of the pulse method in the radar, and when the antenna switches were developed, monostatic radar has become more convenient to use. Before and during the World War II, the forward scatter fence was used for aircraft detection (Cherniakov et al., 2005c). These were bistatic radars, but their geometry was similar to the forward scatter configuration, where the targets flew near the transmitter-receiver baseline. These radars used continuous wave (CW) transmitters, but due to some drawbacks such as the narrow coverage area (since the radar lost the target once it flew out of the fence), it was found that these radars provided very limited utility for the air defense. Only when the adjacent fences were deployed, an approximate position and velocity could be estimated. This problem further caused the system to be more complex.
Consequently, most of the early forward scatter fences were eventually replaced by the monostatic radars, which possess a much better spatial coverage area and location accuracy (Willis, 1995, Abdullah, 2007).

In the mid of the 20th century, the United States attempted to deploy the bistatic radar several times. The United States successfully built and deployed three forward scatter over the horizon (OTH) fences for detecting ballistic missiles launched from the Soviet Union. Ironically, the advantage of the forward scatter, i.e. the steep enhancement of the RCS, had not been really known at that time. As the advantages of the FSR system became clear, along with the advances which enabled the implementation of long-range systems, numerous efforts had been done and concentrated in this area during the past decade. Nowadays, the microwave fences are widely used in the security application to protect a large territory (H.M et al., 2014, Honey, 2000).

2.5. THE WAVELET TRANSFORM

Jean Morlet, a French geophysical engineer, discovered the idea of the wavelet transform in 1982, providing a new mathematical tool for the seismic wave analysis. Morlet first introduced the idea of wavelets, as a family of functions constructed, from the translations and dilatations of a single function which is known as the “mother wavelet”. A lot of researchers (Grossmann, Meyer, Mallat, Daubechies, etc.) further developed and enhanced this new signal-processing tool. The wavelet analysis represents the next logical step, after the Fourier and short-time Fourier transformation, as a windowing technique with variable-sized regions. The wavelet analysis allows the use of long-time intervals, which require a more precise low-frequency information, and shorter regions where high-frequency information is needed. One major advantage afforded by the wavelets is the ability to perform the local analysis, that is, to analyze a localized area of a larger signal. Therefore, the wavelet analysis is capable of revealing the aspects of data which other signal analysis techniques have missed, such as in the aspects of trends, breakdown points, discontinuities in higher derivatives, and self-similarity. Furthermore, as it can afford a different view of data than those presented by the traditional techniques, the wavelet analysis can often compress or de-noise a signal without any appreciable degradation (Zemmour, 2006).

The expression in Equation (2.5) produces a redundant transform. Thus, to avoid the redundancy produced by the above expression, the translation b and scaling, a parameters have to be discrete. One of the most popular discretization methods consists of changing the scaling a by $2^j$ and the
translation b by \(2^j n\), where \(j\) is the level of decomposition. This produces the dyadic wavelet, as shown in Equation (2.12) below (San Emeterio et al., 2006):

\[
\psi_{2^j}(t) = \frac{1}{2^j} \psi_j\left(\frac{t}{2^j}\right)
\]  

(2.2)

The dyadic discrete wavelet transform (DWT) of a signal \(x(t)\) can be obtained using (San Emeterio et al., 2006):

\[
DWT_x(j, n) = CWT_x(2^j, 2^j n) = \frac{1}{\sqrt{2^j}} \int_{-\infty}^{\infty} x(t) \psi\left(\frac{t}{2^j} - n\right) dt
\]  

(2.3)

The previous expression produces orthogonal, non-redundant, wavelet decomposition. The DWT of a signal can be computed by means of a digital filter bank tree, combined with decimation blocks (Boashash, 1992). More on DWT will be discussed in the next chapters.

### 2.6. INTRODUCTION TO ARTIFICIAL NEURAL NETWORKS

The human brain provides proof of the existence of massive neural networks that can succeed at those cognitive, perceptual, and control tasks in which humans are successful. The brain is capable of computationally demanding perceptual acts (e.g. recognition of faces, speech) and control activities (E.g. body movements and body functions). The advantage of the brain is its effective use of massive parallelism, the highly parallel computing structure, and the imprecise information-processing capability. The human brain is a collection of more than 10 billion interconnected neurons. Each neuron is a cell (Figure 2.3) that uses biochemical reactions to receive, process, and transmit information.

Treelike networks of nerve fibers called dendrites are connected to the cell body or soma, where the cell nucleus is located. Extending from the cell body is a single long fiber called the axon, which eventually branches into strands and sub strands, and are connected to other neurons through synaptic terminals or synapses.

The transmission of signals from one neuron to another at synapses is a complex chemical process in which specific transmitter substances are released from the sending end of the junction. The
effect is to raise or lower the electrical potential inside the body of the receiving cell. If the potential reaches a threshold, a pulse is sent down the axon and the cell is ‘fired’.

Artificial neural networks (ANN) have been developed as generalizations of mathematical models of biological nervous systems. A first wave of interest in neural networks (also known as connectionist models or parallel distributed processing) emerged after the introduction of simplified neurons by McCulloch and Pitts (1943). (McCulloch and Pitts, 1943)

The basic processing elements of neural networks are called artificial neurons, or simply neurons or nodes. In a simplified mathematical model of the neuron, the effects of the synapses are represented by connection weights that modulate the effect of the associated input signals, and the nonlinear characteristic exhibited by neurons is represented by a transfer function. The neuron impulse is then computed as the weighted sum of the input signals, transformed by the transfer function. The learning capability of an artificial neuron is achieved by adjusting the weights in accordance to the chosen learning algorithm.

Figure 2.3 Mammalian neuron

2.6.1. NEURAL NETWORK ARCHITECTURES

The basic architecture consists of three types of neuron layers: input, hidden, and output layers see Figure (2.4). In feed-forward networks, the signal flow is from input to output units, strictly in a feed-forward direction. The data processing can extend over multiple (layers of) units, but no feedback connections are present. Recurrent networks contain feedback connections. Contrary to feed-forward networks, the dynamical properties of the network are important. In some cases, the activation values of the units undergo a relaxation process such that the network will evolve to a
stable state in which these activations do not change anymore. In other applications, the changes of the activation values of the output neurons are significant, such that the dynamical behavior constitutes the output of the network.

There are several other neural network architectures (Elman network, adaptive resonance theory maps, competitive networks, etc.), depending on the properties and requirement of the application. The reader can refer to Bishop (1995) for an extensive overview of the different neural network architectures and learning algorithms (Bishop, 1995).

A neural network has to be configured such that the application of a set of inputs produces the desired set of outputs. Various methods to set the strengths of the connections exist. One way is to set the weights explicitly, using a priori knowledge. Another way is to train the neural network by feeding it teaching patterns and letting it change its weights according to some learning rule. The learning situations in neural networks may be classified into three distinct sorts. These are supervised learning, unsupervised learning, and reinforcement learning. In supervised learning, an input vector is presented at the inputs together with a set of desired responses, one for each node, at the output layer. A forward pass is done, and the errors or discrepancies between the desired and actual response for each node in the output layer are found. These are then used to determine weight changes in the net according to the prevailing learning rule. The term supervised originates from the fact that the desired signals on individual output nodes are provided by an external teacher (Arbib, 2003).

Figure 2.4 (a) Artificial neuron, (b) Multilayered artificial neural network
• Feed-forward networks

Feed-forward ANNs (Figure 2.5) allow signals to travel one way only; from input to output. There is no feedback (loops) i.e. the output of any layer does not affect that same layer. Feed-forward ANNs tend to be straightforward networks that associate inputs with outputs. They are extensively used in pattern recognition.

• Feedback networks

Feedback networks (Figure 2.12) can have signals travelling in both directions by introducing loops in the network. Feedback networks are very powerful and can get extremely complicated. Feedback networks are dynamic; their 'state' is changing continuously until they reach an equilibrium point. They remain at the equilibrium point until the input changes and a new equilibrium needs to be found. Feedback architectures are also referred to as interactive or recurrent, although the latter term is often used to denote feedback connections in single-layer organizations.

![Figure 2.5 An example of a simple network](image)

2.6.2. THE LEARNING PROCESS

The memorization of patterns and the subsequent response of the network can be categorized into two general paradigms:

1. **Associative mapping** in which the network learns to produce a particular pattern on the set of input units whenever another particular pattern is applied on the set of input units. The associative mapping can generally be broken down into two mechanisms:
• Auto-association: an input pattern is associated with itself and the states of input and output units coincide. This is used to provide pattern competition, i.e. to produce a pattern whenever a portion of it or a distorted pattern is presented. In the second case, the network actually stores pairs of patterns building an association between two sets of patterns.

**Hetero-association: is related to two recall mechanisms:**

• nearest-neighbor recall, where the output pattern produced corresponds to the input pattern stored, which is closest to the pattern presented, and

• Interpolative recall, where the output pattern is a similarity dependent interpolation of the patterns stored corresponding to the pattern presented. Yet another paradigm, which is a variant associative mapping is classification, i.e. when there is a fixed set of categories into which the input patterns are to be classified.

2 **Regularity detection** in which units learn to respond to particular properties of the input patterns. Whereas in associative mapping the network stores the relationships among patterns, in regularity detection the response of each unit has a particular 'meaning'. This type of learning mechanism is essential for feature discovery and knowledge representation.

Every neural network possesses knowledge which is contained in the values of the connections weights. Modifying the knowledge stored in the network as a function of experience implies a learning rule for changing the values of the weights.

Following the way learning is performed, we can distinguish two major categories of neural networks:

• **Fixed networks** in which the weights cannot be changed, i.e. dW/dt=0. In such networks, the weights are fixed a priori according to the problem to solve.

• **Adaptive networks** which are able to change their weights, i.e. dW/dt not= 0.

All learning methods used for adaptive neural networks can be classified into two major categories:
• **Supervised learning** which incorporates an external teacher, so that each output unit is told what its desired response to input signals ought to be. During the learning process global information may be required. Paradigms of supervised learning include error-correction learning, reinforcement learning and stochastic learning. An important issue concerning supervised learning is the problem of error convergence, i.e. the minimization of error between the desired and computed unit values. The aim is to determine a set of weights which minimizes the error. One well-known method, which is common to many learning paradigms is the least mean square (LMS) convergence.

• **Unsupervised learning** uses no external teacher and is based upon only local information. It is also referred to as self-organization, in the sense that it self-organizes data presented to the network and detects their emergent collective properties. Paradigms of unsupervised learning are Hebbian learning and competitive learning (Carpenter and Grossberg, 2017).

### 2.6.3. **TRANSFER FUNCTION**

The behavior of an ANN (Artificial Neural Network) depends on both the weights and the input-output function (transfer function) that is specified for the units. This function typically falls into one of three categories:

- Linear (or ramp)
- Threshold
- Sigmoid

For **linear units**, the output activity is proportional to the total weighted output.

For **threshold units**, the output is set at one of two levels, depending on whether the total input is greater than or less than some threshold value.

For **sigmoid units**, the output varies continuously but not linearly as the input changes. Sigmoid units bear a greater resemblance to real neurons than do linear or threshold units, but all three must be considered rough approximations (Aleksander and Morton, 1990).
2.7. RELATED WORK

2.7.1. FORWARD SCATTERING RADAR

The FSR has been used and it is known for a long time; some of the main literature devoted to the forward scattering radar is given in (Cherniakov et al., 2004, Skolnik, 1970). Generally, there is a lack of recent publication on FSR, most of the available literature is too old specially the theory behind FSR and mostly available on text books. Earlier publications, pertaining to the forward scattering, were devoted to estimating the RCS of an object at the forward scattering. Among others, the paper by Hiatt, Siegel and Weil (Hiatt et al., 1960), which was published in 1960, provides a theoretical analysis and various experimental results to prove that the RAM coatings did not impose any effect for the forward scattering when applied on the highly conducting objects which were larger than the wavelength of the carrier. Nevertheless, the advantages of the FSR became known much later; these included the increase in the RCS of the object at the forward scattering.

Glaser’s (Glaser, 1985) work presented a fast and simple approach for estimating the effective forward scattering RCS for the different targets at various operating frequencies. This was followed by Chernokov and Krutikov (Chesnokov and Krutikov, 1996) who experimentally confirmed that the RCS, at the forward scattering, was bigger than the one in the monostatic case by 30 - 40 dB, depending on the frequency of the carrier.

Blyakhman and Runova (Blyakhman et al., 2000) discussed the target detection and estimated the detection zones at the forward scattering. They showed that the detection zone of a FSR was dependent on the type of the object and its flight trajectory. They calculated the bistatic RCS of the objects, related to the XY Cartesian co-ordinates to estimate the detection zones. Gould, Orton and Pollard (Gould et al., 2002), on the other hand, suggest that the detection is always lost at zero Doppler. This area is known as the ‘dead zone’, as shown in Figure 2.6.
Boyle (Nezlin et al., 2007) suggested that areas worthy of investigating are the system issues of the FSR. These include the system configurations and system parameters, such as the operating frequencies, power levels, and baseline distance.

Most recent literature in FSR is available on text book titled, ”Bistatic Radar”, principles and applications, 2007” by D.V.Nezlin et.al and edited by Prof Cherniakov from university of Birmingham. All that delayed the deployment of FSR in practical applications.

2.7.2. TARGET DETECTION IN FSR

Raja Abdullah (Abdullah and Ismail, 2006) Discussed the FSR technology, the current and possible applications as well as the limitations of FSR and feasibility study to the automatic ground target detection and classification, also the extraction of features from the radar measurements was introduced. The author proved the proposed that FSR system has a huge potential to be used as an alternative system for ground target detection and classification based on methods used (PCA as feature extraction) and the classification algorithm (k-nearest neighbor classifier.) by a real experiment of three vehicles carried out on a public road.
Mohamed K.H in (Mohamed et al., 2008, Alla et al., 2009) touched the problem of extracting the Doppler signature in different interference environments by using Hilbert Transform and Wavelet technique in order to predict the existence of target. Two experimentations have been done to collect the FSR signal under the influenced of high clutter, the proposed method gives a good result with some reservations of wavelet issues. Soon after, Rashid (Rashid et al., 2010, Rashid and Binti, 2012) studied the effect of clutter on the automatic target classification (ATC) accuracy in forward scattering radar (FSR), It is shown that using conventional clutter-uncompensated ATC system can achieve high target classification accuracy at high SCR only, but the accuracy drops significantly with SCR decreasing. The employment of clutter-compensated ATC system is shown to improve significantly the classification accuracy at low SCR.

Raja Abdullah (Abdullah et al., 2011) continued in the same field with new improvements in the existing method proposed by Mohamed K.H in (Mohamed et al., 2008, Alla et al., 2009) by considering a rough environment (receiver and surrounding noises), Results show that target detection using a Hilbert transform is applicable only for certain conditions but target detection employing the wavelet technique is more robust against clutter and noise. An inclusive comparison of various wavelet threshold selection rules for different types of wavelet filters and levels of decomposition is conducted to study the effect on target detection with FSR Two sets of field experiments were carried out to validate the proposed method, and target signals under the influence of large clutter were successfully detected using the proposed method with a confidence level exceeding 75%. Then Kama (Othman et al., 2017) implemented the Haar and Meyer wavelet technique in FSR which gives more detailed scales and variation information from the measured signals. The results from the wavelet technique show that they could find the similarity between signals of each target and dissimilarity between different targets.

In 2009 Mutaz Salah (Salah et al., 2009) Keep working on target detection in FSR, in addition he proposed speed estimation method by using standard deviation to become with automatic system for detection. Two phase were designed: the first one (training) create a database (Speed vs. Standard deviation) which will generate the final relationship of the two parameters then it will move to the second phase (testing) where the speed compared to the database with aid of video
camera as reference. By analyzing over 850 car signatures the proposed method shows a better accuracy compared to Blyakhman (Blyakhman et al., 2000).

T. Zeng In 2011 (Zeng et al., 2011) investigate on accurate signal modelling for detecting moving target in FSR by modifying the existing model algorithm by using numerous simulations. He claim that all the existing signals model and algorithm are built based on the assumptions that the baseline is long, diffraction angle is small and velocity direction of the target is approximately perpendicular to the baseline and the ground-based FSR system is characterized by short baseline and large diffraction angle, and the velocity direction of the target is not always perpendicular to the baseline. Therefore in many cases, the above assumptions introduce significant errors to the imaging results in the ground-based FSR. In the light of the ground-based FSR system, the signal model and imaging algorithm in traditional SISAR imaging technology are modified and gives good results.

Cheng Hu (Hu et al., 2012) state that, the received signal in forward scatter radar (FSR) depends on the targets electrical size and trajectory, which are unknown a priori As a result, in practical situations, it is impossible to obtain the accurate reference function at the reception side. That’s why he proposed signal processing algorithm which includes the construction of the adaptive reference functions and the identification of target velocity and its observation time by adaptation of optimal filter (quasi-optimal). He tested the algorithm performance is analytically determined under practical motion trajectories such as different motion directions and baseline crossing points, which indicate the effectiveness of the proposed algorithm in a practical case for FSR. As result he found that the proposed methods are suitable for the identification of target parameters, and in particular when observing target time and speed. By knowing of those parameters there is possibilities to obtain accurate target recognition.

Nurul Asyikin (Daud et al., 2014) discussed on forward scatter radar cross section of different target specification by conducted a simulation software for analysis many cars model, the study showed the effects of different target specifications on RCS radiation pattern at different angle for each frequency.
Novel studies was proposed by Chr. Kabakchiev (Kabakchiev et al., 2014, Kabakchiev et al., 2016) he used GPS radio shadow instead of previous FSR models in order to build passive forward scatter radar system. Investigation on different moving objects were introduced. The results show that from FS-GPS radio shadows of different objects can be extracted information about the parameters of the object (size, speed and direction of movement, distance to the receiver) from the width, shape and length of the received FS shadow. The occurrence of FS shadow is essential physical phenomena, which can be used to extract some useful information about the objects that create it. Then in (Garvanov et al., 2015) he proved the forward scattering GPS radio shadows system can be used for detecting road vehicles in urban environment. Stanislav Hristov (Hristov et al., 2015) follow the previous study of target shadow with the practical aspects of the target profile reconstruction in a single node ground-based forward scatter radar (FSR) system and discussing the target return signal for three different cars measured in real outdoor environment. The study proves that modelling approach can be successfully used for simulation of the Doppler phase history, which is required in the procedure of complex envelope extraction. The similarity of the reconstructed and original profiles demonstrates that TSPR delivers results suitable for both visual interpretation of target profile and ATC.

2.7.3. CLASSIFICATION TECHNIQUES FOR GROUND TARGET IN FSR

In a number of recent works, it was shown that FSR can be effectively used for ground target detection, and in particular automatic vehicle recognition and classification using different techniques and scenarios (Kruse et al., 2004, Adbullah, 2005, Cherniakov et al., 2005a, Cherniakov et al., 2006, Abdullah, 2007, Raja, 2007). Bellow a number of studies have been done on this topic.

Cherniakov in 2005 (Cherniakov et al., 2005b) work on the evaluation of a network of Forward Scattering (FS) radar micro sensors for the detection and classification of ground targets based on pervious study of short range forward scattering radar in (Cherniakov et al., 2004). The system power budget were operating in line of sight (LOS) conditions, was evaluated at both theoretical and experimental level in terms of power budget analysis and resolution. He demonstrated that an excellent resolution is achievable; the potential resolution of the system is equal to a target’s horizontal dimension. The dynamic range of the system is also shown to be very high. In addition, a number of practical targets are considered as simulation examples over a wide range of radar
carrier frequencies. In 2007 (Cherniakov et al., 2006) he proceeding the same study and he proved that FSR system has a huge potential to be used as an alternative system for ground target detection and classification shown the of using FSR plus technology of micro-sensor. This study followed by Ildar Urazghildiiev (Urazghildiiev et al., 2007) proposed another solution based on using vehicle height and length and height profiles obtained by a microwave (MW) radar sensor, then a precise feature vector can be extracted, and simple deterministic algorithms can be applied to determine the vehicle class. Field trials using a spread-spectrum MW radar sensor system operating on these principles have been carried out. They confirm that accurate classification of a large number of vehicle classes can be reached.

S. Makal (Makal et al., 2008) had use image technique formulation to obtain the Electric Field Integral Equations (EFIEs) in order to classify cylindrical targets from their ultra wide-band radar returns. Then, the EFIEs are solved numerically by Method of Moment (MoM). Because of wide frequency range of the ultrawide-band radar signal, the database to be used for target classification becomes very large. To deal with this problem and to provide robustness, wavelet transform is utilized. Application of wavelet transform significantly reduces the size of the database. The coefficients obtained by wavelet transform are used as the inputs of the artificial neural networks (ANNs). Then, the actual performances of the networks are investigated by Receiver Operating Characteristic (ROC) analysis. Therefore, the compressed inputs of the neural networks are determined and a dataset is formed. RBF, GRNN and MLP are investigated in this work. According to the testing and training rates, the best classifier is the MLP. To support this result, sensitivity and specificity values and the ROC curves are obtained and it is observed that MLP is better than the other networks.

Abdullah, RSA (Abdullah et al., 2007) become with new system that use neural network-based methodology with various type of training algorithm, It reiterates the uniqueness and the ability of the neural network implementation to accurately classify unknown vehicle signature on the available training data, the result showed good classification accuracy. Ibrahim, NK (Ibrahim et al., 2009) on the other hand, prove the potential and utilization of Neural Network (NN) by comparing the K Nearest Neighbor classifier and conventional method (PCA) with the proposed method, the result shows that neural networks can be effectively employed in FSR as an automatic
classifier. After implementing Multi-Layer Perceptron (MLP) back-propagation neural network trained with three back-propagation algorithm which gave very promising results in vehicle recognition and vehicle categorization. 10% of overall data was misclassified in vehicle recognition and only 2% of overall data was misclassified in vehicle categorization.

J.X. Fang (Fang et al., 2007) proposed novel ground vehicle classification approach using unmodulated CW radar. The radar is set up to look forward down to the road; vehicles are modelled as body targets composed of multiple scattering centers. Analysis shows that the spatial distribution of scattering centers can be derived from the Doppler signature of radar echo. Hough Transform is performed to estimate the distribution which is then used for classification. In experiments, vehicles are classified into three types at an average accuracy of 94.8%.

Pisane, J. (Pisane, 2013, Pisane et al., 2014) designed and developed three novel, distinct automatic target recognition (ATR) the radar images, the bistatic complex radar cross-section (BS-RCS), and the bistatic radar cross-section (BSRCS) of the targets based on passive bistatic signals. As for the classification they divide the observed targets into predefined classes (extremely randomized trees or subspace methods). A key feature the approach is breaking the recognition problem into a set of sub-problems by decomposing the parameter space, which consists of the frequency, the polarization, the aspect angle, and the bistatic angle, into regions and build one recognizer for each region.

Mohamed K.H.M and Kanona (H.M et al., 2014) claimed that all previous studies did not consider a rough environment analysis in ground target classification systems, and all experiments have been on ideal environment which significantly effect on classifier output. After adding simulation noises to the FSR signal output NN used as classifier. As result it was found that classification using an ANN is robust against noise to a certain extent of noise that is why they develop and enhance classification process in (Kanona et al., 2018)

Abdullah (Abdullah et al., 2015b) addressed the important of feature extraction process in FSR system by evaluating three different technique, manual and automatic reduction technique (PCA and Z-score). The main objective of this study to analyze the most suitable feature extraction algorithm to classify ground vehicles based on their physical size. Then he continued in (Abdullah
et al., 2017, Abdullah et al., 2015a) by improving the classification accuracy by the combination of Z-score and neural network (NN). As the number of features increases, the classification accuracy increases. The highest percentage of classification accuracy can be achieved when using NN5 system.

Aziz, NH Abdul and Abdullah, RSA (Aziz and Abdullah, 2016) had use LTE signal as a source for passive bistatic radar (PBR) for detection and location on the ground moving target depend on bistatic radar cross section (RCS). Conventional processing used as classification approach which we performed a simulation using Computer Simulation Technology (CST) Microwave studio. The simulation results show that largest area of ground moving target, SUV had better outcome compared to other ground moving target which reliable with Babinet’s principle, which declares a target of physical cross-sectional area is proportionate to RCS. In 2017 (Aziz et al., 2017) he roll in his previous study but this time detecting the human instead of vehicles, real experiments were done by testing and evaluating different human size. It is discovered that the PSD of the individuals are inversely proportional to their heights, In PCA, data of the individuals show a good convergence in terms of their respective groups.

Abdullah, RSA (Raja Abdullah et al., 2016a, Abdullah et al., 2016) proposed passive FSR system that can exploit the peculiar advantage of the enhancement in forward scatter radar cross section (FSRCS) for target detection and recognition using LTE signals, this paper illustrates the first classification result in the passive FSR system. The great potential in the passive FSR system provides a new research area in passive radar that can be used for diverse remote monitoring applications. In (Raja Abdullah et al., 2016b) he presented the latest feasibility studies and experimental results from using LTE signals in PBR applications. Details are provided about aspects such as signal characteristics, experimental configurations, and SNR studies. Six experimental scenarios are carried out to investigate the detection performance of our proposed system on ground-moving targets. The ability to detect is demonstrated through use of the cross-ambiguity function. The detection results suggest that LTE signals are suitable as a source signal for PBR.
CHAPTER THREE
METHODOLOGY

3.1 DATA SET

The data used in this study brought from related works listed in the previous chapter done by M. Khalfalla and Raja Abdullah they made real experiment for ground target vehicle which is represented by typical public road transport then N.K. Ibrahim and Raja Abdullah continued their study by made ACS which is automatic classification system using Artificial Neural Network Approach in Radar Target Classification, by using different type of vehicles each target have special signature which is used in this study. One car is selected which is (combi) as shown in table 1, each vehicle has unique signature as in Table 3.1.

Table 3.1 Vehicle-categories

<table>
<thead>
<tr>
<th>Vehicle Category</th>
<th>Example of car models in the training data</th>
<th>Representative car model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Small</td>
<td>Honda Civic, Peugeot 206, Ford Ka, BMW, Vauxhall Combi</td>
<td></td>
</tr>
<tr>
<td>Medium</td>
<td>VW Golf, Peugeot 406, Vauxhall Astra, Ford Focus, Mercedes E-class, VW Passat, BMW</td>
<td></td>
</tr>
<tr>
<td>Large</td>
<td>Renault Traffic</td>
<td></td>
</tr>
</tbody>
</table>


Table 3. 2 Vehicles signature

<table>
<thead>
<tr>
<th>Vehicles name/ type</th>
<th>Signature</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vauxhall Combi / small</td>
<td><img src="image1" alt="Signature Image" /></td>
</tr>
<tr>
<td>Vauxhall Astra / medium</td>
<td><img src="image2" alt="Signature Image" /></td>
</tr>
<tr>
<td>Renault Traffic / large</td>
<td><img src="image3" alt="Signature Image" /></td>
</tr>
</tbody>
</table>
3.2 ADDITIVE WHITE GAUSSIAN NOISE

Additive white Gaussian noise is a basic noise model used in Information theory to mimic the effect of many random processes that occur in nature. The modifiers denote specific characteristics:

- 'Additive' because it is added to any noise that might be intrinsic to the information system.
- 'White' refers to idea that it has uniform power across the frequency band for the information system. It is an analogy to the colour white which has uniform emissions at all frequencies in the visible spectrum.
- 'Gaussian' because it has a normal distribution in the time domain with an average time domain value of zero.

AWGN is often used as a channel model in which the only impairment to communication is a linear addition of wideband or white noise with a constant spectral density (expressed as watts per hertz of bandwidth) and a Gaussian distribution of amplitude. The model does not account for fading, frequency selectivity, interference, nonlinearity or dispersion. However, it produces simple and tractable mathematical models which are useful for gaining insight into the underlying behavior of a system before these other phenomena are considered.

- Gaussian distribution:

In probability theory, the normal (or Gaussian) distribution is a very commonly occurring continuous probability distribution—a function that tells the probability that any real observation will fall between any two real limits or real numbers, as the curve approaches zero on either side. Normal distributions are extremely important in statistics and are often used in the natural and social sciences for real-valued random variables whose distributions are not known.

The normal distribution is immensely useful because of the central limit theorem, which states that, under mild conditions, the mean of many random variables independently drawn from the same distribution is distributed approximately normally, irrespective of the form of the original distribution: physical quantities that are expected to be the sum of many independent processes (such as measurement errors) often have a distribution very close to the normal. Moreover, many
results and methods (such as propagation of uncertainty and least squares parameter fitting) can be derived analytically in explicit form when the relevant variables are normally distributed.

The Gaussian distribution is sometimes informally called the bell curve. However, many other distributions are bell-shaped (such as Cauchy's, Student's, and logistic). The terms Gaussian function and Gaussian bell curve are also ambiguous because they sometimes refer to multiples of the normal distribution that cannot be directly interpreted in terms of probabilities.

A normal distribution is:

\[ f(x, \mu, \sigma) = \frac{1}{\sigma \sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \]  

(3.1)

The parameter \( \mu \) in this definition is the mean or expectation of the \( \sigma^2 \) distribution (and also its median and mode). The parameter \( \sigma \) is its standard deviation; its variance is therefor. A random variable with a Gaussian distribution is said to be normally distributed and is called a normal deviate.

If \( \mu = 0 \) and \( \sigma = 1 \) the distribution is called the standard normal distribution or the unit normal distribution denoted by and a \( N(0, 1) \) random variable with that distribution is a standard normal deviate.

**3.2.1 ADDING WHITE GAUSSIAN NOISE**

Signal to noise ratio (often abbreviated SNR or S/N) is measure used to quantify how much a signal has been corrupted by noise, its defined as the ratio of signal power to noise power corrupting the signal. A ratio higher than 1:1 indicates more signal than noise, while SNR is commonly quoted for electrical signal, it can applied to any form of signal, so here we selected the white Gaussian noise in this study because its common technique that experimented in many researches, to know the real power for FSR that used in we made a lot of experiments by adding random level of noise, after analysis by using NN and the calculation of the error we get that the power is 100dBm, so from here added different noise started from 100dBm to -39dBm to the signals signatures shown in (Table3.3).
The code that we used it to generate the noise is:

\[ y = \text{awgn}(x, \text{snr}, '\text{measured}') \]  

(3.2)

The above code is used to add white noise to the different target to simulate different noise environment. Where \( y \) is the variable to save the output, \( \text{SNR} \): signal to noise ratio to add it (dBm) and \( x \): is the original signal. “Measured”: AWGN measures the power of \( x \) before the adding noise. The below table (3) shows the three vehicle’s variables names that used in this study with 30 different noise level.
Figure 3. Car signature with Different noise level
### Table 3.3 Noise Levels

<table>
<thead>
<tr>
<th>Astra variables</th>
<th>Combi variables</th>
<th>Traffic variables</th>
<th>SNR/dBm</th>
</tr>
</thead>
<tbody>
<tr>
<td>Y</td>
<td>c</td>
<td>m</td>
<td>100</td>
</tr>
<tr>
<td>y1</td>
<td>c01</td>
<td>m1</td>
<td>90</td>
</tr>
<tr>
<td>y2</td>
<td>c02</td>
<td>m2</td>
<td>80</td>
</tr>
<tr>
<td>y3</td>
<td>c03</td>
<td>m3</td>
<td>70</td>
</tr>
<tr>
<td>y4</td>
<td>c04</td>
<td>m4</td>
<td>60</td>
</tr>
<tr>
<td>y5</td>
<td>c05</td>
<td>m5</td>
<td>50</td>
</tr>
<tr>
<td>y6</td>
<td>c06</td>
<td>m6</td>
<td>40</td>
</tr>
<tr>
<td>y7</td>
<td>c07</td>
<td>m7</td>
<td>30</td>
</tr>
<tr>
<td>y8</td>
<td>c08</td>
<td>m8</td>
<td>20</td>
</tr>
<tr>
<td>y81</td>
<td>c09</td>
<td>m9</td>
<td>17</td>
</tr>
<tr>
<td>y82</td>
<td>c091</td>
<td>m91</td>
<td>14</td>
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<tr>
<td>y83</td>
<td>c10</td>
<td>m10</td>
<td>11</td>
</tr>
<tr>
<td>y9</td>
<td>c11</td>
<td>m11</td>
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</table>
3.3 THE WAVELET TRANSFORM

The wavelet analysis consider as one of the most valuable and effective evolving mathematical and signal processing tools for the last twenty years. Mathematically, the wavelet is a waveform, \( \psi(t) \) of the effectively limited duration which has an average value of zero, as in the following equation:

\[
\int_{-\infty}^{\infty} \psi(t)d(t) = 0 \tag{3.3}
\]

Comparing the wavelets with the sine waves, as in Figure 3.2, is the basis of the Fourier analysis. It is important to highlight that sinusoids do not have limited duration as they extend from minus to plus infinity. Similarly, when the sinusoids are smooth and predictable, the wavelets tend to be irregular and asymmetric.

*Figure 3.2 (a) sine wave; (b) wavelet*
The wavelet also comprises of a function which can be obtained by scaling and translating a single main function called the ‘mother wavelet,’ as given by (Aleksander and Morton, 1990):

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}} \psi\left(\frac{t-b}{a}\right)$$  \hspace{1cm} (3.4)

Where $a$ is the dilation or scale, and $b$ is the translation (or position).

The dyadic discrete wavelet transform (DWT) of a signal $x(t)$ can be obtained using (San Emeterio et al., 2006):

$$DWT_x(j,n) = CWT_x(2^j, 2^j n) = \frac{1}{\sqrt{2^j}} \int_{-\infty}^{\infty} x(t) \psi\left(\frac{t}{2^j} - n\right) dt$$  \hspace{1cm} (2.4)

The previous expression produces orthogonal, non-redundant, wavelet decomposition. The DWT of a signal can be computed by means of a digital filter bank tree, combined with decimation blocks.

3.4 WAVELET DE-NOISE

Wavelet de-noise can be summarized as (i) Decomposition, (ii) Threshold of the coefficients in the transformed domain, and (iii) Reconstruction of the de-noised signal by the inverse transform (San Emeterio et al., 2006) ; the following sub-section will provide more description of wavelet de-noise.

3.4.1 DECOMPOSITION

As highlighted in the earlier section, discrete wavelet transform (DWT) is used instead of the continuous wavelet transform. The discrete wavelet analysis is based on the concept of multi-resolution analysis (MRA). With the MRA, a signal is recursively decomposed into a sum of details and approximations at the different levels of resolution. As shown in Figure 3.3, the details represent the high-frequency components, while the approximations represent the low-frequency components of the signal. The decomposition algorithm is fully recursive. At each stage of the
MRA, the signal is passed through a low-pass filter, called the scaling filter, and a high-pass filter (the wavelet filter).

![Diagram of wavelet decomposition]

Figure 3. Details and approximations at the different levels of resolution

### 3.4.2 Threshold Detail Coefficients

After the signal decomposition using discrete wavelet transform, the signal is left with a set of wavelet coefficients which correlate with the high frequency sub-bands. These high frequency sub-bands consist of the details in the signal. If these details are small enough, they might be omitted without substantially affecting the main features of the signal. In addition, these small details are often those associated with noise; therefore, by setting these coefficients to zero, the noise from the signal is essentially filtered out. This has become the basic concept behind thresholding - setting all frequency subs-band coefficients which are less than a particular threshold to zero, and using these coefficients in an inverse wavelet transformation to reconstruct the signal.

### 3.4.3 Reconstruction

After thresholding, the reconstructing process will be carried out, in which, these components the approximation and details can be re-assembled into the original signal without any loss of information. This process is known as the IDWT (inverse discrete wavelet transform), or in other words, the wavelet reconstruction, where the wavelet analysis involves filtering and down sampling, and the wavelet reconstruction process consists of up sampling and filtering by reconstruction filters) (Mallat, 1989).
3.5 ARTIFICIAL NEURAL NETWORKS

3.5.1 NEURAL NETWORK ARCHITECTURES

The basic design consists of 3 forms of neuron layers: input, hidden, and output layers. In feed-forward networks, the signal flow is from input to output units, strictly in a very feed-forward direction, the information process will extend over multiple (layers of) units, however no feedback connections are unit present. Recurrent networks contain feedback connections. Contrary to feed-forward networks, the energizing properties of the network are unit vital. In some cases, the activation values of the units endure a relaxation method such the network can evolve to a stable state within which these activations don't amendment any longer. The changes in activation values to the output neurons is necessary for different applications.

![Figure 3.4 NF Tool](image)

Regarding neural network for this study (table 4) describes the factors or parameters that affect the output.

Table 3.4 Neural Parameters

<table>
<thead>
<tr>
<th>Name</th>
<th>Combi</th>
</tr>
</thead>
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<td>Data size</td>
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<tr>
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<td>Hidden layer function</td>
<td>Sigmoid</td>
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<td>Training Algorithm</td>
<td>Levenberge Marquardt</td>
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<td>Output layer function</td>
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<td>Testing</td>
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</tr>
<tr>
<td>Validation</td>
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</tbody>
</table>
3.5.2 NEURON MODEL (TANSIG, LOGSIG, PURELIN)

An elementary neuron with R inputs is shown below. Each input is weighted with an appropriate \( w \). The sum of the weighted inputs and the bias forms the input to the transfer function \( f \). Neurons may use any differentiable transfer function \( f \) to generate their output.

\[
a = f(\sum_{i=1}^{R} W_i P_i + b)
\]

(3.5)

\( a = f(\mathbf{W} p + b) \)

**Figure 3.5 single feed-forward network**

Multilayer networks often use the log-sigmoid transfer function (logsig).

\[
a = \logsig(n)
\]

**Figure 3.7 Log-sigmoid transfer function**
The function (logsig) generates outputs between 0 and 1 as the neuron's net input goes from negative to positive infinity. Alternatively, multilayer networks may use the tan-sigmoid transfer function (tansig).

\[ a = \text{tansig}(n) \]

Figure 3. 8 Tan-sigmoid transfer function

Occasionally, the linear transfer function purelin is used in Backpropagation networks.

\[ a = \text{purelin}(n) \]

Figure 3. 9 linear transfer function

If the last layer of a multilayer network has sigmoid neurons, then the outputs of the network are limited to a small range. If linear output neurons are used the network outputs can take on any value.

In back propagation it is important to be able to calculate the derivatives of any transfer functions used. Each of the transfer functions above, tansig, logsig, and purelin, have a corresponding derivative function: dtansig, dlogsig, and dpurelin. To get the name of a transfer function's associated derivative function, call the transfer function with the string 'deriv'.

- **Feed forward Network**

A single-layer network of S logsig neurons having R inputs is shown below in full detail on the left and with a layer diagram on the right.
Feed-forward networks often have one or more hidden layers of sigmoid neurons followed by an output layer of linear neurons. Multiple layers of neurons with nonlinear transfer functions allow the network to learn nonlinear and linear relationships between input and output vectors. The linear output layer lets the network produce values outside the range -1 to +1.

On the other hand, if you want to constrain the outputs of a network (such as between 0 and 1), then the output layer should use a sigmoid transfer function (such as logsig).

*Figure 3. 10 general function approximate for feed-forward*
3.6 DESIGN AND IMPLEMENTATION

We discussed the methodology of this thesis which consist de-noising using the wavelet and the classification method (neural network) and their parameters, this will show how to design and implement the previous mentioned methods in details.

![Diagram showing system phases](image)

**Figure 3.11 System phases**

The above figure show the phases of the proposed enhance classification system for ground target, in phase one the selected car signatures with different noise level inserted in matrix format to the workspace with (25001*1) dimension then this signals injected to phase two, the wavelet 1D through many process after selecting the appropriate de-noise algorithm in this case (SYM) and filter level, after save the de-noise signal the neural network fitting tool used in the last phase, target and input will be tested after the training process, then mean square error and regression calculated to show the relation between the inputs. The below figures show the GUI steps for the wavelet and neural network as well.

### 3.6.1 MOTHER WAVELET ALGORITHM

To determine which wavelet technique to be implemented, the noised and original signals are putted for experiments under four different famous (common) de-noising techniques which are: SYM, DB, DMEY and HAAR. The experiments concluded by that SYM are the best technique to be adopted and implemented for classifying the targeted noised signal since it keep the signal near and very similar to the original signal considering exceeding the suitable de-noising level. The
below Figures (3.12-3.16) show the implementation of different mentioned techniques for the same original signal.

![Figure 3.12 Original signal](image)

**Figure 3.12 Original signal**

![Figure 3.13 SYM](image)

**Figure 3.13 SYM**

![Figure 3.14 DB](image)

**Figure 3.14 DB**

![Figure 3.15 DMEY](image)

**Figure 3.15 DMEY**

![Figure 3.16 HAAR](image)

**Figure 3.16 HAAR**
CHAPTER FOUR
RESULTS AND DISCUSSION

4.1 EXPERIMENTAL SETUP

In this research many experiments are made to the noisy signals get the obtained results. The below table (4.1) shows the used parameters and its specifications for the experiments conducted.

Table 4.1 Experiment Setup

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<thead>
<tr>
<th>Parameter</th>
<th>Specification</th>
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<tbody>
<tr>
<td>OS</td>
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<td>Simulation Software</td>
<td>MATLAB</td>
</tr>
<tr>
<td>De-Noising Technique</td>
<td>WAVELET</td>
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<tr>
<td>Classification mechanism</td>
<td>Artificial Neural Network Fitting Tool</td>
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<td>NN Sample Data size</td>
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<tr>
<td>Number Hidden layer (neurons)</td>
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<td>Validation</td>
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</table>
4.2 RESULTS

After De-noise to the original signatures of the selected vehicle neural network trained with the original signal several times, then De-noise signals tested. The bellow Figures shows neural output which is a plot for (validation, training and testing states). Mean Square Error (MSE) and Regression (R) plots shows the error between inputs and targets.

![Figure 4. 1 C validation performance at 1000 epoch (MSE)](image)
Figure 4. 2 C function fit (target & output)

Figure 4. 3 C Regression plot (training, validation and testing)
Figure (4.1) shows the Combi validation performance $1.15e$-13 at epoch 1000, mean square error MSE in the y axis and epoch in the x axis, the difference between output and the target this approximation is better if MSE smaller (close to zero), Figure (4.2) show the fit function between the target and the input, when the fit fall along a $45^\circ$ degree line (perfect fit) means that the outputs are equal to the target, Figure (4.3) show the regression for (training, validation ,testing and overall) which display the network output with respect target, this measures the correlation between correct outputs and those provided by the network, when person’s correlation coefficient (R) is closer to one (1) the approximation is better , also when the fit along $45^\circ$ it is perfect.

The figures bellow show neural network for (c6, c8, c9 and c13 as a samples) with the same discussion above, more results in appendixes.
4.3 RESULTS DISCUSSION

The neural network trained by 30 level of different noise levels for Combi car after the signals are de-noised on early stage by a wavelet as pre-step. The conducted experiments results and gives good performance for classification compared to the previous studies. The below Figure (4.8) shows clearly that the new implemented integration of a wavelet and neural network improves the classification of the ground targets. Moreover Table 4.2 shows that the previous system threshold for target classification stops at -5 SNR, while the new implemented used can classify the target up to -19 SNR which is a very high level of noise that at this level the previous studies give 13% as a classification regression and fitting with the original target signal.

Table 4. 2 Results comparison

![Figure 4. 8 Classification performance](image-url)
Table 4. 3 Results comparison

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CHAPTER FIVE
CONCLUSION AND RECOMMENDATIONS

5.1. CONCLUSION

Several experiments are made to determine the best mother wavelet technique among four different techniques which are: Haar, Daubechies (db), Symlets(sym) and Meyer (dmey). The results of those experiments is to adopt sym as preferred mother wavelet technique for de-noising the signals. In conclusion, the conducted experiments and analysis proofed that using wavelet as a preprocessing step before classifying FSR signals under noisy environment, improve the percentage of classification accuracy of the captured target signal.

5.2. RECOMMENDATIONS

Finally, it is highly recommended to adopt an automated mechanism to integrate the two steps of de-noising and classifying to be treated as a single unit for time and effort management. Moreover, the future researcher can apply and experiment other type of noise, rather than White Gaussian noise and use another NN techniques rather than fitting tool.
REFERENCES


ZEMMOUR, A. I. 2006. The Hilbert-Huang transform for damage detection in plate structures.

APPENDIX

The figures below show different GUI steps that used for de-noising signals

Prepare noised signals

Open 1D wavelet
Import specific noised signal from work space

Select (SYM) mother wavelet technique
Select appropriate SYM level

Analyze the noised signal.
Click de-noise button

Display de-noised signal

Save de-noised signal
NEURAL NETWORK GUI (FITTING TOOL)

Fitting Tool Wizards

Data Select (input & target)
Sample for Training, Validation and Testing is selected

Number of Hidden Layer
Input Training & its' result