ABSTRACT

RADAR SIGNAL CHARACTERISTIC EXTRACTION WITH FFT-BASED TECHNIQUES

by Jason Ryan Pennington

This research project develops computationally efficient digital signal processing algorithms for digital wideband receivers to determine the existence of radar signals and, if radar signal(s) are present, extract in real time, pertinent signal characteristics such as frequency, signal power, modulation type, and pulse width. Unlike a conventional communication receiver, the digital wideband receiver algorithms considered in this project assume no a priori knowledge about the number of radar signals and their characteristics. Two types of radar signals, namely, pulsed continuous-wave (CW) and chirping signals, are considered in this thesis. Different techniques are exploited to optimize receiver performance. The receiver algorithms developed in this project can successfully detect multiple signals with different characteristics.
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Chapter 1

Introduction

1.1 Background

In most cooperative communication systems, the transmitted signals have known characteristics, such as frequency and modulation type. Furthermore, the power of the signal, within a specific range, is known. Since the system is a cooperative system, the receiver design has knowledge of the transmitter’s design. In these cases, the system is optimized fully to make an efficient communication system used for transmitting information, such as voice or data. However, radar signals are used to locate and track the path of a craft [1] and is designed to avoid being detected and jammed. As a result, unlike a communication system receiver, the wideband receiver, for radar signal detection, usually has no knowledge about characteristics of transmitted signal.

In developing a digital wideband receiver, there are inherent obstacles to overcome because this receiver assumes no \textit{a priori} knowledge of the signal(s) to be detected. With a wideband receiver, a certain bandwidth is monitored and, if a signal is detected in the band, the characteristics of the signal are determined. This receiver is part of a larger electronic warfare (EW) system, which is described in Chapter 3, where other instruments use the outputs from the wideband receiver to take action on this signal if such action is determined to be needed[2].

This area of research is a niche environment because the applications of the technology, being able to detect signals in a non-cooperative system, are in military applications. Its major functionality is detecting enemy radar systems whose characteristics are unknown. Developing smarter receivers to perform these tasks will directly impact the security of the United States and its friendly countries. It will help protect pilots while flying missions in hostile territory to avoid being detected by enemy radar. To disrupt the enemy’s radar, signal characteristics need to be determined so proper countermeasures can be taken.
1.2 Problem Statement

One of the more challenging points of the problem is that the system has to be a real-time system. The system must react in microseconds to avoid having a plane shot down. We need to develop technologies to ensure that the EW system is not overly computationally intensive so that current processors can handle the load of the real-time calculations [3].

Not only must the system be fast for real-time applications but the system must be accurate. If the system detects a signal that does not exist, then jamming signals are transmitted that are not needed. This provides the sender’s position to the enemy and also uses resources that should be spent detecting valid signals.

Moreover, the radar signals can have very short duration; therefore, the developed EW receiver needs to be able to determine signal characteristics based on a limited number of data points in real time, while avoid generating false alarms.

1.3 Goals

In this research project, we developed EW receiver technologies to detect radar signals and determine their characteristics. Three goals of this research are to:

1. Improve the signal characteristic estimation for pulsed Continuous Wave (CW) signals as compared to the current accepted algorithm for characteristic extraction.

2. Demonstrate the ability to accurately estimate the signal characteristics of chirping signals, including the added characteristic of chirp rate for this type of signal.

3. Implement an encoder to detect pulsed CW and chirping signals simultaneously, while maintaining characteristic estimation accuracy.

1.4 Methodology

First, an understanding of the performance of the current algorithm and how our proposed alternative algorithms compare to it will be explored. The algorithms will be compared in two characteristics of an electronic warfare (EW) receiver: sensitivity and dynamic range. These characteristics will be compared with pulsed CW signals at first. Next the accuracy of the algorithms will be studied with chirping signal inputs. Finally, a description of how the encoder which extracts signal characteristics is implemented will be given. Along with the working principles of the encoder, a description of the methods by which the encoder makes its decisions and why those decisions are made will be demonstrated in their entirety.
1.5 Overview

This thesis will explore two possible radar signals: pulsed CW signals and chirping signals. We will explore the performance of different Fast Fourier Transform (FFT) [4] based EW receiver technologies. Chapter 2 covers fundamental digital signal processing concepts used in this project such as discrete-time Fourier Transform (DTFT), spectral leakage, window selection, chirping signals, and autocorrelation. Chapter 3, gives a basic introduction to the EW Receiver[2] and some of the characteristics that an EW receiver carries. Next, in Chapter 4, we compare performance of four different FFT-based EW receiver technologies using pulsed CW signals as a testing signal. Then, in Chapter 5, based on the study results provided, we chose the best FFT-based EW receiver technology to detect chirping signals and compare their performances. Chapter 6 describes how to determine the signal characteristics and summarizes them in a PDW. Conclusions are drawn in Chapter 7.
Chapter 2

Signal Processing Review

An understanding of digital signal processing concepts are necessary before investigating the
details of the EW Receiver. The concepts used in EW receiver development are introduced
in this chapter. The topics covered will be the Discrete-Time Fourier transforms (DTFT)[4],
Spectral Leakage[4], Window Selection[4], Autocorrelation[4], and chirping signals[5].

2.1 DTFT

The DTFT is a well known function used to convert a time-domain sequence, $x[n]$, into the
frequency domain. The DTFT of $x[n]$ is given by:

$$X(e^{j\omega}) = \sum_{-\infty}^{\infty} x[n]e^{-j\omega n},$$

(2.1)

where $x[n]$ is a sampled signal. A sampled sinusoid can be represented as:

$$x[n] = \cos(2\pi f \frac{n}{f_s}),$$

(2.2)

where $f$ is the frequency of the signal and $f_s$ is the sampling frequency.

The DTFT of a sinusoid sequence should only have a non-zero value at $\omega = (2\pi) \frac{f}{f_s}$ which
is the digital counterpart of $f$. However, practicality limits us to take only a finite number
of samples when calculating the DTFT. The consequence of the limited number of samples
introduce the sidelobes in the spectrum, this is also known as spectral leakage[6].

Moreover, the DTFT is a continuous function of $\omega$ and is very computationally inefficient;
because of this, the Fast Fourier Transform (FFT)[4] is used to calculate the sampled DTFT
of a sequence with finite length of $N$, where $N$ must be a power of two and is the length of
the input. The FFT algorithm takes advantage of symmetries in the DTFT function when
the number of samples is a power of two. The DTFT algorithm has a complexity of $N^2$;
however, the FFT has a complexity of $\frac{N}{2} \log(N)$ and there are implementation techniques that can be utilized to further improve the performance of the FFT operation [7]. The FFT operation only returns sampled DTFT values at specific frequencies that are multiples of the frequency resolution, $f_r$:

$$f_r = \frac{f_s}{N}.$$  \hspace{1cm} (2.3)

When the signal frequency is not a multiple of the resolution, the FFT result of a sinusoidal function will have non-zero values at multiple places instead of just one. For example, when sampling a sinusoidal signal whose frequency is 247.2 MHz using 2.56 GHz sampling rate and then taking the 256-point FFT, the resulting magnitude spectrum is shown in Fig. 2.1. The signal energy is spread in the FFT result since the FFT cannot return the signal frequency component at 247.2 MHz. This phenomenon is referred to as spectral leakage[8].

![Figure 2.1: Example of Resolution Issue with DTFT](image)

### 2.2 Spectral Leakage

The phenomenon of spectral leakage occurs when the frequency of the input signal is not a multiple of the FFT frequency resolution. When spectral leakage takes place, the energy of the signal is spread across, or leaked, into multiple adjacent bins of the FFT result [9]. In Fig 2.2a, the graph shows the FFT result when the frequency of the signal is a multiple of the frequency resolution. Figure 2.2b shows what occurs in the FFT result when the frequency is increased by 20 percent of the frequency resolution. The noise floor is approximately $-300$ dB for the first case but, due to spectral leakage, the bins adjacent to the maximum are
Figure 2.2: Effect of Spectral Leakage

(a) Input frequency is a multiple of frequency resolution
(b) Frequency is not a multiple of frequency resolution

affected the most but all the bins show an increase in power. This is an undesired effect because, if there is a weaker signal present, the spectral leakage may prevent the detection of the weaker signal. One way to minimize this effect is to multiply the sampled data with a window function before performing the FFT operation.

### 2.3 Window Selection

Many tapered windows have been discussed and explored in Digital Signal Processing textbooks. The well-known Rectangular, Hanning, and Blackman windows are compared in this section[4]. First, the rectangular window has unity value for the duration of the window and is zero otherwise. This duration is denoted by $T$. The next window, the Hanning window, is described by the following equation:

$$w_{\text{hanning}}[n] = 1 + \cos \left( \frac{2\pi n}{2M + 1} \right). \quad (2.4)$$

The Blackman window given by:

$$w_{\text{blackman}}[n] = 0.42 + 0.5\cos \left( \frac{2\pi n}{2M + 1} \right) + 0.08\cos \left( \frac{4\pi n}{2M + 1} \right) \quad (2.5)$$

where $M$ is the length of the window. Each window has two important characteristics that determine how well it performs in specific applications. The first characteristic is the width of the mainlobe. This is denoted as $\Delta_{ML}$ and is defined as the mainlobe bandwidth in normalized frequency. The width of mainlobe determines how well a window function can
separate two signals with different frequencies. The second characteristic is relative sidelobe level defined as the relative amplitude, in dB, of the second lobe to the main lobe, denoted: $A_{sl}[4]$. The relative sidelobe level determines the maximum spectral leakage energy level outside the mainlobe.

If the FFT is taken upon sampled data then, inherently, there is a rectangular window that multiplies the signal before the FFT operation. This will not produce the most accurate estimate of the signal. To obtain better performance, multiplication by a Blackman Window
or a Hanning window may provide needed benefits.

Figure 2.3 shows the frequency response for a Rectangular and a Blackman window. The purpose of this graph is to show the difference in side lobe attenuations. The Rectangular window’s first side lobe is approximately -13 dB from the mainlobe (normalized to zero). The first sidelobe of the Blackman Window is about -61 dB. This will reduce spectral leakage. Inversely, the Blackman window has a wider main lobe compared to the Rectangular window. A wide mainlobe will limit the EW receiver’s capability to separate signals that are close in frequency and affect the performance of the frequency estimation [10]. Shown in Fig. 2.4, the Hanning Window and Blackman Window are compared. The Blackman Window has a wider mainlobe but lower sidelobes to reduce spectral leakage [8]. Since we would like to reduce the spectral leakage by at least 50dB, the Blackman Window will be used in our study.

2.4 Autocorrelation

Autocorrelation is widely used in signal processing applications. The autocorrelation of a signal $x$ can be written as:

$$R_{xx}(l) = \sum_{-\infty}^{\infty} x[n]x[n-l].$$

One advantage of autocorrelation is that noise in the received signal is reduced. For a corrupted sinusoidal signal, its autocorrelation is illustrated in Fig. 2.5. As shown in Fig. 2.5, the noise generates a spike at the middle of the waveform of the resulting signal and the period of the sinusoidal signal is easier to observe. For an $N$-point signal, the length of its autocorrelation is $2N - 1$. This increase in number of data points is beneficial because, after taking the FFT of the result of the autocorrelation, the frequency resolution will be improved and the noise energy in each bin will be reduced. Because of this improvement, the signal frequency estimation based on the FFT of its autocorrelation, will be more accurate and autocorrelation allows the EW receiver to detect weaker signals. In this thesis, autocorrelation is applied to improve EW receiver performance.

2.5 Chirping Signals

Chirping signals are signals that change in frequency. Unlike a continuous wave signal, which is a sinusoidal with fixed frequency, the frequency of a chirping signal is time-varying. The rate of change in frequency is referred to as the chirp rate. The chirp rate is measured in Hertz per second [11]. Chirping signals have been used in radar applications to reduce power requirement. In this thesis, research is limited to studying how to extract characteristics of chirping signals that change frequency linearly with time. A chirp signal is defined as
follows:

\[ x(t) = \cos(2\pi ft + \pi cr t^2 + \phi), \]

(2.7)

where \( cr \) is the chirp rate, \( f \) is the starting frequency, and \( \phi \) is the phase of the signal. A linear chirping signal is illustrated in Fig. 2.6 where we can see the frequency increase.

Figure 2.5: Upper Plot: Time domain signal with noise, Lower Plot: Autocorrelation of the above signal.

Figure 2.6: Linear, Chirping Signal Waveform
Chapter 3

EW Receiver Review

The EW system consists of three instruments: Electronic Support Measure (ESM), Electronic Counter Measures (ECM), and Electronic Counter-Counter Measures (ECCM). A simple EW system architecture is illustrated in Fig. 3.1. The ESM’s main function is to survey the environment and detect any signals. The detected signal characteristics are summarized in the Pulse Descriptor Word (PDW). The ESM detects any signal, friendly or not; then, the ESM will report the identified enemy signals to the (ECM) where proper action can be taken. The ECCM is the equipment designed to defend against an enemy ECM system.

![Flow diagram of EW System](image)

Figure 3.1: Flow diagram of EW System

This thesis focuses on the ESM aspect of the wideband receiver design which detects any signal friendly or not and extracts its characteristics. The ESM also determines if the signal is friendly but this determination is beyond the scope of this thesis. This thesis will explore the method used by the EW receiver of the ESM to generate the PDW. The data in the PDW contains the characteristics of the signal that the rest of the system uses to determine if the signal is an enemy signal or not. This information is then passed on to the ECM to be further used in jamming or disrupting the enemy radar signal. Further details of the EW receiver and the PDW generator are given in Chapter 6.

EW receivers need to be able to operate in real time [2]. If the PDW is not generated and passed along within a few microseconds, it could be too late for the rest of the system to react to the signal in question. This seems obvious: the enemy signal tries to avoid being jammed, radar signals with finite duration can be used to track and attack objects and if the EW system cannot react quickly enough then there is no need for the system.
The next criterion for an EW receiver is its bandwidth. The EW receiver must have a sufficient bandwidth to handle an input range of 1 to 18 GHz. Since this is a very wide range, it is divided into subbands. The optimum subband bandwidth is determined by the best technology. A bandwidth less than 500 MHz is unacceptable for these types of applications because the signal’s carrier frequency is not known and the EW receiver must be able to determine the frequency of the signal in the wide range as described above. If the receiver is low cost, more than one receiver can be used to cover a desired bandwidth. This type of system is beyond the scope of this thesis [2].

The third characteristic required of a EW receiver is its ability to detect multiple radar signals at different frequencies [2]. The minimum frequency separation between signals is referred to as the resolution of the EW receiver; the EW receiver might report two signals whose frequencies separation is less than the resolution as one signal. If this is the case, the frequency estimation will be off for at least one of the signals; then, proper action cannot take place on one or both of the incoming signals. Frequency resolution is an important characteristic of an EW receiver and the resolution must be sufficient to handle four simultaneous signals. This is considered to be a maximum for an EW receiver considered in this thesis.

The fourth requirement for a EW receiver is the relationship between sensitivity and dynamic range [2]. Sensitivity is the measure of how well a receiver can detect weak signals; if a receiver can detect very weak signals, it has high sensitivity. A very sensitive EW receiver is more likely to detect a non-existent signal. This situation is called false alarm. A false alarm needs to be avoided since it will trigger a follow-up action of the EW system requiring system resources and thus reduce the capability of the EW system handling a real radar signal. Moreover, if an EW receiver is highly sensitive and a very strong signal is introduced, that signal will generate false alarms due to spectral leakage. This is not an ideal situation since it would be advantageous to have a receiver able to detect a very strong signal and also a weak signal concurrently. The difference in the peaks of these signals is referred to as the receiver’s dynamic range. An ideal EW receiver should have high sensitivity and dynamic range; however, as demonstrated in later chapters, these two requirements are conflicting. An EW system engineer usually needs to make the decisions about the trade-offs between sensitivity and dynamic range.

There are additional receiver requirements [12]. This includes its capability of determining the modulation type and the Angle of Arrival (AOA). Modulation type determination will be discussed later but the AOA detection is beyond the scope of this thesis AOA measurements require more than one antenna and, in this thesis, only a single antenna system is considered.

Now we discuss some concepts used throughout this thesis. We use the EW receiver based on the conventional FFT operation as a framework to explain these concepts. A simplified EW receiver diagram is illustrated in Fig. 3.2. The EW receiver consists of an antenna, amplifier, Analog-to-Digital Converter (ADC), and a PDW encoder. The antenna continuously receives ambient signal which is then amplified and digitized before further processing. This type of EW receiver takes a frame of input data, multiplies the data by a window function, and then calculates the FFT. The signal frequency, power, time-of-arrival, and pulse width are
determined based on the results of the FFT operation.

3.1 Noise in the EW Receiver

The major noise sources in an EW receiver are thermal noise, amplifier noise, and quantization noise.

![Flow diagram of noise in the EW Receiver](image)

**Figure 3.2: Flow diagram of noise in the EW Receiver**

3.1.1 Thermal Noise

Thermal noise is present in any environment. This noise is a measurable quantity and needs to be considered because the estimate for the power of the signal will be affected by it. Thermal noise is dependent upon the receiver bandwidth: with our sampling frequency of 2.56 GHz, the noise density is $-114$ dBm/MHz. The noise floor would then be [5]:

$$N_f = -114 + 10 \log_{10} \left( \frac{2560}{2} \right)$$

From this we get our noise floor to be approximately -83 dBm.

3.1.2 Amplifier Noise

The amplifier is used to amplify the received signal before A/D conversion. The amplifier provides gain to both the incoming signal and thermal noise; it also introduces its own additional noise. The power of the noise introduced though the amplifier can be calculated by amplifier noise figure. The amplifier noise figure (NF) is defined as:

$$NF = 10 \log_{10} \left( \frac{SNR_{in}}{SNR_{out}} \right) = SNR_{in,dB} - SNR_{out,dB}$$

The amplifier noise figure indicates or is a measure of the degradation of the SNR due to the amplifier. This is commonly misunderstood because when a signal is amplified it is thought that the SNR should improve. However, this is not the case since the noise is also
amplified. So, the question arises, why is this amplification done if it reduces the SNR. This is done because, at this stage, the signal has been attenuated by the medium through which it traveled. The next step is the digitization. Quantization noise could overpower the signal if the amplification is not performed. If the amplification block was removed, the signal would not be recognizable after digitization.

3.1.3 Quantization Noise

![Quantization Noise](image)

Figure 3.3: Visualization of Quantization Noise

In the conversion from an analog signal to a digital signal, some information is lost. This loss comes from the inability to sample with infinite precision; the ADC sets discrete values for the continuous signal and, in doing so, noise is introduced.

Figure 3.3 shows the means by which the digitizing process will introduce noise due to the fact that the stepped values do not coincide with the values for the continuous signal everywhere. The amount of noise introduced depends on the number of bits used by the ADC for its conversion. The higher the number of bits, the better the resolution; this results in less noise introduced. This process however, leads to a slower A/D conversion rate; so, there is a trade-off between the number of bits used and the speed. The speed of the ADC affects the bandwidth of the receiver. The resolution of the ADC is given as [13]:

$$Resolution_{ADC} = \frac{2v_s}{2^b}$$  \hspace{1cm} (3.3)

where $v_s$ is the saturation voltage of the ADC and $b$ is the number of bits used by the ADC.
3.2 False Alarm and Threshold Determination

The EW receiver must determine if a signal is present or not. This is probabilistic determination that uses a threshold measure to make this decision. Only signals with a magnitude above the threshold are considered a valid signal. The threshold for detecting a signal cannot be too low or too high. If the threshold is too high, the receiver will have poor sensitivity; if the threshold is too low, the receiver will have a high probability of false alarm, denoted $P_F$. A false alarm is when a signal is reported as present when there is not a signal, this detrimental to a receiver because the resources will be used to jam a signal that is not there. For an EW receiver based on the conventional FFT operation, its $P_F$, can be calculated based on analysis in the frequency domain. Consider a signal of the form:

$$x = x_s + n$$ \hspace{1cm} (3.4)

where $x_s$ is the signal being estimated and $n$ is the random noise, or Additive White Gaussian Noise (AWGN). Since, the concern is with the effects of $n$ on the system, $x_s$ is taken to be zero. $x$, is multiplied by a window function, which is chosen to be the Blackman window in our study; then, the FFT is performed on the data. This is done many times to get a histogram, shown in Fig. 3.4. The histogram depicts the magnitude values measured in a certain bin of the FFT. This distribution has been found to be Rayleigh [5]. The variance in the noise will affect the threshold value; it is also shown that, from the Rayleigh distribution, a threshold can be chosen with a corresponding $P_F$.

The Rayleigh probability density function given by [14]:

![Figure 3.4: FFT bin Histogram](image_url)
where $x$ is assumed to be greater than or equal to zero.

From this distribution, a value for $x$ can be chosen as our threshold. The area under this function to the right will define our $P_F$ [5]. If we increase this value, $P_F$ will decrease but our sensitivity will suffer.

It is noteworthy to state that the histogram of the noise depends on the EW receiver processing method. For some processing methods, there might be no analytic model of the noise histogram, and the thresholds need to be determined empirically.
Chapter 4

FFT-Based EW Receiver Comparison

An EW receiver needs to have a balance of three characteristics: sensitivity, dynamic range, and probability of false alarm, $P_F$. An ideal EW receiver should have high sensitivity, wide dynamic range, and low $P_F$. However, these goals often contradict each other and we need to keep a good balance between them. In this chapter, we summarize our investigation of different technologies for pulsed-CW radar signal detection. Our goal is to extract as much information efficiently from a limited number of data points as possible while satisfying all the requirements.

4.1 Detection Algorithms

The technologies under investigation are zero-padding and autocorrelation in combination with the Blackman Window and FFT. Autocorrelation has shown added benefits to improving the accuracy of signal characteristic extraction [15]. Zero-padding also increases frequency resolution and has other advantages in frequency analysis [4]. In our receiver study, we assume that each frame of data to be analyzed consists of 256 points. The EW receiver technologies under investigation are summarized below.

4.1.1 256 Data point - Blackman Window - FFT

This method is the current method that is used for FFT-based EW receiver design [2]; we will consider this to be our base case or the case which we plan to improve. This method consists of taking 256 data points, then filtering with the Blackman window, followed by the FFT. The Blackman window is used to reduce spectral leakage and the FFT operation allows the receiver to identify the signal’s frequency. This method has advantages in implementation. The FFT is an efficient algorithm, and the operations for multiplying by the Blackman
window can be optimized by multiplying by the Blackman window coefficients during the time between samples.

4.1.2 256 Data Point - Blackman Window - 256 Point Zero Pad - FFT

This approach pads 256 zeros after the 256 data points. This method generates a finer spectral resolution and results in a better estimation of frequency. Moreover, the noise power is spread across 512 points instead of 256 points in the frequency domain; this technique can improve receiver sensitivity but increases calculation complexity since the 512-point FFT needs to be calculated.

4.1.3 256 Data Point - Blackman Window - Autocorrelation - FFT

This approach introduces autocorrelation after the Blackman window coefficients multiply the data. Since the result of the autocorrelation has 511 points, one zero is added after the autocorrelation result so that a 512-point FFT can be conducted. This addition of the autocorrelation is beneficial because the autocorrelation of a sinusoid at a particular frequency will result in a sinusoid of the same frequency, but noise does not correlate thus generating a peak at index 0. Since autocorrelation increases the size of FFT operation, the noise power per FFT bin is reduced and the receiver sensitivity can be improved. However, it is noted that the autocorrelation and a longer FFT need to be calculated.

4.1.4 256 Data Point - Autocorrelation - Blackman Window - FFT

In this method, the order of the Blackman window and autocorrelation are reversed. Once again, there are zeros added to the signal after the autocorrelation to ensure it is a power of two in length. In this case, since the autocorrelation is taken first, a longer Blackman window needs to be used. As a result, this method will need even more resources for computation compared with the previous methods.

4.1.5 512 Data Point - Blackman Window - FFT

We assume that data length is only 256 points and our goal is to extract as much information as possible from these 256-points of data. We include the traditional FFT-based EW receiver with a 512 point frame size in our simulation to use as a comparison. This case is included to show the performance that would be obtained by actually doubling the amount of data. If the amount of data is doubled, then we will see a definite increase in performance just
because there is more information that can be obtained from the data. This will be used to show a best case scenario from the 256 data point perspective. If 256 data points are collected with a specific method being used, and the performance is comparable to the 512 case, then our purpose will be complete. This will not be the case but a demonstration of how close the other methods come to this case will be presented.

4.2 Pulsed CW Signal - Characteristic Study

The methods introduced above will be compared in the EW receiver characteristics of sensitivity and dynamic range. These characteristics are indicative of how well these methods would perform in an EW Receiver.

4.2.1 Sensitivity

Sensitivity has been described earlier as a measure of how well a receiver can detect weak signals. Detecting weaker signals can be difficult because the avoidance of false alarms is also imperative. There is a balance between these scenarios because of the threshold used to determine if the signal is a valid signal. This is used to guarantee the $P_F$ needed by the EW Receiver.

Simulation Process

The first step in determining the sensitivity is to determine the threshold for each method described above. The threshold determination is described in Section 3.2. We used Gaussian noise with unity variance as the signal and studied the histogram of the magnitude of the FFT. We determined the threshold based on the assumption that $P_F$ should be $10^{-7}$. The threshold values for each method are shown in Table 4.1.

Once the thresholds have been determined for each case, then a value for SNR can be used to set a test signal’s power. Then, by generating this signal and using the various methods described to detect the signal, Probability Of Detection, $P_D$, can be found for each method. A signal is considered detected if the signal surpasses the threshold in power. This process will then be completed for different values of SNR.

The simulation of these signals at the particular SNR will show $P_D$. In this fashion, we have a balance between $P_F$, and $P_D$. By choosing $P_F$ first we will error on the side of the probability of false alarm, then by doing our sensitivity study based on $P_F$ the resulting $P_D$ can determined.
Table 4.1: Thresholds for each method

<table>
<thead>
<tr>
<th>Method</th>
<th>Threshold</th>
</tr>
</thead>
<tbody>
<tr>
<td>256 Blackman Window</td>
<td>36.1</td>
</tr>
<tr>
<td>256 Blackman Window Zero pad</td>
<td>35.4</td>
</tr>
<tr>
<td>256 Blackman Window Autocorrelation</td>
<td>1054.5</td>
</tr>
<tr>
<td>256 Autocorrelation Blackman Window</td>
<td>2681.1</td>
</tr>
<tr>
<td>512 Blackman Window</td>
<td>52.3</td>
</tr>
</tbody>
</table>

Figure 4.1: Sensitivity Study

Results and Conclusions of Sensitivity Study

The EW receiver sensitivity study is shown in Fig. 4.1. The blue dashed line shows the $P_D$ for the base case, or first method, the 256 data points with Blackman-Window. It is shown that at $-3$ dB SNR there is a $P_D$ of 90 percent. This is the value that will be improved with other methods. For example, the green circle line shows the $P_D$ for the 256-data-point-with 256-zero-padding case. For this case there is a 90 percent chance of detecting a signal with an SNR of $-3.5$ dB. This is a slight increase in sensitivity without too many more calculations.

Next, is the Blackman-Window-with-Autocorrelation method, this method does have the added calculation of the autocorrelation, but improves sensitivity by 1 dB from the base case.

Lastly, the 512-data-point-then-Blackman-Window method is included to show how well taking more data will help the sensitivity; it represents a goal for the 256 data point methods. The graph shows that the autocorrelation then Blackman Window method can achieve the sensitivity very close to the 512-data-point-then-Blackman-Window method. This is a good result, but, since dynamic range and sensitivity are inversely related, the dynamic range suffers greatly in the Autocorrelation-then-Blackman-Window method as shown in the next section.
4.2.2 Dynamic Range

The maximum difference in power two signals can have and still be detected is the dynamic range of the EW receiver. It will be shown that the dynamic range depends on the proximity of the two signals in frequency.

Simulation Process

To determine the dynamic range of each of the methods, we first chose a frequency difference. Next, from the sensitivity study, we set the power of the first signal to have a detection rate of 99 percent. Then the power of the second signal is increased until the probability of detecting the first signal is 90 percent. Now we have two signals with a difference in power. The weak signal is detected at a rate of 90 percent and in this situation our dynamic range for the particular frequency difference will be the difference in power between the two signals.

![Figure 4.2: Effect of Dynamic Range on Detecting Two Signals](image)

(a) 40 dB Power Difference  (b) 60 dB Power Difference  (c) 80 dB Power Difference

The process of increasing the power of the second signal is shown in Fig. 4.2. In Fig. 4.2(a), the power difference is 40 dB. This is a detectable situation; both the signals can be detected because they both exceed the threshold. In Fig. 4.2(b), the power difference is 60 dB. Here it is shown that the weaker signal may be over taken by the stronger signal; visually, it can be assessed that the signal is still there but the threshold may cause false alarms. Finally, in Fig. 4.2(c), with a power difference of 80 dB, the weak signal is not represented visually at all.

The above graphs were produced with the Blackman window then FFT method, and a frequency difference of 115 MHz. For these parameters the dynamic range has been determined to be about 50 dB.

Results and Conclusions about Dynamic Range

Following the dynamic range estimation procedure described earlier, we determine the dynamic range of each method under investigation at different frequency differences. The
The simulation result is shown in Fig. 4.3. The results for the dynamic range are shown as a function of frequency difference.

As with the sensitivity study, the blue dashed line is the 256-data-point-then-Blackman-window. This case is the base case against which other methods will be compared. We first examine the 256-data-point-Blackman-window-with-256-zero-padding and 256-Blackman-window-then-autocorrelation method in the green circle line and red asterisk line, respectively. These methods produce slightly worse dynamic range metrics when the frequency difference is greater than 45 MHz; the dynamic range is much better in the range is 28 MHz to 40 MHz. The reason is that both methods have more data points in frequency domain thus improving frequency resolution.

On the other hand, we see the Autocorrelation-then-Blackman-window dynamic range is much worse. The explanation is that applying Blackman window after autocorrelation does not reduce spectral leakage; this method has a very low dynamic range. The 512-data-point-then-Blackman-window method generates the best dynamic range and none of methods based on 256 point data can achieve dynamic range close to it.

Based on the sensitivity and dynamic range study result, we determine that, among the three new methods based on 256-point data, 256-Blackman-Window-then-Autocorrelation methods deliver the best performance. It improves receiver sensitivity by 1 dB, improves dynamic range at narrow signal frequency difference and only suffers a slight dynamic range performance degradation when signal frequency difference is wide. As a result, we will conduct further investigation on this method’s signal characteristics estimation accuracy. The traditional the 256-data-point-then-Blackman-window method is used as a comparison. These results are included in the next chapter.
Chapter 5

FFT Chirping Signals

The methods described so far have been used for pulsed CW signals. These methods can also be used for chirping signals provided that the chirping rate is not too high. Chirping signals have been used for radar applications due to the low sidelobes produced by this technique and its low power requirement. Pulse CW signal can be consider as a chirping signal with chirping rate as zero. In the previous chapter, we found that among the three alternative technologies under investigation, the Blackman-Window-with-Autocorrelation delivers the best performance. Therefore, in this chapter, the study of how well chirping signals can be estimated using the conventional Blackman-Window and Blackman-Window-with-Autocorrelation methods and the adjustments needed to be made to compensate for the chirp rate effects.

5.1 Chirping Signal - Characteristic Study

5.1.1 Sensitivity

As described in Section 4.2.1, the sensitivity study is based on the signal surpassing the threshold. We use the same threshold for the CW and chirping signals since our receiver is designed to detect both. Therefore, for chirping signals, they must also pass the same threshold to be considered detected. This is an issue because the energy in the maximum-energy bin in a pulsed CW signal is higher than in a chirping signal even if the signals themselves have the same power. This occurs because, in a chirping signal, the energy is spread over multiple bins. This effect is similar to spectral leakage in that the signal’s energy in the adjacent bins must be considered and approximated to get an accurate measure of the signal power. Since the signal power is used to determine if the signal is detected, further investigation is needed.

One possible solution would be to determine another threshold, one which the chirping signal must surpass in power. This is an infeasible solution since the system would become too complex. As the signal is being detected in a particular frame, there is no knowledge if that
particular frame is part of a pulsed CW signal or chirping signal, or the particular detection could later be determined to be a false alarm that is not part of any signal. An ability to go back and check if the signal is chirping or pulsed CW and use the respective threshold would take enormous amounts of memory and time and would be extremely difficult to implement in a real-time system. Moreover, if we implement different thresholds for chirping signals, we would need to have different thresholds for chirping signals with different chirp rates. As a result, we use the same threshold for both chirping and pulse-CW signals.

Results and Conclusions for Chirping Signal Sensitivity Study

The sensitivity will depend on the chirp rate. This is in addition to the dependence on signal power; as a result, the sensitivity study shown here will include three dimensional graphs with the probability of detection, $P_D$, being the third dimension.

![Graphs showing sensitivity study results](image)

**Figure 5.1: Sensitivity Study**

Shown in Fig. 5.1 the Blackman-Window-with-Autocorrelation method has better sensitivity. This is apparent around $-5\,dB$ where the Blackman-Window-with-Autocorrelation method still has a $P_D$ higher than 90 percent until $-4\,dB$. A similar improvement in sensitivity has been demonstrated for the pulsed CW signal case, and is reinforced here.

If the chirp rate is taken to be zero, then this is the pulsed CW case. These results match the results shown in the sensitivity study for the pulsed CW case. It is also apparent that the sensitivity decreases as chirp rate increases; this is due to the spreading of the signal power over multiple bins.
5.1.2 Dynamic Range

The dynamic range, like sensitivity, will be affected by the chirp rate and the effect it has on the spectrum of a frame. The spreading of the power of strong signal will interfere with the weaker signals; this will negatively affect the dynamic range. To get a better understanding of how the chirp rate will impact the dynamic range, a study similar to the one performed for the pulsed CW case was completed. In this study, we will also have three dimensional graphs where the chirp rate, frequency difference, and the dynamic range for the particular inputs will be calculated. For this study the two signals will have the same chirp rate.

Results and Conclusions for Chirping Signal Dynamic Range Study

In Fig 5.2, the results for the dynamic range study for chirping signals are shown. First we notice at a chirp rate of zero (or equivalently a pulsed CW signal) the dynamic range is about 55 dB after 50 MHz frequency difference. It is also shown that the dynamic range for the Blackman-window-autocorrelation method is increased in the 25 MHz to 40 MHz range.

In this simulation, the two methods, the Blackman-window, and the Blackman-window-then-Autocorrelation, show similar dynamic range. When signal frequency difference is less than 40MHz, the Blackman-window-then-Autocorrelation method has a larger dynamic range, and when signal frequency difference is larger than 50MHz, the Blackman-window method can achieve a slightly larger dynamic range. This is consistent with the results shown for the pulsed CW signals in Section 4.2.2. Overall, there was no major difference between these two methods but a minimal amount of difference in a specific range of frequency differences.

5.1.3 Frequency Estimation

A coarse way of determining the frequency of the incoming signal is by taking the FFT, finding the bin that contains the highest value, and then multiplying it by the frequency resolution. The frequency resolution was defined in 2.3. If \( f_s \) is 2.56 GHz and \( N \) is 256, the resolution would then be 10 MHz per bin. If the FFT is then taken and the maximum bin is \( k_0 = 30 \) (bins are zero indexed), then the frequency estimate would be:

\[
f' = \frac{f_s}{N} k_0. \tag{5.1}
\]

In this case \( f' \), would then be 300 MHz but, if the input frequency was in the range of ±5 MHz, the maximum bin would still be \( k_0 = 30 \). This estimation is within half a bin. Since \( N \) is inversely related to the resolution, increasing \( N \) will give a better resolution which will provide a better estimate. While this is true, there are two reasons why increasing \( N \) may not be possible. The first is this will increase the complexity of the calculation of the
FFT. The FFT algorithm is of order $\frac{N}{2} \log(N)$ increasing $N$ will increase the time it takes to perform an iteration of calculations, making it difficult to build a real time system. Secondly, radar systems might use short pulsed signals which limit the application of an EW receiver based on a long stream of data. Therefore, frequency estimators that use large amounts of data [16], unfortunately, cannot be used for this application.

Since this estimate will be used in jamming a signal, accurate frequency estimation is desirable. One technique available is to relate the magnitude at the peak bin to the highest adjacent bin. The frequency distance between the actual signal frequency and frequency of the maximum bin can be calculated with these values. Depending on the type of window used, this ratio will take a slightly different shape. Understanding this shape will make the resulting frequency estimation better.

**Interpolation Method**

The frequency estimate given in (5.1) is not the most accurate method. Interpolating methods can be used to increase the accuracy of the frequency estimate [17]. To make our frequency estimate more accurate than (5.1) the term $k$ will be introduced. This represents the offset, or the distance of the true frequency is from the detected maximum in the FFT, or $k_0$.

The parameter, $k$, is shown in Fig. 5.3 as the difference in the bin with the red asterisk to the maximum bin in the overall FFT. The range for $k$ is [-.5 ,.5] then $kf_r$ is the difference in $MHz$ the FFT result is off from the true frequency, where $f_r$ is defined in (2.3); this is
because if the actual frequency could be at most a half bin away from $k_0$, and the frequency could be before or after $k_0$, if it is before, $k$ will be negative [18].

To determine $k$ we needed to find the relationship between the ratio of $X_0$ and $X_1$, where $X_0$ is the amplitude of the FFT result at the maximum and $X_1$ is the higher of the two adjacent bins. This ratio will be called $r$ as defined in Eq. 5.2; $r$ will then be used to calculate $k$ [19].

\[ r = \frac{X_0}{X_1}. \quad (5.2) \]

MATLAB\textsuperscript{TM} was used to calculate and plot the relationship between $r$ and $k$, and is shown in Fig. 5.4. In Fig. 5.4, the $x$-axis is the $r$ term which ranges from $[1, 1.7]$; a value of one on the $x$-axis means that the input frequency is exactly between two bins and the offset for this should be the corresponding value of 1 equivalent to $k = 0.5$. This value of 1 represents half of a bin. The upper bound for the $x$-axis is 1.7. This means that as the frequency gets closer to the next bin, the ratio $r$ approaches 1.7 and the offset should correspond to zero.

Using the basic MATLAB\textsuperscript{TM} curve fitting tool, we fitted a quadratic equation to this data. The equation is provided in the upper left corner of Fig. 5.4, $x$ is the ratio between $X_0$ and $X_1$ and $y$ is the offset for half a bin. Rewriting this equation in these terms yields:

\[ 2k = 0.62332r^2 - 3.1394r + 3.512 \quad (5.3) \]

After $k$ has been determined, we can update (5.1) to be:
This method of curve fitting the ratio \( r \) to the value for \( k \) was done for the Blackman-Window and Blackman-Window-with-Autocorrelation methods.

Results and Conclusions for Chirping Signal Center Frequency Estimation

When applying the FFT to a chirping signal, the FFT peak amplitude will occur at the center frequency of the chirping signal. Figure 5.5 shows the results for the center frequency estimation in chirping signals with Blackman-Window and Blackman-Window-with-Autocorrelation methods. For both methods, the frequency estimation error is lowest for high SNR and zero chirp rate. This is expected since the signal is strong and there is no leakage caused by the chirping. Then, if the signal power is decreased, the frequency estimation worsens. Similarly, if the power of the signal is fixed and chirp rate is increased, the frequency estimation suffers. For the Blackman-Window-with-Autocorrelation method, the error is lower but for both methods as the chirp rate gets above 1000 \( MHz/\mu s \) and the SNR is lower than 5 dB the estimate error peaks under these conditions.

5.1.4 Chirp rate Estimation

Based on the center frequency estimation the chirp rate can be determined. To estimate the chirp rate, two frames of data (sampling frequency: \( f_s \), frame size: \( N \)) and the center frequency estimates are used. We will denote the center frequency estimate of frame \( a \) as

\[
f = (k_0 + k) \frac{f_s}{N}
\]  

(5.4)
Based on $CF_1$ and $CF_2$ the change in center frequency can be calculated. Then dividing the change in frequency by the time duration of one frame, $TD$, in (5.5), the chirp rate estimation is calculated in (5.6):

$$TD = \frac{N}{f_s}, \quad (5.5)$$

$$CR = \frac{CF_1 - CF_2}{TD}. \quad (5.6)$$

In Fig. 5.5, it was shown that the frequency estimation accuracy progressively declined as chirp rate increased. This same effect will be shown in Fig. 5.6, were the estimation of the chirp rate is shown, since the chirp rate estimation is dependent on the frequency estimation.

It is also noticed that for the Blackman-Window method in Fig. 5.6 there is a ripple where there are peaks and valleys in the chirp rate estimation. This phenomena will be discussed later when the implications of reducing the frame size are discussed.

We can also make note that the Blackman-Window-with-Autocorrelation has better accuracy in frequency estimation, making it, also, more accurate in chirp rate estimation.

### 5.1.5 Power Estimation

The estimation of power is very straightforward especially if the signal is on an FFT bin. If this is the case, then the result from the FFT will provide the power estimation. Since this cannot be guaranteed, the use of the offset or $k$ value from the frequency estimate is used to
correct for the power lost due to spectral leakage.

**Power Estimation Method**

The method for determining the power of the signal provides the SNR of the signal. The SNR of the signal is defined as:

\[
SNR = \frac{P_s}{P_n}
\]

where \(P_s\) is the signal power and \(P_n\) is the noise power.

The first step is finding the power of the signal. This is done by using the power of the bin corresponding to the signal. The power in the bin may be an underestimate due to spectral leakage. Because of this, a curve fitting approach was used to determine the relationship between the offset calculated in the frequency estimation method, and the percent of the power that is lost at that particular offset. This was done in MATLAB\textsuperscript{TM} and the result is shown in Fig. 5.7.

Next, the power of the noise is needed. This is done by finding the median of the FFT result. This has been found to be an accurate representation of the power of the noise per bin because we do not know how many signals exist and to what extent the spectral leakage, rabbit ear effect, and chirping signal power has affected the spectrum. The total power of the noise, however, is the median value times the number of bins in the FFT. This adjustment will be taken into account later so that the procedure is generalized for any length FFT.

Now that a ratio between the signal power and noise power of one bin can be calculated, the ratio is then used in another curve fitting process in which the SNR calculated in fre-
frequency domain is mapped to the SNR in time domain. We need to conduct this mapping for both Blackman-Window and Blackman-Window-with-Autocorrelation methods independently. This mapping result of Blackman-Window method is shown in Fig 5.8.

From the curve fitting shown in Fig. 5.8 we obtain the power estimate of the signal. The next section will show the methods to measure the accuracy of this power estimation algorithm.
Simulation Process

To determine goodness-of-fit of our method we first generate a signal with a random frequency and at a given power. The signal is then passed as the input to both the Blackman-Window and Blackman-Window-with-Autocorrelation methods. Next, we use the curve fitting method described in Fig 5.8 to adjust the estimate given from the FFT result. This process is done 10,000 times to get an absolute value of the error in power estimation.

Introducing a non-zero chirp rate introduces the spreading of signal power over the adjacent bins in the FFT result. We have shown how this affects the sensitivity, dynamic range, and frequency estimation. In the estimation of power, this spreading must be considered to gain a more accurate estimation of the power of the signal. In the next section, a curve fitting method will be described to adjust the power estimate based on the chirp rate.

Chirp rate adjustment for Power estimation

![Graph showing Power Difference (dB) vs Chirping Rate for Blackman Window and Blackman Window with Autocorrelation](image)

Figure 5.9: Power lost due to Chirp rate

Since the chirp rate spreads the energy of the signal, we used MATLAB™ to simulate how much power is lost for a given chirp rate. Figure 5.9 is the graph that relates the power lost due to the chirp rate. Once the signal is detected, the chirp rate can be estimated. Then the chirp rate can be used to determine how much power to add to the FFT result estimate. Curve fitting the plots in Fig 5.9 will provide the equation used to relate chirp rate to the power lost due to the chirp rate. The input being the chirp rate and the output will be the amount of power to add back to the power estimation from the FFT result. In the next section the accuracy of the power estimation method will be discussed.
Results and Conclusions for Chirping Signal Power Estimation

Figure 5.10 shows the results for the power estimation study. The dependence on chirp rate is obvious. This dependence is due to the energy spreading to adjacent bins due to the chirp rate. The maximum error is experienced when the chirp rate is high and the power is low and the maximum power estimation error is about 6 dBm.

Figure 5.10: Power Estimation Study

5.2 Effects of Reducing Frame Size

As shown in the previous section, when chirp rate is high, the signal chirp rate and power estimation is less accurate. The reason is that when chirping rate is high, the chirp signal power spreads over multiple FFT bins thus making signal characteristic estimation difficult. Reducing the size of the FFT from 256 data points to 128 data points will increase the accuracy of the frequency and power estimate in chirping signals because the smaller change in frequency in the shorter duration frame will reduce the spreading signal’s energy. This is advantageous if the detection of higher chirp rates are needed. Decreasing the number of points in the FFT usually makes the frequency estimate worse because the frequency resolution is reduced, this is still generally true for pulsed-CW signals. However, using the interpolation methods described in Section 5.1.3, the frequency estimation for the 128 pulsed-CW case will still be accurate. Chirping signals differ from pulsed-CW signals and, in this section, we will explore the benefits of reducing frame size for chirping signals with high chirp rate. As we will show in this section, when frame size is reduced, the signal center frequency estimation, chirp rate estimation, and power estimation are improved for chirp signals with high chirp rate. However, it needs to be noted that, by reducing frame
size, we sacrifice the receiver sensitivity and the maximum number of signals to be detected simultaneously.

5.2.1 Frequency Estimation

Figure 5.11 shows the frequency estimation for 128 data point center frequency estimation study. We can compare this study to the 256 data point center frequency estimation, shown in Fig. 5.5. We see that for all chirp rate and power values, the 128 data point estimation outperforms the 256 data point case.

![Frequency Estimation](image)

Figure 5.11: 128 Data Point Frequency Estimation Study

5.2.2 Chirp rate Estimation

Since the frequency estimation was improved through reducing the number of points in a frame, the chirp rate estimation will also improve, shown in Fig. 5.12. The chirp rate estimate has been improved from the 256 data point case for both the Blackman-Window and Blackman-Window-with-Autocorrelation methods. As opposed to the 256 data point case we do not experience the same drastic increase in error as the chirp rate increases. This accuracy is due the shorter frame length.

Also noticed in Fig. 5.12, when chirp rate is increased there is a wave like effect in chirp rate estimation. This ripple warranted further investigation. We fixed the power of the signal at -65 dBm, and plot the chirping rate estimation error at different chirp rates, the result is illustrated in Fig. 5.13. As shown in Fig. 5.13, at higher chirp rates the ripple is more apparent, and the valleys of the Blackman-Window method coincide with valleys
in the Blackman-Window-with-Autocorrelation method but the Blackman-Window-with-Autocorrelation has twice as many valleys. For Blackman-Window method, the valleys happen at 800 MHz/µs, 1200 MHz/µs, 1600 MHz/µs, and 2000 MHz/µs. For Blackman-Window-with-Autocorrelation method, the valleys happen at 800 MHz/µs, 1000 MHz/µs, 1200 MHz/µs, 1400 MHz/µs, 1600 MHz/µs, 1800 MHz/µs, and 2000 MHz/µs. After careful investigation, we found that the chirp rate estimation error valleys occur at the chirp rates which generate signal frequency change equivalent to the multiple FFT bin frequency resolution. For 2.56GHz sampling rate, the time duration of one 128-point frame is 0.05 µs and the FFT frequency resolution is 20MHz. The 400 MHz/µs chirp rate generates 20MHz center frequency change equivalent to the 128-point FFT frequency resolution. Since the Blackman-Window-with-Autocorrelation doubles the size of FFT, the period of chirp rate estimation valleys is thus reduced by 50 percent.

At chirp rates that cause frequency change equivalent to multiples of the frequency resolution, the resulting k value will be the same in both frames. This will result in a better estimation of the chirp rate because the frequency estimation error is biased the same way. However, if the chirp rate is such that the frequencies result in opposite signed values for k the frequency estimation error is compounded resulting in a worse chirp rate estimate making the peaks shown in Fig. 5.13. This effect is more apparent under high chirp rate which cause higher frequency estimation error and thus higher chirp rate estimation error.

![Figure 5.12: 128 Data Point Chirp Rate Estimation Study](image)

5.2.3 Power Estimation

We have already stated that as chirp rate increases a spreading of the spectrum. This is why we reduced the frame size. This will reduce the spreading of the spectrum due to chirp
rate. We have also shown that when the frame size is 256 points an adjustment for the power estimate based on chirp rate is needed, as demonstrated in Fig 5.9. Figure 5.9 shows how much power to add back to the signal power estimate based on chirp rate. Next, we can compare this figure to the scenario where the frame size is 128 points. This is shown in Fig. 5.14, we see that even at 2000 MHz/µs the power adjustment is only 1 dBm for the Blackman-Window case and 2 dBm for Blackman-Window-with-Autocorrelation case.

Figure 5.13: Chirp rate estimation error ripple investigation

Figure 5.14: Power Estimation Error Study
The frequency estimation accuracy was increased by reducing the frame length and this improved the chirp rate estimation. The power estimation has been shown to depend on the chirp rate estimation. However, reducing the frame length reduces this dependency. This study is shown in Fig. 5.15 where the power was not adjusted with respect to the chirp rate. Comparing this power estimate graph to Fig. 5.16 where the power estimate was adjusted by the chirp rate. This study was completed by averaging 10,000 iterations for each power and chirp rate pair. These results show that by reducing the frame size, we can get a better power estimate and the power estimation adjustment based on chirp rate is not necessary. This statement is consistent with the result shown in Fig. 5.14.

Figure 5.15: Power Estimation Error Study
Figure 5.16: Power Estimation Error Study
Chapter 6

Encoder

In an EW receiver, the functionality of the encoder is to output a PDW summarizing all of the characteristics of the detected signals. The encoder generates the PDW based on the result of FFT. In previous chapters, we studied different processing methods applied before the FFT operation to improve the system sensitivity, dynamic range, and estimation accuracy. In this chapter, we will describe the design of our encoder which can detect multiple pulsed CW and chirping signals. The development of an encoder is considered the most challenging part of an EW receiver because it is very difficult to handle all possible cases. Some of the cases cannot even be solved because there is no knowledge of the incoming signals. For example, just because one signal is detected at a certain frequency does not mean another signal cannot be at that frequency as well. This can occur even if the signals are close enough in frequency that the frequencies cannot be separated; this and other issues, make developing an encoder a daunting task.

Before describing our encoder design, rabbit ear effects will be introduced the first. The rabbit ear effect, is the effect that occurs in the FFT result when a frame of the FFT is not completely filled with data[5]. The trouble with this effect is the resulting increased noise floor. The high noise floor amplitude produces effects similar to spectral leakage where the noise floor is higher when the rabbit ear effect occurs. As shown in Fig 6.1, for the first half of the frame (50 ns), the frame is empty; then, the signal arrives and fills the rest of frame. The Blackman window has then been applied to the signal to get the waveform

6.1 Rabbit Ear Effect

The rabbit ear effect, is the effect that occurs in the FFT result when a frame of the FFT is not completely filled with data[5]. The trouble with this effect is the resulting increased noise floor. The high noise floor amplitude produces effects similar to spectral leakage where the noise floor is higher when the rabbit ear effect occurs. As shown in Fig 6.1, for the first half of the frame (50 ns), the frame is empty; then, the signal arrives and fills the rest of frame. The Blackman window has then been applied to the signal to get the waveform
shown in Fig. 6.1a; the FFT result of this waveform is shown in Fig. 6.1b. We see a peak at the frequency of the signal but the noise floor is about $-35$ dB.

![Time Domain](image1)

![Frequency Domain](image2)

**Figure 6.1: Partially Filled FFT Frame**

We will look at a situation where two signals completely fill the frame. This is shown in Fig. 6.2. Again the time domain signal is shown with the Blackman Window applied in Fig. 6.2a. Then the FFT result is in 6.2b. Here, it is apparent that there are two signals with about 40 dB power difference. This is within the receiver’s dynamic range and both signals are detectable. The pulsed CW signal frequencies occur at 257 MHz and 374 MHz; the frequencies are 117 MHz apart. In our dynamic range study (Section 4.2.2), this frequency difference is in the range where the Blackman Window and the Blackman-Window-with-Autocorrelation methods can reach the maximum dynamic range of slightly more than 50 dB and a little under 50 dB, respectively. So, when the frame is completely filled with data from the signals, both signals are detectable.

Now, if a strong signal arrives in the middle of a frame, the situation becomes more difficult to detect. Shown in Fig. 6.3, this situation is the same as Fig 6.2, the only difference is the time of arrival of the strong signal. Because the time of arrival for the strong signal has...
changed to the middle of the frame, this signal has invoked the rabbit ear effect in this FFT, Fig. 6.3b; now the weaker signal that previously was easy to detect, will probably not be detected. It is barely recognizable in the FFT result in Fig. 6.3b (note: this signal does not contain any noise.) It is worthy of notice that in the latter case, since the strong only fills the fill half of the frame, the energy difference between strong and weak signals are actually less than the energy difference in the previous case.

To further understand the rabbit ear effect, Fig. 6.4 shows how the spectrum is affected when a frame is not filled with data. This is compared to the full frame of data in Fig. 6.4c. The noise floor is obviously a lot lower in the full frame case; in the partially filled frame case, the noise floor is higher, shown in Fig. 6.4d, but also, when noise is introduced, the noise will more effectively influence the spectrum in a way to generate false alarms or peaks over the threshold in the main lobe of the detected signal. This is opposed to the mainlobe in the full frame of data; these samples are more spread out and the noise would have to be very large in power to cause a peak over the threshold in the mainlobe. Noise in the partially filled frame would easily make a peak over the threshold; this would then become a false alarm.

An EW receiver must be able to handle the complications of the rabbit ear effect. There are many other types of EW receivers [20] and their performance under the rabbit ear effect scenario is the limiting factor in their practicality.

### 6.2 TOA and PW Estimation

The estimates of Time of Arrival (TOA) and Pulse Width (PW) are also included in the PDW. The rudimentary approach is to define the TOA as the frame the signal was first detected. In this scenario, the frame duration, $T_{\text{frame duration}}$, of the FFT result defined in
(6.1) is the coarse estimate of the TOA.

\[ T_{\text{frame duration}} = \frac{N}{f_s} \]  

where \( N \) is the FFT frame size and \( f_s \) is the sampling frequency.

A more accurate estimation can be obtained by considering the power estimate in each frame. If three or more frames are detected, the ratio between the power of the first/last frame to the average power of the full frames can be used to determine the duration of the signal in the first/last frame.

### 6.2.1 Description and Reasoning

Shown in Fig. 6.5, the waveform has been divided in the 100\( ns \) frame lengths given by (6.1), where \( N \) is 256 and \( f_s \) is 2.56 \( GHz \). For each of these four frames a power estimate has been calculated, these estimates are shown in Table 6.1. The frames that contain a full frame of data have the most accurate estimation of the signal’s power. The first frame and last frame also have an estimate for power but these values are lower than the full frame
Figure 6.5: Visualization of TOA Estimate

<table>
<thead>
<tr>
<th>Frame Number</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time (ns)</td>
<td>0-100</td>
<td>100-200</td>
<td>200-300</td>
<td>300-400</td>
</tr>
<tr>
<td>Power Estimate (dBm)</td>
<td>-61.8</td>
<td>-45.7</td>
<td>-44.07</td>
<td>-61.8</td>
</tr>
</tbody>
</table>

Table 6.1: Power Estimates per Frame

estimates.

(a) Curve Fit Blackman Window

(b) Curve Fit Blackman Window with Autocorrelation

Figure 6.6: Partial Filled Frame Power
To improve TOA and PW estimates, we used Fig 6.6 to relate the average power of the full frame estimates to how much data occupies the first or last frame. Curve fitting Fig. 6.6 allowed us to improve the accuracy of the TOA and PW for certain situations. These scenarios are illustrated in Fig. 6.8 where the adjustments have been applied. We compare these estimates to Fig. 6.7 where the adjustment has not been applied.

To compare Fig. 6.8 to Fig. 6.7 we first compare 6.7a to 6.8a and the adjusted TOA and PW estimates are more accurate. This is true for both the Blackman-Window method and Blackman-Window-with-Autocorrelation for TOA and PW estimate.

Looking closer at the adjusted TOA and PW estimate error we see that the error increases as the power increases. For a higher powered sinusoid, the TOA and PW estimates will experience a little more error on average because less of the frame needs to be filled with data to be detected. This increases the amount of time the adjustment needs to compensate.
for and this will introduce more error. Conversely, signals with lower power also experience more error in the TOA and PW estimations with adjustment. This is because signals that are low in power need to occupy more the frame to be detected. If the signal does not occupy enough of the frame the frame will not detect the signal. If the signal is not detected in the frame that it arrives in then the signal will be detected in the next frame. This frame will consequently be treated at the arrival frame. The curve fitting will be applied to this frame and the TOA estimate can only get worse. The same argument can be applied to the time of departure (TOD) estimate and the pulse width estimation is defined as $TOD - TOA$. To get a better accuracy for these estimates, it could be implemented that the encoder only uses the adjustment method for signals that are higher than a certain power threshold. Some investigation into what power threshold should be used to make this decision. This change could make the TOA and PW estimates more accurate.
6.3 Encoder Working Principles

We developed three principles for the encoder design which are introduced in this section.

6.3.1 Principle 1: Minimum 3 detected for chirping signal

Description and Reasoning

As stated in Section 2.5, the chirping rate is assumed to be linear. The encoder takes advantage of this assumption to determine chirp rate. The maximum chirp rate is limited by the hardware implementation technologies. In our study, we assume the maximum chirp rate is $2\text{GHz}/\mu\text{s}$. A chirping signal generates peaks at different FFT bins in consecutive frames due to its changing frequency. With a sampling rate of 2.56 GHz, and the number of data points per FFT frame, $N$, is set at 128, the calculation of the maximum number of bin-shift is as follows:

$$\Delta f_{\text{max}} = CR_{\text{max}}(\text{frame duration})$$  \hspace{1cm} (6.2)

$$\text{frequency resolution} = \frac{f_s}{N}$$  \hspace{1cm} (6.3)

$$\text{max number of bins} = \frac{\Delta f_{\text{max}}}{\text{res}}$$  \hspace{1cm} (6.4)

From the frame duration (6.1), and maximum chirp rate, $CR_{\text{max}}$, is $2\text{GHz}/\mu\text{s}$, the maximum change in frequency is determined by (6.2). Then the number of bins the maximum change represents is calculated with the frequency resolution (6.3), and shown in (6.4).

The maximum bin-shift caused by the maximum $2\text{GHz}/\mu\text{s}$ chirp rate is is five bins. In other words, if one chirp signal generates a peak at bin 13 in one frame, assuming the same signal is still present in the next frame, then a peak should be observed in the range between bin 8 and 18. From this we can determine if two peaks in consecutive frames are generated by the same chirp signal. However, it is possible that we might link two peaks caused by noise in consecutive two frames as an indication of a chirp signal. To limit this possibility, a chirp signal is detected only if it is detected in at the least three frames. Since the chirp rate is linear, we know what the third frame must have a detection at the bin number equivalent to the second bin number plus the bin number difference between the first to the second detections, or mathematically:

$$B_{f3} = B_{f2} + (B_{f2} - B_{f1})$$  \hspace{1cm} (6.5)

where $B_{fa}$ is the bin number of the detection in frame $a$. 

45
6.3.2 Principle 2: Minimum 2 detected for Pulsed CW

Detecting pulsed CW signals is difficult because the enemy obviously does not want them to be detected. To make pulsed CW signals less detectable, they are made as short as possible. Along with this, there is a limit as to how short a signal can be to be detected by an EW receiver. For our encoder, we make sure two frames are detected for a pulsed-CW signal. With the number of data points being 128 and the sampling frequency being 2.56 GHz, $T_{frame\ duration}$ is 50 ns. Since we detect two frames, it is possible to think we could detect any 100 ns length signal. This is not necessarily the case, for a low powered signal that starts half way into a frame only one frame will be filled. The starting frame and the ending frame will be half filled. So, for lower powered signals a longer duration is needed to detect the pulsed-CW signals but for higher powered signals a detection can occur with less data in a frame, meaning the signal could be shorter than 100 ns in duration and still be detected.

The reason we set the minimum detection for a pulsed CW signal to two frames and not just one is because of the rabbit ear effect described in Section 6.1. When a frame is not completely full, the rabbit ear effect can cause false alarms at different frequencies; for this reason, there must be at least two frames detected. The pulse-CW signal has a fixed frequency and the chance to have peaks caused by rabbit ears and noise at the same bin in consecutive frames is small. As a result, by increasing the required number of detected frames to two, the effect of false alarms due to the rabbit ear effect is reduced. To further increase this minimum detection requirement limits the EW receivers capability of detecting short pulsed-CW signals.

6.3.3 Principle 3: Skipping a frame

In the case where a signal is low in power there may be a situation where a frame in the middle of the signal is not detected. Similarly, during the middle portion of a signal, another signal could arrive or depart. In this situation there is a chance that the arriving/leaving signal causes the rabbit ear effect and this could cause a frame in the original signal to be missed. For these reasons, the ability to skip a frame in the duration of a signal has been implemented in our encoder design. It should also be noted that the skipped frame does not count in the minimum of three detections for the chirping signal or minimum of two detections for the pulsed-CW signal.

6.4 Encoder System Details

Flow Diagram

Based on the three principles described in the previous section, an encoder is developed. The encoder’s logic will be the same for the Blackman-Window and the Blackman-Window-with-
Autocorrelation case. The results will be different because of the bins detected with different algorithms. Now a demonstration of how the encoder works will be conducted.

First, there are five different states any particular bin in the FFT can be in, the first is DETECTED. A bin in the DETECTED state means that this particular FFT bin surpasses the threshold. But for now we do not know if the bin is linked to a chirping signal, a pulsed-CW signal or is a false alarm. Next, if, later, a DETECTED bin is determined to be part of a signal, then the bin is flagged as a SIGNAL bin. For the handling of skipped bins, there are two states, referred to as, TMP SKIP or temporary skip, and SKIP. The first state refers to a bin that has yet been determined if it refers to a bin that is in the middle of the signal, or is a bin that represents the termination of a signal. The second state, or SKIP state, refers to a bin that is in the middle of a signal. For a bin that is skipped in the middle of a signal the state of the particular bin will be set as TMP SKIP at first then changed to SKIP, but a bin that represents the termination of a signal remains in the TMP SKIP state. The fifth and final state is the INITIAL state, every FFT bin is in the INITIAL state originally.

Once the data is sampled, those data points are passed to the FFT algorithm described in Chapter 4 i.e., the Blackman-Window, or the Blackman-Window-then-Autocorrelation. From the result of either one of the algorithms, the bins of a particular FFT frame, say the $k^{th}$ frame, are noted as DETECTED if their magnitudes are above the threshold. This operation is shown in Fig. 6.9 bubble number 1.

Next, in bubble number 2, the DETECTED/SIGNAL bins in frame $k - 2$ are considered. These detections will be the starting point for determining if there is a signal that is at least three frames in duration. The three frames under consideration are $k - 2$, $k - 1$, and $k$. In bubble number 3, the decision is made if, for a DETECTED/SIGNAL bin in frame $k - 2$, there are associated DETECTED/SIGNAL bins in frames $k - 1$ and $k$ that satisfy the condition of being a chirping signal. If it is then all three bins in frame $k - 2$, $k - 1$, and $k$ will set to SIGNAL as indicated in bubble number 4, otherwise, if there is an associated SIGNAL/DETECTED bin in frame $k - 1$ then the bin in would be signal position of frame $k$ is set to TMP SKIP, shown in bubble number 6. Bubble number 7 then shows a situation where if there is a DETECTED/SIGNAL bin in frames $k - 2$ and $k$ the bin in would be signal position of frame $k - 1$ is flagged as a TMP SKIP bin because this bin could be a skipped bin in the middle of a signal. Once this is complete bubble 5 shows us repeating this process for the next DETECTED/SIGNAL bin in frame $k - 2$. After all the DETECTED/SIGNAL bins in frame $k - 2$ are considered we continue our investigation in Fig. 6.10.

In Fig. 6.10, we start with TMP SKIP bins in frame $k - 1$. In bubble 2, we find the bins in frame $k - 2$, $k - 3$, and $k - 4$ associated with a TMP SKIP bin in frame $k - 1$. These bins should be marked as SIGNALS and if there is no detection in frame $k$ then these bins are double checked to be a valid signal, in bubble number 6. If they are a valid signal the PDW is generated in bubble number 7. Going back to bubble number 3, if the TMP SKIP bin in frame $k - 1$ has an associated detection in frame $k$ and $k - 2$ then the TMP SKIP is changed to a SKIP, this officially marks that bin as a bin that is in the middle of a signal that was not detected by the FFT in frame $k - 1$ and the bin in frame $k$ is marked a SIGNAL. Once again in bubble number 5 we check to make sure we consider every TMP SKIP bin in frame $k - 1$. Then finally, in bubble number 8 the frame number is incremented by 1 and the whole
### Table 6.2: Encoder Example 1: PDW Results

<table>
<thead>
<tr>
<th>Units</th>
<th>Start freq (MHz)</th>
<th>End Freq (MHz)</th>
<th>Chirp Rate ((MHz/\mu s))</th>
<th>Power (dBm)</th>
<th>Start Time (ns)</th>
<th>Pulse Width (ns)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual</td>
<td>450</td>
<td>673</td>
<td>1500</td>
<td>-50</td>
<td>250</td>
<td>150</td>
</tr>
<tr>
<td>Estimates</td>
<td>449.491</td>
<td>672.868</td>
<td>1471.691</td>
<td>-52.756</td>
<td>249.761</td>
<td>151.783</td>
</tr>
</tbody>
</table>

process starts again.

Special consideration needs to be taken for pulsed-CW signal which only requests two detections. For the sake of simplicity, this process is not displayed in either Fig. 6.9 or Fig. 6.10.

## 6.5 Encoder Simulation

### 6.5.1 System and Signal Characteristics

To simulate our encoder under realistic conditions we simulated an A/D converter, along with the A/D converter we considered the thermal noise, amplifier noise, and quantization noise. Our thermal noise was set at -83 dBm. Next the amplifier noise was considered. The amplifier noise figure is 10dB. Lastly, the quantization noise, we consider an A/D converter that uses 10 bits to convert the analog signal to a digital signal. The encoder generates PDW based on FFT result of the Blackman-Window-with-Autocorrelation method.

### Example 1: Detecting a Chirping Signal

Shown in Fig. 6.11 is a very simple case where there have been three consecutive frames that have detected a signal. The signal started at 250 ns and continued for a pulse width of 150 ns. For this plot, a sampling frequency of 2.56 GHz was used with 128 point FFT making each frame 50 ns in duration and signal consists of three frames. The fourth frame indicated shows that the signal has ended and that frame is the first frame that does not contain a signal. Once the signal has been determined to end, the PDW is generated. The characteristics of the signal to be determined are the starting frequency, ending frequency, chirp rate, signal power, starting time, and pulse width. Table 6.2 shows the estimates for the signal characteristics.

### Example 2: Detecting a pulsed-CW Signal

In Fig. 6.12 a pulsed CW signal is detected at 512 MHz, at 250 ns. This signal was detected in two frames with a true pulse width of 100 ns. In Table 6.3 the PDW results along with
the input values for the characteristics are given. We see that the power estimation is about 1.5 dBm off and the frequency estimate is off by 1.29 MHz.

Example 3: Skipping a frame

In Fig. 6.13, we see that the second frame of the signal was missed but, since one frame is allowed to be skipped, we still associate the first frame (at 250 ns), with the two frames after the skipped frame. Because of this ability to allow a frame to be skipped, we have successfully detected the signal with accurate results. There is a price to pay for this ability. This price is response time with respect to the ending of a signal. The PDW is generated after the signal is considered to have ended. Since we are allowed to skip a frame the PDW cannot be generated until the signal is missing for two consecutive frames.

In this situation, for the skipped frame, we do not have signal characteristic measurements; for this situation we disregard that frame in averaging the power but we do include it in our pulse width estimate.

Example 4: Simultaneous signal detection

An EW receiver must have the ability to detect signals simultaneously. This does not mean that two signals have to arrive at the same time and fill up the frame. Signals can arrive and end at any point and the EW receiver must be able to handle these situations. As described earlier in Section 6.1, the rabbit ear effect is a difficult problem to minimize but here is a demonstration of an ability to detect multiple signals simultaneously.

Figure 6.14 shows two signals: one chirping and one pulsed CW. The pulsed CW arrives at 200 ns and the chirping signal arrives at 250 ns. Both signals are detected successfully and the PDW is generated. The results are shown in Table 6.5.
<table>
<thead>
<tr>
<th></th>
<th>Start freq (MHz)</th>
<th>End Freq (MHz)</th>
<th>Chirp Rate (MHz/µs)</th>
<th>Power (dBm)</th>
<th>Start Time (ns)</th>
<th>Pulse Width (ns)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual</td>
<td>508</td>
<td>885</td>
<td>1500</td>
<td>-50</td>
<td>250</td>
<td>250</td>
</tr>
<tr>
<td>Estimates</td>
<td>509.180</td>
<td>885.029</td>
<td>1517.957</td>
<td>-53.692</td>
<td>249.182</td>
<td>247.602</td>
</tr>
<tr>
<td>Actual</td>
<td>317.669</td>
<td>317.669</td>
<td>Pulse-CW</td>
<td>-30</td>
<td>200</td>
<td>350</td>
</tr>
<tr>
<td>Estimates</td>
<td>316.461</td>
<td>316.461</td>
<td>Pulse-CW</td>
<td>-33.341</td>
<td>200.000</td>
<td>350.926</td>
</tr>
</tbody>
</table>

Table 6.5: Encoder Example 4 - PDW Results

Referring to Table 6.5, we see that both the frequency estimates are within 2 MHz and the chirp rate, are fairly accurate. The power, TOA (start time), and PW estimations are also accurate. The ability to estimate these characteristics of one signal is easier since the spectral leakage is known to come from the only signal present. When there are two signals with a 20 dBm power difference, the spectral leakage could interfere with the other signal’s estimates. This issue is worsened when the signals are chirping. In this example, our encoder is still able to generate accurate estimations.

The four examples shown in this section demonstrate the capability of our encoder to detect different kinds of signals and generate accurate estimates.
1. Bins greater than the threshold in frame $k$ are flagged as DETECTED.

2. For each DETECTED/SIGNAL bin in frame $k - 2$.

3. Is there a DETECTED/SIGNAL bin at $k - 2$, $k - 1$, $k$?

4. Mark bin in $k$ as SIGNAL.

5. End?

6. DETECTED/SIGNAL at $k - 1$.

7. DETECTED/SIGNAL at $k$.

8. Set bin at $k$ to TMP SKIP.

9. Set bin at $k - 1$ to TMP SKIP.

Connector 1

Figure 6.9: Flow diagram Part 1
1. For each TMP SKIP at frame $k - 1$

2. Find Associated Signal for TMP SKIP

3. DETECTED at $k$ for associated signal

4. TMP SKIP changed to SKIP; DETECTED to SIGNAL

5. End?

6. Validate the signal meets requirements

7. Output PDW

8. Proceed to frame $k + 1$

Figure 6.10: Flow diagram Part 2
Figure 6.11: Encoder Example 1

Figure 6.12: Encoder Example 2
Figure 6.13: Encoder Example 3

Figure 6.14: Encoder Example 4
Chapter 7

Conclusion

In this thesis, we applied autocorrelation to improve the performance of an FFT-based EW receiver. Our results show that, by taking autocorrelation of windowed input signal, we are able to improve the receiver sensitivity, frequency estimation accuracy, and chirping rate estimation accuracy. The receiver’s dynamic range is also improved for signals with small frequency differences.

During our research, we discovered that, for a chirping signal, its chirp rate estimation accuracy depends on chirp rate. The chirp rate estimation error also experiences a ripple whose period is determined by the duration of frame and chirp rate discovered. We also find that, to detect a chirp signal, an FFT with longer frame size will not necessarily deliver more accurate chirp rate and power estimates. To the best of the author’s knowledge, these two phenomena have not been described in available EW receiver literature.

Based on Blackman-Window-with-Autocorrelation-FFT approach, we successfully developed an EW receiver design which can detect pulsed-CW and chirping signals and output a PDW that consists of the signal’s chirping rate, frequency, power, time-of-arrival, and pulse width. Our receiver can avoid the negative impacts of the rabbit ear effect which describes the signal spectrum spreading caused by a signal appearing or terminating in the middle of an FFT frame. The research work presented in this thesis can significantly improve the next generation of EW receiver design.

7.1 Recommendations for Future work

The follow-up work listed below is recommended for anyone who would like to continue work on EW receiver development.

1. Currently, our EW receiver assumes that no two radar signals have the same frequency at the same time. It is desirable to improve the encoder to handle a situation where a chirping signal can overlap in frequency with a pulsed-CW signal or another chirping...
signal with an opposite sign in chirp rate so that both signals share a bin in the same FFT frame.

2. Currently, our EW receiver can detect and differentiate pulsed-CW and chirping signals. Most of radar systems use either pulsed-CW, chirping signal, or BPSK signals. Adding the PBSK signal detection functionality to the encoder will complete the functionality of our EW receiver design.

3. We have shown some advantages with changing the frame length of the FFT, with longer FFT frames, sensitivity/dynamic-range is improved and the frequency resolution is better and, with shorter FFT frames, the TOA and PW estimates are more accurate. For a chirping signal with high chirp rate, the shorter FFT frame might deliver a better performance compared to the FFT with longer size. There has been some work into using multiple, up to three, lengths of FFT frames to detect pulse-CW signal. To apply multiple FFT frame size for chirping signal detection might lead to great performance improvement in EW receiver.
Bibliography


