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An Intelligent System For High Resolution Radar Systems

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Dedication

to my
beloved sons Ricardo & Gael, Husband, Mother, Siblings & family
With Love

AN INTELLIGENT SYSTEM FOR HIGH RESOLUTION RADAR SYSTEMS

by

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Abstract

Cognitive radio is a recent, novel approach that integrates machine perception software into wireless systems. The term *cognitive radio* was first used by Joe Mitola. The concept and the term *cognitive radio* quickly caught the attention and interest of many in the communications field. Cognitive radios are capable of making decisions and selecting or modifying the operating parameters of a radio. Given these capabilities, it is feasible to build a cognitive radar system as introduced by Simon Haykin in 2006. Cognitive radar, as described by Haykin, is an intelligent system that must be aware of its environment, uses prior knowledge, and builds on learning through interaction of the radar with the environment. The main objective of this dissertation is to develop an intelligent system for adaptive high-resolution radar with cognitive capabilities that has the potential for providing intelligent decisions making process to determine the optimal mode of operation the radar should operate in a given environment.

An intelligent system model with a cognitive engine is developed to create a radar with cognitive capabilities, thereby allowing the radar to have awareness of its environment and to adapt its operating characteristics, take action, and learn from experience gained. A cognitive engine determines the optimal system parameters for performing autonomous tasks using the information collected from the participant engines. The functionalities of the engine are identified and presented. The design and analysis of its performance is discussed and a specific application of airborne surveillance on a dessert environment, based on the proposed cognitive engine in intelligent radar system, is demonstrated.

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Chapter 1

Introduction

Cognitive radar is a promising concept, and the motivation of adding cognition to a system is to increase system performance while reducing human intervention. In typical radar systems, target detection is fully automated, but target recognition and decision-making require human involvement. Additionally, the system performance is not fully reliable due to unstable operator performance that varies between operators. By removing critical decision-making responsibilities from the human operator, the intelligent system will be more reliable and the possibility of human operator error is eliminated. The flexibility of the proposed system will provide intelligent decisions about mode of operation, detection, tracking, and classification. The question under consideration is whether the intelligent radar system with cognitive capabilities changes modes of operation intelligently, which is the main focus of this dissertation.

An intelligent radar system with cognitive capabilities is introduced in this dissertation. Additionally, a model for the cognitive engine is developed for intelligent radar systems. Functionalities of the proposed cognitive system are identified and discussed as well.

1.1 Previous Work and Motivation

The idea of cognitive radar originated in 2006 with the publication of a paper entitled "Cognitive Radar: a way to the future" authored by Simon Haykin and it has come a long way since its initial publication seven years ago. Simon Haykin, motivated by the echolocation system of a bat, described the novel idea of cognitive radar [Hay05], and followed that by an invited paper that appeared in a book edited by Fulvio Gini [Gin06]. With these two seminal contributions, the idea of cognitive radar was introduced. Haykin's work demonstrated that cognitive radar builds on three basic ideas: 1) intelligent signal processing, 2) feedback from the receiver to the transmitter, and 3) preservation of the information content of radar returns. The radar system described in his work constitutes a dynamic closed feedback loop encompassing the transmitter, environment and receiver. This was then expanded

to the idea of cognitive radar networks in 2005 [Hay05]. The system described in this publication, which included several radars working together in a cooperative manner and exhibited the capability to preserve environment information, was shown to be much better than the radar components are capable of achieving individually. In 2007, cognitive radar was applied to the area of remote sensing, and was described in [Hay07]. In 2009, Dr. Haykin introduced a new discipline, called Cognitive Dynamic Systems, which built on existing principles in statistical signal processing, information theory, and utilized new ideas drawn from neuroscience and game theory. The study of cognitive dynamic systems was motivated by ideas drawn from cognitive neuroscience, particularly, cognitive radar [Hay09]. In 2013, cognitive radar of a monostatic kind was also presented by Haykin, addressing mathematical aspects of cognitive radar, Bayesian estimation, which included a Kalman filter as a special case, and dynamic programming, which included reinforcement learning for function approximation. In this exposition, Dr. Haykin also introduced a two-state model, which embodies a deterministic target model and a dynamical entropic-state model [Hay13]. In 2014, a novel design of a cognitive radar hybridized with a phased array radar having a low probability of intercept transmit beam forming was also introduced. The proposed radar receiver estimates the interceptor range and the direction of arrival, using the extended Kalman filter and a Genetic algorithm as feedback to the transmitter [Bas14, Wan08, Wan09, Rom09, Wei09]. Although the automatic detection/tracking [DeM07] and recognition of targets [Rog95, Rot90, Zyw96, Ala08, Bil06, Li10] have been addressed previously, the problem of automatically identifying objects commonly encountered in a desert border-surveillance environment has not been analyzed before this study. Since border security remains a key issue in homeland security, it is imperative to develop radar systems that can help to optimize the capabilities of the border guards, surveillance operator, and command staff assigned to secure this strategic region. Given the lack of sufficient coverage from sensors and cameras, it is especially important to build a system that is able to detect threats at an acceptable rate, without overloading the overall surveillance system with false alarms. The motivation for adding automatic detection and recognition capabilities to a radar system is to increase and stabilize the radar system performance by reducing the need for human intervention.

The system proposed in this research can shift critical decision-making responsibilities from human operators to the radar itself.

1.2 Proposed Intelligent Radar System

An intelligent radar system emulates the functionality of an expert human operator by combining a cognitive engine (e.g., a neural network, knowledge base, and decision-support rule base) and the radar. The objective of creating a cognitive radar in this dissertation is accomplished by providing the radar system with an intelligent, cognitive engine with the capability to: 1) integrate intelligent signal processing, which adapts and learns to separate the signal from the noise, and extract information from the acquired signals; 2) provide feedback from the transmitter to the receiver for intelligent decisions on the system objectives and priorities based on various inputs; and 3) learn from interactions with the environment and input from the knowledge bases. This integration will enable the intelligent radar system to change modes of operation and decide on its next course of action.

The proposed system is illustrated in Figure 1.1. The intelligent system consists of a closed-loop system that includes the radar system, the environment, the signal acquisition, the cognitive engine, the prior knowledge, and the feedback link. The system starts when the transmitter signal generator sends the signal to start the detection and estimation process as the starting mode. The radar returns produced by the environment are fed into the signal acquisition block, which uses signal processing to extract information from the acquired signals to be sent to the cognitive engine block. Some key parameters, including the amplitude, signal to noise ratio (SNR), velocity, radar cross section (RCS), and the probability of false alarm and probability of detection, are described in the next section. The cognitive engine block addresses what action should be taken. This block analyzes information from several sources, including the information sent by the signal acquisition block, as well as information about the environment provided by the "prior knowledge block." This block also makes intelligent decisions about the mode of radar operation and sends decisions to the radar system block to intelligently generate the appropriate signal for the next course of action. The cognitive engine generates signals with the specified parameters using the signal generator within the radar block. The prior knowledge base is necessary because the cognitive engine's performance is enhanced if it knows about its surrounding

environment. The prior knowledge block acquires and accumulates comprehensive knowledge from the surrounding environment and uses knowledge-based techniques. Additionally, the knowledge base contains information about prior experiences with the given environment. The decisions on mode of operation for the radar, with respect to possible targets, are based on the target's range, velocity, and RCS.

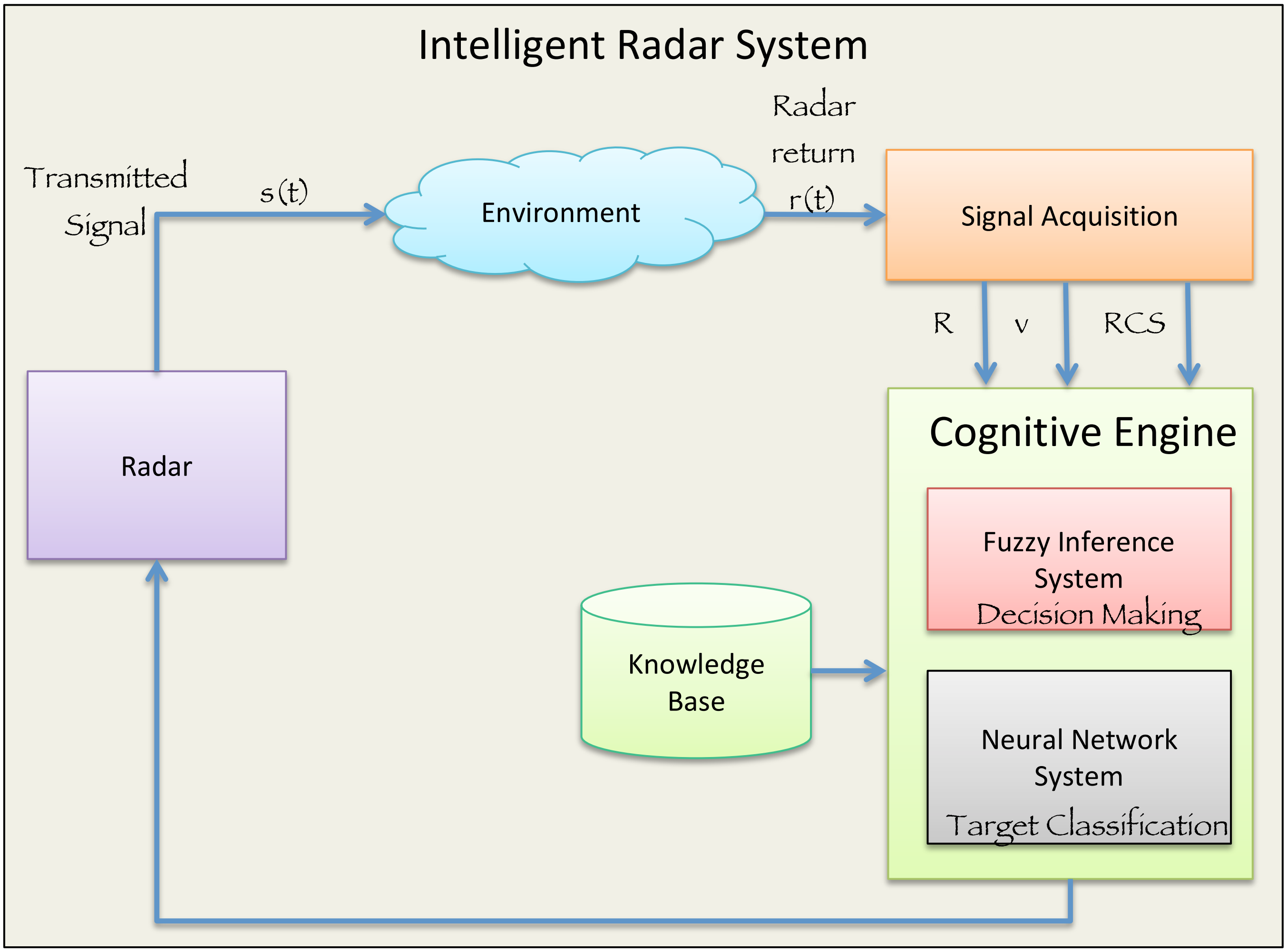

Figure 1.1: Intelligent Radar System Conceptual Model.

1.3 Overview of Dissertation

The content of this dissertation is organized as follows:

Chapter 2 provides a discussion of the fundamentals of radar modes of operation by describing the detection and estimation, Doppler, high-resolution and ISAR modes. The detection and estimation mode detect should be chosen to detect an object in the environment and estimate it's range. Doppler

mode uses the Doppler principle to determine the object's velocity. The high-resolution mode provides a high-resolution range profile as a one-dimensional signature of the object. The Inverse Synthetic Aperture Radar mode provides a high-resolution two-dimensional signature of the object.

Chapter 3 provides the details on algorithms from the literature. Furthermore, it describes the Cognitive System with details on the Cognitive Engine and key technologies used therein. The conceptual model of the cognitive engine is also proposed where the cognitive engine consists of observing, planning, learning, decision-making and acting states.

Chapter 4 describes the artificial neural network system design. The model of a neural network to classify the objects is also described in this chapter. Some simulation and results are presented and the implementation of the neural network is also presented.

Chapter 5 describes the fuzzy logic inference system design. It provides the details on the fuzzy system's operational stages, the rule-based model, and the fuzzy inference example.

Chapter 6 describes the experimental results for three different case studies.

Chapter 7 is the conclusion, containing a summary of the dissertation and an outline of proposed future enhancements.

Chapter 2

Intelligent Radar System

The proposed intelligent radar system is defined such that the radar senses the environment, understands the environment, acts on the knowledge, and learns from previous actions and results. The intelligent system consists of the following blocks: (a) radar system, (b) environment, (c) signal acquisition, (d) cognitive engine, and (e) database. While the cognitive engine addresses what actions are required to meet a given objective, the radar system establishes how the action can be executed by routing the most appropriate mode. Before proceeding to discuss the details of the functionalities of the proposed intelligent radar system, it is worth providing clarification about the terminology, which is presented in the following sections.

2.1 Radar Fundamentals

The main purpose of this chapter is to introduce the concepts of radar and discuss the modes of operation. The processing of the modes of operation is a subsystem of the intelligent decision-support block. In general, the first basic operation of radar is to transmit an RF signal that is analyzed and processed to obtain the range, velocity, and direction of the target. The radar is capable of detecting, locating, and identifying moving targets such as a person, vehicle, etc. [Mah05]. The radar has four modes of operation: 1) initial target detection and estimation, 2) Doppler, 3) high-resolution, and 4) inverse synthetic aperture radar. The radar must be adjusted from one mode to the next in order to obtain the final high-resolution images that will be used by the neural network for recognition purposes. The system extracts useful information from each of the subsystems and adjusts certain parameters in the system to intelligently decide which mode of radar operation should be next.

First, Mode 1 should be chosen to detect an object in the environment. Once a target has been detected, it is desirable to track its velocity. The radial speed of the target can be directly estimated in Mode 2 using the Doppler principle, which states that the speed of a moving object will affect the frequency of the return signal. After determining the target's velocity by measuring the Doppler shift of

the reflected signal, the system should change to Mode 3 or Mode 4, depending on the velocity output. Mode 3 can provide a high-resolution range profile as a one-dimensional signature of the target of interest, while Mode 4 is an imaging technology that can provide a high-resolution two-dimensional signature of the target.

2.1.1 Initial Target Detection and Estimation (Mode 1)

The most fundamental problem in radar is detection of a target. This requires determining whether the received signal is from a reflecting target or is only noise. This mode uses moving target indicator principles to detect the targets of interest. The moving target indicator can distinguish between low-speed or stationary targets and high-speed targets. For this dissertation, target detection is accomplished by the radar receiver employing an envelope detector followed by a threshold decision to detect the presence of a target. The input signal to the receiver is composed of the radar signal to be detected, and the additive zero means white Gaussian noise. The return signal, then is described by

$$r(t) = s(t) + n(t) \tag{2.1}$$

where:

$s(t) = \sin(w_0 t)$ is the transmitted signal,
$w_o = 2\pi f_0$, f_0 is the frequency, and
n(t) is the zero-means white Gaussian noise.

Target detection is based on two hypotheses, either the target is present or it's not [Wha71]. In other words, a target is detected when $r(t)$ exceeds the threshold value, v_T. The two decision hypotheses are

$$H_0: r(t) = n(t) \; No\ target\ detected$$

$$H_1: r(t) = s(t) + n(t) \; Target\ detected \tag{2.2}$$

where H_0 is hypothesis zero, no target is present, only noise, and H_1 is hypothesis one, for which a target is present, with noise. The Neyman-Pearson criterion is used to derive the decision rule as described in [Wha71].

The receiver should choose the correct hypothesis with high probability. The objective is to maximize the probability that a target is detected in the presence of noise, while minimizing the probability that a receiver mistakenly declares a target present when only noise is present.

To maximize the probability that the receiver will detect a target in the presence of noise is known as the probability of detection and is defined in (2.3).

$$P_d = P(D_0|H_1) = \int_{V_T}^{\infty} p_1\,(r)dr \tag{2.3}$$

To minimize the probability that the receiver will miss, by declaring a target to be present when only noise is present, is to minimize the probability of false alarm, which is defined in (2.5) and can be expressed in terms of the Neyman-Pearson threshold.

$$P_{fa} = P(D_1|H_0) = \int_{V_T}^{\infty} p_0\,(r)dr \tag{2.5}$$

These two conditional probabilities are related to each other. Expressing these quantities in terms of the decision region and the likelihood function one can determine the decision rule.

$$V_n = \frac{p_1}{p_0} \underset{H_0}{\overset{H_1}{\gtrless}} V_T \tag{2.6}$$

where p_0 and p_1 represent the prior probabilities for the data given hypothesis 0 and 1, and V_T is the threshold value.

It is important to know that increasing P_d by lowering the detection threshold results in an increase in the P_{fa}. The desire to maximize P_d to improve performance will be accomplished by using a likelihood ratio test.

If a target is detected, the range of the target it determined by estimating the time delay between the transmitted, *s(t)* and the returned signal, *r(t)*. The signals are described in equation (2.7) and (2.8).

$$s(t) = \sin(2\pi f_0 t) \tag{2.7}$$

$$r(t) = \sigma * \sin\big(2\pi f_0 (t - D)\big) + n(t) \tag{2.8}$$

where:

$n(t)$ is the zero-means white Gaussian noise,

σ is the attenuation factor, and

D is the time delay which the signal travel from the transmitter to the target and back to the receiver.

A common method of calculating the time delay is to compute the cross-correlation function of the received signal with the transmitted signal as shown in (2.9).

$$R_{rs}(\tau) = \int r(t) r * (t - \tau)dt \tag{2.9}$$

To find the range of the target equation (2.10) is used

$$R = \frac{c\tau}{2} \tag{2.10}$$

where:

R is the target's range,
c is the speed of light, $c = 3 * 10^8 m/s$, and
τ is the delay, in seconds. The factor of ½ is needed to account for the two-way time delay.

Once a target has been detected, it may be desirable to track its velocity. The intelligent illuminator block sends the decision to the intelligent illuminator to make adjustments to the transmitted signal to illuminate the environment based on the decision made from the receiver considering the range of the target.

2.1.2 Doppler (Mode 2)

Some radars measure the radial speed of the target directly, using the Doppler principle, which states that the speed of a moving object will affect the frequency of the return signal. The Doppler frequency determines the target radial velocity and can distinguish between moving and stationary targets [Mah05]. If the target happens to be moving, the reflected signal will have a frequency different from the one that was transmitted. The difference between these frequencies is referred to as a Doppler shift. The Doppler shift can be positive or negative depending on whether the target is coming toward, or moving away from, the radar. If the signal bounces off the target, and if the object is moving towards the radar, then the signal is compressed and the frequency is shifted up. If the target is moving away from the radar, then the frequency is shifted down.

Mode 2 uses a different transmitted signal. The intelligent decision-support makes the decision to select this mode once a target has been detected and the distance of the target obtained. It then sends this information to the intelligent illuminator to change the parameters, including the new signal from the signal generator and illuminate the environment to get the target's velocity.

It is typical for this mode of operation to use a series of pulses as the transmitted signal. The series of pulses hits the target and is reflected back with a Doppler shift on the return signal. The returned signal is then multiplied by a complex exponential with a certain phase. The reflected signal is of the form

$$r(t) = s(t - \tau_0)e^{j2\pi f_d(t-\tau_0)} \tag{2.11}$$

where:

f_d is the Doppler shift, and

τ_0 is the delay associated with the target.

In order to detect the frequency shift between the transmitted signal and the received signal, The Fourier Transform (FT) of both the transmitted and received signals is obtained and the analysis of the spectrum of the two signals is performed. The shift of the spectrum shows the Doppler shift. To calculate the velocity, the Doppler shift, the carrier frequency of the radar, and the speed of light are used in the calculation:

$$f_d = \frac{2v}{c} f_c \tag{2.12}$$

where:

f_d is the Doppler shift,
v is the target radial velocity,
c is the speed of light, and
f_c is the carrier frequency.

Equation (2.13) is used when there is an angle between the radar line of sight and the target:

$$f_d = \frac{2v\cos\theta}{\lambda} \tag{2.13}$$

where:

$2v\cos\theta$ is the radial velocity,
λ is the wavelength, and
θ is the total angle.

Having established the target detection and range, the velocity needs to be obtained. The velocity processing is determined by means of measuring the change in frequency if the target is moving. This shift in frequency is known as the "Doppler Shift" [Mah05]. From the Doppler shift in frequency, the velocity of the target can be found by (2.12). Unless the target is moving at an extremely high speed relative to the speed of light, the Doppler shift will be small and very difficult to determine from one pulse. The solution, then, is to transmit a signal containing repeated pulses. That is, a series of pulses is needed to measure the Doppler shift. Once the target's velocity is obtained by measuring the Doppler shift of the reflected signal, the system can intelligently change the mode of operation to high-resolution, or get the Inverse Synthetic Aperture Radar (ISAR) immediately, depending how fast the target is moving.

2.1.3 High Range Resolution (Mode 3)

Mode 3 is used as the high-resolution range profile produces a one-dimensional signature of the target of interest. High-resolution is a representation of the time domain response for the target to a high-range resolution radar pulse. The typical transmitted signal for this mode of operation is a step frequency or a chaotic signal. The comparison of the step frequency signal and research on the appropriate chaotic signal is performed in this research study. The step frequency signal is a series of short pulses varied in frequency by a small frequency step and is defined as:

$$s(t) = Ae^{j\theta(t)}e^{j\omega_0 t} \tag{2.14}$$

The image generation and processing is performed using MATLAB scripts. The simplest way to implement a target model is to represent it as a collection of point scatters. Each scatterer, therefore, is characterized by a distance from the radar and by the strength of reflection. The radar cross section (RCS) is enhanced by larger number of point scatters and is dependent upon aspect angle to radar.

To obtain a range profile, the step frequency signal is used. The radar then collects the received signal as a complex sample of the target reflectivity. By obtaining the Inverse Discrete Fourier Transform (IDFT), the target's reflectivity is obtained as a function of time. Using the IDFT will give the RCS of the scatterer and its location.

It is desirable not only to detect, but also to identify, the target as belonging to a certain category. The images for this research are ground and air vehicles, such as Cessna, helicopter, cars, and trucks. High resolution of obtained radar images is of much importance in the application of border security.

2.1.4 Inverse Synthetic Aperture Radar (Mode 4)

Inverse Synthetic Aperture Radar (ISAR) is an imaging technology that is used to obtain high-resolution 2-D images [Mah05] using advanced signal processing techniques, to give a detailed image of the target. ISAR is basically a variation of SAR that can be used to provide images of targets like aircraft. ISAR processing techniques are used for this mode because of its advantages when it comes to imaging target at high resolutions. It works by emitting a signal and then recording the strength of the reflected signal. The pulses are emitted at an angle, and very little of the signal will be reflected back towards the radar, which corresponds to a darker spot on the scattering image.

Mode 4 uses a stepped frequency waveform of M bursts, and each burst is in the form of N stepped frequency pulses to form a matrix of pulses. To find the frequency of the nth pulse in a burst, equation (2.15) is used

$$f_n = f_0 + n\Delta f \tag{2.15}$$

where:

f_0 is the initial frequency in a burst and
Δf is the frequency step between pulses.

Range resolution is a metric that describes the radar system ability to detect targets in close proximity to each other as different targets [Mah05], and is defined as:

$$\Delta r_s = \frac{c}{2\beta} \tag{2.16}$$

where:

$\beta = \frac{1}{\Delta\tau}$ is the bandwidth and
$\Delta\tau$ is the pulse width.

If we consider N pulses frequency stepped by *f,* the slant range resolution is defined by equation (2.17):

$$\Delta \mathrm{r} = \frac{c}{2(\mathrm{N}-1)\Delta \mathrm{f}} \tag{2.17}$$

The Doppler resolution is approximately 1/T where T is the integration time. With this we can conclude the cross range resolution to be:

$$\Delta r_c = \frac{c\Delta f d}{2w_c f_c} = \frac{\lambda}{2w_c T} \tag{2.18}$$

This equation can help us to form an image by simulation. The matrix of the form *m x n* dimensions represents the range-Doppler, which, in turn, will be the ISAR image of the objects. To form the image, the transfer function is considered to be the sum of the hot spot steady state responses:

$$H = \sum_1^n A_L \, e^{i2\pi f T_L} \tag{2.19}$$

where $T_L = \frac{2R_L}{c}$, $A_L = 1$, and H is the sum of phasors.

By obtaining the IDFT, the target's reflectivity is obtained as a function of time. Use of the IDFT gives the RCS of the scatterer and its location. Table 2.1 describes typical characteristics and description of associated targets.

Table 2.1: Typical characteristics and description of targets.

RCS Characteristics	Description	Value
Land targets	Truck	RCS = 200 m^2
	Car	RCS = 100 m^2
Air targets	Cessna	RCS = 1.5 m^2
	Helicopter	RCS = 40 m^2

A parametric representation of the target outline is used as a feature set for classifying targets. The IDFT of the matrix $H(k,j)$ is taken for each row. After the IDFT, the discrete Fourier transform (DFT) is computed for each column of

$$h(k,n) = \sum_{j-1}^{N-1} H(k,j)e^{i2\pi f/N} \tag{2.20}$$

$$D(m,n) = \sum_{j-1}^{M-1} h(k,n)e^{-i2\pi m/M} \tag{2.21}$$

The ISAR technique will generate a 2-D high-resolution image of a target. The matrix obtained will then be used in the neural network to classify the targets. The classification of the targets will be performed using a neural network and is described in more detail in Chapter 4.

Chapter 3

Cognitive System

The proposed intelligent system is defined such that the radar senses the environment, understands the environment, acts on the knowledge, and learns from previous actions and results. The intelligent system consists of the following blocks: (a) radar system, (b) environment, (c) signal acquisition, (d) cognitive engine, and (e) database. While the cognitive engine addresses actions required to meet a given objective, the radar system establishes how the action can be executed by routing to the most appropriate mode. Computer simulation within the MATLAB environment allows the set up of experiments similar to those that could be done in a laboratory, but without having to put together the physical components. We can simulate and generate the intelligent radar system design in the form of a model-based design that can be simulated, tested, and validated as one unit.

The proposed system is an intelligent radar system, whose intelligence mostly comes from the cognitive engine with the support of learning in machine intelligence. A cognitive engine is a means of intelligence that manages cognition capabilities in radar so that it can intelligently control the radar to implement a cognitive cycle. The cognitive engine implements the cognitive loop to understand the abilities of environment sensing, reasoning, learning, and acting. A cognitive engine is required for decision-making and learning in a radar system to efficiently exploit the available resources and improve the performance of the radar system.

3.1 Cognitive Engine

The cognitive engine, which realizes intelligent learning and reasoning in the system, and implements the cognitive cycle, is the key component of the radar. When Mitola [Mit99, Mit00] proposed the concept of cognitive radio, he defined a cognitive cycle with observe, orient, plan, decide, act, and learn stages. This idea shows the interaction between cognitive radio, the outside world, and decision-making. Besides Mitola's cognitive cycle, some other researchers have provided other cognitive cycle models. Research at Virginia Tech proposed a cognitive cycle to maximize channel

capacity through adjustments of modulation and encoding modes in various channel conditions. Haykin proposed a cognitive cycle from the perspective of efficient spectrum usage. The cognitive engine term in this dissertation is defined to embody observing, planning, learning, decision-making, and acting, which can be taken as the process of a finite state machine. The cognitive engine responds to the operator's commands by configuring the radar for whatever mode of operation, operating frequency, waveform, or signal is required.

The conceptual model proposed consists of observing, planning, learning, decision making and acting states is illustrated in Figure 2.1.

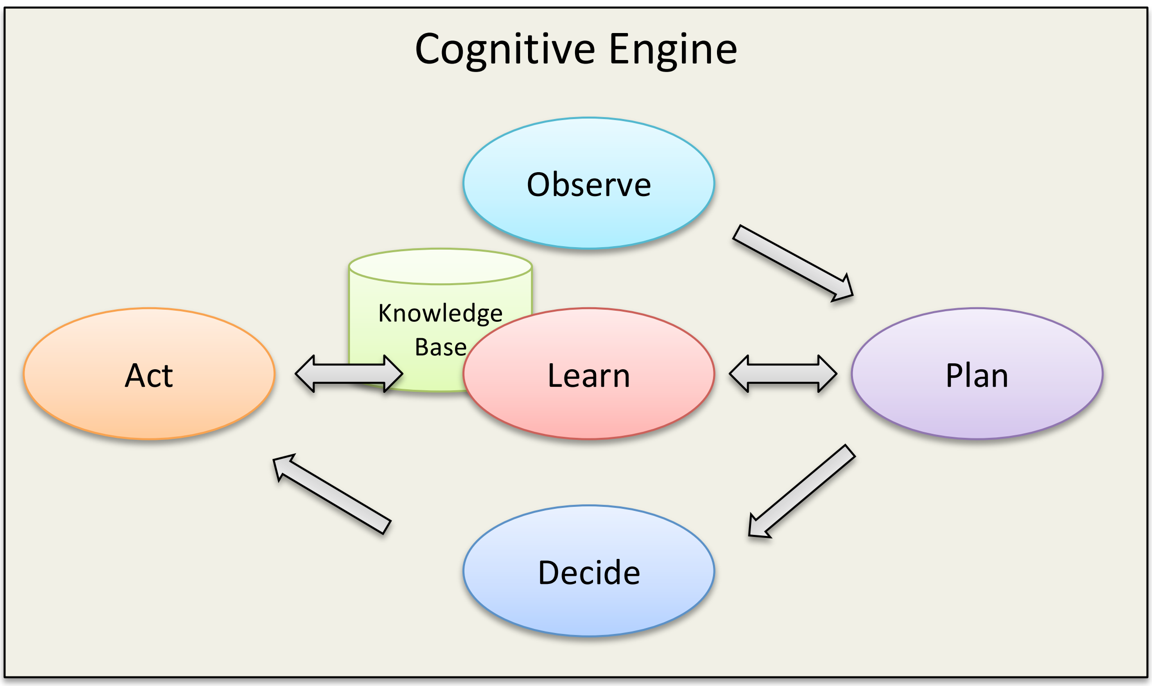

Figure 2.1: Cognitive Engine Cycle.

The cognitive engine should be in control of the radar, deciding whether there is a target, what the alternative actions are, deciding which is appropriate, and performing the most appropriate actions. The cognitive engine has rules, priorities, and actions.

As shown in Figure 2.1, the cognitive engine executes the loop from the Observe state to the Act state continuously and the cognitive information flows to form a complete cognitive loop. The loop starts with the "Observe" state were the radar "observes" information about the environment. "Plan"

state produces objectives according to the radar's needs and current environment. The "Decide" state identifies objectives and executes the appropriate algorithms. The "Act" state implements the result of the decision and changes the radar accordingly. These changes are observed again, when entering the next cycle. In the "Learn" state, the radar obtains knowledge from experiences and stores the knowledge in the knowledge base to guide the execution of the "Decide" state.

3.2 Cognitive Engine Key Technologies

The cognitive engine is a placeholder for all intelligent technologies that make it cognitive radar. The cognitive engine integrates methods and algorithms for implementing functions of the cognitive cycle. The implementation of these functions requires a variety of intelligent technologies: neural networks, knowledge representation, machine learning, knowledge-based, case-based reasoning and fuzzy logic that have been applied successfully in building cognitive engines [He10]. The key of cognitive radar is learning, which is accomplished by implementing machine learning technology in the cognitive engine. Machine learning is a vast field with many options to choose from in deciding the architecture of the cognitive engine. Neural networks, and Bayes learning are common techniques, but there is currently no standard for cognitive radar learning. A major consideration is also the choice of knowledge representation, and how well the learning algorithm is situated to work with the knowledge base.

The knowledge base stores the general knowledge related with the radar such as deduction of parameters like a target's range, velocity, and RCS. This knowledge is used for the reasoning process. The knowledge base stores the observed data of the environment and the characteristics of the targets. These data are the object for learning and the basis for implementation of learning.

Case-based reasoning involves obtaining solutions for new issues based on past experiences and cases. It works similar to an expert system that uses the knowledge base to make intelligent decisions. The system obtains knowledge from experiences and updates the knowledge base. It performs matching and selection on the contents in the rule-base and case-base. Machine reasoning algorithms include rule-based system, case-based reasoning, artificial neural networks, fuzzy logic, and genetic algorithms.

Learning involves obtaining new knowledge, and identification of current knowledge, to improve the performance. This, in a nutshell, is the capability of learning from experiences, and is the most important feature of cognitive radars. Artificial neural networks can be used for solving complex problems that are chaotic, or difficult to model, because they are mainly inspired by human brain. A human brain is capable of computationally demanding perceptual actions, has indefinite information processing, and is a collection of 10 billion interconnected neurons that forms a parallel information processing system. The brain learns by altering the strengths of connections between neurons, and by adding, or deleting, connections between neurons, and these connections can be modified, based on experiences. Artificial neural networks are made up of interconnecting artificial neurons that mimic the properties of biological neurons by imitating certain aspects of information processing in the brain, in a highly simplified way. A key feature of neural networks is an iterative learning process. The learning in a neural network is defined by the change of weight values between neurons. In order for the cognitive engine to learn and make intelligent decisions, it must acquire, store, and learn from knowledge.

The cognitive engine's primary task is to optimize some important metric of the radar, and it does so by continually attempting to improve its performance by making decisions based on what it has learned over time.

Chapter 4

Artificial Neural Network System for Target Recognition

The objective of cognitive radar in this research is to provide the intelligent system with the capability to not only detect, but also recognize, and classify targets in the appropriate class. The application in this research is surveillance radar that is capable of detecting the different targets listed in Table 2.1: air and land targets.

The classification of the targets is performed using an artificial neural network trained with high-resolution images of these classes. The automatic recognition can be implemented using artificial neural networks because they have proven capable of correctly classifying objects based on noisy images [Rot90, Rog95]. Moreover, there are multiple examples in which neural networks have played an integral part in controlling complex electromechanical systems [Fei12, Qiu10, Gut09, Cha08, Sha09]. An artificial neural network is defined as an interconnected group of artificial neurons that uses a computational model for information processing and performs useful computation through a process of learning to obtain knowledge [Hay94]. The knowledge obtained is stored using interneuron connection strength, commonly known as synaptic weights. A learning algorithm is a function that modifies the synaptic weight of the network in an orderly fashion and is used to perform the learning process and to obtain a desired design objective. Once the optimal operation mode has been determined, its parameters are fed into a neural network that determines the type of object being detected by the radar. Figure 4.1 shows the simplest case of the neural network, which is the feed forward architecture, where a set of system inputs is multiplied by a set of adjustable weights that are then fed into a set of processing elements, which produces a set of outputs. The outputs are then fed into another layer of weights that feeds another layer of processing elements to produce the final output of the neural network.

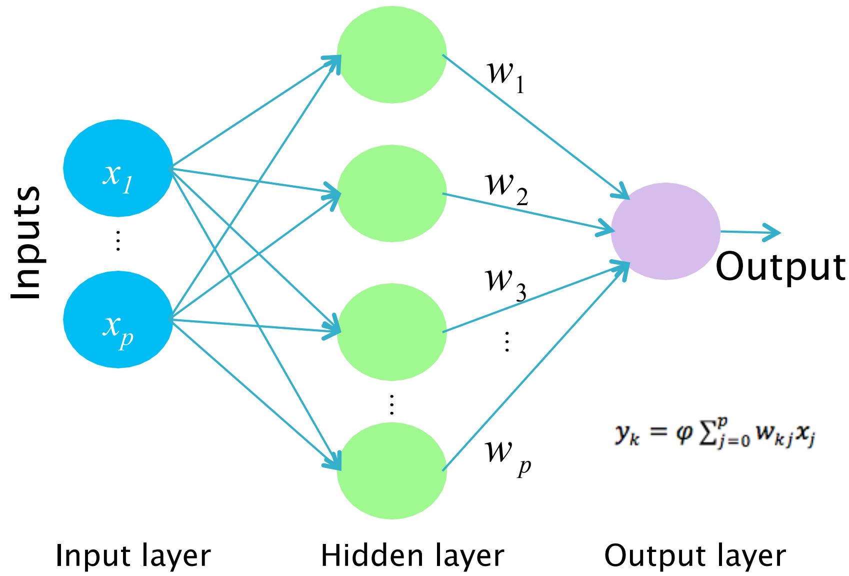

Figure 4.1: Neural Network Structure.

The output of the k^th^ neuron is defined by

$$y_k = \varphi\left(\sum_{j=0}^{p} w_{kj} x_j\right) \tag{4.1}$$

where:

ϕ	is the transfer function,
p	is the number of neuronal synapses, or inputs,
x_j	are the input signals, and
w_{kj}	are the synaptic weights of neuron k.

The model of a neural network to classify the targets included in this research is shown in Figure 4.2. This model is based on a feed-forward neural network that consists of a single hidden layer with 60 neurons in the hidden layer, a tangent sigmoid as the transfer function, and a linear function in the output layer. The input vectors consist of 2-D images of the air and land targets, which are pre-processed and transformed into a one-dimensional vector before being presented to the neural network. There is only one target value associated with each input vector. The target output is the corresponding classification of the target shown in the 2-D image.

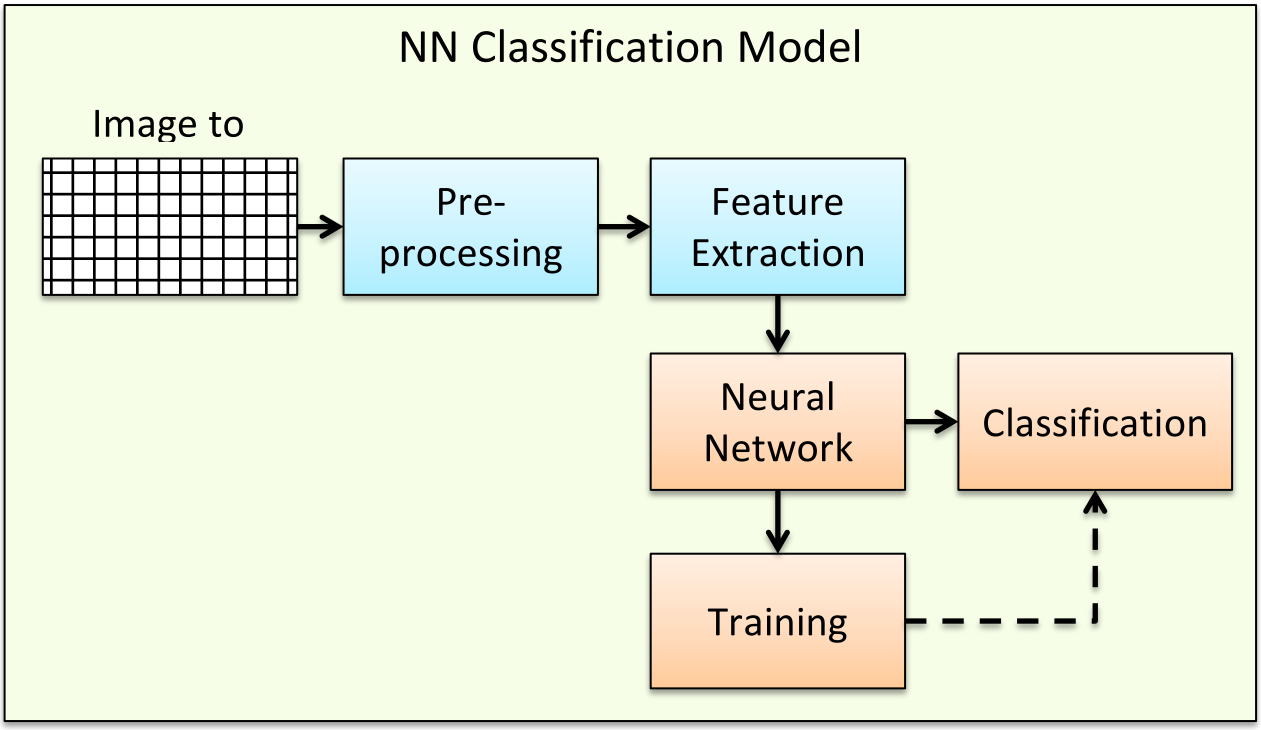

Figure 4.2: Neural network classification model.

4.1 Radar Target Detection Simulation and Results

It is assumed that the air and land vehicles are in the radar line of sight. It is also assumed that 20dB SNR is a reasonable detection threshold. The vehicles have the maximum Doppler frequency, since the targets are in the radar's line of sight. The system uses typical and different waveforms for different modes of operations. As mentioned previously, it is assumed that the operation modes are selected appropriately to perform the target detection task. Table 4.1 shows the parameters used for the detection radar system simulation. To test the detection of the target, a sinusoidal signal was used as the transmitted signal. The radar return consisted of this signal with a time delay and noise added to the signal. The MATLAB script was run and if a target was detected, the range of the target was determined from the time delay between the transmitted and the returned signal.

Table 4.1: Radar System Parameters.

Symbol	Description	Value
F_o	Carrier Frequency	1 GHz
F_p	PRF	10 kHz
Δf	Stepped Frequency step size	5 MHz
N	Number of stepped frequency steps	512
M	Number of burst for ISAR processing	100
τ	Pulse width	0.1 μsec

For this study, the intent is to develop a radar system that operates with a 90% probability of detection and a probability of false alarm of 1E-6. That is, the probability that a target was detected in the presence of noise. The probability of false alarm was minimized so that the target is found when noise is present. To achieve the specified performance, the signal to noise ratio (SNR) was obtained. A simulation was performed in MATLAB and a signal was successfully detected using the procedure described below. The general detection performance of the radar is addressed in the previous section. A detailed example of a single target detection is provided. Presenting the complete detection processes for a single target will not only help to clarify the radar theory, but will also help in understanding how the detection elements produce the information necessary to feed the neural network in charge of classifying the target. Although the results shown in this subsection are for a Cessna airplane, they illustrate the process followed to detect the other types of targets. The reader should keep in mind that there are many detection techniques and the procedure described in this section is just one of them.

To obtain the range profile, matched filtering of the returned signal, using a simulated version of the transmitted pulse, was performed. The inverse synthetic aperture radar provides high-resolution maps of remote targets, like a terrain. ISAR is used to provide target images, like those of aircraft or land vehicles. In order to simulate the Cessna, various point scatterer models of a Cessna will be used as the targets from which signals will be received by the radar and

processed using stepped frequency and ISAR techniques. MATLAB is used to simulate the target returns. The Cessna scatterers are computed in Cartesian coordinates manually on paper. The radar is located at the origin. Amplitudes for the scatterers are varied according to their orientation to the radar, to simulate a more realistic target. An equation is established for the range of each hotspot. 18 hotspots are used, as shown in Figure 4.2, in order to visualize the Cessna by adding the distance between each hotspot to the reference point. These points realistically represent the dominant scatterers from the Cessna. A 2-D image provided by the ISAR for a Cessna airplane is shown in Figure 4.3. The 2-D image of the target is mapped using the HRR and Doppler profiles.

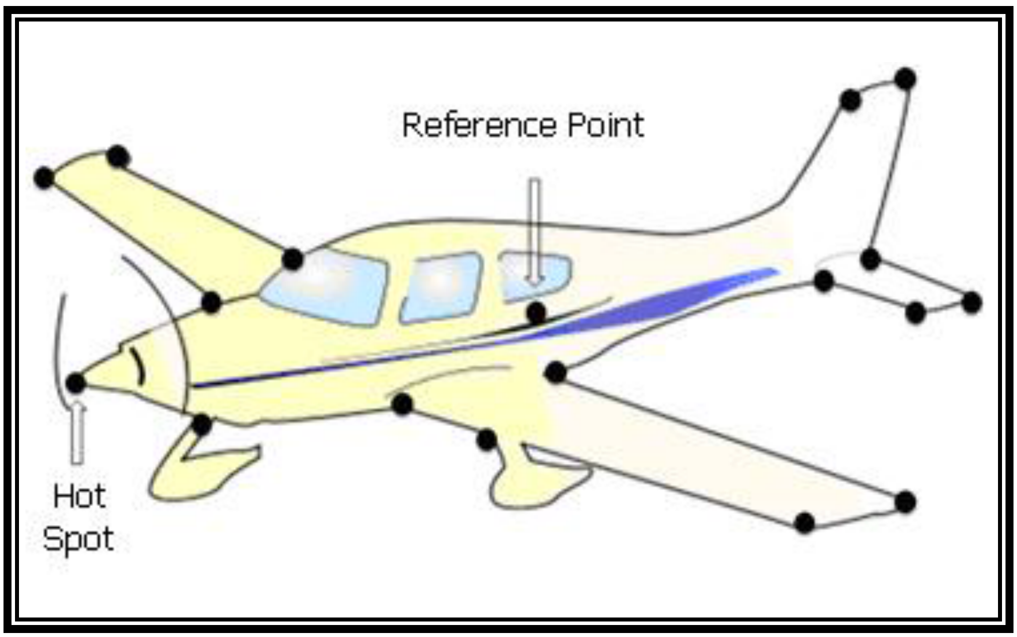

Figure 4.3: Cessna image.

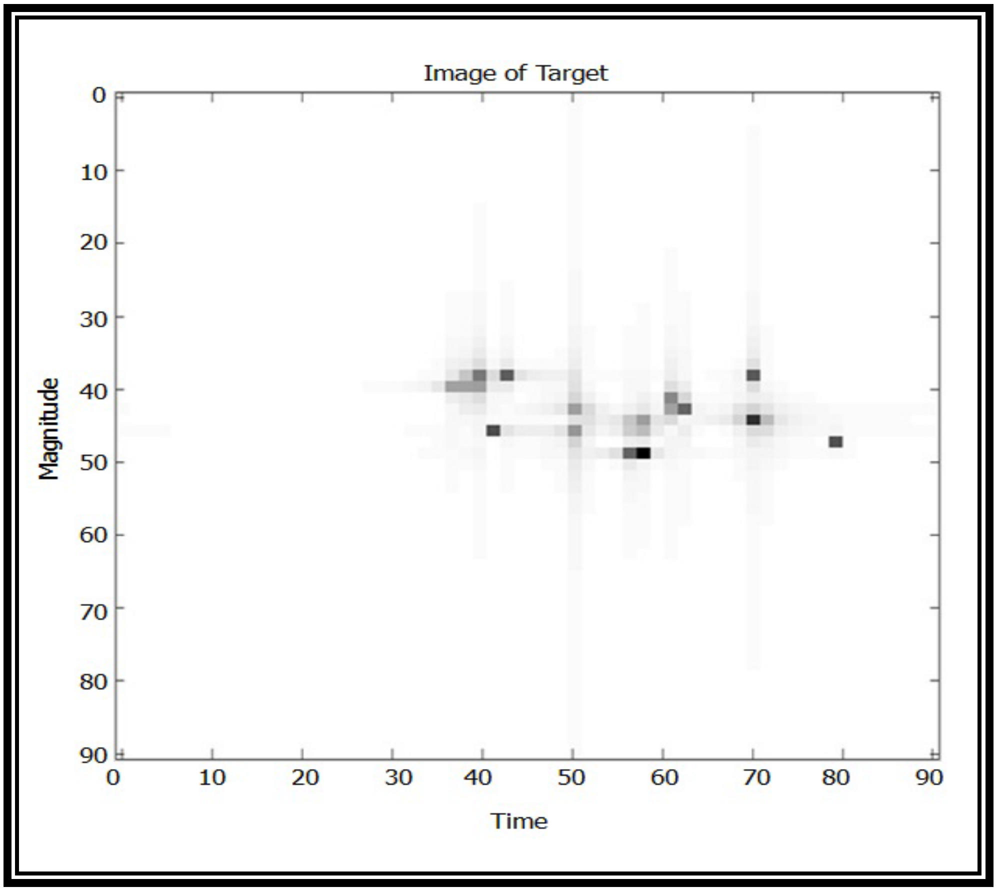

Figure 4.4: Cessna 2-D image.

4.2 Artificial Neural Network Implementation

Once the target has been detected using the information provided in Figure 4.3 and Figure 4.4, a neural network is implemented, in MATLAB, to classify the objects based on the ISAR's 2-D image. Each figure is represented by a 60 by 60 matrix, in which each of the 3600 input values represent the range profiles. The dataset used for the training and testing of the neural network consisted of 40 images for each of the four types of objects. Each image has a different signal-to-noise-ratio for the returning signal. For each of the classes 17.5% of the original dataset is reserved for testing. The network uses the Levenberg-Marquardt algorithm [Hag94] for training, due to its superior speed and performance compared to the classic back-propagation algorithm. MATLAB's Neural Network toolbox includes these training algorithms and hence is unnecessary to develop custom programs to implement them. To find the optimal number of hidden neurons for the neural network, an exhaustive search was performed over a wide range of possible values. Although preliminary experiments include as few as two or five

neurons, and as many as 100 hidden neurons, it is fairly clear that the best performance is obtained by setting the number of hidden neurons in the range shown in Table 4.2. Given the results presented in this table, 60 hidden neurons are used for the test set.

Table 4.2 shows the percentage of correct classifications for different numbers of hidden neurons for each of the target classes. The classification performance for the different types of targets is shown in Table 4.3, with the percentages of correct classifications highlighted in yellow.

Table 4.2: Percentage of correct classifications.

Target\# of Hidden Neuron	50	55	60	65
Cessna (1)	97%	94%	97%	90%
Truck (2)	97%	93%	96%	90%
Helicopter (3)	78%	78%	84%	90%
Plane (4)	96%	93%	96%	90%
Overall	**92%**	**90%**	**93%**	**90%**

Table 4.3: Classification for each of the target classes for the test sets.

NN Classification \ Actual Class	Truck	Cessna	Helicopter
Truck	**83%**	29%	14%
Cessna	17%	**71%**	0%
Helicopter	0%	0%	**86%**

A direct comparison with the correct classification rates provided using other methods (Table 4.4) is not possible, given that this is the first time that this set of targets has been used. Both land targets

can be correctly identified more than 80% of the time, which is a performance similar to those studies that deal exclusively with land targets [Ala08, Bil06, Li10]. Another set of desirable characteristics of the neural network produced for this research is that vehicles are never mistaken for pedestrians, and pedestrians can only be mistaken for other land targets.

Table 4.4: Comparison of performances with other automatic radar recognition systems.

Target	Performance
Commercial aircraft [Zyw96]	96%-98%
Tanks [Li10]	96%
Pedestrians, animals, tracked or wheeled vehicles and clutter [Bil06]	88%-96%
Military vehicles [Ala08]	88%-91%
Border surveillance	80%
Pedestrians, planes and boats [Mah05]	67%
Pedestrians, wheeled and tracked vehicles (human performance) [Bil06]	39%

More importantly, the overall performance is far superior to the human performance mentioned in [Bil06] and to the performance reported in [Mah05], which are the only other studies that include a combination of objects that operate in land and air. These results show that this dissertation research not only presents an original contribution (addressing the border surveillance environment for the first time), but also that the approach selected and its implementation compare well against others' works in the research area of radar target classification.

In summary, a radar system for sending and receiving signals reflected from objects commonly encountered in a border surveillance environment (Cessna airplanes, trucks and pedestrians) is then simulated in MATLAB. The returning signals contain noise, making the detection and identification of the target difficult. The cross-correlation of the returned signal is accurately calculated, providing the

information necessary to assess if the target was successfully detected. The spectrum of the autocorrelation of the signal is also obtained and then used by the ISAR technique to obtain 2-D high-resolution images of four different types of targets relevant to border surveillance. The target classification of the images is implemented using neural networks trained using the Levenberg-Marquardt algorithm. The classification rates are better than those reported for human operators, proving the potential of the proposed approach to alleviate the problems caused by the unreliability of manned radar systems.

Chapter 5

Fuzzy Logic System

Fuzzy logic and fuzzy sets are effective tools for modeling complex problems. Because of their model-free, granulation, and approximation capabilities, these techniques do not need a mathematical model of the system in question, which may be difficult, if not impossible, to obtain for complex systems [Jai99]. Fuzzy set theory proposed by Zadeh [Kli96] can deal with the vagueness and uncertainty residing in the knowledge possessed by human beings or implicated in numerical data, and allows representation of the system parameters with linguistic terms.

An expert cannot, usually, express his or her knowledge in precise numerical term such as “50 mph is fast”, but can formulate knowledge by using words from natural language. For example, an expert can say, “the speed is fast” for a given speed. So the knowledge that can be extracted from an expert consists of statements that include descriptors like “slow,” “most probably,” etc. For that reason, linguistic variables play an important role in fuzzy logic; they are usually defined as fuzzy sets with appropriate membership functions. Values corresponding to the degree of membership within a fuzzy set are then used for system input and output, and are represented by words or sentences. A fuzzy set is created to describe the linguistic variables in more detail. The linguistic variable “speed,” for example, may have overlapping categories of “slow,” “fast,” and “average”. Once these categories are defined, the fuzzy set is obtained, and a membership function is then developed for each category in the set.

By definition, an expert is a person who is extremely knowledgeable about the subject. The role of the knowledge engineer is to elicit the knowledge of interest from the experts and to express it in some operational form of a required type. It is therefore desirable to develop a computer program that can incorporate the expert knowledge and give advice comparable in quality with the advice of the expert. There are different approaches to extracting knowledge from experts in order to build up a rule-based system.

Most decisions that experts make are logical decisions, in which they look at the situation and make a logical decision based on the situation. The generalized form of such a decision is a collection of IF-THEN statements that describe the desired effect, and which are in the form:

If X, Then Y

X

Therefore, Y

The IF-THEN format of the rules makes it easier for a problem-solving expert to verbalize his insights, which can then be encoded in software. As many rules as necessary can be supplied in order to describe the decision-making process adequately. Fuzzy logic is designed to deal with reasoning that is approximate rather than accurate. Rules are usually expressed in the form:

If X, Then Y

mostly X

Therefore, mostly Y

The reasoning with fuzzy logic requires a set of rules to be defined. Fuzzy logic principles will be used for decision-making. A fuzzy logic system for processing information that uses a collection of fuzzy membership functions and rules will be used to reason about data obtained from the radar.

The fuzzy logic system is implemented using the MATLAB Fuzzy Logic toolbox to aid the intelligent system with decisions, which the radar needs in order to perform, based on the radar objectives and priorities.

A typical configuration of a fuzzy inference system (FIS) is shown in Figure 5.1 [Men95]. A fuzzy inference system is the process of formulating the mapping of a given input to an output using fuzzy logic. The mapping provides a basis from which decisions can be made.

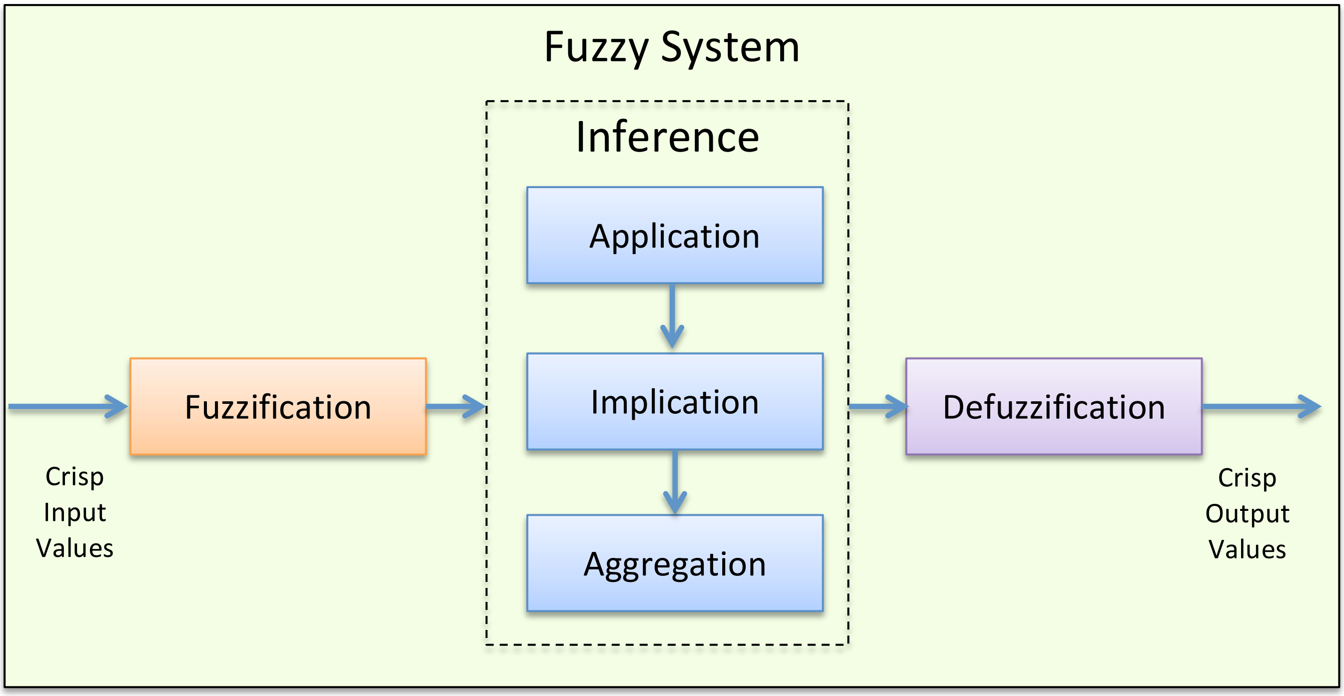

Figure 5.1: Fuzzy System.

5.1 Operation Stages in Fuzzy Inference Systems

5.1.1 Fuzzification Process

Exact values are referred to "crisp" values, to differentiate from the values in fuzzy sets. The fuzzification process defines fuzzy sets and determines membership degrees of crisp inputs in appropriate fuzzy sets. Input data are most often crisp values. The task of the fuzzifier is to map crisp numbers into fuzzy sets. As is pointed out in [Zad65], this relationship rests on the facts that in most real situations, the question is not "whether" a given object is or is not a member of a group, but "the degree to which" the object belongs to that group. A fuzzy set can be considered as a generalization of classical, or crisp, set theory [Lin96] in which the degree of membership for each element, binary in crisp set theory, is allowed to range over the unit interval [0,1]. A fuzzy set is a set without a crisp boundary to its membership function.

A fuzzy set is completely characterized by its membership functions. To define a membership function is to express it as a mathematical formula. There are different classes of parameterized functions that can be defined by a small number of parameters. These parameterized functions are

commonly used to define membership functions of one dimension, which are membership functions with a single input. There are several parameterized membership functions, such as the triangular, trapezoidal, Gaussian, sigmoid and the bell-shaped. The triangular and trapezoid membership functions are the most commonly used in practice, for their simplicity. A membership function is intended to approximate a smooth transition between two regions of membership, the region completely outside the set and that completely inside the set.

5.1.1.1 Membership Functions Development

The membership functions are used to translate real conditions into fuzzy logic values. The input values obtained from the radar measurements are defined as input variables and are represented by fuzzy membership functions. The modes of operation are represented by output variables. Different membership functions were created for the target's RCS, distance, speed, and the radar mode of operation. Membership functions are given in the figures below.

1) RCS

   The RCS membership function is a three-pronged triangular membership function representing the target's RCS that are low, medium, and high.

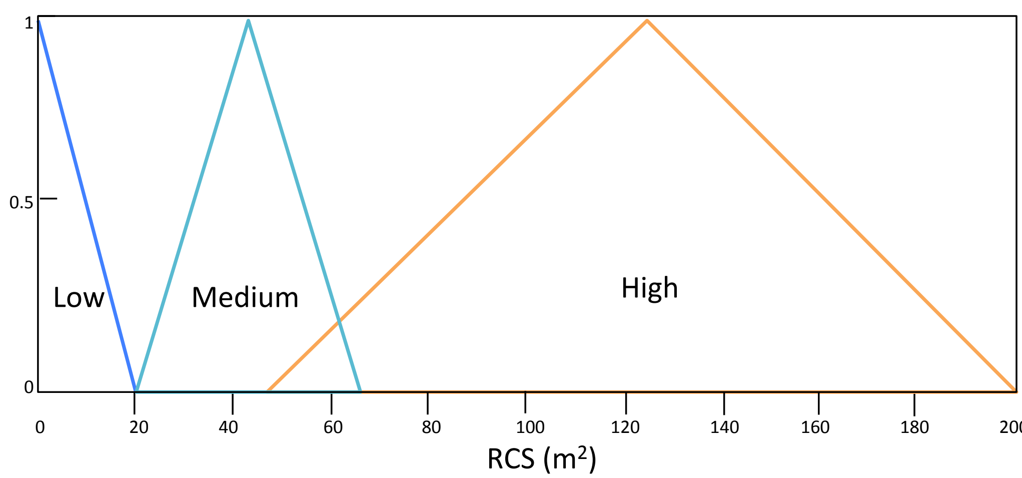

Figure 5.2: RCS Membership Functions.

2) Distance

The distance membership function is a three-pronged triangular membership function representing target's position that are close, medium, and far from the radar. The radar maximum range is 5000 feet.

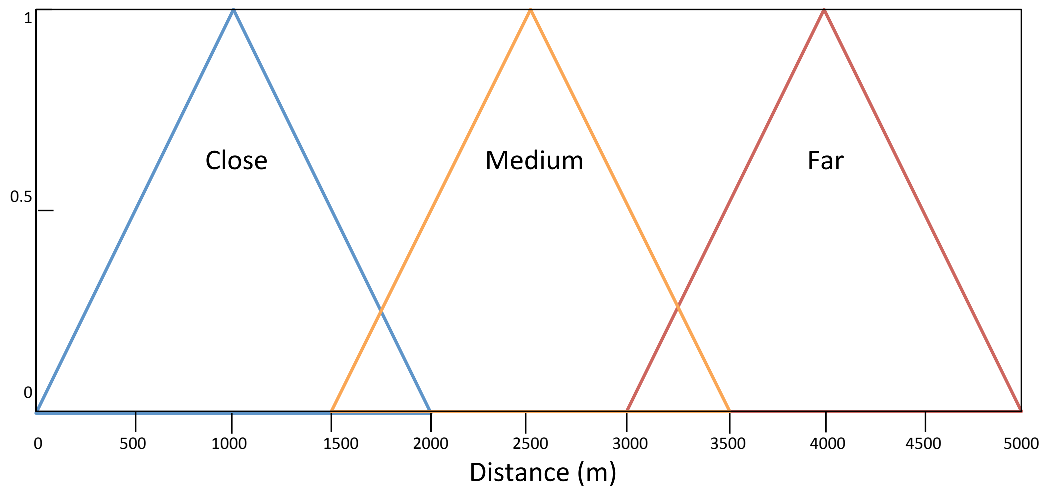

Figure 5.3: Distance Membership Functions.

3) Speed

The speed membership function is a one-pronged triangular and two trapezoid membership function representing target's velocity that are slow, average, and fast. The speed assumption for the objects been used in this process are as follows:

Table 5.1: Target Speed.

Targets	Speed (mph)
Truck	180
Car	150
Cessna	188
Helicopter	200

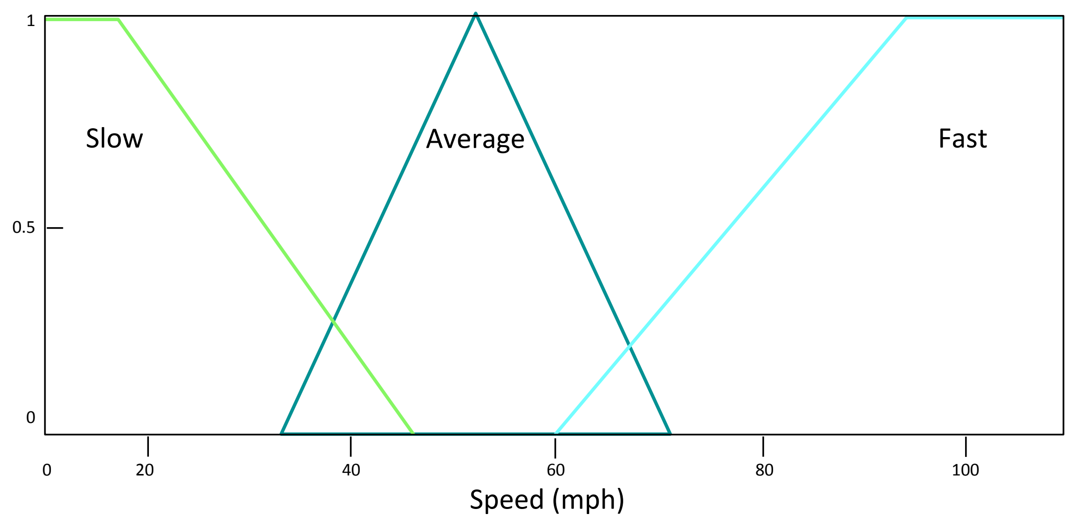

Figure 5.4: Speed Membership Functions.

4) Radar Mode of Operation

   The radar mode membership function is a four-pronged triangular membership function representing radar mode of operation that are Detection/Estimation Mode, Doppler Mode, High Resolution Mode and ISAR Mode. The Detection/Estimation Mode is when the radar detects and estimates the target's range. Doppler Mode is the target's speed estimation. High Resolution Mode is the 1-D image of the target and ISAR Mode is for the target's 2-D image.

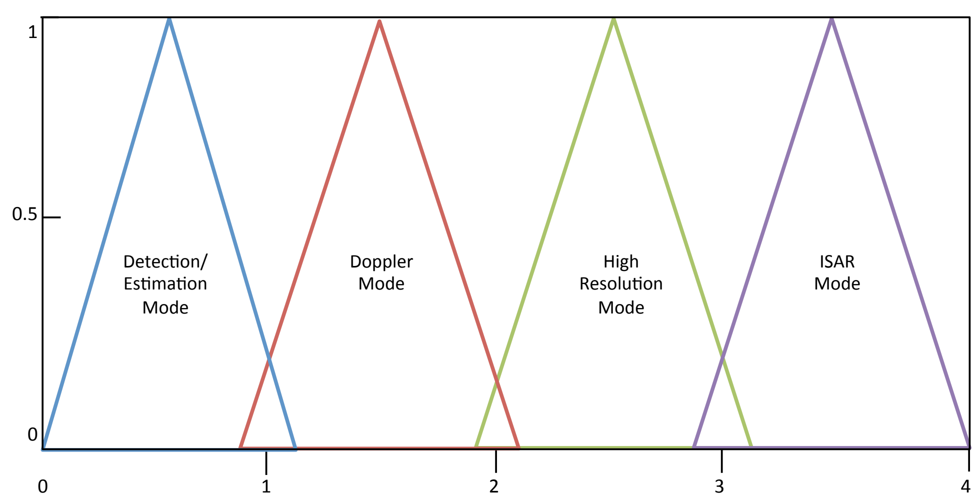

Figure 5.5: Radar Modes Membership Functions.

5.1.2 Inference Process

The inference process is divided into application, implication and aggregation. In the application process, the conjunctive method (MIN) is used. In the implication process, the truncation method is used and in the aggregation process, the disjunctive method (MAX) is used.

5.1.3 Defuzzification Process

The defuzzification process calculates the crisp output. This step could be optional, since it is useful for converting the fuzzy output to a crisp number. The centroid method is the most commonly used method, which is used in this dissertation. In the centroid method, the crisp value of the output variable is computed by finding the value of the center of gravity of the membership functions for the fuzzy value.

Defuzzification can be obtained by calculating the center of gravity (COG):

$$COG = \frac{\int_a^b \mu_A(x)x dx}{\int_a^b \mu_A(x)dx} = \frac{\sum_{x=a}^b \mu_A(x)x}{\sum_{x=a}^b \mu_A(x)} \tag{5.1}$$

5.2 Rule Base Model

Several rules constitute a fuzzy rule-based system. Fuzzy rules are a collection of IF-THEN statements that describe how the system should make a decision regarding classification of an input or control of an output. The fuzzy rule uses IF-THEN statements, such as

If speed is SLOW AND distance is CLOSE, then the radar should operate in ISAR mode.

where the *speed* and *distance* are the input variables, *ISAR Mode* is an output variable, *SLOW and CLOSE* are membership functions defined on the respective input variables.

In fuzzy rule-based systems, the rule base is formed with the assistance of human experts. A fuzzy rule states in what situation which action should be taken.

The MATLAB Fuzzy Logic Toolbox is used for the software implementation of the rule base. A detailed algorithm to implement the rule base for decision-making is shown in Figure 5.6. The algorithm starts by creating a rule-base table based on the number of inputs and outputs, as well as the

number of linguistic values for each input and output, as shown in Table 5.2. The output value for each possible combination of input linguistic values should also be obtained; in this case the radar mode which will be displayed by the system. All the fuzzy inference system information such as variable names, RCS, Distance, Speed, and Radar Modes and their membership functions should be entered. The fuzzy rule-based system is then created with 27 rules from the combination of the number of inputs and outputs in order to make decisions about the radar priorities and the next course of action for the radar. The system evaluates the output of the fuzzy ruled based system for given inputs to obtain the radar mode of operation. The last step of the algorithm is to generate the solution surface for the input values and the defuzzified output values as shown in Figure 5.6.

Table 5.2: Rule base linguistic variables

RCS	Distance	Speed	Radar Mode
Low	Close	Slow	Detection & Estimation
Medium	Medium	Average	Doppler
High	Far	Fast	High Resolution
			ISAR

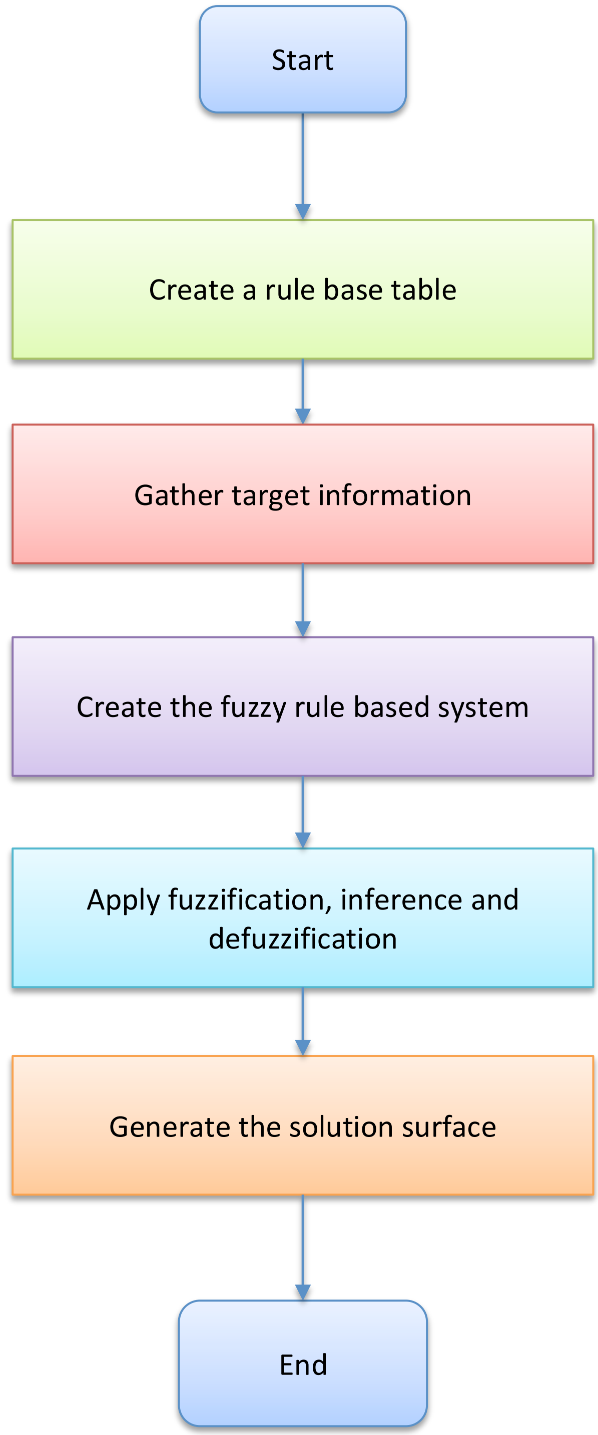

Figure 5.5: Rule Base Algorithm.

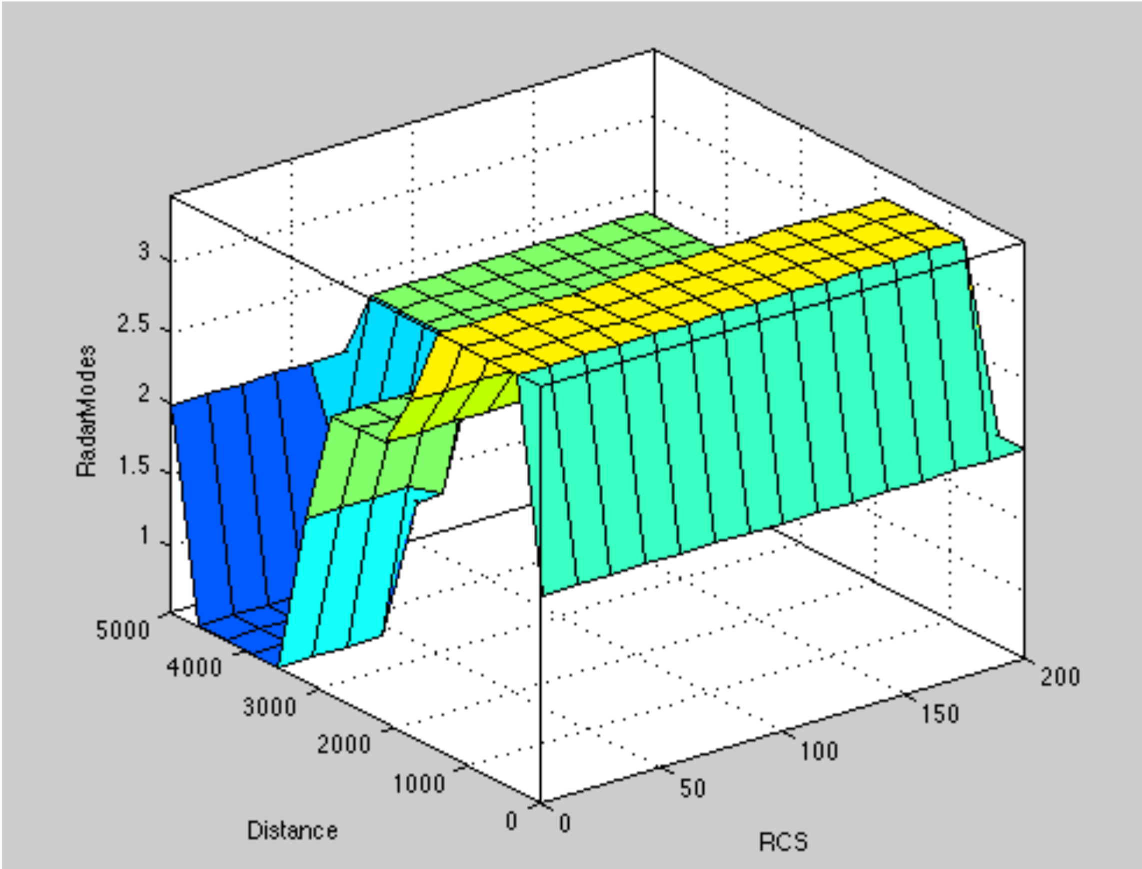

Figure 5.6: Solution Surface.

5.2 Fuzzy Inference Example

Compute the optimal radar mode for the following target's inputs:

[DISTANCE SPEED] = [1550 42] = Radar Mode

Rule1: IF distance is MEDIUM and speed is AVERAGE

THEN Mode is High Resolution Mode.

Rule 2: IF distance is CLOSE and speed is AVERAGE

THEN Mode is ISAR Mode.

The following four steps are performed, in order to obtain the Radar Mode.

Step1: Find the fuzzy set membership values for the input

Step 2: Apply OR operator (max)

Step 3: Apply implication operator (min)

Step 3: Apply aggregation method (max)

Step 4: Defuzzify (centroid)

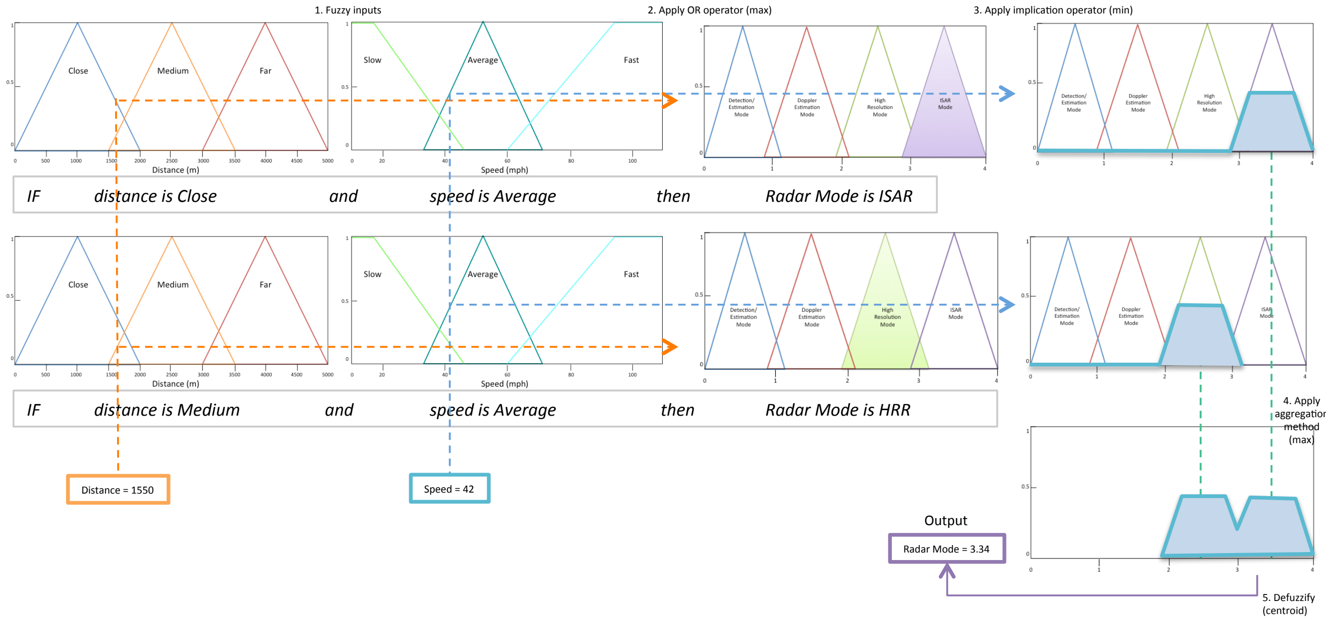

Figure 5.7: Fuzzy Inference System Example.

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Chapter 6

Experimental Results

The main purpose of this chapter is to describe the overall experiment results. The MATLAB Fuzzy Logic Toolbox and Neural Network Toolbox are used for the software implementation of the intelligent system. The details of the system and results are described in the next sections.

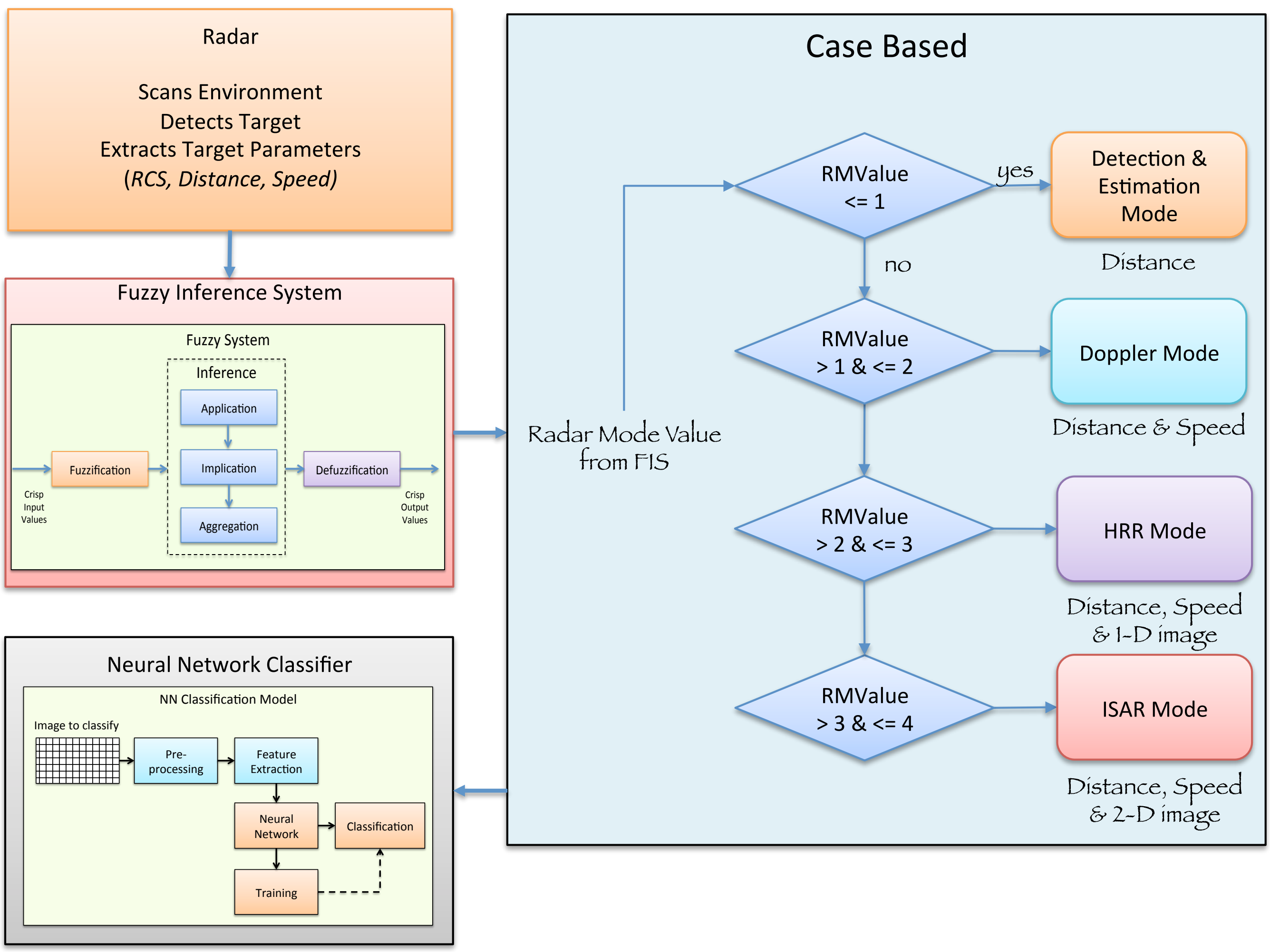

Figure 6.1: Intelligent System Software Implementation.

After the radar scans the environment and detects an object, the radar extracts the target information, such as the RCS, distance, and speed. The target information obtained is then used in the Fuzzy Inference System to evaluate the output. The Fuzzy Inference System outputs the crisp value, which is then used (in the decision-making) to decide and act upon the radar, selecting the mode of radar operation that is appropriate. The classification of the object is done after obtaining the high range resolution profiles.

The Radar System as shown in Figure 6.2 is composed of the following components. The first component is the waveform generator that can be designed based on the environment, targets, and requirements. The transmitted signal is then radiated towards the target and the pulse is propagated and reflected by the target. The receiver then collects the echoes and forms the data, which then will be processed.

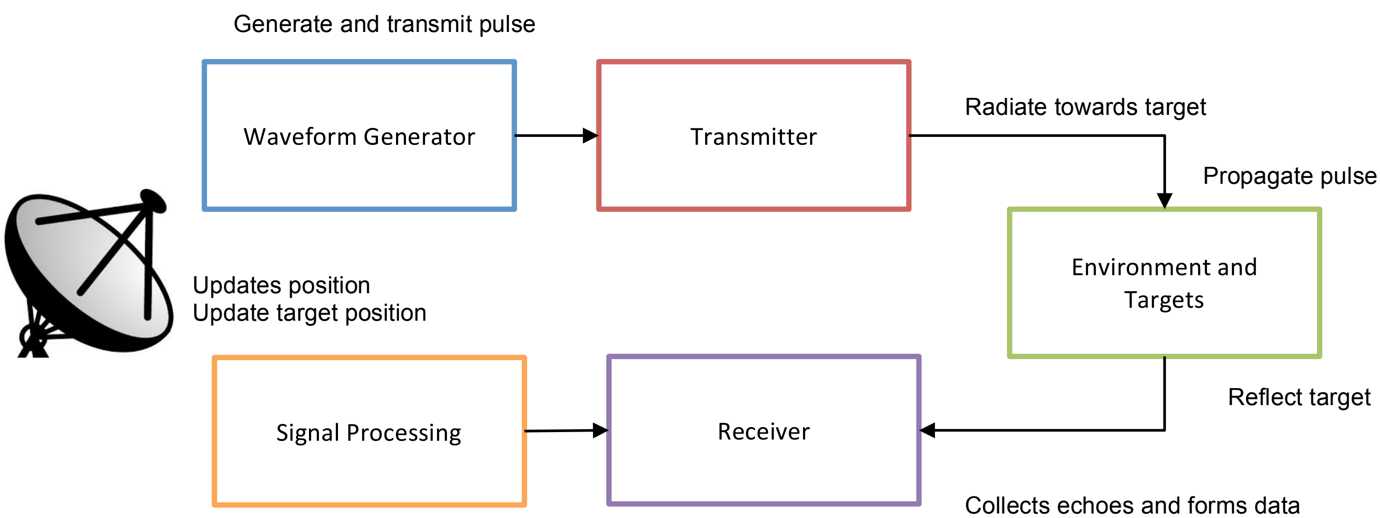

Figure 6.2: Radar System Block Diagram.

6.1 Case Study # 1

6.1.1 The Radar and the Environment for Case Study #1

The radar illuminates its surroundings, like a searchlight, and picks up part of the energy scattered by the objects it illuminates. The transmitter generates a pulse, which hits the target, and produces an echo received by the receiver. By measuring the location of the echoes in time, the range of the target can be obtained. The radar detects targets with at least one square meter radar cross section at

a distance of up to 5000 meters from the radar and a probability of detection of 0.9 and probability of false alarm below 1e-6. The radar scans the environment and detects an object:

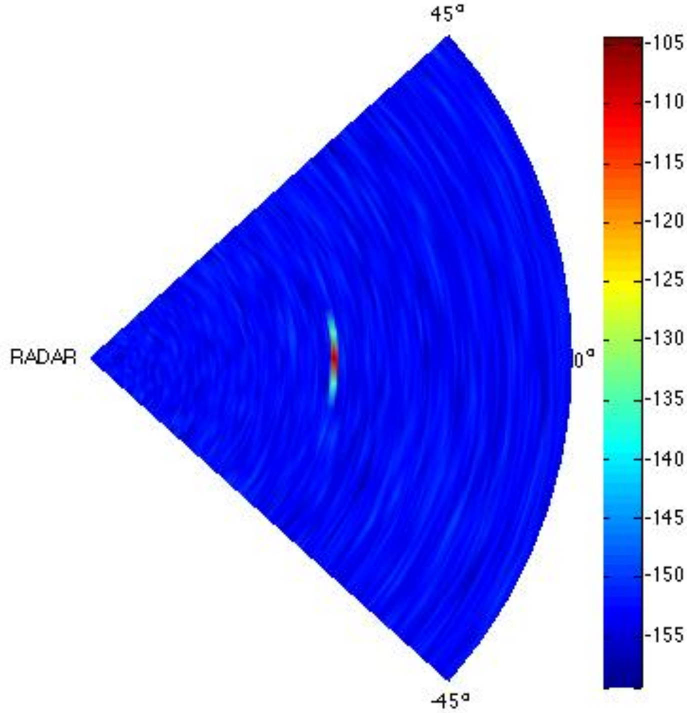

Figure 6.3: Target Detected.

6.1.2 FIS Results for Case Study # 1

The radar detects an object with the following parameters:

Table 6.1: Case Study #1 Parameters.

Target Parameters	Values
RCS (m^2)	1.5
Distance (m)	2501
Speed (m/s)	20

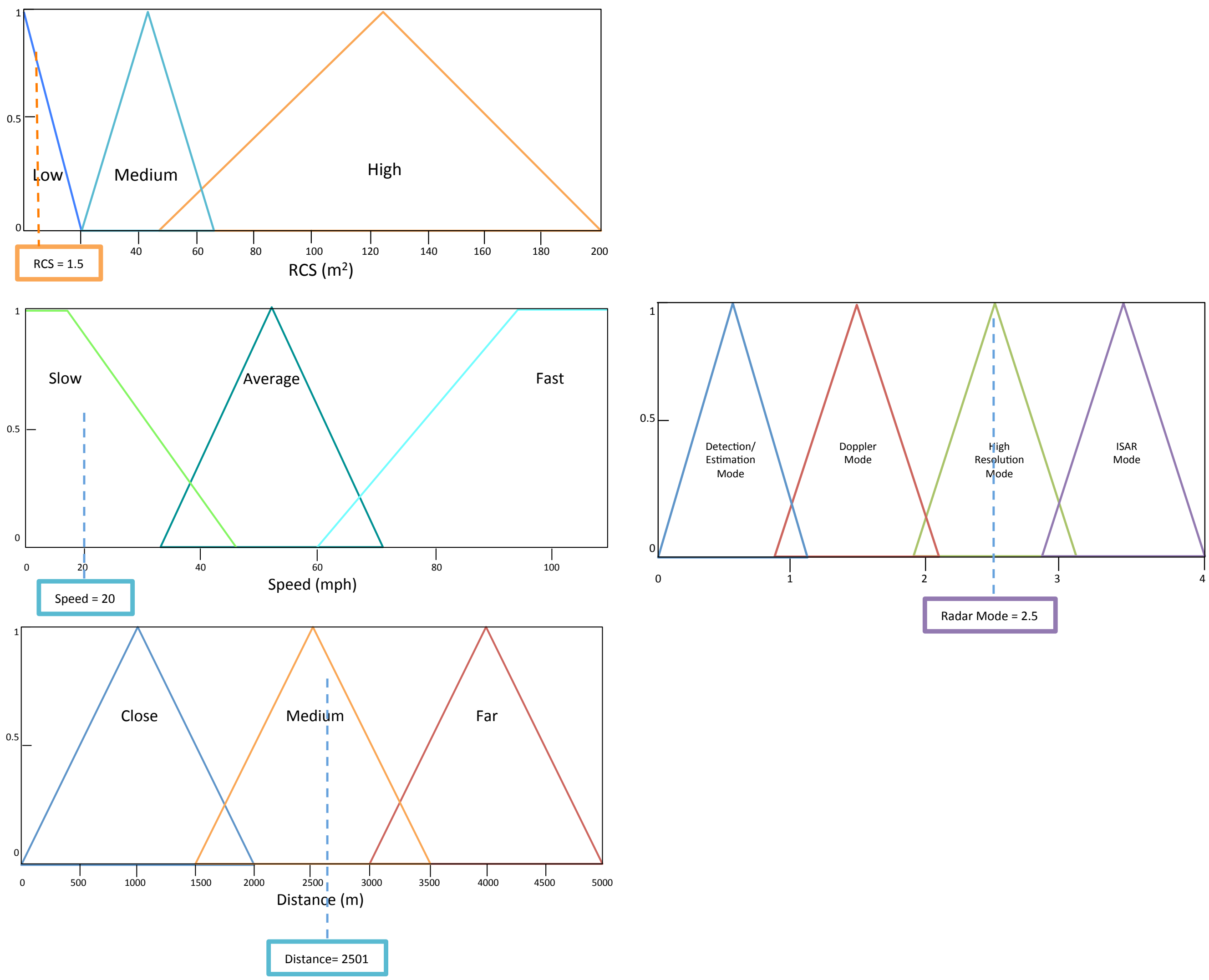

Figure 6.4: FIS Output

The Fuzzy Inference System output is used as the input to the Case-Based decision-making, in this case the Radar should operate in HRR Mode. The HRR Mode obtains the estimated distance and speed as well as the HRR profile of the target as shown in Figure 6.3. Table 6.2 shows the results of the HRR Mode given the input parameters.

Table 6.2: Case Study #1 Results.

	Parameters	Results
ACTUAL	RCS (m^2)	1.5
	Distance (m)	2501
	Speed (m/s)	20
ESTIMATED	Radar Mode	HRR
	Estimated Distance (m)	2525.0
	Estimated Speed (m/s)	19.3
	Approaching/Moving Away from Radar	Approaching

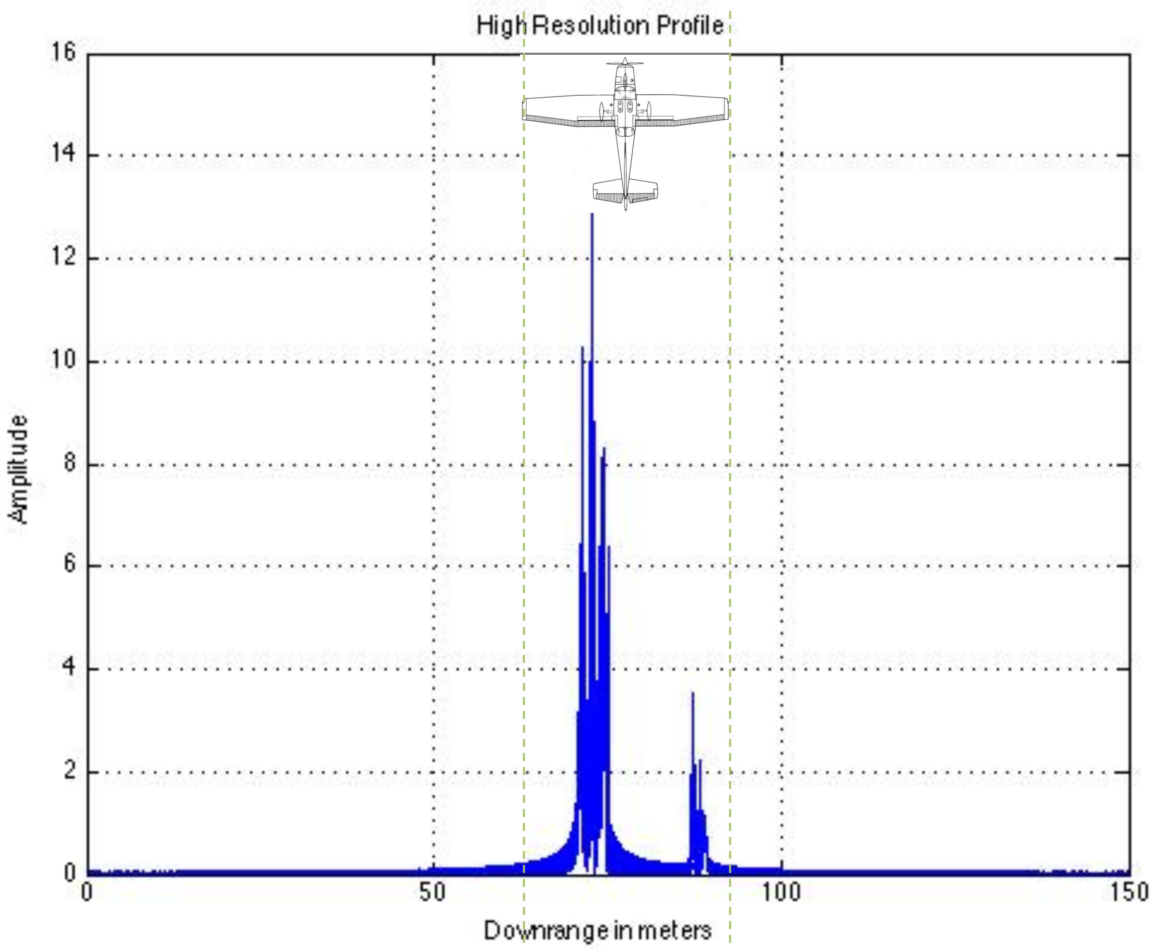

Figure 6.5: High Resolution Profile for RCS = 1.5

6.1.3 Neural Network Classification for Case Study # 1

When the training is complete, the network performance can be checked and determine if any changes need to be made to the training process, the network architecture or the data sets. The epoch indicates the iteration at which the validation performance reached a minimum. Figure 6.5 doesn't indicate any major problems with the training. The validation and test curves are very similar.

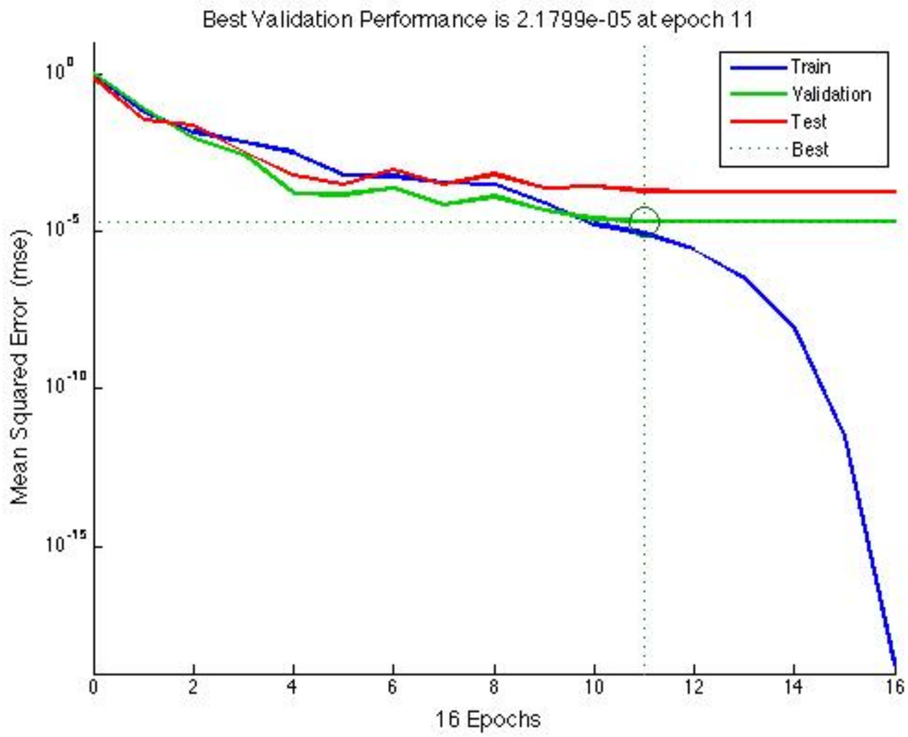

Figure 6.6: NN Classification for RCS = 1.5

After analyzing the neural network performance after training, the target classification takes place. In this case the classification is a Cessna and Figure 6.6 is displayed.

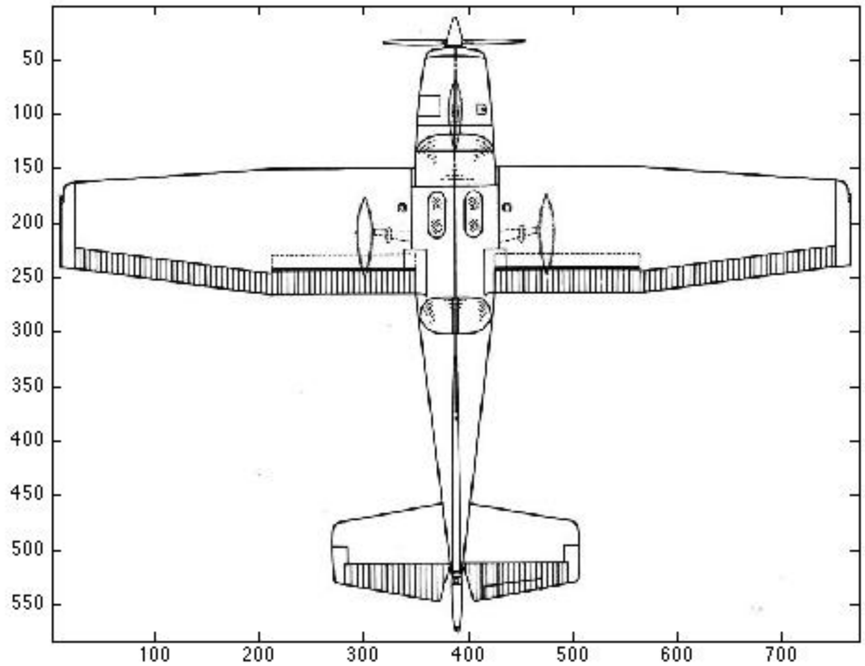

Figure 6.7: NN Classification for RCS = 1.5

6.2 Case Study # 2

6.2.1 The Radar and the Environment for Case Study #2

The radar illuminates its surroundings and picks up part of the energy scattered by the objects it illuminates. The transmitter generates a pulse, which hits the target, and produces an echo received by the receiver. By measuring the location of the echoes in time, the range of the target can be obtained. The radar scans the environment and detects an object:

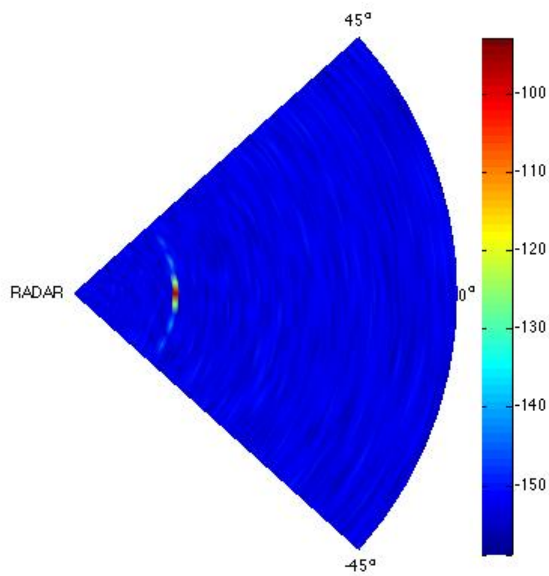

Figure 6.8: Target Detected

6.2.2 FIS Results for Case Study # 2

The radar detects an object with the following parameters:

Table 6.3: Case Study #2 Parameters.

Target Parameters	Values
RCS (m^2)	1.5
Distance (m)	1300
Speed (m/s)	50

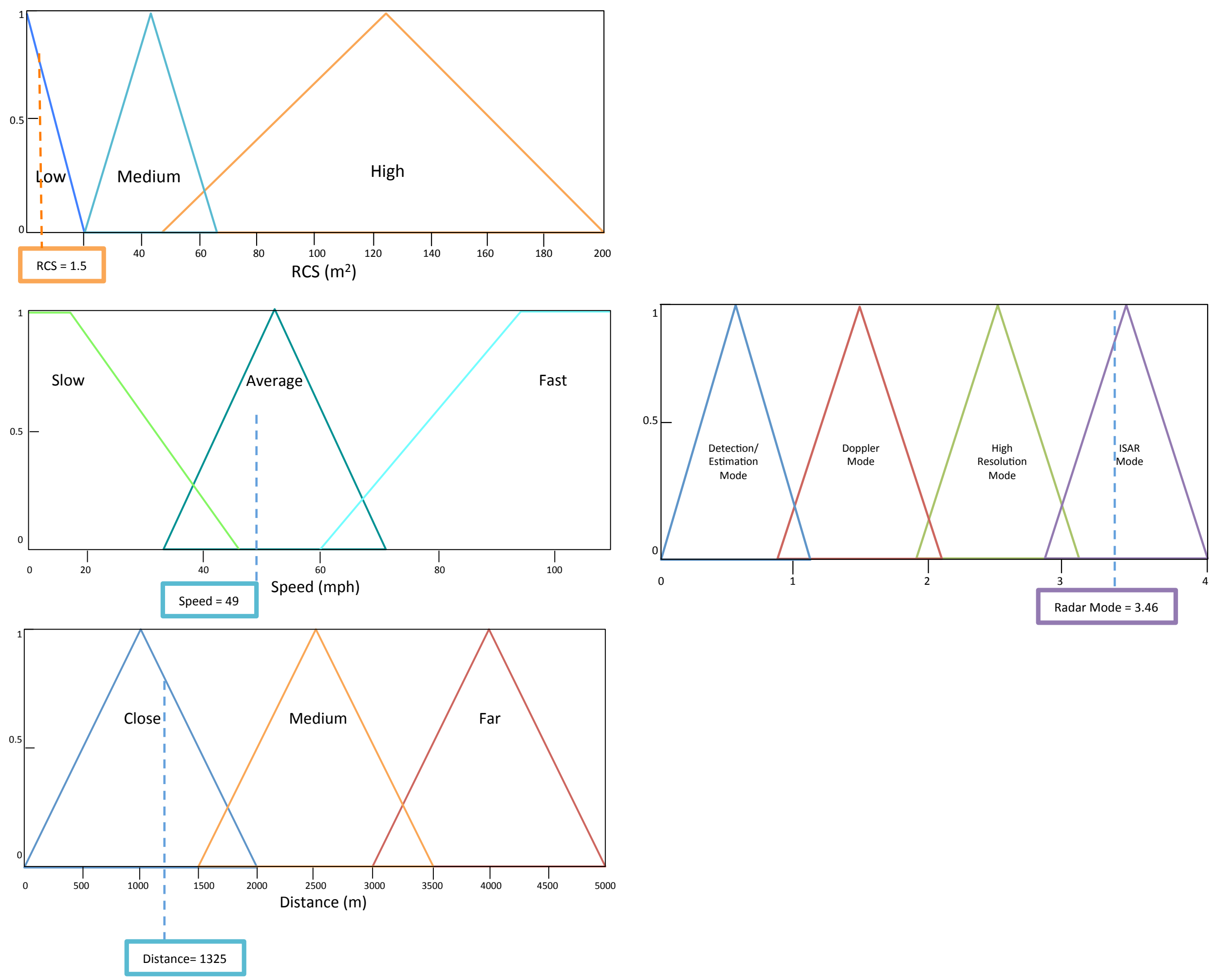

Figure 6.9: FIS Output

The Fuzzy Inference System output is used as the input to the Case-Based decision-making, in this case the Radar should operate in ISAR Mode. The ISAR Mode obtains the estimated distance and speed as well as the ISAR 2-D image of the target as shown in Figure 6.9. Table 6.4 shows the results of the ISAR Mode given the input parameters.

Table 6.4: Case Study #2 Results.

	Parameters	Results
ACTUAL	RCS (m^2)	1.5
	Distance (m)	1300
	Speed (m/s)	50
ESTIMATED	Radar Mode	ISAR = 3.46
	Estimated Distance (m)	1325.0
	Estimated Speed (m/s)	49.2
	Approaching/Moving Away from Radar	Approaching

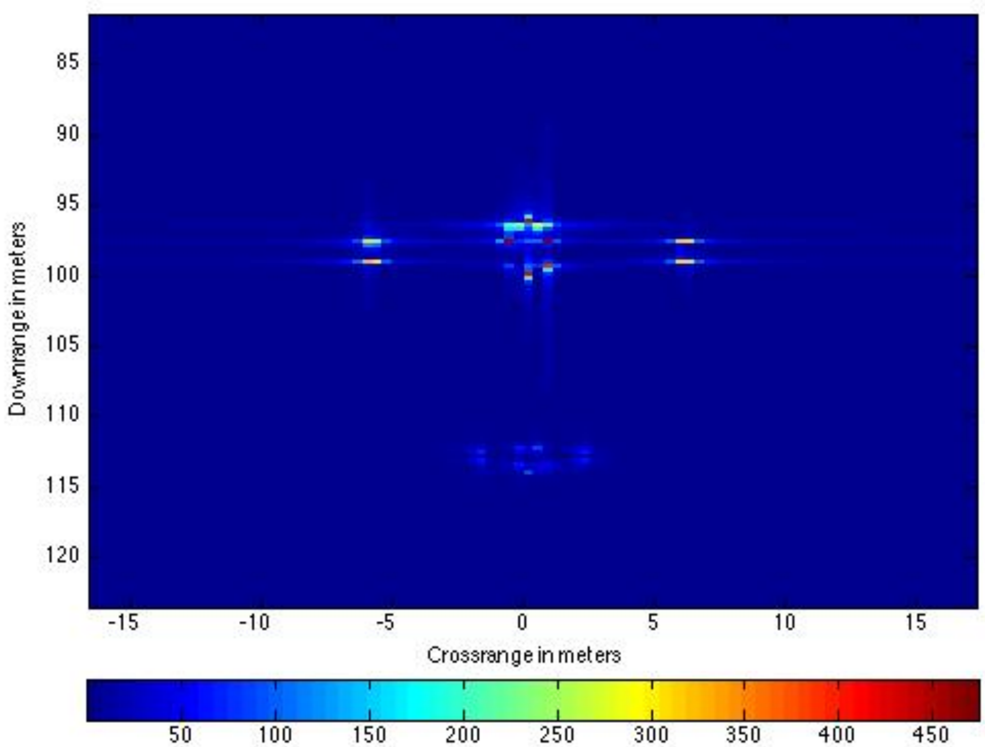

Figure 6.10: ISAR Image for RCS = 1.5

6.2.3 Neural Network Classification for Case Study # 2

After analyzing the neural network performance after training, the target classification takes place. In this case the classification is a Cessna and Figure 6.6 is displayed.

6.3 Case Study # 3

6.3.1 The Radar and the Environment

The radar illuminates its surroundings, like a searchlight, and picks up part of the energy scattered by the objects it illuminates. The transmitter generates a pulse, which hits the target, and produces an echo received by the receiver. By measuring the location of the echoes in time, the range of the target can be obtained. The radar scans the environment and detects an object:

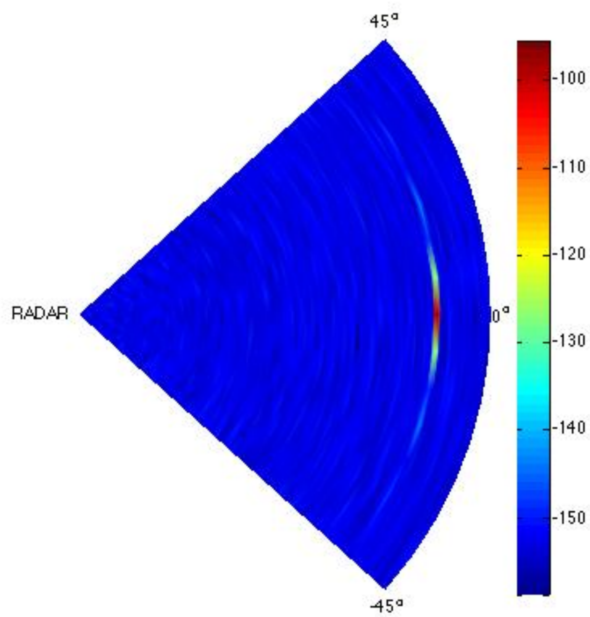

Figure 6.11: Target Detected

6.3.2 FIS Results for Case Study # 3

The radar detects an object with the following parameters:

Table 6.5: Case Study #3 Parameters.

Target Parameters	Values
RCS (m^2)	100
Distance (m)	4301
Speed (m/s)	98

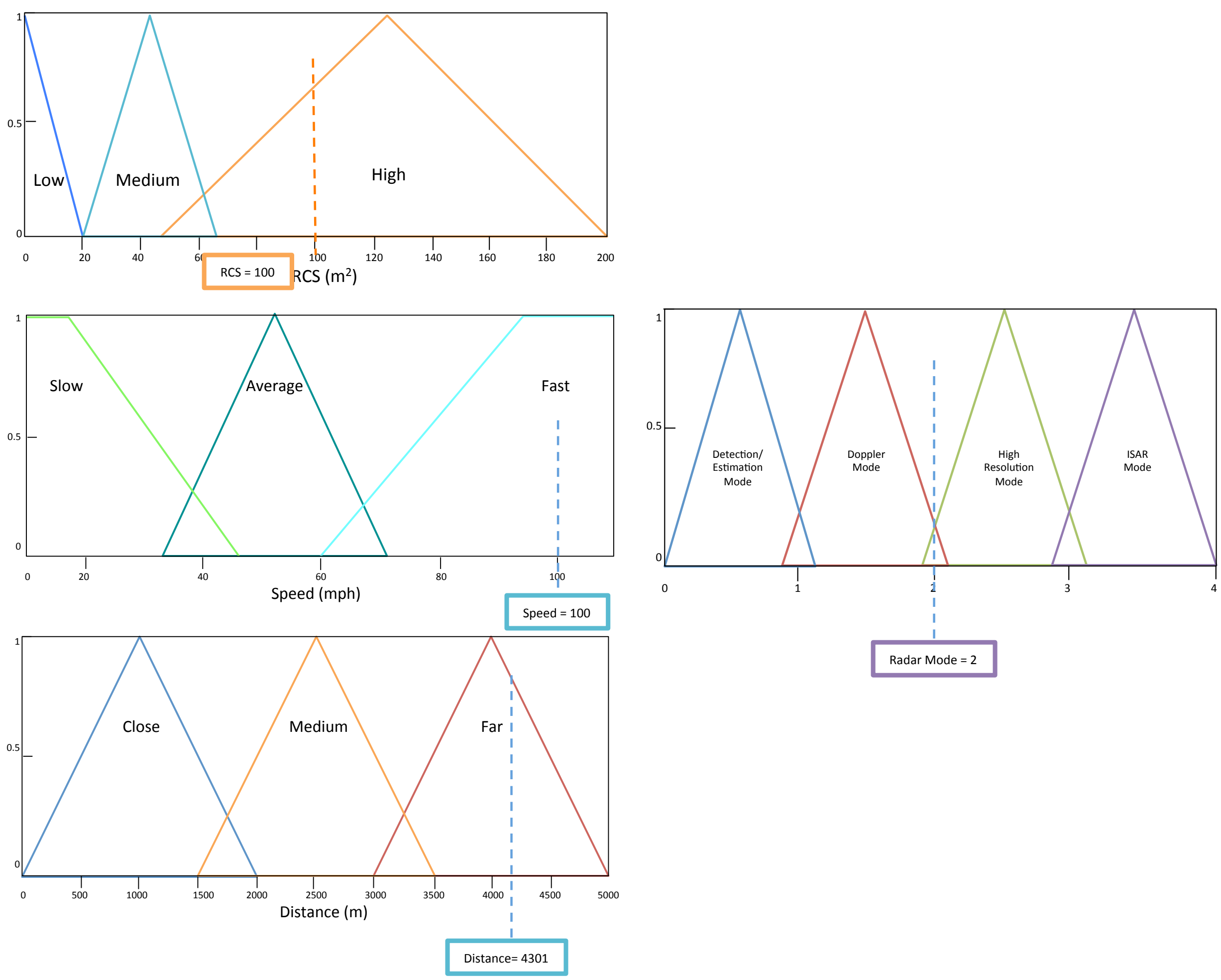

Figure 6.12: FIS Output

The Fuzzy Inference System output is used as the input to the Case-Based decision- making, in this case the Radar should operate in Doppler Mode. The Doppler Mode obtains the estimated distance

and speed of the target as shown in Figure 6.13. Table 6.6 shows the results of the Doppler Mode given the input parameters.

Table 6.6: Case Study #3 Results.

	Parameters	Results
ACTUAL	RCS (m^2)	100
	Distance (m)	4301
	Speed (m/s)	98
ESTIMATED	Radar Mode	Doppler = 2
	Estimated Distance (m)	4325
	Estimated Speed (m/s)	100.1
	Approaching/Moving Away from Radar	Moving Away

The Doppler processing exploits the Doppler shift caused by the moving target. The first step in Doppler processing is to generate the Doppler spectrum from the received signal. To be able to estimate the Doppler shift of the target, we first need to locate the targets through range detection. Once the range of the target is successfully estimated, the Doppler information for each target is also estimated. Doppler estimation is essentially a spectrum estimation process. Doppler processing processes the data across the pulses. For example if 10 pulses are used, there are 10 samples available for Doppler processing. Because there is one sample from each pulse, the sampling frequency for the Doppler samples is the pulse repetition frequency (PRF). The number of pulses determines the resolution in the Doppler spectrum, which determines the resolution of the speed estimates. The Doppler spectrum can be generated using a periodogram as shown in Figure 6.13. To estimate the Doppler shift associated with the target, the locations of the peaks are obtained in the Doppler spectrum.

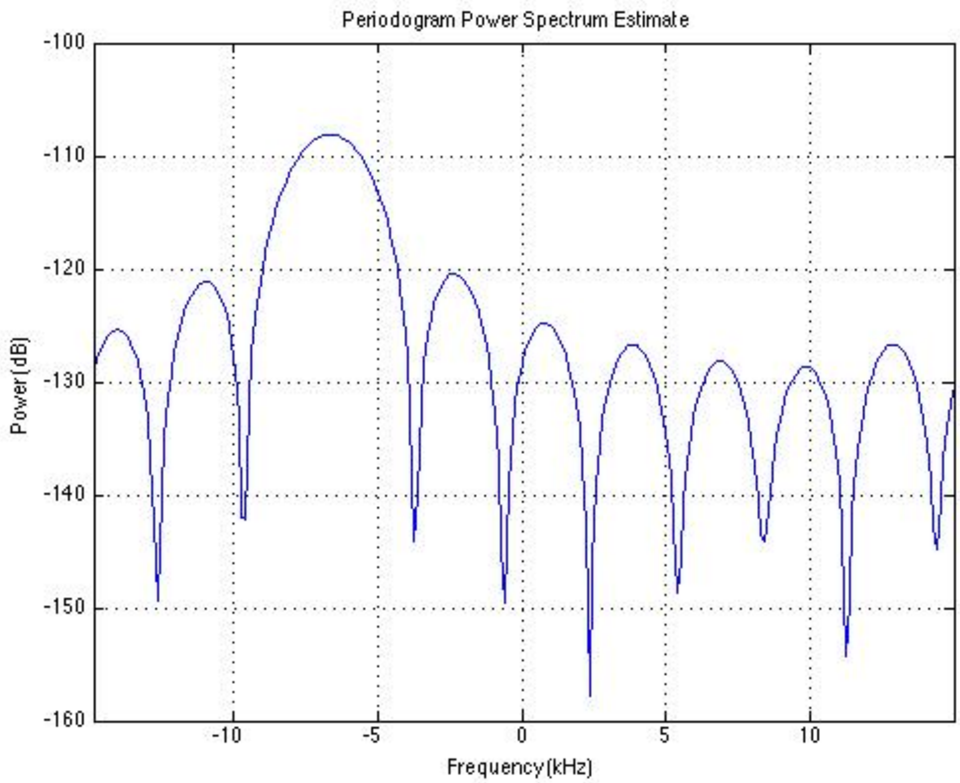

Figure 6.13: Doppler for RCS = 100.

The intelligent radar system was simulated using MATLAB and the signal analysis and measurements were performed for different case studies. The cognitive engine developed provides the system with capabilities to integrate signal processing, which adapts and learns to extract information, provide feedback for intelligent decisions and learns from interactions with the environment.

Chapter 7

Conclusion

This research met the research objectives as described in Section 1.2 of this dissertation. The application of interest is the international border security because of the challenging problems with the large open border between the US and Mexico. The protection of assets and populations of people from terrorism and the prevention of illegal crossing of the border are some key drivers for this application.

This dissertation employed radar, neural networks, and fuzzy logic techniques. The proposed intelligent radar system's "intelligence" comes mostly from the cognitive engine with support of learning in intelligent systems. The cognitive engine implemented the cognitive loop to understand the abilities of environment sensing, reasoning, learning and acting. The cognitive engine was required for decision-making and learning in the radar system to efficiently exploit the available resources and improve the performance of the radar system.

A detailed algorithm to implement the rule base for decision-making was performed. The fuzzy rule-based system helped in the decision-making regarding radar priorities and the next course of action for the radar.

The target classification of the images was also implemented using neural networks trained using the Levenberg-Marquardt algorithm. The classification rates were better than those reported for human operators, proving the potential of the proposed approach to alleviate the problems caused by the unreliability of manned radar systems.

By obtaining the control parameters for each of the modes of operation the system intelligently decides which mode of operation should be used, employing the case based system. A complete analysis of the overall system was performed for this dissertation by having a system of systems, which include the radar, fuzzy logic, and neural network systems. The overall performance is better to the human performance, which is the only other methodology that includes a combination of objects that operate in land and air.

Future Work

Further improvements in the overall radar system opens opportunities for more research in both areas: machine intelligence and radar systems. The study of chaotic signals can enhance the target detectability and aid in the formation of high-resolution images of targets. Chaotic signals have good range-Doppler resolution and excellent side lobe suppression characteristics that promise immense potential for high-resolution imaging applications. Using real data obtained from the Sandia National Laboratories' KA-BAND SAR (http://www.sandia.gov/RADAR/images/ka_band_portfolio.pdf), could enhance the over all system, especially the classification system.

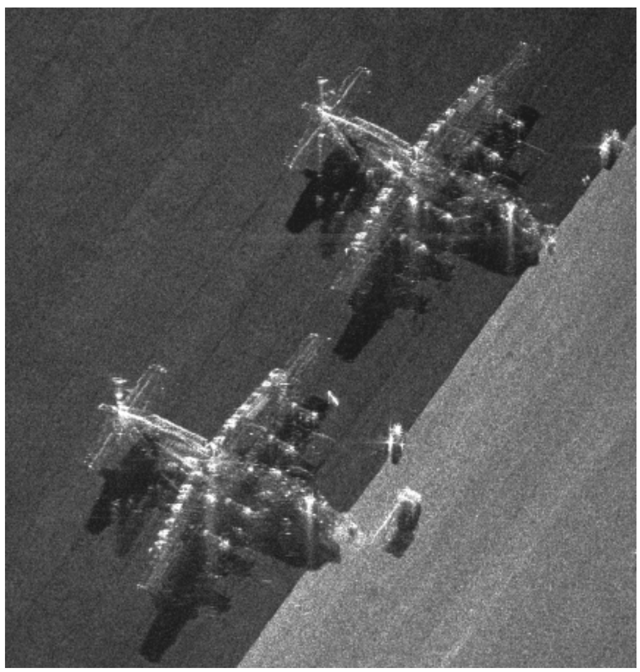

Figure 7.1: KA-BAND C-130s on flight line 4-inch resolution.

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"Multi-Mode Radar Target Detection and Recognition Using Neural Networks," in *International Journal of Advance Robotic System*, pp. 9:177, 2012. doi: 10.5772/52073.

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Vita

Janette C Briones was born on November 22, 1975 to Maria Helia Bencomo. She is the mother of Ricardo and Gael, and wife of Ricardo Briones. She earned her Bachelor of Science degree in Electrical Engineering and her Master of Science degree in Computer Engineering in May 2002 from the University of Texas at El Paso. As a graduate, she was working as a Research Assistant in the Neuro-Fuzzy Lab under the supervision of Dr. Patricia Nava. She designed a Rule-Based Expert System for Analysis of Sleep Data. She also worked on a method for membership function generation from training data in a UNIX environment using C and C++ code. As a PhD student she worked at the Digital Communications & Navigation Branch of the Communication Division at the National Aeronautics and Space Administration's Glenn Research Center (GRC) at Lewis Field in Cleveland, OH as a radio engineer and test data analysis for the General Dynamics SDR S-Band supporting the SCaN Testbed project. Supported the successful pointing of the medium gain antenna using the Antenna Pointing System and acquisition of S-Band single access service from the Tracking and Data Relay Satellite for the first time on September 13, 2012, using the General Dynamics (GD) software defined radio (SDR). Responsible for experiment planning, implementing and testing allowing the first bit error rate (BER) curve test taken on the GD software defined ratio through the S-band Tracking and Data Relay Satellite link. Developed a neural network and a linear digital automatic gain control algorithms to estimate the received power and calculate the signal to noise ratio and continue to test the TDRS pointing and checkout of the GD SDR automatic gain control. As the STRS Co-lead, she has worked with the NASA Technical Standards Program and submitted the STRS Architecture Standard for adoption as a NASA standard. Responsible of developing an STRS Application Repository Web-based interface for users to submit and retrieve STRS compliant applications. She earned her PhD in Electrical and Computer Engineering in May 2014.

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