

AUTOMATIC RADAR ANTENNA SCAN ANALYSIS IN ELECTRONIC WARFARE

A THESIS

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By

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August 2010

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ABSTRACT

AUTOMATIC RADAR ANTENNA SCAN ANALYSIS IN ELECTRONIC WARFARE

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Estimation of the radar antenna scan period and recognition of the antenna scan type is usually performed by human operators in the Electronic Warfare (EW) world. In this thesis, we propose a robust algorithm to automatize these two critical processes. The proposed algorithm consists of two main parts: antenna scan period estimation and antenna scan type classification. The first part of the algorithm involves estimating the period of the signal using a time-domain approach. After this step, the signal is warped to a single vector with predetermined size (N) by resampling the data according to its period. This process ensures that the extracted features are reliable and are solely the result of the different scan types, since the effect of the different periods in the signal is removed. Four different features are extracted from the signal vector with an understanding of the phenomena behind the received signals. These features are used to train naive Bayes classifiers, decision-tree classifiers, artificial neural networks, and support vector machines. We have developed an Antenna Scan Pattern Simulator (ASPS) that simulates the position of the antenna beam with respect to time and generates synthetic data. These classifiers are trained and tested with the synthetic data and are compared by their confusion matrices, correct classification rates, robustness to noise, and computational complexity. The effect of the value of N and different signal-to-noise ratios (SNRs) on correct classification performance is investigated for each classifier. Decision-tree classifier is found to be the most suitable classifier because of its high classification rate, robustness to noise, and computational ease. Real data acquired by ASELSAN Inc. is also used to validate the algorithm. The results of the real data indicate that the algorithm is ready for deployment in the field and is capable of being robust against practical complications.

Keywords: electronic warfare signal processing, antenna scan type, antenna scan

period estimation, antenna scan analysis, pattern recognition, naive Bayes classifiers, decision trees, artificial neural networks, support vector machines.

ÖZET

RADAR ANTEN TARAMALARININ OTOMATİK ANALİZİ

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Bu çalışmada Elektronik Harp (EH) dünyasında el değmemiş bir problem olan ve çoğunlukla insan operatörler tarafından gerçekleştirilen anten tarama periyodu kestirimi ve anten tarama tipinin otomatik tanınması için bir algoritma önerilmektedir. Önerilen algoritma iki temel kısımdan oluşmaktadır: anten tarama periyod kestirimi ve anten tarama tipi sınıflandırma. Algoritmanın ilk kısmı sinyalin periyodunu zaman alanında kullanılan bir yöntemle kestirir. Periyod kestirildikten sonra, sinyal, periyoduna göre tekrar örneklenerek, boyutu önceden belirlenmiş, N elemanlı bir dizi haline getirilir. Bu işlem, çıkartılan özelliklerin güvenilir ve sadece anten tarama tipine bağlı özellikler olmasını sağlar, periyodun etkilerini ortadan kaldırır. Sinyalleri oluşturan etkiler de düşünülerek dört değişik öznitelik çıkartılmakta ve kullanılmaktadır. Çıkartılan bu öznitelikler kullanılarak Bayes, karar ağacı, yapay sinir ağları ve destek vektör makinaları sınıflandırıcıları eğitilir. İlk aşamada Anten Tarama Örüntüsü Benzetim programı yazılarak üretilen sentetik veriler kullanılmıştır. Bu sınıflandırıcılar hata matrisleri, doğru sınıflandırma oranları, gürültüye karşı dayanıklılığı ve hesaplama karmaşıklığı açısından karşılaştırılmaktadır. Her sınıflandırıcı için N parametresinin ve değişik gürültü seviyelerinin başarımlar üzerindeki etkisi incelenmiştir. Karar ağacı sınıflandırıcısı, yüksek doğru sınıflandırma oranı, gürültüye karşı dayanıklılığı ve hesaplama kolaylığı nedeniyle en uygun sınıflandırıcı olarak belirlenmiştir. Sonuçlar, yüksek sınıflandırma doğrulukları ile problemin çözüldüğünü göstermektedir. Algoritmayı geçerlemek için sentetik verilerin yanı sıra ASELSAN A.Ş. tarafından sağlanan gerçek veriler de kullanılmıştır. Gerçek verilerin sonuçları, algoritmanın sahada kullanıma hazır olduğunu ve pratikteki sorunlara karşı dayanıklı olduğunu göstermektedir.

Anahtar sözcükler: elektronik harp sinyal işleme, anten tarama tipi, anten tarama

periyodu kestirimi, anten tarama analizi, örüntü tanıma, Bayes sınıflandırıcılar, karar ağaçları, yapay sinir ağları, destek vektör makinaları.

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to my family ...

Chapter 1

Introduction

Military operations are executed in an information environment where the electromagnetic spectrum is becoming increasingly more complex. Electromagnetic devices are being used stand-alone and in networks by both civilian and military organizations and individuals for intelligence, communications, navigation, sensing, information storage, and processing, as well as a variety of other purposes [1]. Vulnerability in this relatively new dimension of warfare could mean a battle may be lost without even getting into contact with hostile units.

Different technological methods and military doctrines have evolved in time as the use of the electromagnetic spectrum expanded vastly in many different bands. For this very purpose, an umbrella term, Electronic Warfare (EW) is used to define any activity which has a purpose to control the spectrum, attack an enemy, or impede enemy assaults via the spectrum. The goal of electronic warfare is to deny the opponent the advantage of, and ensure friendly unimpeded access to, the electromagnetic spectrum [24]. According to the above goals, EW is divided (by US and NATO doctrines) into three main divisions: Electronic Support (ES), Electronic Attack (EA), and Electronic Protection (EP). Electronic Support's main aim is to detect, define, recognize, and locate any electromagnetic emission particularly important for the mission. Electronic Attack, on the other hand, tries to suppress the spectrum use of the hostile units by attacking with directed electromagnetic energy or with anti-radiation missiles. Electronic protection tries

to ensure the use of the electromagnetic spectrum even in any situation where EA is employed by hostile units.

Besides these, signal intelligence (SIGINT) missions are employed on a day-by-day basis in peace time to give support to EW operations in war time. SIGINT is responsible for recording, analyzing, and forming parameter databases of the electromagnetic emissions of particular importance. SIGINT is also divided as electronic intelligence (ELINT) and communication intelligence (COMINT) in which ELINTs usually aim non-communicative emissions like radars. SIGINT is closely related to ES and in some context is the same. According to the views of the US military “the distinction between intelligence and ES is determined by who tasks or controls the intelligence assets, what they are tasked to provide, and for what purpose they are tasked” [1]. One can understand from the statement that the operations are quite similar but the purpose and the situation (combat or peace) determines the class of the mission.

This study concentrates on a problem which lies in the grounds of ES and ELINT. Its focus is an aspect of one of the most important threats in the spectrum: radars. Radars (RAdio Detection And Ranging) are used for detection, identification and imaging of objects in the environment. For this purpose, radars emit electromagnetic energy, collect and process the reflections from these emissions. The radar types dealt with in this study are target detection and track radars widely used in the militaries worldwide. The RF signal that they emit has a distinct frequency (operating frequency of the radar), PRI (Pulse Repetition Interval), and PW (Pulse Width). From the return of the pulses, radars try to determine the range, speed, and the direction of the object.

Radars have several operating modes in which they perform different tasks. **Search**, **acquisition**, and **track** are the fundamental modes that they deploy. Different radars may be used for each of these purposes. As the names suggest, each mode is a step towards the final track of the target. Accurate target tracking is crucial for efficient use of weapons against the target. In these different modes, the radar beam is directed to different parts of the volume depending on the purpose. The direction of the beam can be changed electronically, mechanically

or both.

Over the years, different type of volume search methods and target tracking methods have been used in radars. These different methods, usually periodic, were all deployed in various radars of different manufacturers with different parameters. These methods are mostly based on antenna scan type and antenna scan period [25].

When the other side of the picture is considered, from the EW perspective, antenna scan type and antenna scan period are vital data for use in different parts of EW systems. These parameters can be used effectively in both emitter classification and for the timing of Electronic Counter Measures (ECM) [25]. Change of scan type is also very crucial in determining the level of threat from the radar. The recognition and the estimation of period of the scan is done by EW technicians or EW officers. Despite the importance of these parameters, there is nearly no study in the open literature for automatic recognition. This is mainly because of the “classified” nature of EW studies.

The only work that is transparent related to the problem is two patents that are issued in the U.S.A [30]. The first patent, issued in 1980 describes a scan pattern generator probably finding use in EW simulators. In 2004, another patent has been issued to automatically recognize scan type, by a Lockheed Martin employee [12]. In this patent, Laplace, Fast and Discrete Fourier transforms are used. The basic scan types are determined and sample data from each type are saved in a database. The newly recorded signal is transformed to the frequency domain and correlated with the previously saved samples in the database. The type that results in the maximum correlation is stated to be the scan type of the radar. A closer look into this patent shows us that most parts of the process are left vague and the remaining transparent part is quite trivial. The change of the scan period and the variation of other parameters such as antenna beamwidth are probably assumed foreseen and looks far from robust.

Despite the scarce source of earlier work on the problem itself, some studies have been encountered in the time series data mining field from which valuable insights have been acquired. Genetic algorithms are used by Povinelli, to find

hidden temporal patterns in time series. In this study, temporary tendencies and the patterns that are possible to be observed in the future of the time series are estimated using genetic algorithms [18]. A different approach, also encountered, tries to find patterns in time series by feeding in the slopes of the series to artificial neural networks [27]. The time series is partitioned into smaller linear parts and the slopes of these smaller parts are used to extract patterns in the series. Taking Euclidean distance between the two time series to be compared may look like a trivial solution but the length of these series in time complicates the problem even if the overall pattern is the same. This problem is encountered in the speech processing field in vowel classification [11]. Vowels of each person have a shape that is quite the same but the length and the frequency of this signal varies from person to person. Dynamic Time Warping (DTW) uses linear programming to find the best possible match between different samples of the signal. If both the shape of the signal and its length changes in the same class, DTW fails to find a similarity. In our problem both the signal length (period) and its shape (because of the position of the EW receiver and radar) change in one class of data causing DTW to fail. DTW method is also used to find different patterns in series of different application areas [8, 9]. Another metric of similarity between different lengths of time series, based on state transitions of a Markov model is proposed in [28]. Similarity of time series is sometimes performed by transforming the data to another domain. The popular transforms are the Discrete Fourier Transform and Discrete Wavelet Transform [14, 19]. A comparison of these two different transforms in terms of accuracy and computational load is explored in [29].

In this thesis, an algorithm is proposed to determine both the antenna scan type and the scan period. The processed data correspond to the parameters measured in a conventional EW receiver from a particular radar. This algorithm completely automates the antenna scan analysis without the need of a human EW operator. It is also the first holistic open research output for this particular application. The proposed algorithm also provides a framework to analyze and classify periodic signals with different periodicities effectively and can be used in other fields of application as well.

The thesis is organized as follows: Chapter 2 gives fundamental information

about electronic warfare with emphasis on radars and their distinctive parameters. The primary focus is the antenna scan types and the scan periods. Chapter 3 explains the simulator coded to synthesize the radar signals. Chapter 4 describes the problem and gives an overview of the algorithm. It continues with the details of each step of the algorithm with the intermediate results. At the end of the chapter, validation of the algorithm with real signals and a comparison of the classifiers is presented. Chapter 5 concludes the thesis and provides some possible future research directions.

Chapter 2

Electronic Warfare Fundamentals

Radars use electromagnetic waves to be aware of the environment. Some radars are only used for target detection, some are used for tracking specific targets, some are deployed to get images of the ground. The class of radars dealt with in this study is **conventional pulsed radars** whose fundamental purpose is to search and track airborne targets. Continuous wave (CW) radars can also be dealt with without any problem.

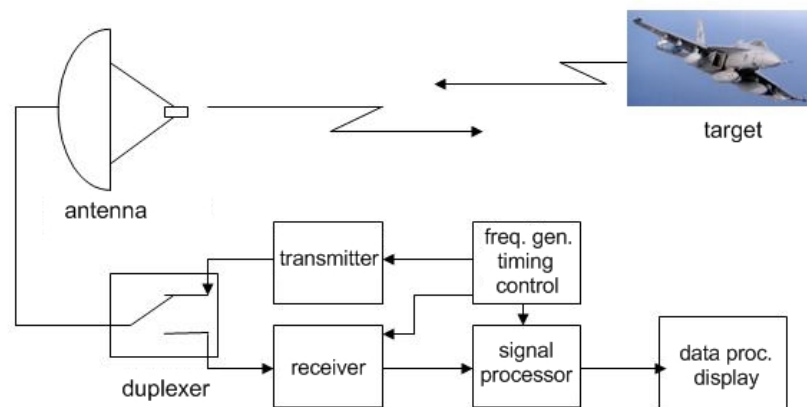


Figure 2.1: A typical radar block diagram.

These radars emit electromagnetic pulses with a particular peak power. The

wave travels all the way to the target at the speed of light and bounces back from the target back to the radar. The received signal reflected from the target is used to determine the target's range and direction. Some radars also estimate the Doppler velocity of the target with respect to the radar [15, 21]. The received power from a target is formulated by the well known radar equation [21]:

$$P_r = \frac{P_t G_t G_r \lambda^2 \sigma}{(4\pi R^2)^2} \quad (2.1)$$

where

P_r : received power

P_t : transmitted power

G_t : transmitter antenna gain

G_r : receiver antenna gain

λ : wavelength

σ : radar cross section

R : range.

Electronic Warfare (EW), on the other hand, tries to provide information about the radars in the environment and tries to jam them if possible. EW aims to protect the platform while the platform performs its mission. Detecting enemy radar pulses and classifying them are very important for the platform to be protected. The received power with an EW receiver can be found as follows:

$$P_r = \frac{P_t G_t G_r \lambda^2}{4\pi R^2} \quad (2.2)$$

If the received power is higher than the sensitivity level of the receiver, the pulse and its four main parameters are measured: frequency (F), pulse width (PW), pulse amplitude (PA), direction of arrival (DOA), and time of arrival (TOA). These parameters are measured for a CW radar by chopping up it into small pulses. The sensitivity level of the receiver depends on the bandwidth and the noise figure of the receiver. All the received pulses are classified and associated with each emitter by the de-interleaving algorithms. PRI (pulse repetition interval) of the emitter is found by using the above primary parameters in the de-interleaving process [17]. Figure 2.2 illustrates these basic parameters. The distinct parameters that characterize a specific radar are F, PW, PRI, Antenna

Scan Type (AST), and Antenna Scan Period (ASP). These parameters are usually sufficient to determine which radar has emitted the particular pulse EW receiver has received. Another very critical piece of information is whether a radar is tracking the platform or not. This can also be inferred from AST. In the following part, the fundamental parameters that address a specific radar are explained. A detailed treatment of these parameters can be found in an excellently illustrated introductory book by Stimson [22].

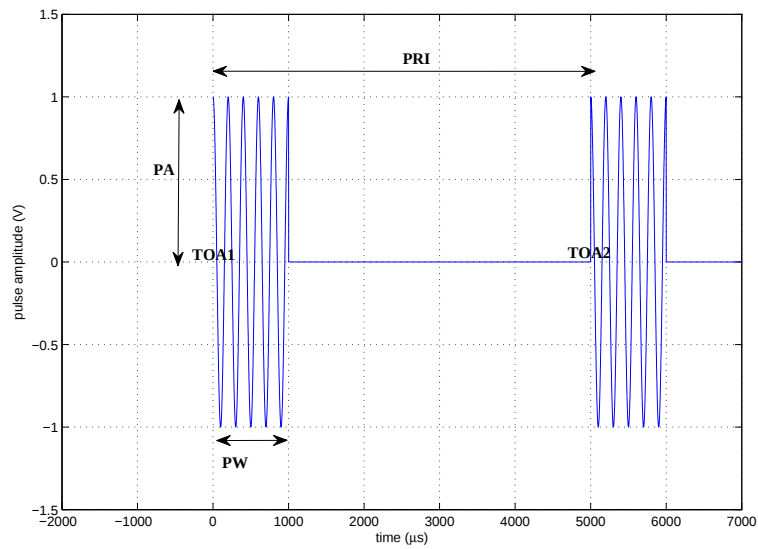


Figure 2.2: Measured parameters of a typical radar pulse.

Frequency (F)

Each pulse sent by the radar is modulated with a certain frequency, the operating frequency of the radar. Frequency of conventional radars ranges between 1–40 GHz. Some radars also employ frequency hopping and frequency agility against jamming. F is generally used extensively in de-interleaving the pulses and emitter classification.

Pulse Width (PW)

PW is the length of the pulse in time and is usually constant for a specific radar. The range of PW is $14 \mu\text{s}$ to 1 ms. PW determines the range resolution

of the radar.

Pulse Amplitude (PA)

PA is the received power of the pulse at the EW antenna. This is directly related to the radar peak power, radar antenna gain, radar position, propagation loss (proportional to range and F), platform's position in space and EW antenna gain.

Direction of Arrival (DOA)

Direction of arrival, as the name suggests, is the direction of the radar in the azimuth plane with respect to the platform. There are different algorithms employed in EW systems. DOA is usually found from PA ratios of different directional antennas on the platform. Some EW systems also use phase interferometer systems which have comparably low errors with respect to amplitude techniques.

Pulse Repetition Interval (PRI)

PRI is the time between the pulses of the radar, sometimes called pulse repetition period (PRP) as well. It is found easily by differentiating TOA's of consecutive pulses whose emitters are the same. Radars utilize different kinds of PRI patterns. Constant, stagger, and agile PRI are the typical modes of PRI. As the name implies, in the constant PRI mode, the PRI is constant. In the stagger mode on the other hand, PRI has a deterministic pattern. In the agile mode, it has some random PRI pattern [21].

Antenna Scan Type and Period (AST-ASP)

Antennas are the crucial and indispensable part of the radar architecture. These devices are used to radiate and receive electromagnetic waves. There is a wide variety of antennas specialized for different fields of application. Radar systems use different types of antennas to accomplish their function [21].

Antennas have different parameters to describe their functionalities: antenna

radiation pattern, directivity, gain, 3 dB beamwidth etc. Radiation pattern describes the spatial distribution of the radiated power. Directivity describes how well the antenna can concentrate the input power in one direction in space. Gain takes into account the losses and inefficiencies that reduce the total radiated power from the antenna. The 3 dB beamwidth describes the angular sector where the power radiated is more than half of the maximum power radiated in the boresight direction of the antenna [6].

Antenna's radiation pattern determines the instantaneous field of view of the radar. Typically 3 dB beamwidths, both in azimuth and elevation, of the antenna are used to calculate the visible part of the space for radar. The coverage of the antenna beamwidth is usually not sufficient for the radar's requirements. To overcome this problem, the antenna is steered, either electronically or mechanically, to the desired part of the space [25]. Considering a hemisphere of the space to be covered, the number of steering positions can be found by the following equation:

$$N = \frac{2\pi}{\Delta\theta\Delta\phi} \quad (2.3)$$

where $\Delta\theta$ and $\Delta\phi$ are the azimuth and elevation beamwidths respectively.

Every radar uses a different search-and-track strategy to cover the specific region it is interested in. These search strategies are called the antenna scan type (AST) of the radar. The commonly encountered ASTs are: circular, sector, raster, helical, and conical. Antenna scan period (ASP) has a very large range whose true value is usually acquired from intelligence agencies of countries. The next section describes each scan type and how it is seen from the EW receiver.

2.1 Antenna Scan Types and Their Characteristics

As mentioned in the previous section, radars have directional antennas that direct their beams towards different parts of space as time passes. This, of course, affects directly the power received in the EW receiver. The calculation of the received

power as a function of the antenna orientation can be found as:

$$P_r(t) = \frac{P_t G_r \lambda^2}{4\pi R^2} G_t(\theta(t), \phi(t)) \quad (2.4)$$

where P_r , P_t , G_r , λ , and R are as before and $G_t(\theta(t), \phi(t))$ is the transmit antenna gain of the radar at the azimuth and elevation angles where EW receiver is located at time t .

Figure 2.3 illustrates a generic antenna pattern and a respective EW receiver plotted on a unit sphere. As the antenna (beam) is turned, the EW receiver shown sees different PAs for each pulse it receives. The term $\frac{P_t G_r \lambda^2}{4\pi R^2}$ in Equation (2.4), which is independent of time, is assumed constant because the geometry (angle and range) between the radar and the EW receiver is assumed to be changing negligibly. This assumption is valid for stationary engagement scenarios and scenarios where the antenna scan type is much faster than the system platform which is mostly the case in EW.

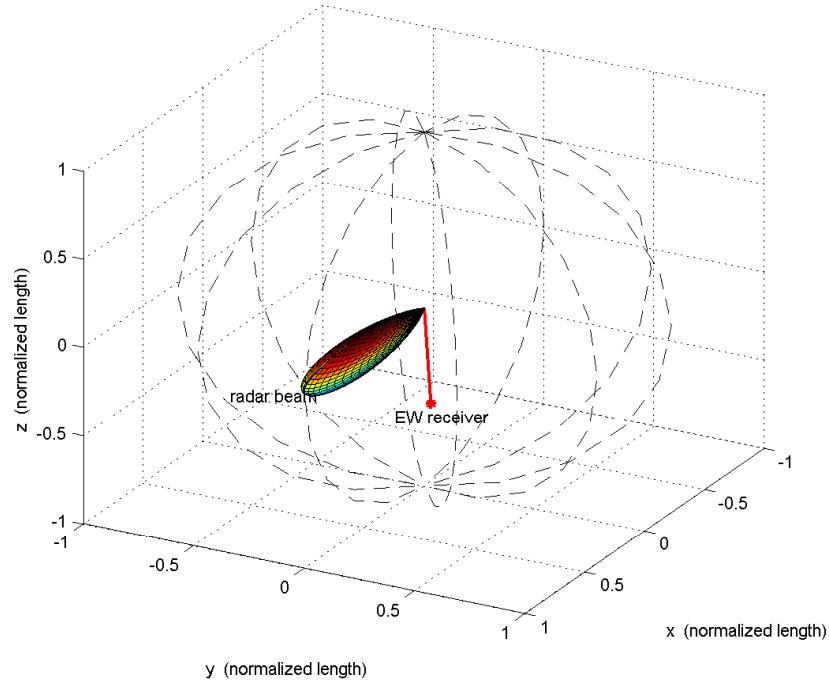


Figure 2.3: An example radar antenna pattern.

The corresponding PA versus time graph is illustrated in Figure 2.4. It can be

seen that as the antenna turns to different parts of the volume, the received power changes according to the gain of the antenna at the angle where the EW receiver is located. In the following parts, ASTs mentioned above will be explained. The received power in the EW receiver will be depicted and the scan type will be introduced. The following scan types and their definitions can be found in [4] and [25].

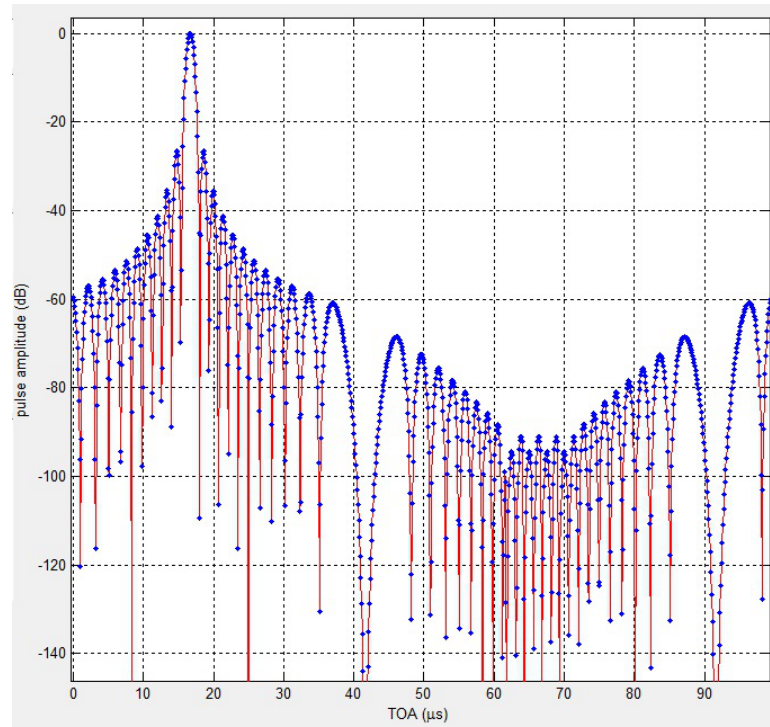


Figure 2.4: PA received by the EW receiver as time passes.

The five different signals (PA versus TOA) received by the EW receiver from the five ASTs identified in this thesis are illustrated in Figure 2.5. Each of them will be explained in detail in the following parts.

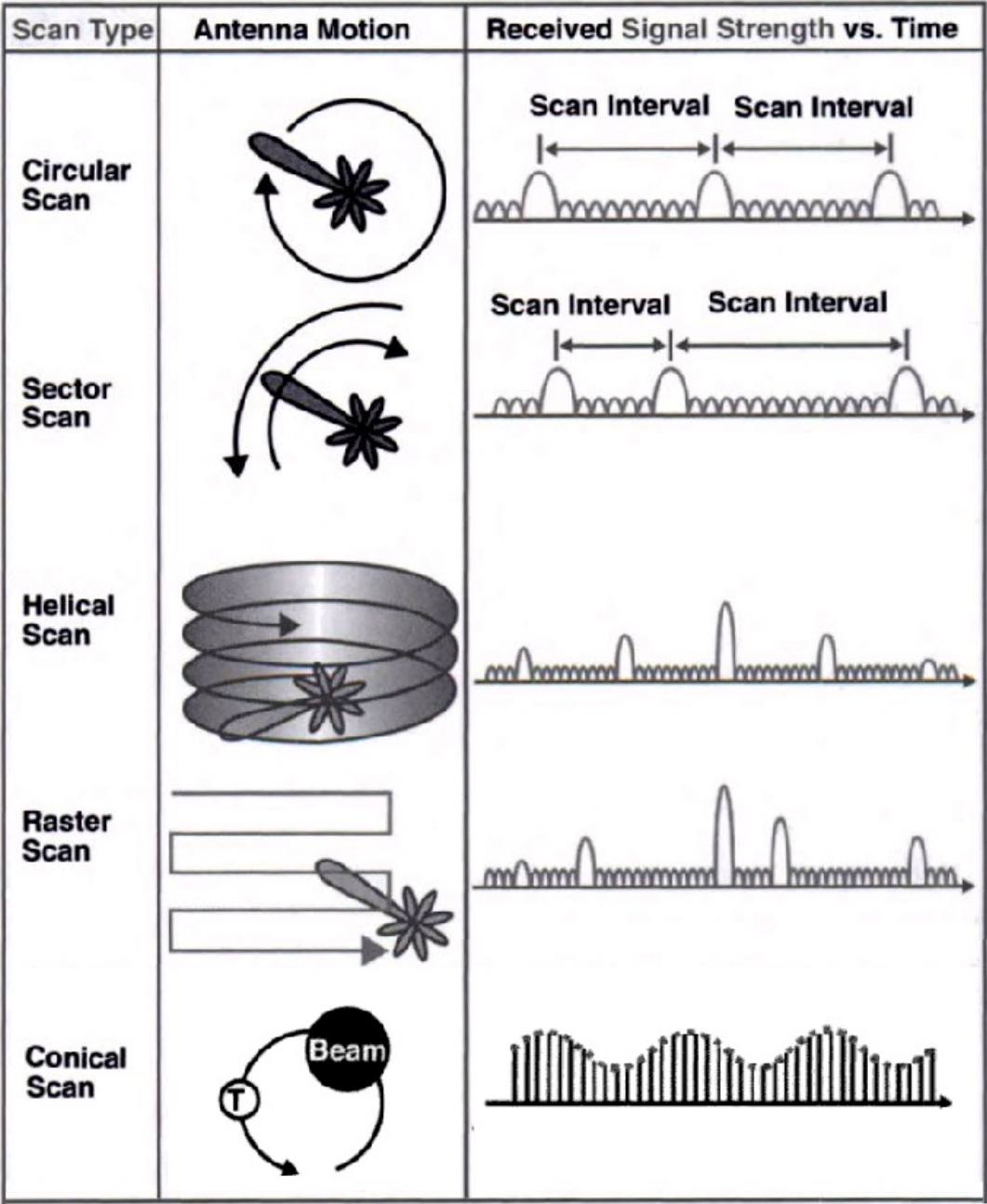


Figure 2.5: Circular, sector, helical, raster, and conical scan signals reprinted from [3].

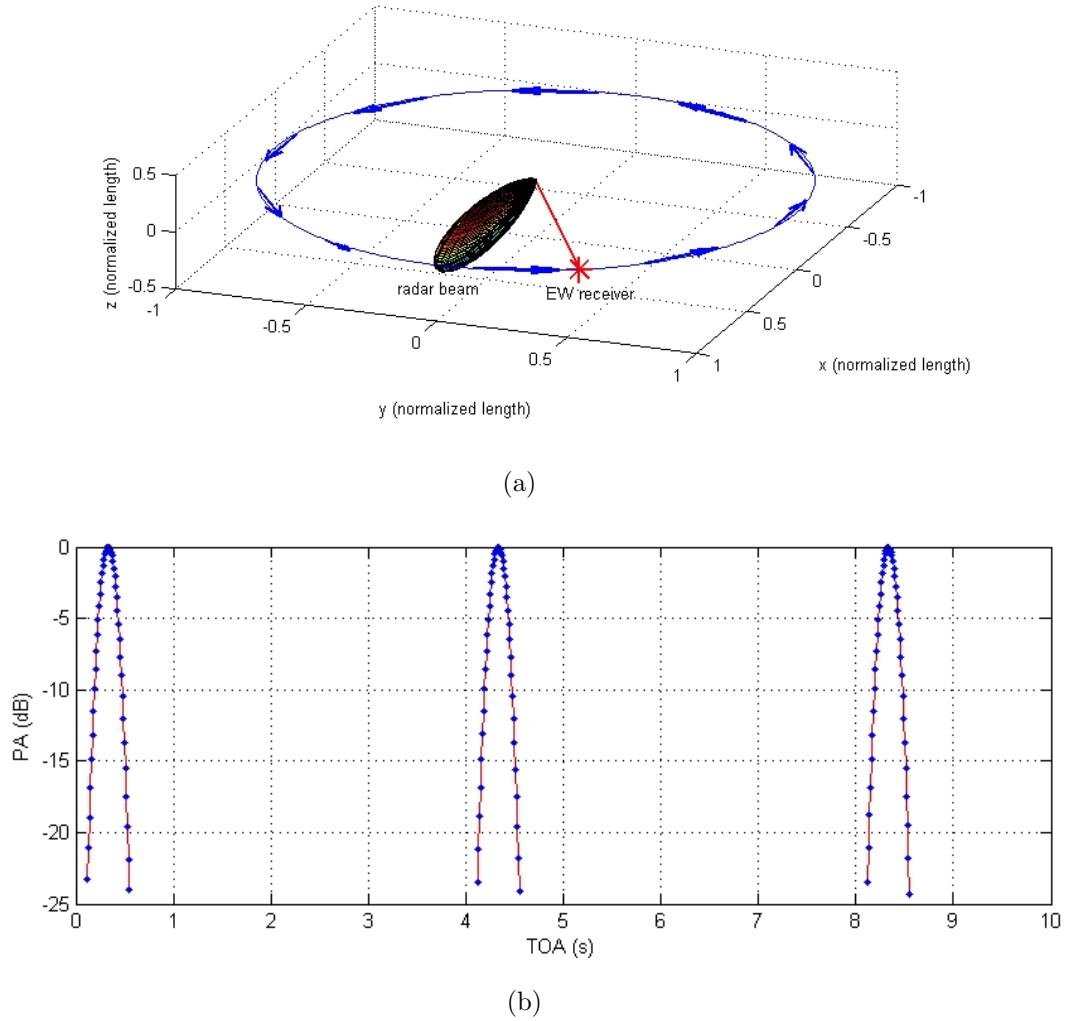


Figure 2.6: Circular scan properties: (a) the main beam positions and (b) the corresponding PA versus TOA graph.

Circular Scan: Circular scan is widely seen in search radars. The radar continues to scan the azimuth plane, 360° completely, with constant angular speed. The antenna has a large elevation beamwidth to see the whole elevation space. These kind of beams are called fan beams. The EW receiver effectively samples the antenna pattern of the radar antenna with sampling period PRI. This is because of the fact that the pulses are received with PRI intervals in time. Figure 2.6 illustrates the main beam positions and the received PA with respect to TOA. The scan period has quite a large range in the order of 1–10 seconds.

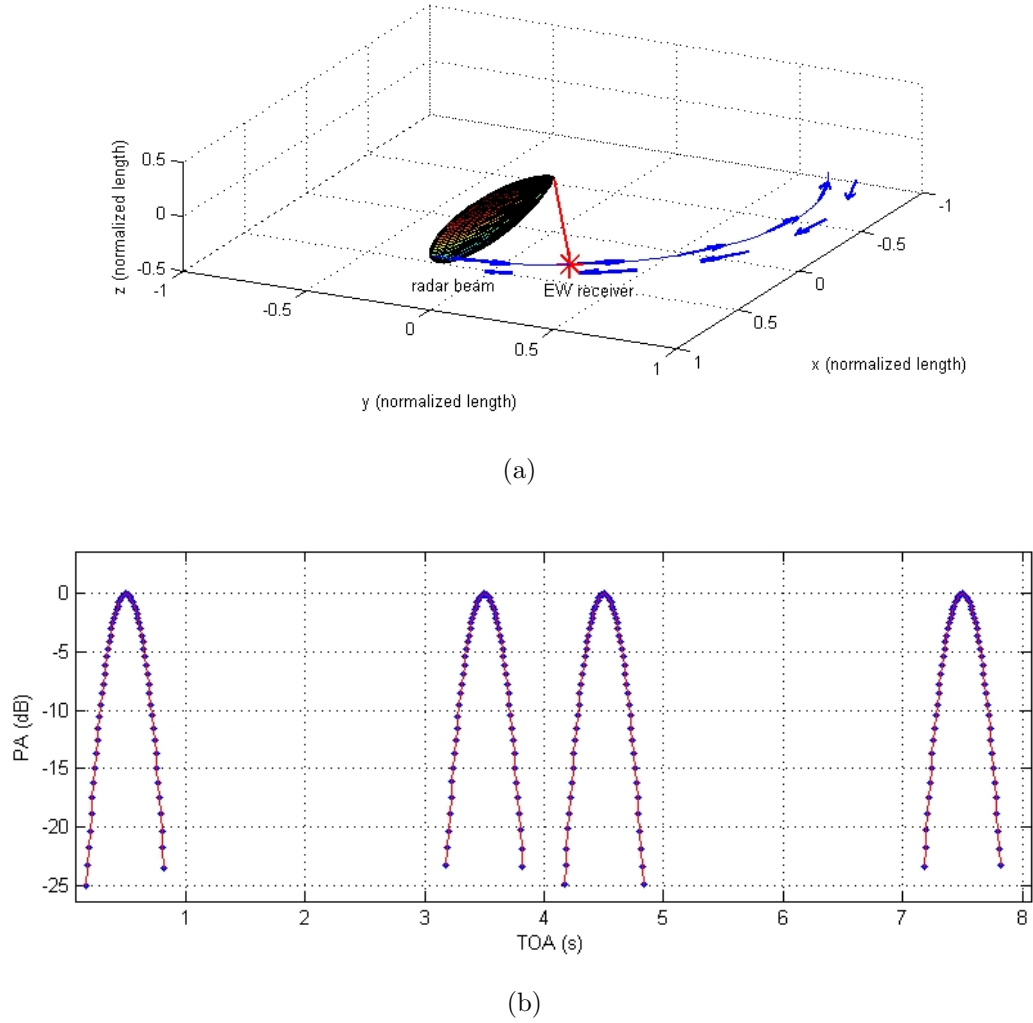


Figure 2.7: Sector scan properties: (a) the main beam positions and (b) the corresponding PA versus TOA graph.

Sector Scan: Another search scan type is the sector scan. The radar scans a specific angular sector back and forth with constant angular speed. The EW receiver receives periodic and symmetric main beams as shown in Figure 2.7(a). Figure 2.7 shows the antenna movement and the received PA time history. For each full period, two main beams are expected in this scan type. The PA received in both of the peaks are equal in magnitude. The scan period is in the order of seconds.

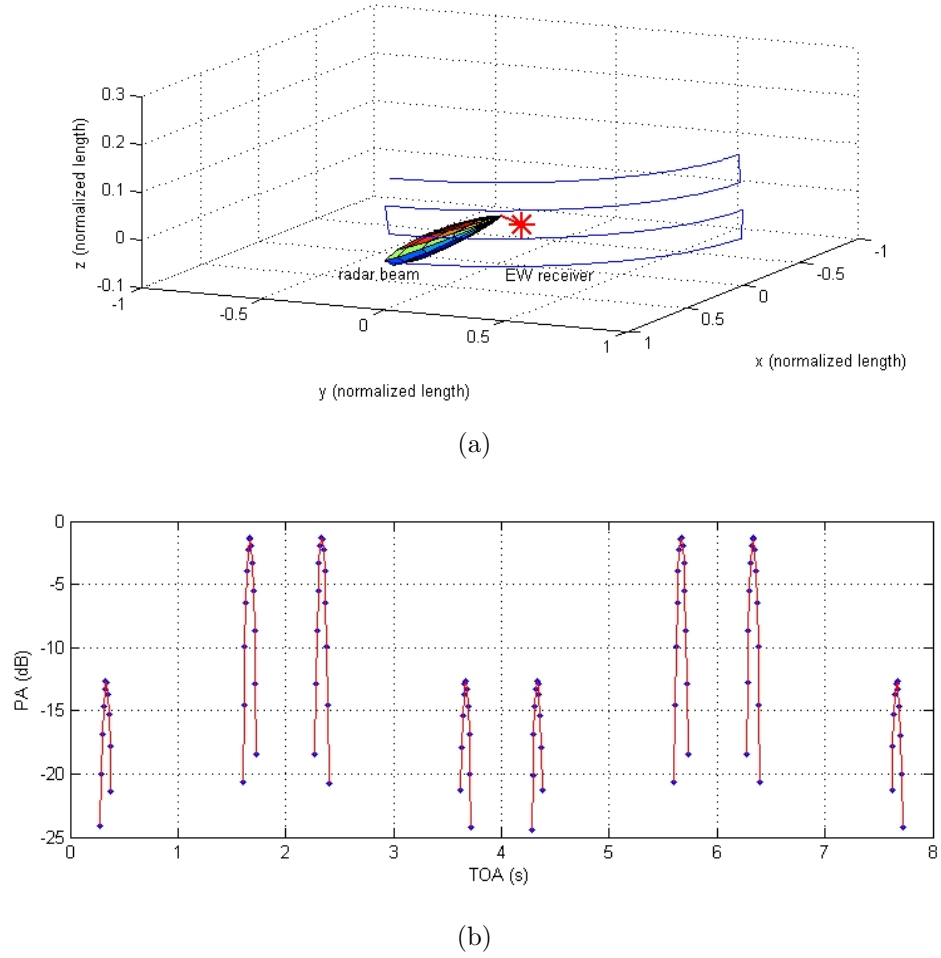


Figure 2.8: Raster scan properties: (a) the main beam positions and (b) the corresponding PA versus TOA graph.

Raster Scan: The two scan types described above search in only azimuth, but raster scan searches both in azimuth and elevation. The radar scans a specific angular sector in azimuth and then increases its elevation after finishing the sector. It can have several bars in the elevation. The word raster comes from the fact that the movement of the beam looks like the raster scan on TV screens. The full period is constant. Since the elevation is also involved in this scan type, there is an additional loss in the PA received because of the elevation pattern of the antenna. Figure 2.8 shows the antenna movement and the received PA time history. In each full period, for each bar of the raster scan, a main beam is intercepted. However, the received PA changes depending on the elevation of the EW receiver.

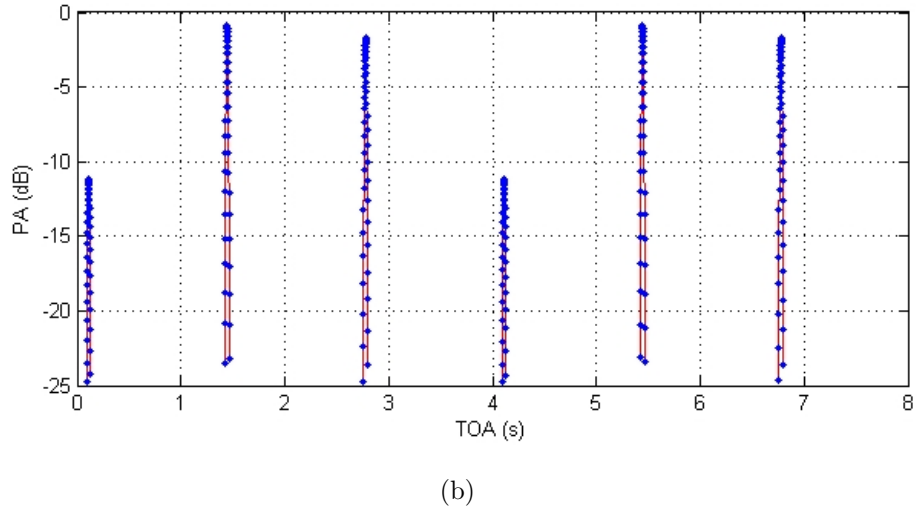
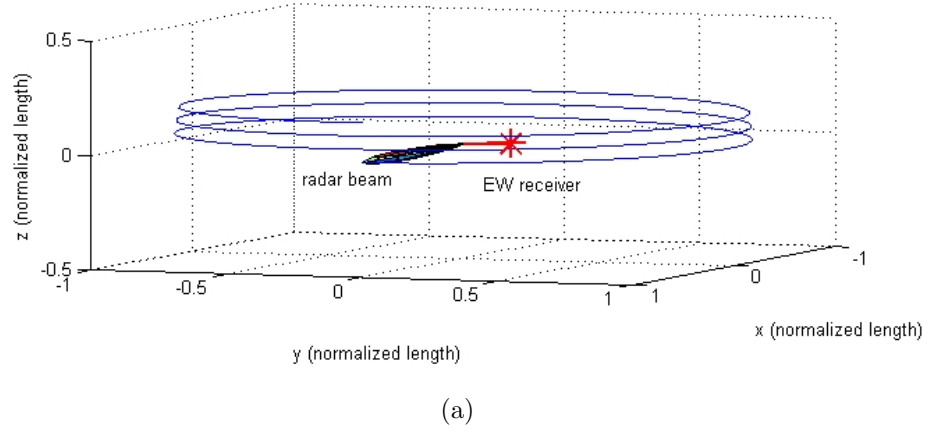


Figure 2.9: Helical scan properties: (a) the main beam positions and (b) the corresponding PA versus TOA graph.

Helical Scan: Helical scan is also encountered in different types of radars. In this particular scan, the radar revolves 360° several times like the circular scan. However, the elevation is also changed in each revolution so that the radar scans a specific sector in the elevation as well. After a complete scan period, the elevation is set back to where the scan has started at the beginning. The fact that the shape of the scan resembles a helical shape is where the name comes from. The movement of the beam is shown in Figure 2.9(a). The received PA-TOA graph, shown in Figure 2.9(b), is similar to the circular scan except that the peaks of the pattern change because of the motion in the elevation plane.

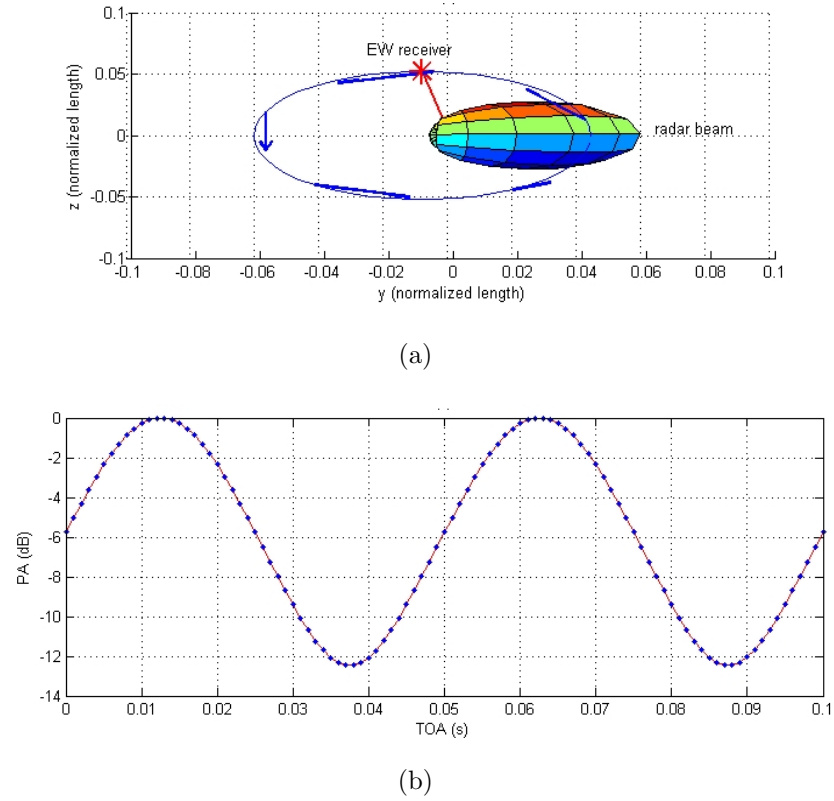


Figure 2.10: Conical scan properties: (a) the main beam positions and (b) the corresponding PA versus TOA graph.

Conical Scan: This scan type is very important because it signifies that the radar is particularly dealing with the platform EW receiver is on. It signals that the radar is trying to lock-on to the platform. The beam makes conics around the platform, trying to place the platform right on the 3 dB beamwidth. Figure 2.10(a) illustrates the movement of the antenna. It first shows the start of the track process, eventually the track process converges to the perfect track in which constant PA time history is seen. The received signal, illustrated in Figure 2.10(b) is like a sinusoid because of the conical action. As the lock gets better, the amplitude of the sinusoid decreases. The period of the sinusoid is distinct for every radar. Finally, when it is locked completely, that is the platform is on the 3 dB beamwidth, the received signal has a constant PA. The complete lock of this scan is sometimes called a fixed scan. The tracking process is illustrated in Figure 2.11. At the start of the track, there is an oscillation in the PA graph because of the beam getting closer and farther from the EW receiver.

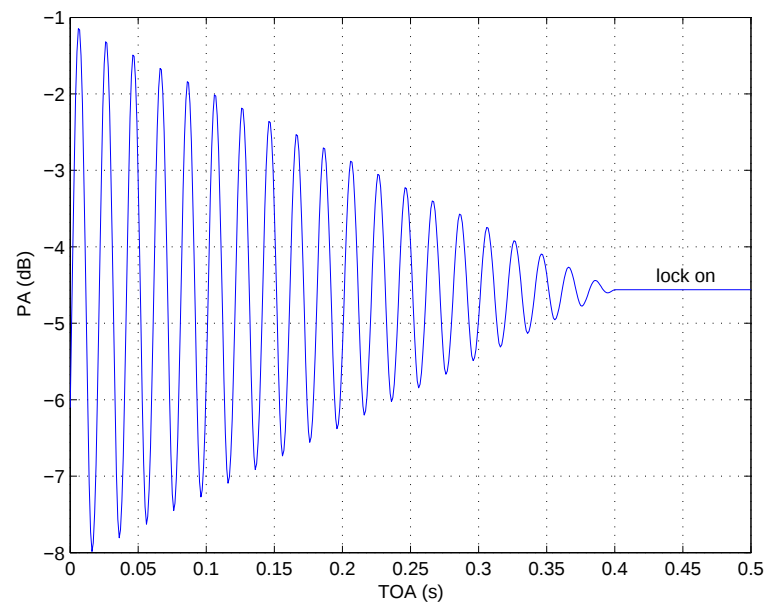


Figure 2.11: A conical scan radar tracking the target illustrating the lock-on process.

Chapter 3

Antenna Scan Pattern Simulator

Acquiring recorded EW data is very hard if not impossible. Because of very scarce source of data, simulation of a EW receiver is performed using a MATLAB program. This section introduces the radar model used and the MATLAB program coded.

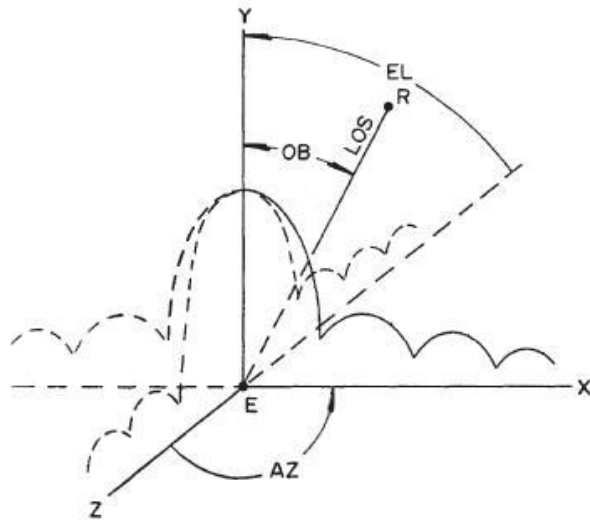


Figure 3.1: 3-D antenna pattern and the antenna gain at the EW receiver R [30].

Antenna Scan Pattern Simulator (ASPS) simulates the position (azimuth and elevation) of the antenna beam with respect to time. The power received from a

EW receiver is modeled according to the antenna pattern of the radar antenna and the PRI of the radar. The received power as a function of antenna orientation was given in Equation (2.4).

Figure 3.1 illustrates the antenna gain at the EW receiver. As explained before, the radar antenna rotates as time passes, changing the gain seen from the EW receiver (that is the $G_t(\theta(t), \phi(t))$ factor in the received power) in time. The simulator calculates the beam positions according to the scan type chosen and then determines the gain seen by the EW receiver using the receiver's azimuthal and elevational position. The radar is assumed to be at the origin of the coordinate system. The received power is calculated for each pulse of the radar using its TOA and the beam's position. The resulting PA versus TOA graph is plotted in Figure 3.2. The constant terms such as the propagation loss and EW receiver antenna gain are all assumed to be constant in the calculations. The noise level in the EW receiver is simulated by the addition of zero-mean Gaussian noise with desired power to the signal. The sensitivity level of the receiver is included in the simulations.

A Graphical User Interface (GUI), shown in Figure 3.2, is coded to ease the simulations. Each part of the GUI is explained below in detail.

3.1 TOA

This part (Figure 3.3) enables the user to input the TOAs of the pulses of radar and implicitly sets the PRI of the radar. The GUI enables three different choices for inputting the TOA. One can input directly from the edit box under the pop-up menu, from a MATLAB variable in the workspace and from a .mat file saved in the directory. The TOA values of the pulses also determine the sampling points of the antenna pattern. This part also defines the total simulation time.

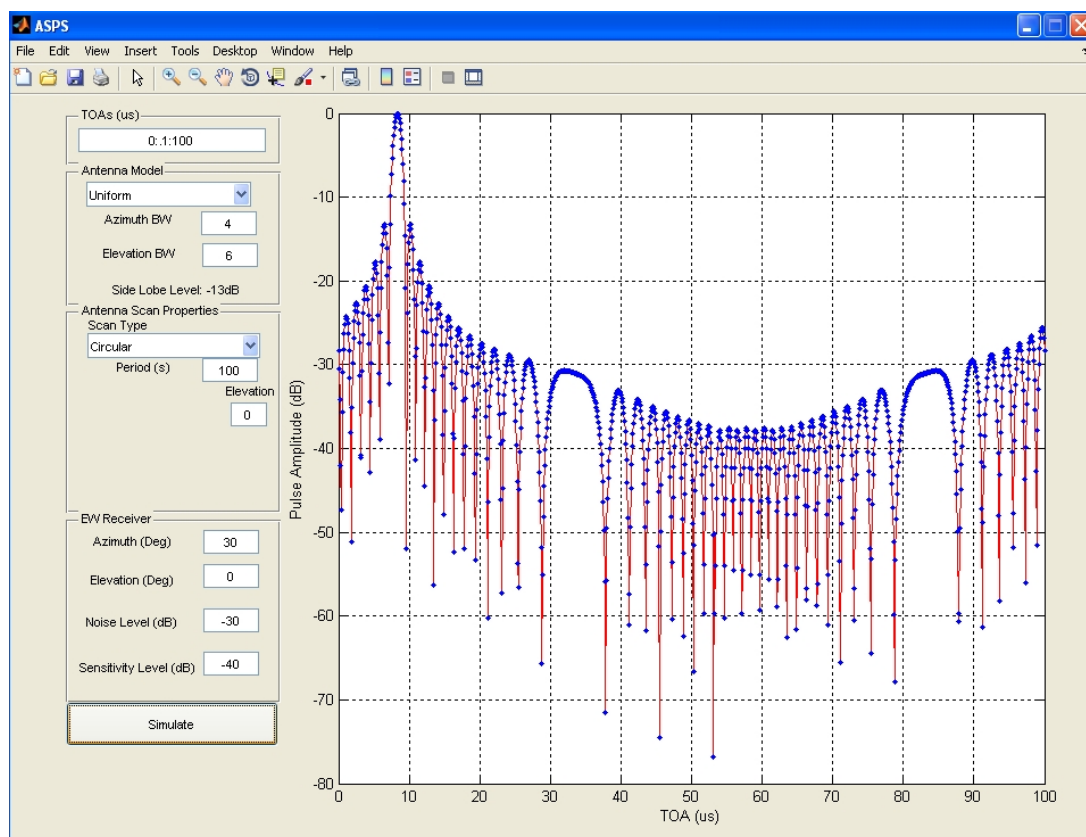


Figure 3.2: ASPS GUI.

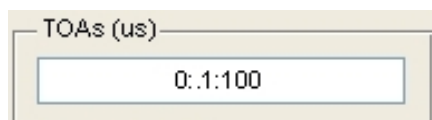
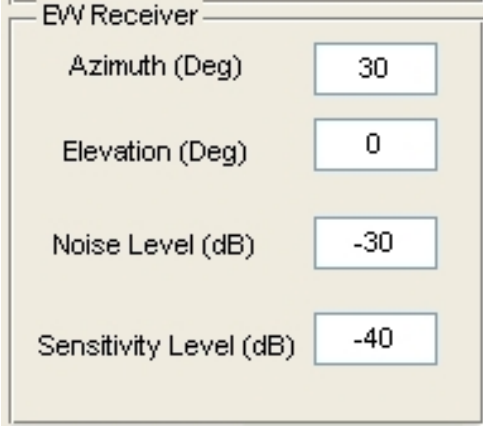


Figure 3.3: TOA input part of the GUI.

3.2 EW Receiver Properties

This part (Figure 3.4) inputs the EW receiver properties and receiver position with respect to the radar. The azimuth and the elevational position of the receiver is given in degrees. It is assumed that the EW receiver is stationary (or moves by a negligible amount compared to the radar) throughout the simulation time. The noise and the sensitivity level of the receiver can be configured as well. Gaussian noise with desired power is added to the signal level. Signals with amplitude below the sensitivity level of the receiver will be ignored because it is quite likely

that they are noise. This comes from the detection mechanism of the EW receiver.



The image shows a graphical user interface window titled "EW Receiver". It contains four input fields, each with a label and a numerical value in a text box:

Parameter	Value
Azimuth (Deg)	30
Elevation (Deg)	0
Noise Level (dB)	-30
Sensitivity Level (dB)	-40

Figure 3.4: EW receiver position with respect to the radar.

3.3 Antenna Model

The antenna model and its beamwidth are configured in this part (Figure 3.5) of the GUI. Six different antenna models are implemented in the simulator: uniform, triangle, Hamming, Taylor, Poussin, and Blackman. The side lobe levels of the antenna patterns differ in each case. The user also inputs the beamwidths in azimuth and elevation. The simulator calculates the number of elements needed to achieve the input beamwidth for the particular model. After this calculation, simulator synthesizes a pattern for azimuth and elevation. According to the receiver's position, it calculates the pattern gains in azimuth and elevation and multiplies them with each other to find the overall pattern at the particular azimuth and elevation. The different parameters needed for each model can be input as well by changing the pop-up menu.



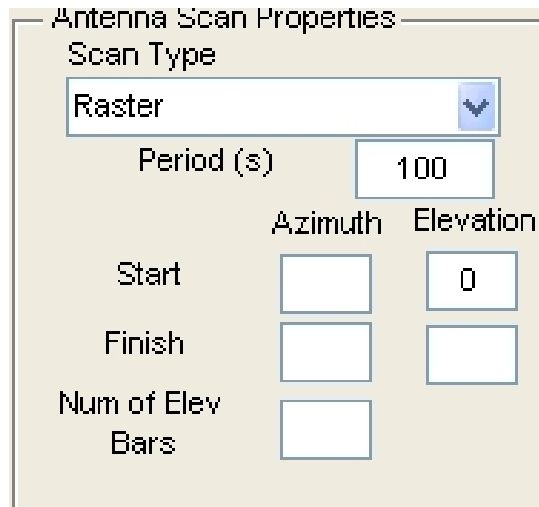
Figure 3.5: Antenna model and beamwidth configuration panel.

3.4 Antenna Scan Type Properties

This part (Figure 3.6) of the GUI lets the user choose the AST properties. The scan type of the radar is selected first. According to the scan type, different edit boxes are enabled with respective parameter names. The user inputs the parameters for the particular scan type. Circular, sector, raster, helical, and conical scans are simulated by the environment. Period is the common parameter for all of the scan types. Sector scan needs the start-finish positions in the azimuth and the elevation position of the beam. Raster scan acquires the start-finish positions in azimuth and elevation with the number of bars in the elevation. Conical scan type needs the target azimuth and elevation position and squint angle of the radar. All of the above parameters are used to calculate the beam position at a specific point in time which is basically the TOA of the pulse. The pulse with the maximum power is normalized to 0 dB.

3.5 Antenna Scan Pattern Plot

The axes in these parts (Figure 3.7) are used to plot PA versus TOA of the simulated scenario. The zoom, pan, and rotate buttons of the figure can be used to explore the signal further.



The figure shows a configuration panel titled "Antenna Scan Properties". It contains the following elements:

- Scan Type:** A dropdown menu with "Raster" selected.
- Period (s):** A text input field containing the value "100".
- Start:** A label with two input fields: "Azimuth" (empty) and "Elevation" (containing "0").
- Finish:** A label with two input fields: "Azimuth" (empty) and "Elevation" (empty).
- Num of Elev Bars:** A label with one input field (empty).

Figure 3.6: Antenna scan properties configuration panel.

3.6 Beam Positions

The simulator also illustrates how the beam scans the volume as time passes. It divides the whole simulation time into 10 intervals. It illustrates the beam position at these time points and also plots the position of the EW receiver to see the effects of the rotation of the beam. An example of a circular scan is given in Figure 3.8, where the beams and the EW receiver position are illustrated.

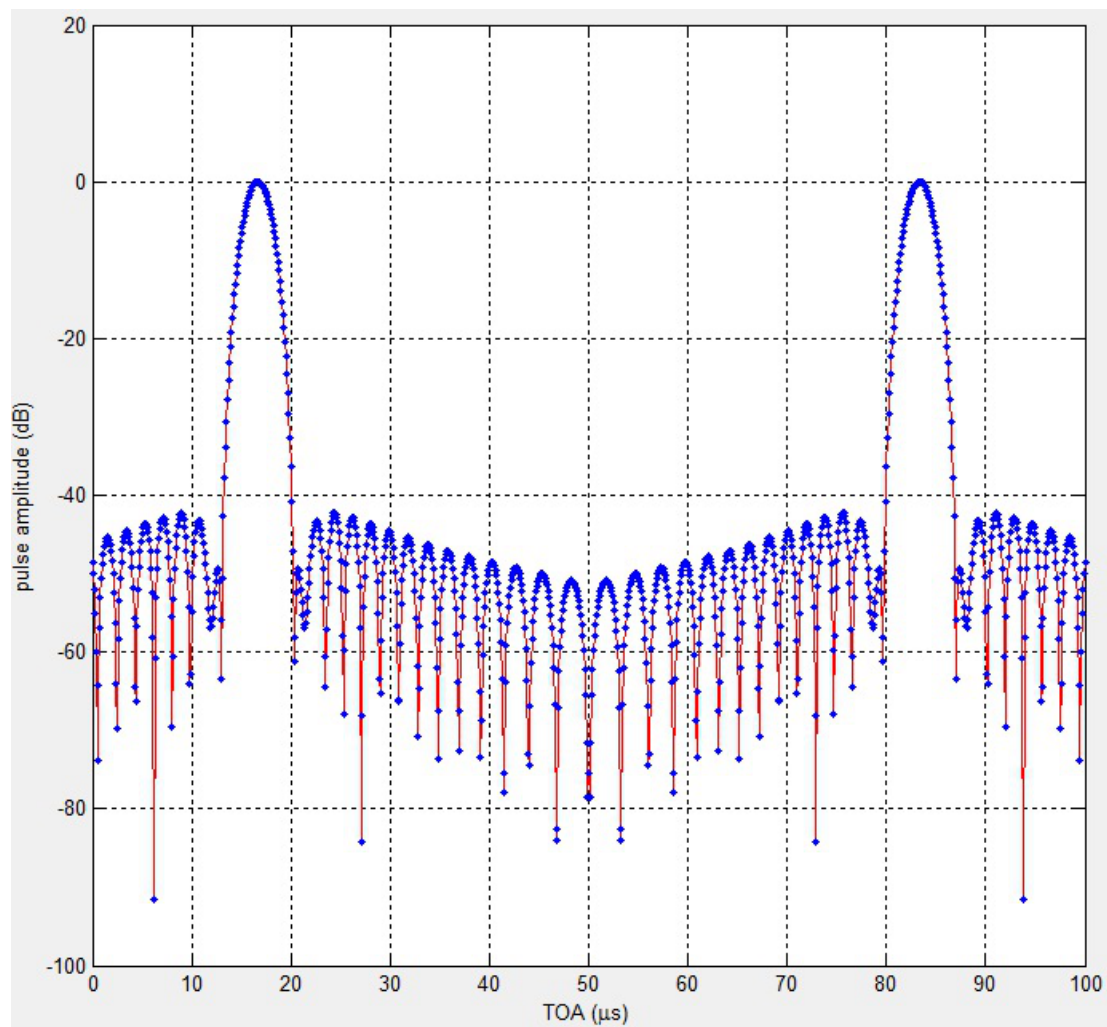


Figure 3.7: PA versus TOA plot for a sector scan.

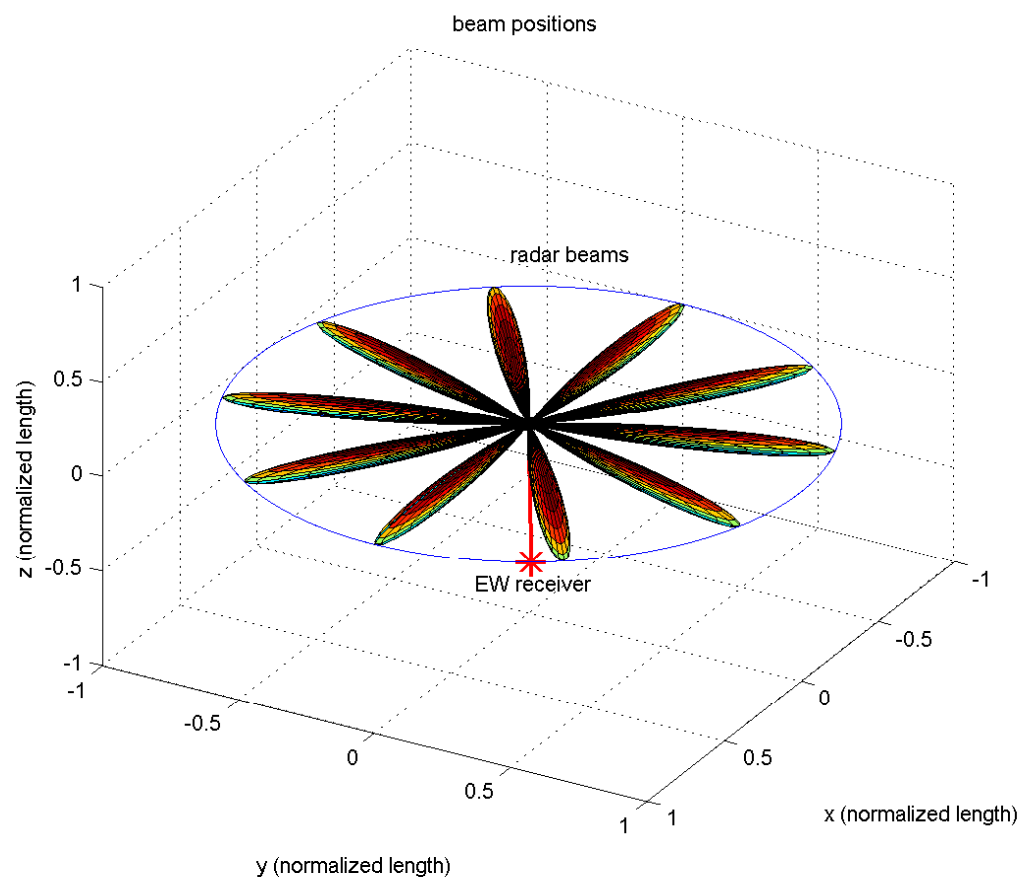


Figure 3.8: Beam positions and the EW receiver in a circular scan.

Chapter 4

Antenna Scan Type Recognition Algorithm

Antenna scan analysis problem can be ideally formulated as finding the angles between the radar main beam and the EW receiver as time passes and then trying to classify the radar scan pattern into one of the most encountered scan types. This information is supposed to be inferred from the power received from the radar. However, the problem is complicated in various ways: the radiation pattern and the location of the radar antenna are completely unknown to the EW system, and the parameters of the scan types vary vastly (antenna scan period, number of bars in raster, sector width etc.) which is almost always the case in the practical world. Trying to check all the possible received power outcomes and defining a metric (e.g., Euclidean distance) to measure the similarity would exhaust any computation power feasible. The deficiency of vital information has lead the study to suboptimal solutions in which the main phenomena for recognition, period and main beam positions and numbers, are used.

This chapter starts with an overview of the algorithm. It is first presented as a general algorithm because the proposed algorithm framework can be used in other applications such as vowel classification in speech recognition as well. Following the main framework, application of the algorithm to the specific problem of radar

antenna scan analysis is explained with a running example. The parameters of the general algorithm are also tuned to the signals of interest in Section 4.2. The results of the intermediate parts are also given as the algorithm is explained. The algorithm is validated by both synthetic data generated by ASPS and real data acquired and provided by ASEL SAN Inc.

4.1 Overview of the Algorithm

This section explains the proposed algorithm step by step with general inputs and outputs suitable for the classification of any periodic signal. The algorithm can be used, not only for the particular problem of this thesis, but also to classify uniformly or non-uniformly sampled periodic signals. The parameters such as the thresholds or the value of N should be chosen according to the specific signals involved.

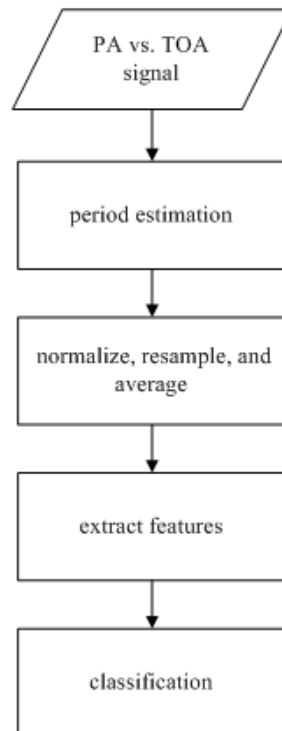


Figure 4.1: The overall flowchart of the algorithm.

4.1.1 The Input Signal

We assume that the input signal $x[l]$ is a discrete-time sequence obtained by properly sampling the original signal $x(t)$ above the Nyquist rate. The sampling procedure is as follows:

$$x[l] = x(lT_s) \quad l = 0, 1, \dots, L - 1 \quad (4.1)$$

Although uniform sampling is employed in many applications, in some cases, non-uniformly sampled signals can be encountered as well. Uniformly sampled signals are much simpler to handle. Calculating the period of a uniformly sampled signal is easier and less complex, usually independent from the method used. If one has a non-uniformly sampled signal, it is better to resample the signal with a sampling rate suitable to the signal so that it becomes uniformly sampled. Different interpolation (linear, polynomial etc.) techniques can be applied for resampling.

4.1.2 Period Estimation

A signal $x[l]$ is considered periodic if a period value T exists such that

$$x[l] = x[l + mT] \quad \forall l, m. \quad (4.2)$$

The smallest value of T that satisfies this equation is called the fundamental period. Period estimation has attracted a lot of interest over the years especially in the speech processing area [5, 10, 16, 31]. The problem is sometimes called (fundamental) tone estimation or pitch estimation as well. There are solutions to the problem in the time and the frequency domains.

Frequency-domain methods use the fundamental idea behind the Fourier transform. The period is estimated by looking at the peaks of the frequency content. This method works well for sinusoids, since it was designed for this purpose, but it possesses some problems when the signal is not a sinusoid. For example, if the spectrum of the signal itself is broad, the peaks may be illusive when estimating the fundamental frequency.

Time-domain methods are particularly useful for period estimation of non-sinusoidal signals. These methods define some kind of similarity metric, and by this metric, try to maximize the similarity with the lagged versions of the signal. The lag where the similarity is maximized becomes the period of the signal which is quite intuitive. Absolute magnitude difference function (AMDF) uses the difference of the signal and lagged versions of the signal as a metric [31]. Autocorrelation function is also employed in which the correlation between the signal and its lagged versions are used as a similarity metric. There are modified versions of these techniques to enhance the results of period estimation [31].

The backbone of our algorithm is the period estimation part. This part affects the overall performance of AST classification significantly. The period estimation method should be chosen suitably, according to the properties of the signal.

4.1.3 Normalize, Resample, and Average

This part mainly describes the preprocessing stage before the features are extracted. It tries to minimize the noise and transform the signal into standard dimensions, eventually improving the quality of the features.

The signal can be normalized so that the features are not affected by the range of the signal. The most suitable normalization technique should be chosen among the different normalization techniques (e.g., range normalization, standard deviation normalization) according to the signal properties.

The input signal could be from a set where the sampling rates and the number of samples could be widely varying, which is the case in our application. To extract reasonable features from this type of signal, it is better to have the same number of samples and the sampling rate should be somewhat similar. This improves the quality of the features and reduces their dependency on the length of the signal and the sampling rate.

The number of samples (N) that define the signal sufficiently well is determined by analyzing the signal. The sampling interval of the original discrete-time

signal with total length L is changed from T_s to $\frac{T}{N}$ after the resampling procedure by:

$$x_r[k] = x[\text{round}(\frac{kT_s}{T}N)] \quad k = 0, 1, \dots, \lfloor \frac{(L-1)T}{T_s N} \rfloor \quad (4.3)$$

where $x_r[k]$ denotes the resampled sequence and $\lfloor \cdot \rfloor$ indicates truncation. The procedure above uses nearest point interpolation for non-integer $\frac{T}{T_s}$ values. One can also use sinc, linear, or spline interpolation.

If the signal has at least two periods, it can be coherently added and averaged so that the effect of noise is reduced. Assuming the signal has at least M ($L \geq MN$) full cycles, the averaging process for the resampled signal is performed as follows:

$$\bar{x}[k] = \frac{1}{M} \sum_{m=0}^{M-1} x_r[k + mN] \quad k = 0, 1, \dots, N-1 \quad (4.4)$$

4.1.4 Feature Extraction

After the signal has been transformed into N sampled points with the preceding procedures, it is ready for the feature extraction stage. Different features of the signal such as the minimum and the maximum values, mean, standard deviation, skewness, kurtosis or higher-order moments are usually used to describe the probability density function of the signal. The features to be extracted change from signal to signal according to the phenomena that affect the classes. Coefficients of the Fast Fourier Transform (FFT), Discrete Cosine Transform (DCT), and Discrete Wavelet Transform (DWT) are used extensively in the literature [14, 19, 29].

4.1.5 Classification

The classification phase is the intelligence part of the whole system. There is a wide variety of classifiers, to name a few [7]: Bayesian classifier, Gaussian discriminants, artificial neural networks, decision trees, support vector machines etc.

4.2 Application of the Algorithm to Radar Antenna Scan Analysis Problem

4.2.1 The Input Signal

The signal consists of a discrete-time sequence of PAs versus TOAs of the pulses which are either the output of the ASPS or collected via the EW receiver. Figure 4.2 shows an example PA versus TOA signal. The output from these sources

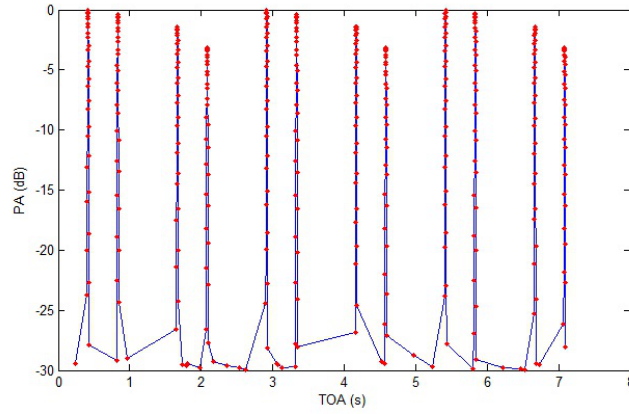


Figure 4.2: An example of signal from a raster scan.

are in dBW (decibel relative to watt). The signal is first transformed from dBW to Volt (V) scale by:

$$\text{voltage} = 10^{(\text{power}/20)} \quad (4.5)$$

It is assumed that the input signal has at least two cycles of the antenna scan. This is important since period estimation phase needs at least a few cycles to accurately estimate the period of the signal. The input signal has a variety of different parameters. The PRI, ASP, azimuth and elevation beamwidth parameters of the radar and the receiver are changed at every signal synthesized so that the classifiers encounter all the different variety of parameters that affect the signal. Parameter selection of synthesized signals is made realistically taking real radar systems as examples.

Some of the signals are assumed to have stagger type PRI which means that the sampling rate is not uniform. As already stated in the previous chapter, working with uniformly sampled signals is much simpler and has less computational complexity. If the signal has stagger PRI, it is resampled in this part with the highest PRI in the stagger levels. During the resampling process, if the signal is not available at a particular time point, interpolation is performed using the two closest points. In some cases, especially when the antenna is looking towards the opposite of the EW receiver, the receiver does not sense any pulses. These points are filled with zeros to make the succeeding computations easier. The flowchart of this part is shown in Figure 4.3. As a result, the signal in Figure 4.2 is transformed into the signal shown in Figure 4.4.

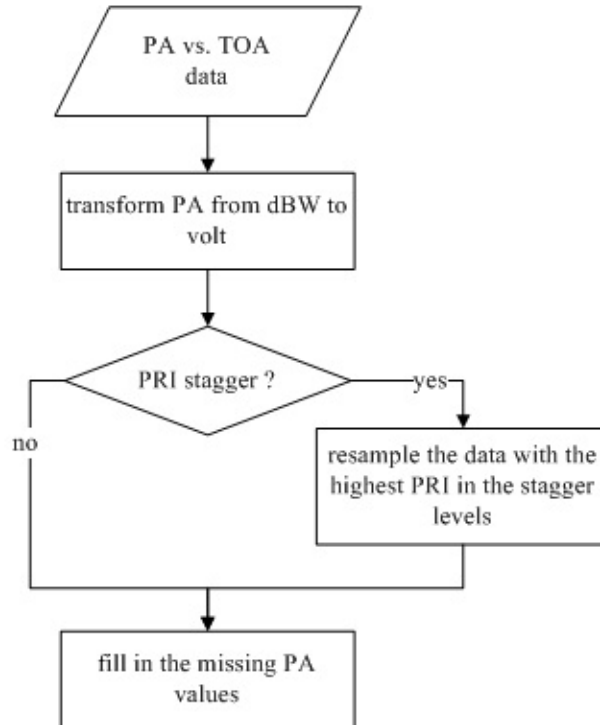


Figure 4.3: Flowchart of the preprocessing performed on the signal.

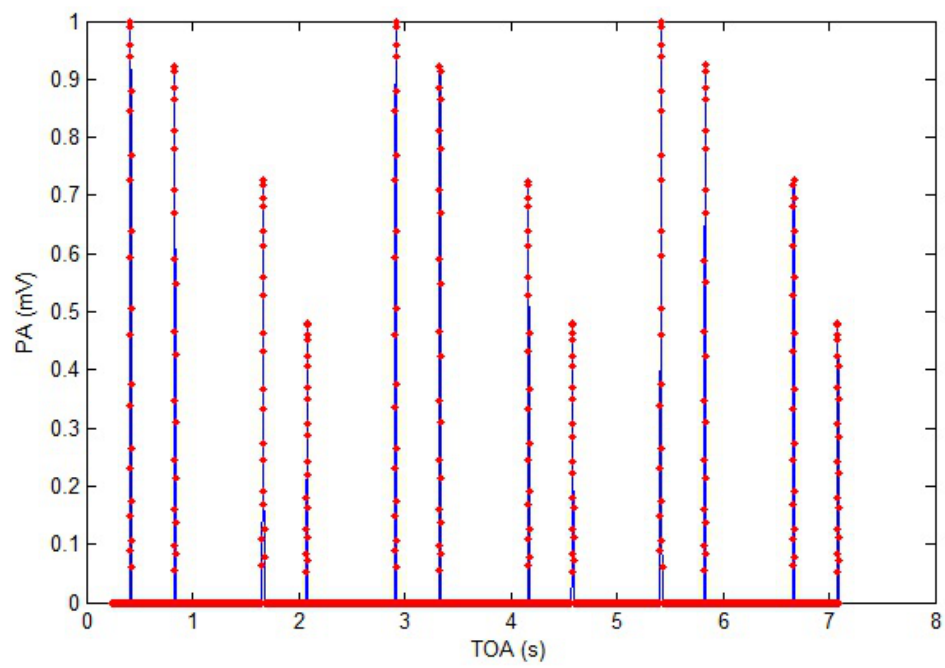


Figure 4.4: Transformed signal ready for period estimation.

4.2.2 Period Estimation

The period estimation is based on the normalized autocorrelation coefficients of the signal, defined as follows:

$$r_{xx}[k] = \frac{\sum_{i=0}^{W-1} x[i]x[i+k]}{\sqrt{\sum_{i=0}^{W-1} x^2[i]}\sqrt{\sum_{i=0}^{W-1} x^2[i+k]}} \quad k = 0, 1, \dots, L - W \quad (4.6)$$

W in Equation (4.6) is the window size that should be chosen such that a compromise between computational complexity and accuracy is reached. In the algorithm, it has been chosen as one third of the signal length ($W = \frac{L}{3}$). An example of $r_{xx}[k]$ is shown in Figure 4.5. The threshold level of 0.98 is also drawn on the figure in dashed lines.

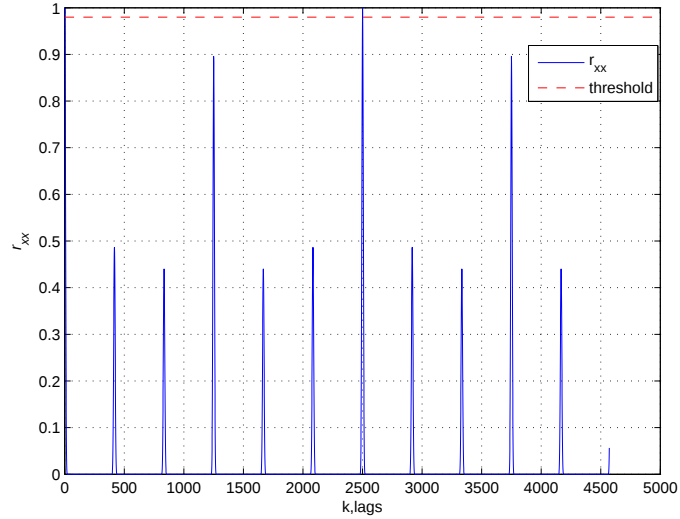


Figure 4.5: Normalized autocorrelation coefficients calculated for the signal.

After calculating the correlation coefficients between the signal and its lagged versions, the algorithm outlined in Figure 4.6 is employed to estimate the final period. Applying the algorithm in Figure 4.6 to Figure 4.5, one can see that the period is 2500 lags.

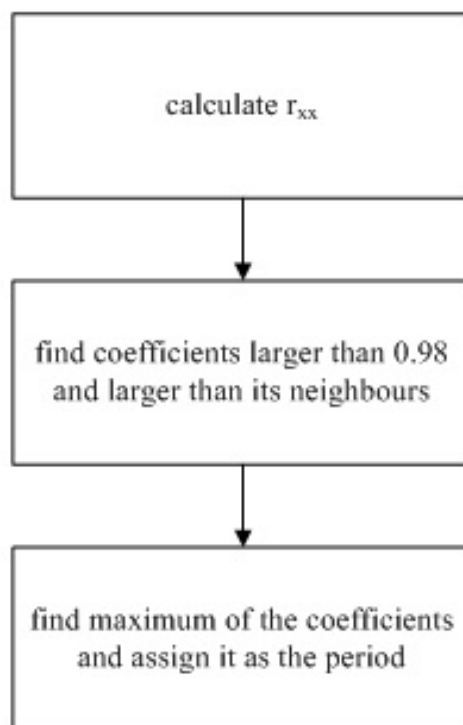


Figure 4.6: Period estimation algorithm.

4.2.3 Normalize, Resample, and Average

This part prepares the signal for the feature extraction phase by normalizing, averaging, and finally resampling the signal.

The normalization process is quite simple where the signal is simply scaled by its maximum value so that the signal varies between 0 and 1:

$$x_{norm}[k] = \frac{x[k]}{\max(x[k])} \quad k = 0, 1, \dots, L - 1 \quad (4.7)$$

This process tries to remove the effects of propagation, since propagation results in a decay in pulse amplitude, proportionate to the distance between the radar and the EW receiver. Here, we are not concerned with the distance and rather concerned with the antenna scan type which is independent of constant decays.

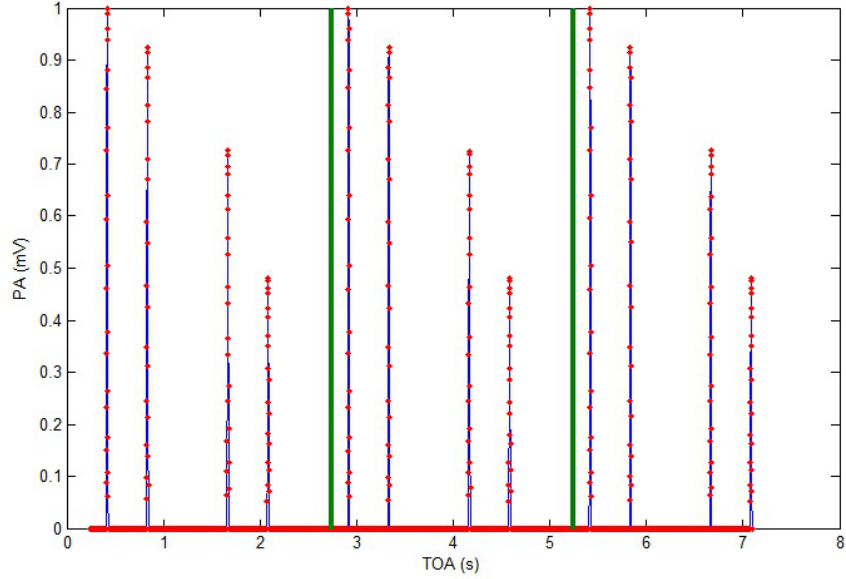


Figure 4.7: Full periods in the signal.

Next, we resample the signal so that the total number of samples from one cycle of a particular scan type is N where the value of N depends on the signal. This process transforms all of the recorded signals from different radars with different PRIs, different ASTs and different ASPs with $\frac{T}{T_s}$ elements into a standard

signal vector with N elements. Here, T is the estimated period and T_s is the sampling interval of the original signal. The process also regularizes the different sampling periods of the signal to $\frac{T}{N}$. The value of N is chosen as 2000 throughout the example signal. This resampling phase also reduces the amount of data because radars use much larger number of pulses per scan period to be aware of the environment, so it becomes a decimation operation. Since a high sampling rate is available before the resampling phase, nearest point interpolation technique can be used with negligible distortion in the signal. This process was defined in Equation (4.3).

Assuming M full cycles of signal are available to estimate the period of the signal, the signal can coherently be averaged using Equation (4.4) to decrease the effect of noise. Figure 4.7 shows the signal with the periodic parts shown in green boundaries. The final version of the signal is pictured in Figure 4.8. From this point on in the text, the word “signal” is used for the final version of the signal.

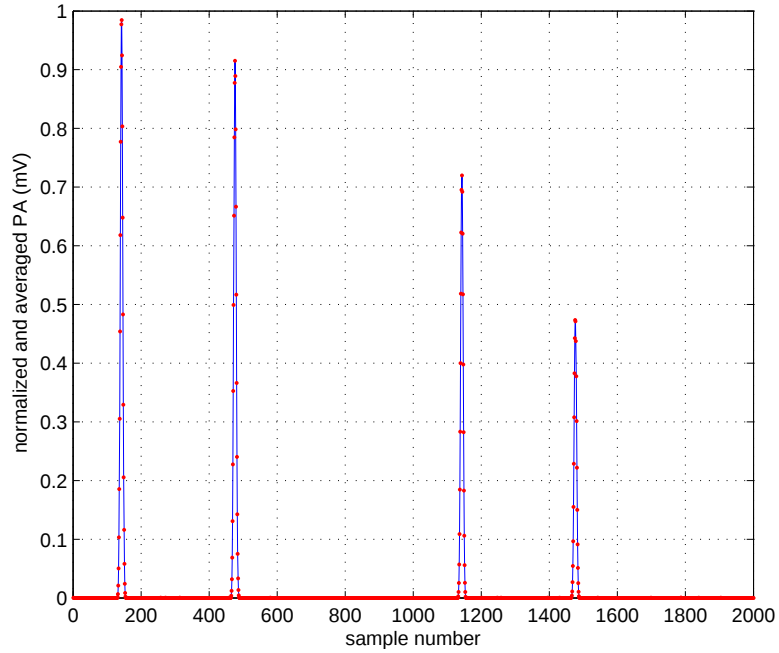


Figure 4.8: Final version of the signal.

4.2.4 Feature Extraction

In this section, we describe the four features selected and used by the algorithm. Input to this part is the preprocessed N element signal with sampling interval $\frac{T}{N}$.

There are a total of 100 data points, 20 from each of the following scan types in the following order: circular, sector, raster, helical, and conical. These signals are synthesized by using the ASPS described in the previous chapter. The parameters (azimuth and elevation beamwidths, sector width, number of bars in raster, scan period etc.) used while generating the signals are very important. The results of the classification phase could be very misleading if the parameters are not set appropriate with the real world examples. Therefore, we have used a classified database which the parameters of the radars are accountable on and have selected these parameters accordingly.

We have attempted to use a number of different features such as the mean, standard deviation, and skewness, but the best results were obtained with the four features described below:

Kurtosis of the Signal

Kurtosis is the normalized fourth-moment of a random variable X and is defined as:

$$\text{kurtosis} = \frac{E[X - \mu]^4}{\sigma^4} \quad (4.8)$$

where μ is the mean and σ is the standard deviation of the random variable.

Kurtosis is a statistical measure of how peaked or how flat the distribution of the random variable is. It can also be seen as a measure of how heavy the tails of the distribution are relative to the Gaussian distribution which has a kurtosis value of 3. Concentrated distributions such as the uniform distribution have kurtosis values less than 3. If the distribution has heavier tails and is more outlier prone, its kurtosis value exceeds 3.

In track modes, radars try to illuminate the threat as much as possible so that they can update the threat's coordinates finely and accurately for a possible

attack. To perform this task, they have to steer the beam such that it is on the platform all of the time. This in turn means that the EW receiver will get all the pulses of the radar with slight differences in amplitude (i.e., a narrow distribution of amplitude) depending on the track scanning type of the radar system. The amplitude variation is approximately uniform. A conical scan signal, which is a uniformly sampled sinusoid, has a kurtosis value of around 1.5. By looking at the signal's kurtosis value, the system will get an idea about its mode and scan. The kurtosis value will be small for conical scan and large otherwise. This fact is confirmed by Figure 4.9 which illustrates that for the conical scan, kurtosis of the signal can be used as a discriminator. Therefore, we select the kurtosis as the first feature:

$$F_1 = \text{kurtosis}(x[k]) \quad (4.9)$$

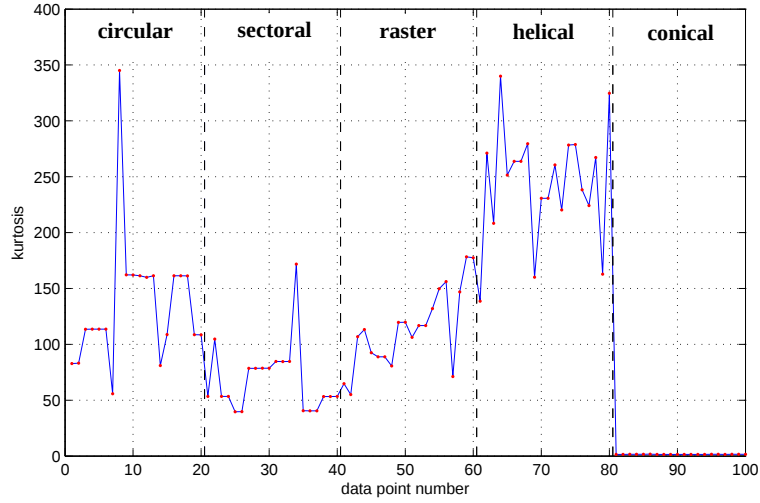


Figure 4.9: Kurtosis values of the different scan patterns.

Cross Correlation of the Signal with the Main Beam

It can be observed by analyzing different scan types and their effect on the EW platform that the position of the main beam differentiates the scans from each other. The phenomenon behind the data reveals this information very clearly. The radar is trying to search different volumes of space with different periodic

strategies. So the relation of the time between the main beams and the amplitude variation of the main beams are the key parameters for a robust recognition system.

First, the algorithm has to detect the main beam in the signal. This can be achieved quite easily by finding the maximum point in the signal. Assuming that there is a main beam in the signal, this has to be the maximum point. From the index of the maximum point, it starts to advance indices until the magnitude drops to 0.01. The process is repeated exactly in the same way for the pulses previous to the maximum point. By using these two points neighboring the maximum point where the amplitude drops to 0.01, it extracts the main beam between these two points. Figure 4.10 illustrates the signal and the main beam detected in the signal. After finding one of the main beams in the signal, the algorithm

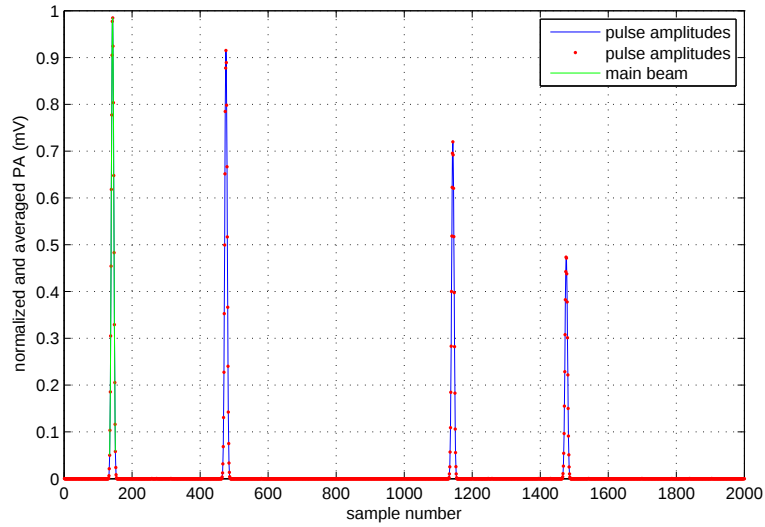


Figure 4.10: Main beam found in the signal.

detects all of the possible main beams in the signal by using the normalized cross correlation between the signal and the main beam found. The normalized cross correlation between two discrete sequences $x[n]$ and $y[n]$ is defined as follows:

$$r_{xy}[k] = \frac{\sum_{i=0}^{V-1} x[i]y[i+k]}{\sqrt{\sum_{i=0}^{V-1} x^2[i]} \sqrt{\sum_{i=0}^{V-1} y^2[i+k]}} \quad (4.10)$$

where V is the length of the main beam vector. Setting a threshold (0.95 is used

in this study) and finding the peaks in the cross correlation values gives all the possible main beams.

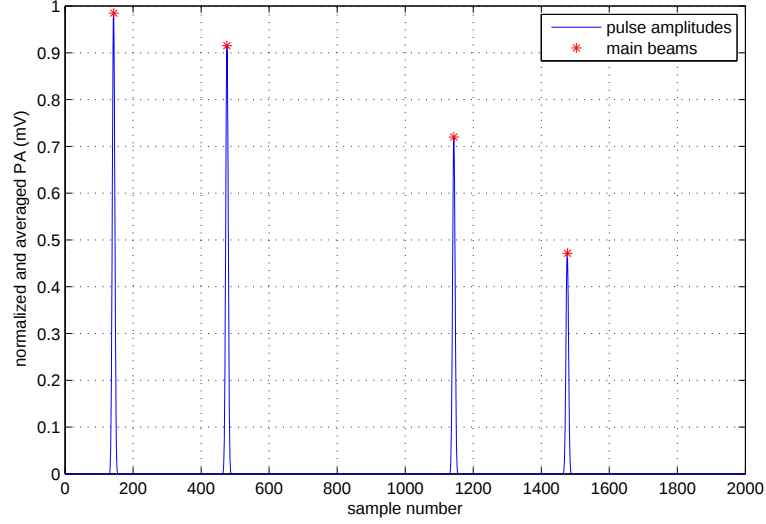


Figure 4.11: Main beams found in the signal.

One would expect the cross correlation value to be large since the patterns of different antennas are very similar near their bore sights. For scan types where no elevational action is involved (circular and sector), the main beams will be exactly the same, ignoring the effect of noise. The threshold can be tuned according to the signal to be able to handle the possible variations in the azimuth pattern caused by the changing elevation angle. Figure 4.11 shows the main beams found in the signal.

After finding the possible main beams in the signal, some very important relations are calculated from the time position and the pulse amplitudes of the main beams.

The number of main beams is an important parameter that can differentiate some scan types from the others. In particular, the circular scan has only one beam in one period which is a valuable feature to discriminate it from the others. Figure 4.12 shows this feature for all the data points. The figure shows that this feature is indeed very useful for classification. Circular and sector scan types are

very visible in the figure by this parameter. It can also be seen that no main beam is found in the conical signal since the pulse variation is not observed. Therefore, we choose the second feature as the number of main beams:

$$F_2 = \text{number of main beams in the signal} \quad (4.11)$$

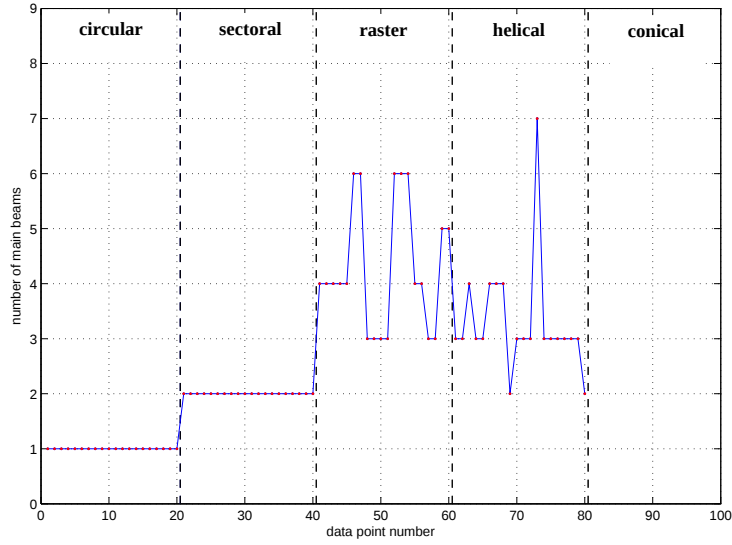


Figure 4.12: Number of main beams found in the signal.

Amplitude variation of the main beams can also be a very useful feature. The range of the main beam amplitudes is used as a measure of the variation by subtracting the minimum amplitude from the maximum amplitude. This feature can differentiate between azimuthal and elevational scan types. More generally, this feature can differentiate the scan types that involve only one plane (azimuth) and the ones that scan both planes (azimuth and elevation). Therefore, the third feature becomes the amplitude variation of the main beams:

$$F_3 = \max(\text{main beam PAs}) - \min(\text{main beam PAs}) \quad (4.12)$$

Figure 4.13 shows the distribution of this feature for all data points. One can see that the variation could not be calculated for circular scan types since this

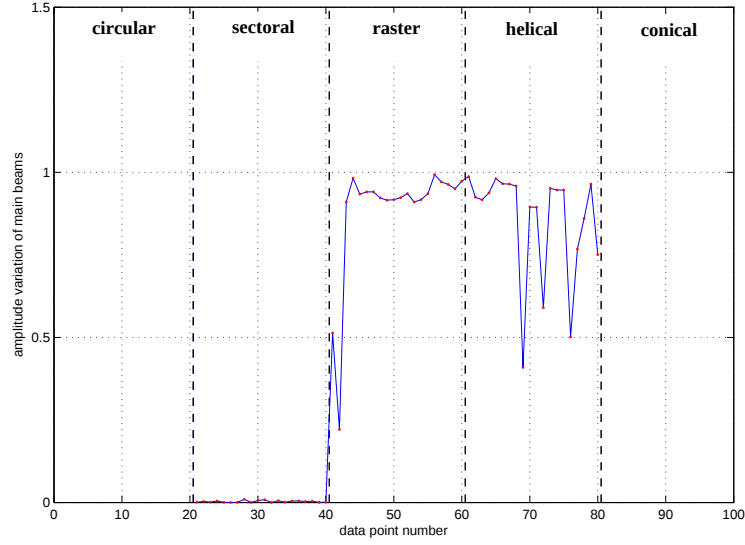


Figure 4.13: Amplitude variation of the main beams in the signal.

type of scan produce only one main beam. Similarly, since the conical scan does not have any distinct main beam, variation of main beams is not calculated as well. However, it is observed that the sector scan type can be separated from the others with this feature.

Time difference between the main beams is also a distinctive parameter between classes. Circular and helical scan types revolve the 360° sector continuously without going back and forth like sector and raster scans. In this case, one expects to see the time difference between the main beams to be very similar. However, in the raster scan, the time difference between the main beams should vary most of the time because of the nature of the scan. The only case where the time difference will be the same is when the EW receiver is in the middle of the scanned sector which is unlikely. For this, $\frac{\max(\text{time differences})}{\min(\text{time differences})}$ is calculated and used as a parameter. This parameter is plotted for all the different data points in Figure 4.14. We observe that this feature is only calculable for helical and raster scans since there should be at least three main beams to calculate the variation of time differences between the main beams. Therefore, the final feature is chosen

as the variation of the time differences:

$$F_4 = \frac{\max(\text{time differences})}{\min(\text{time differences})} \quad (4.13)$$

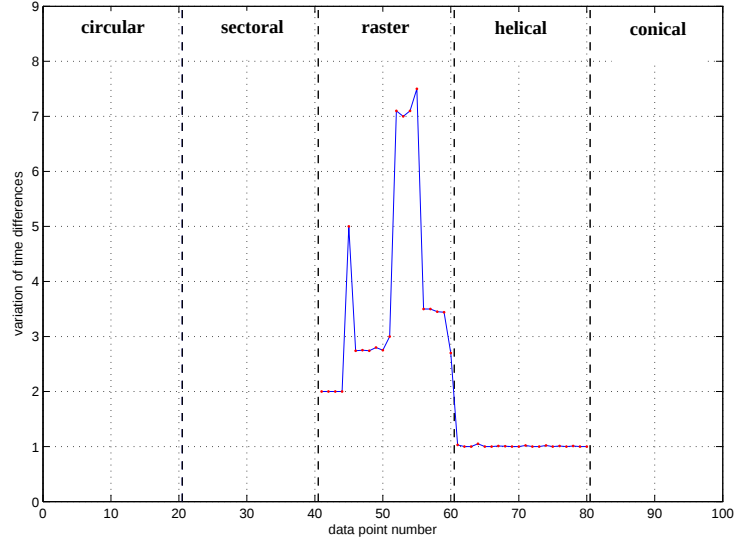


Figure 4.14: Time differences between the main beams in the signal.

4.2.5 Classification

The above features are used in the classification phase. For features that cannot be calculated for different scan types, 10000 value is used as a numeric value for the classification algorithm input as an indicator. For example, a main beam cannot be observed in a conical scan so its features other than the kurtosis cannot be calculated and set as 10000 to ease the calculations in the classification part.

Four different classification techniques are used: naive Bayes, decision tree, multilayer perceptron neural network, and support vector machines. The classification rates according the N parameter of the algorithm is shown to see the effect of the number of samples per period. The classification methods and their results are presented below. An open source machine learning software WEKA, developed by The University of Waikato, is used in the classification process [23].

We have used 4-fold cross-validation technique for training and testing the algorithm. In this cross-validation technique, the data points from each class are randomly partitioned into four groups. In the first run, first part is retained for testing and the remaining is used for training. In the second fold, the second part is retained for testing and the remaining is used for training. All of the data points are tested by this procedure by repeating this procedure four times [26].

4.2.5.1 Naive Bayes

Naive Bayes classifier classifies according to the Bayes' theorem. The classifier calculates the posterior probabilities according to the models of each class. The decision rule for classification is merely picking the hypothesis that is more probable.

Assuming $w_1, w_2, \dots, w_n$ are the classes, $p(x|w_j)$ is the state-conditional density function assuming that the given class is w_j , then the posterior probability is calculated as follows:

$$p(w_j|x) = \frac{p(x|w_j)p(w_j)}{p(x)} \quad (4.14)$$

where $p(x) = \sum_{j=1}^n p(x|w_j)p(w_j)$ is the total probability.

In the training phase, probability models for $p(x|w_j)$ are calculated using the training signal for each w_j . The probability density function is assumed to be a normal distribution and the parameters of the distribution are calculated by maximum likelihood estimation. In naive Bayes method, each of the features are assumed independent and the calculations of the parameters of the model are made accordingly. This assumption greatly simplifies the calculations and the complexity of the model.

The classification phase calculates the posterior probabilities according to Equation (4.14). The class of the signal is chosen as the most probable class according to the calculated posterior probabilities [7].

Figure 4.15 shows the classification results with respect to different N values. It can be seen that for very small N , the signal is undersampled and the features are not correctly extracted, causing errors in the classification. One can conclude from the figure that $N = 1000$ is a good choice in terms of the correct classification rate and computational complexity.

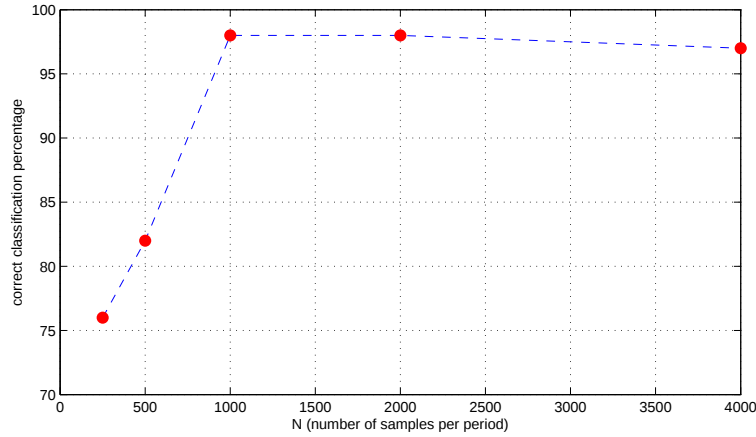


Figure 4.15: Classification results for naive Bayes classifier.

A confusion matrix in the case of $N = 1000$ is shown in Table 4.1.

The effect of noise is also considered and analyzed for this case. The added

		classification result				
		circular	sector	raster	helical	conical
true class	circular	19	1	0	0	0
	sector	1	19	0	0	0
	raster	0	0	20	0	0
	helical	0	0	0	20	0
	conical	0	0	0	0	20

Table 4.1: Confusion matrix for naive Bayes classifier with 98% correct classification rate.

noise affects the detected signal levels because of the thresholding in the detection phase of the pulses. A threshold level of 10 dB above the noise power level is used in this analysis. This threshold value is usually used in EW systems as a good compromise between probability of false alarm and probability of detection [25]. The thresholding limits the range of the PA versus TOA signal. This, of course, may result in the loss of main lobes especially in raster and helical scans, leading to classification errors. For example, because of the limited range of the signal, only one bar of the raster scan may be observed leading to a circular scan classification erroneously. The classification result with respect to the SNR is shown in Figure 4.16 where we used SNR values of 12, 15, 20, 25, 30, 35, and 40 dB. The breakdown in the performance around 25 dB SNR shows us the effects discussed earlier because of the range of the signal. The confusion matrix in Table 4.2 shows the effect more clearly. The limited range of the signal indicates a tendency towards sector and circular scan both of which are only azimuthal scans and are relatively immune to the range of the signal received. We have also observed that when the sinusoidal shape in a conical scan is distorted by loss of pulses, the algorithm also has a tendency towards circular scan.

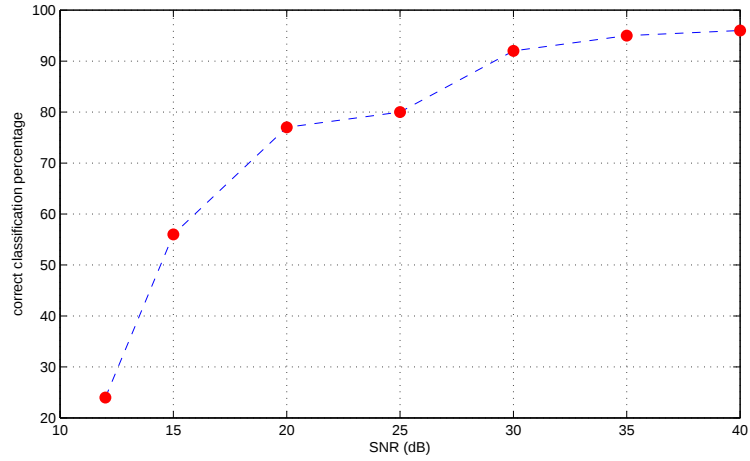


Figure 4.16: Classification results for naive Bayes classifier with respect to different noise levels.

		classification result				
		circular	sector	raster	helical	conical
true class	circular	19	1	0	0	0
	sector	1	19	0	0	0
	raster	6	0	4	10	0
	helical	0	5	0	15	0
	conical	2	0	0	0	18

Table 4.2: Confusion matrix for naive Bayes classifier in the case of 20 dB SNR (77% correct classification).

4.2.5.2 Decision Tree

Decision trees are the most intuitive and natural way of classification [7]. One finds a sequence of test questions starting from a main question and branches all the way to a terminating node where the class of the signal is found. The structure of our problem fits well into a decision tree like structure since each one of the selected features is discriminative for one or two of the scan types. That is, if one knows that the kurtosis value is low, than it is highly probable that it is a conical scan.

There are quite a lot of different tree growing algorithms that use training signals and establish a tree which classifies the signal. The most popular ones are: Classification and regression trees (CART) and C4.5. More information about these algorithms can be found in [7] with an extensive explanation.

Besides the algorithms mentioned above, a relatively newly proposed best first tree (BFTree) learning algorithm is also considered in this study. It is seen that this algorithm comes up with trees that can classify the scans more accurately. The following results are obtained by using the BFTree algorithm. More information about this algorithm can be found in [20].

The tree output of the algorithm is shown in Figure 4.17. The classification results of the decision tree grown in this study are illustrated in Figure 4.18. The same undersampling effect seen in the previous classifier is also seen here with $N = 1000$ being a suitable choice. The confusion matrix for the decision tree when $N = 1000$ is used is given in Table 4.3.

The effect of noise can be seen in Figure 4.19. We see that the previously discussed effects are also seen in the decision-tree classifier in a relatively smaller scale. The confusion matrix for 20 dB SNR case is shown in Table 4.4. The increase in the classification errors of 2-D scans is visible as before.

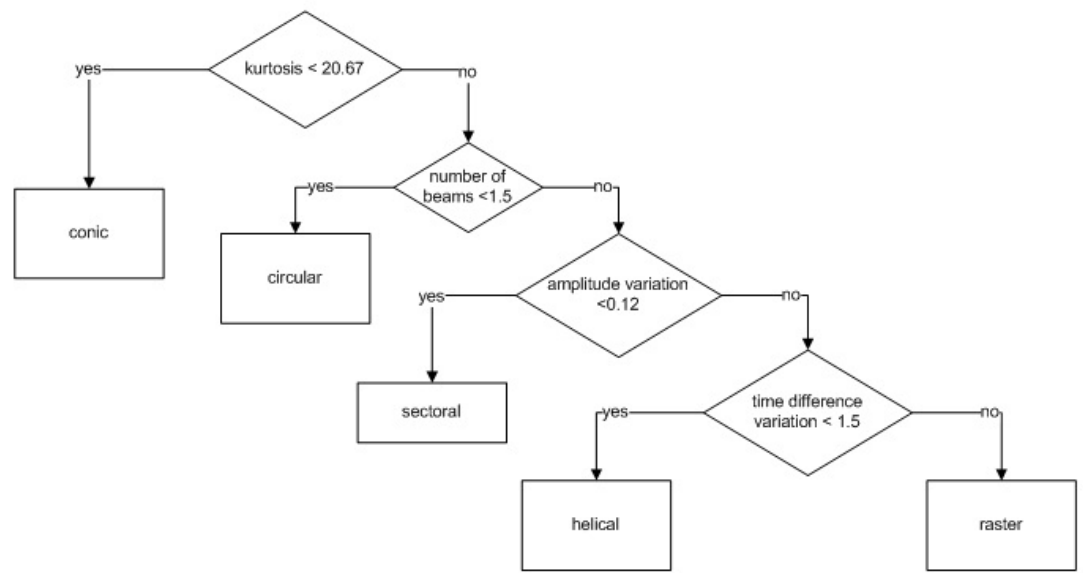


Figure 4.17: The BFTree decision-tree classifier generated and used in this study.

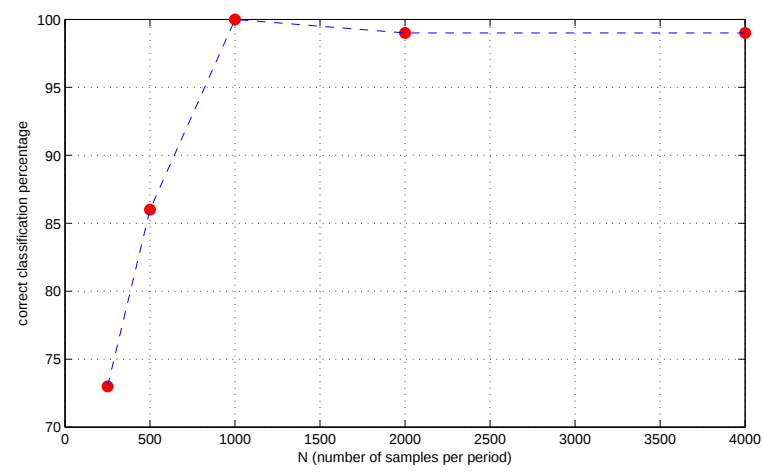


Figure 4.18: Classification results for the decision tree.

		classification result				
		circular	sector	raster	helical	conical
true class	circular	20	0	0	0	0
	sector	0	20	0	0	0
	raster	0	0	20	0	0
	helical	0	0	0	20	0
	conical	0	0	0	0	20

Table 4.3: Confusion matrix for decision-tree classifier with 100% correct classification rate.

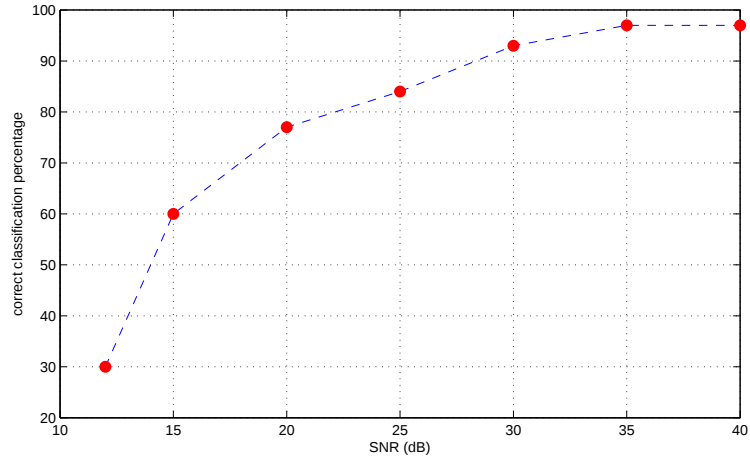


Figure 4.19: Classification results for decision-tree classifier with respect to different noise levels.

		classification result				
		circular	sector	raster	helical	conical
true class	circular	20	0	0	0	0
	sector	1	15	0	5	0
	raster	7	0	8	5	0
	helical	3	3	0	14	0
	conical	0	0	0	0	20

Table 4.4: Confusion matrix for decision-tree classifier in the case of 20 dB SNR (77% correct classification).

4.2.5.3 Artificial Neural Networks

Artificial neural networks (ANN) are classifiers that try to emulate the computational processes in the human brain. They consist of nodes similar to the neurons in the nervous system. The interconnection between nodes is only through weighted sums of the inputs of the neuron. In the neuron itself, a non-linear function called the activation function, is used to model the process in the neuron. There are usually three types of layers in an ANN: an input layer, one or more hidden layers, and an output layer. The input layer has sufficient number of nodes to cover the inputs; the output has also nodes to represent the outputs. The part where the patterns are learnt are the hidden layers of the system. The number of hidden layers and the number of nodes in each hidden layer can be chosen by the designer. Small number of neurons in the hidden layer may not satisfy the user in terms of classification accuracy because the ANN may not be able to learn the patterns sufficiently. However, an excess of neurons in the hidden layer causes a lot of complexity in the training part and it also could lead to “memorization” of the signal instead of “learning” the dynamics of the signal. Due to the presence of distributed nonlinearity and a high degree of connectivity, theoretical analysis of ANNs is difficult. The performance of ANNs is affected by the choice of parameters related to the network structure, training algorithm, and input signals, as well as by parameter initialization [13].

There is a variety of different networks, training methods, and activation functions for different types of applications [13]. A multi-layer (three layer) perceptron with a back-propagation algorithm is used in this study. This is a supervised method which uses a gradient-descent algorithm based on the error at the output. It tries to minimize the error by feeding back the error at the output to update the weights in each epoch.

After the network is trained, classification is performed: the inputs are fed to the ANN with the already converged weights and the class of the signal is determined according to the output.

The classification results with respect to N is depicted in Figure 4.20. The

effect of undersampling and the saturation after a point is also seen in this figure as in the previous classifiers. The confusion matrix for the ANN classifier when $N = 1000$ is given in Table 4.5.

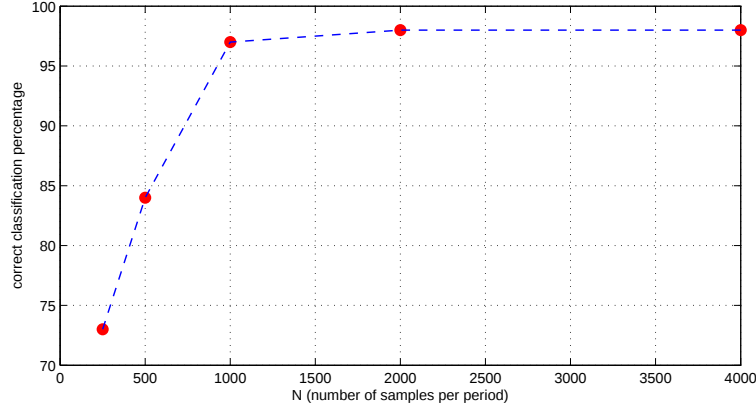


Figure 4.20: Classification results for the ANN classifier.

		classification result				
		circular	sector	raster	helical	conical
true class	circular	20	0	0	0	0
	sector	0	19	1	0	0
	raster	0	2	18	0	0
	helical	0	0	0	20	0
	conical	0	0	0	0	20

Table 4.5: Confusion matrix for the ANN classifier with 97% correct classification rate.

The classification percentages according to different noise levels are illustrated in Figure 4.21. The results show that ANN is less robust to noise effects with respect to the previous classifiers. The confusion matrix for 20 dB SNR case is shown in Table 4.6.

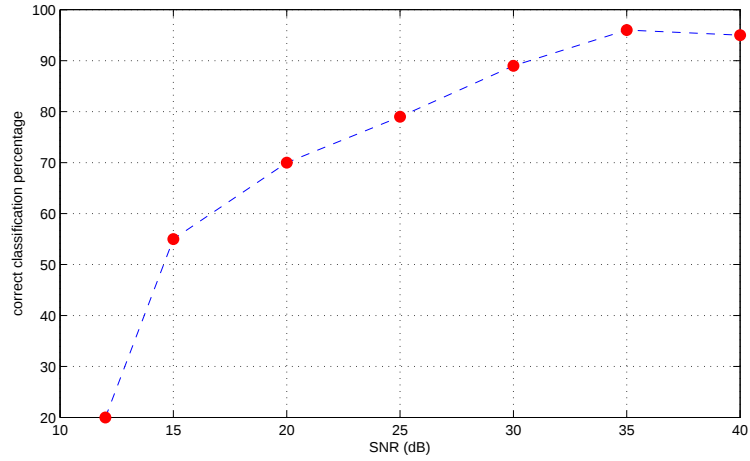


Figure 4.21: Classification results for the ANN classifier with respect to different noise levels.

		classification result				
		circular	sector	raster	helical	conical
true class	circular	20	0	0	0	0
	sector	0	18	0	2	0
	raster	8	1	6	5	0
	helical	3	3	6	8	0
	conical	2	0	0	0	18

Table 4.6: Confusion matrix for ANN in the case of 20 dB SNR (70% correct classification).

4.2.5.4 Support Vector Machines

Support vector machines (SVMs) is a binary classifier that tries to divide the space with hyperplanes where each volume represents a different class. The hyperplane that is expected to be found is a hyperplane that maximizes the margin of separation between the classes. The hyperplane is found by using the data points that are between the classes. These points are very valuable in separating the classes and are called the support vectors. By using these points and by the help of quadratic programming, the hyperplanes that separate the classes are found. If a hyperplane is not sufficient to divide the classes, i.e., the region dividing classes is not linear, one can use different kernels to transform the signal to different spaces [7].

In this study, a linear SVM is trained with the signal without any kernel and one-versus-the-rest classification is performed since there are more than two classes. The cases where $N < 1000$ did not converge. For $N \geq 1000$ values the classification percentage is fixed with 99%.

The confusion matrix for the SVM classifier is shown in Table 4.7.

		classification result				
		circular	sector	raster	helical	conical
true class	circular	20	0	0	0	0
	sector	0	19	0	1	0
	raster	0	0	20	0	0
	helical	0	0	0	20	0
	conical	0	0	0	0	20

Table 4.7: Confusion matrix for support vector machine classifier with 99% correct classification rate.

The effect of noise on classification is shown in Figure 4.22 and the confusion matrix for 20 dB SNR case is shown in Table 4.8.

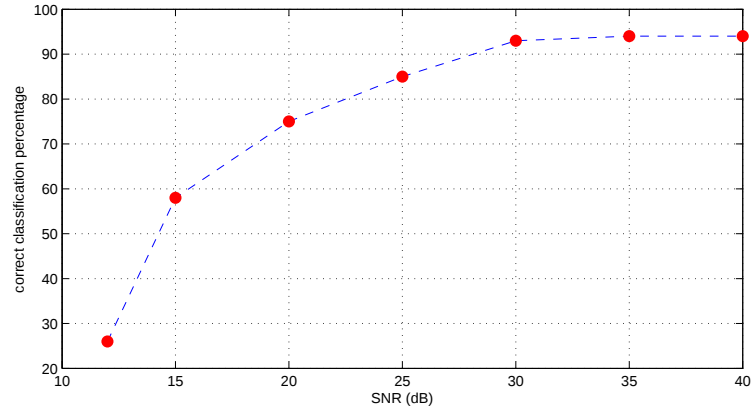


Figure 4.22: Classification results for SVM classifier with respect to different noise levels.

		classification result				
		circular	sector	raster	helical	conical
true class	circular	20	0	0	0	0
	sector	0	18	0	2	0
	raster	7	3	6	4	0
	helical	3	4	0	13	0
	conical	2	0	0	0	18

Table 4.8: Confusion matrix for SVM in the case of 20 dB SNR (75% correct classification).

4.2.6 Validation with Real Signals

ASELSAN Inc. [2] has acquired real world signals from different radars with its own receiver systems using a non-stationary airborne platform on the move. Therefore, the assumption that the EW receiver is stationary in the previous chapters was not met. The signal also had some outliers because of the platform's motion and reflections from the platform. One could see the distortions in the main beam as well because of the reflections. ASELSAN Inc. supplied the signal for only validation purposes and the illustration of the signal was strictly forbidden because of its classification level.

Some modifications to the algorithm had to be made because of the properties of the signal. The threshold levels in period estimation had to be decreased to 0.85 because of the effect of the non-Gaussian noise on the signal. One other implication was that the platform was on the move, which does not give the chance to coherently average M periods of the signal, since the movement of the platform changes the time it sees the main lobe. Thus, instead of averaging all of the periods of the signal, we have chosen the largest main beam and the one period interval around it for feature extraction.

A total of 30 signal vectors have been acquired. The noise level of the data ranged from 20-35 dB SNR. The data consisted of circular, conical, and sector scans only. The decision-tree classifier is used because of its computational simplicity and its high classification rates. The confusion matrix for the real signals is as follows:

		classification result				
		circular	sector	raster	helical	conical
true class	circular	10	0	0	0	0
	sector	0	9	1	0	0
	conical	0	0	0	0	10

Table 4.9: Confusion matrix for real world signals with 97% correct classification rate.

The error rate of the algorithm with the real data is 1 in 30 data points.

We see that the only error seen is a sector-raster misclassification which can be expected because of the similar nature of these scans. This result shows that the algorithm presented in this study can also handle real acquired signals which has outlier-like shot noise and deformed main beams. The platform from which the signal is acquired was also non-stationary, making the classification even harder. The validation phase of the algorithm has ensured that it is robust against the probable complications encountered in the practical world.

4.2.7 Comparison of the Computational Time of the Classifiers

We have also analyzed the time it takes to train and test the classifiers used in the study as an indication of computational complexity of each classifier. A computer with 2.66 GHz processor and 3 GB of RAM is used in the tests. The results obtained with WEKA, given in Table 4.10, shows us that the decision-tree classifier outperforms the other classifiers in terms of computational complexity as well.

classifier	time (s)
naive Bayes	0.08
decision tree	0.05
ANN	0.35
SVM	0.12

Table 4.10: Amount of time needed for training and testing for each classifier.

The robustness against noise presented in the previous sections and low computational complexity of the decision-tree classifier indicates that for this particular application, decision tree is the most suitable choice as a classifier.

Chapter 5

Conclusions and Future Work

This thesis addressed a problem of electronic warfare signal processing where no clear and accessible study is found in the open literature. The conventional solution to the problem is to employ a human operator who listens to the radar tone generated from the pulses received. The operator guesses the scan type and estimates the period with a stopwatch in hand. The experience level of the EW operator is very important for correct decisions. One can see easily that this is an expensive solution and its robustness and accuracy is dependent on the state of the human.

The research for an automatized solution to the problem has lead to an algorithm which is general and can also be used to analyze signals with different periodicities. The algorithm is implemented for the particular problem with different variants of classifiers. The algorithm uses the conventional parameters measured in any of the EW receivers in the market without the need of any other special data acquisition mechanism. It is seen from the results that the classification rates are higher than 90% for most of the cases for synthetic signals. The results have favored the decision-tree classifier. Decision tree has higher classification rates and is more robust against the effects of noise. According to this result, the algorithm's (with the decision-tree classifier) robustness against real world scenarios is also validated with data given by ASELSAN Inc. The classification results are very promising with minor modifications in the algorithm.

The analysis has also shown that the noise level of the receiver is crucial for classification performance. This is mainly because of the fact that signal's range (the difference between the maximum and the minimum value of the signal) decreases with increasing noise level. The range of the signal is very important especially for the patterns that scan both in azimuth and elevation (raster and helical). Range limitation of the signal results in information loss (main beams with different elevation levels are not sensed in the EW receiver) that can not be inferred in any way because of the detection schemes of the EW receivers. The correct classification of raster and helical scans degrades significantly with the signal's range limitation. Circular, conical, and sector scans are more robust to the range limitations of the signal. To make the algorithm more reliable, a simple check of range can be included before the algorithm is executed. A range of greater than 15 dB ($\text{SNR} \geq 25$ dB) ensures correct classification rates above 90%.

The future work involves modifying this algorithm and making online analysis of scan type and period. The main problem is to differentiate a sidelobe from a main lobe by looking at the data in parts instead of whole. There is a need to record the signal and then run the proposed algorithm. A modified version of this algorithm which tries to track the features extracted in this study as signal flows would be more useful for real world systems.

Bibliography

- [1] *3-13.1 Electronic Warfare*. United States Army Joint Publication, 2007.
- [2] ASELSAN Inc., Radar, Electronic Warfare and Intelligence Systems Division. Yenimahalle, 06370, Ankara, Turkey.
- [3] D. Adamy. *Ew 101: A First Course in Electronic Warfare*. Artech House, Massachusetts, 2001.
- [4] D. Adamy. *Introduction to Electronic Warfare Modeling and Simulation*. Artech House, Massachusetts, 2002.
- [5] A. E. B. Resch, M. Nilsson and W. Kleijn. Estimation of the instantaneous pitch of speech. *IEEE Transactions on Audio, Speech, and Language Processing*, 15:813–822, 2007.
- [6] C. A. Balanis. *Antenna Theory Analysis and Design*. John Wiley Sons, New York, USA, 1982.
- [7] R. O. Duda, P. E. Hart, and D. G. Stork. *Pattern Classification*. Wiley-Interscience, New York, USA, 2nd Edition, 2001.
- [8] A. R. E. Keogh. Everything you know about dynamic time warping is wrong. *3rd Workshop on Mining Temporal and Sequential Data*, Seattle, Washington, 22 August 2004.
- [9] Q. W. G. Chen and H. Zhang. Discovering similar time-series patterns with fuzzy clustering and DTW methods. *IFSA World Congress and 20th NAFIPS International Conference*, Vancouver, Canada, 25–28 July 2001.

- [10] X. Gang and T. Liang-rui. Speech pitch period estimation using circular AMDF. *14th IEEE Proceedings on Personal, Indoor and Mobile Radio Communications*, 3:2452–2455, Beijing, China, 7–10 September 2003.
- [11] S. Gangashetty, C. Chandra Sekhar, and B. Yegnanarayana. Extraction of fixed dimension patterns from varying duration segments of consonant-vowel utterances. *Proceedings of International Conference on Intelligent Sensing and Information Processing*, pages 159–164, Chennai, India, 5–7 January 2004.
- [12] T. Greer. Automatic recognition of radar scan type. *United States Patent and Trademark Office*, Patent No: 6,697,007, 2004.
- [13] S. Haykin. *Neural Networks: A Comprehensive Foundation*. Prentice Hall, New Jersey, 1998.
- [14] A. F. K. Chan. Efficient time series matching by wavelets. *International Conference on Data Engineering*, Sydney, Australia, 1999.
- [15] B. Mahafza. *Radar systems analysis and design using Matlab*. CRC Press, Florida, USA, 2000.
- [16] P. Muresan. A new approach to period estimation. *International Conference on Acoustics, Speech, and Signal Processing*, 2:709–712, Istanbul, Turkey, 9 June 2000.
- [17] F. Neri. *Introduction to Electronic Defense Systems*. Artech House, Massachusetts, 2001.
- [18] R. J. Povinelli. Using genetic algorithms to find temporal patterns indicative of time series events. *GECCO 2000 Workshop: Data Mining with Evolutionary Algorithms*, Las Vegas, Nevada, 8–12 July 2000.
- [19] D. Rafiei. *Fourier-Transform Based Techniques in Efficient Retrieval of Similar Time Sequences*. MSc.Thesis, University of Toronto, Canada.
- [20] H. Shi. *Best-first Decision Tree Learning*. MSc. thesis, University of Waikato, New Zealand, 2006.

- [21] M. I. Skolnik. *Radar Handbook*. McGraw-Hill, New York, USA, 1990.
- [22] G. Stimson. *Introduction to Airborne Radar*. SciTech Publishing, New Jersey, 1998.
- [23] The University of Waikato. WEKA 3: Data Mining Software in Java, <http://www.cs.waikato.ac.nz/ml/weka/>.
- [24] Wikipedia. http://en.wikipedia.org/wiki/Electronic_warfare.
- [25] R. G. Wiley. *ELINT: The interception and analysis of radar signals*. Artech House, Massachusetts, 2006.
- [26] I. H. Witten and E. Frank. *Data Mining: Practical Machine Learning Tools and Techniques*. Morgan Kaufmann, San Francisco, 2005.
- [27] Y. Z. Y. Peng and H. Tian. Research of time series pattern finding based on artificial neural network. *International Conference on Machine Learning and Cybernetics*, Xian, China, 2–5 November 2003.
- [28] W. S. Y. Qian, S. Jia. Markov model based time series similarity measuring. *International Conference on Machine Learning and Cybernetics*, Xian, China, 2–5 November 2003.
- [29] A. E. A. Y. Wu, D. Agrawal. A comparison of DFT and DWT based similarity search in time-series databases. *Proceedings of the Ninth International Conference on Information and Knowledge Management*, Mc Lean, VA, 6–11 November 2000.
- [30] T. Zaczek. Antenna scan pattern generator. *United States Patent and Trademark Office*, Patent No: 4,327,417, 1980.
- [31] L. Zeng, Wu and Zhou. Modified AMDF pitch detection algorithm. *Proceedings of the Second International Conference on Machine Learning and Cybernetics*, Xian, China, 2–5 November 2003.