2-D ADAPTIVE PREDICTION BASED DATA COMPRESSION TO LOCATE UNKNOWN EMITTER

BY

ANUPAMA SHIVAPRASAD

B.S. Electrical Engineering
Birla Institute of Technology and Science, Pilani, 1999

THESIS

Submitted in partial fulfillment of the requirements for the degree of
Master of Science in Electrical Engineering in the
Thomas J. Watson School of Engineering
Binghamton University
State University of New York
2001

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Dr. Mark L. Fowler_____**May 1, 2001**
Supervisor
Electrical Engineering Department

Dr. Eva Wu_____**May 1, 2001**
Committee Member
Electrical Engineering Department

Dr. Edward Li_____**May 1, 2001**
Committee Member
Electrical Engineering Department

ABSTRACT

Multiple platform coherent location systems operate by computing the time difference of arrival (TDOA) and frequency difference of arrival (FDOA) among signals received at geographically separated platforms. The bandwidth of the data link between the platforms is limited. Present data compression methods were designed for communication signals and do not fully exploit the characteristics of the radar signal.

A compression scheme, which exploits the characteristics of the radar signal is proposed in this thesis. It is based on the concept of 2-D adaptive prediction and adaptive quantization. The above two techniques together compress the radar signal to be transmitted over the data link. This scheme achieves a compression ratio of 8 in some cases and 4 in almost all cases. The main advantage of this compression scheme is its robustness in the presence of multi-path interference and other forms of perturbations to the signal.
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ACKNOWLEDGMENTS

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I am grateful to Prof. Eva Wu and Prof. Edward Li for acceding to read through my thesis at a short notice and giving me valuable suggestions during the writing of this thesis.

I am indebted to my family for having let me come so far away from home to pursue my interests. Their encouragement and love have helped me see this day.

I am thankful to Bobbi for her love and warmth.

I am grateful to my labmates Chris, Qian, Shu, Uma and Raman for being great friends and helping me get through graduate school.

I would like to thank my fiancé Suresh and my dear friends Sridhar, Nathan, Balaji, Karna and Sihong for putting up with me during the writing phase of this thesis.

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CHAPTER 1. Introduction

A common way to locate electromagnetic radar emitters is to use the time-difference-of-arrival (TDOA) and frequency-difference-of-arrival (FDOA) information from receivers at geographically separated locations. There are other methods that can be used to locate the emitter but the TDOA and FDOA are the most popular. There are three main ways to estimate the TDOA and FDOA values:

1. Coherent Method [1]

2. Non-Coherent Method [2]

3. Semi-Coherent Method [2]

The first two are well-known methods and the third is a new proposed method. The coherent method estimates the TDOA and FDOA values by cross-correlating signals received at different receivers. The non-coherent method extracts time-of-arrival (TOA) and frequency-of-arrival (FOA) at each of the receivers and then computes the TDOA and FDOA. The semi-coherent method extracts a prototype pulse at one of the receivers and transmits this pulse to the other receivers. This pulse is correlated with each of the signals collected at the respective receivers to extract the TOA values and phase values that indirectly give the FOA values. The TDOA and FDOA values are extracted from the above information.

The data link provided for information exchange among receivers is severely restricted in bandwidth. This limitation prevents real time or close to real time transfer of information, which is very crucial in military and wireless phone E-911 applications. Real time transfer and processing of signal data can be made possible by compression. Signal data could be compressed and sent to the receiver, which could then decompress and process it to locate the emitter.

This thesis deals with the application of two-dimensional adaptive prediction based data compression to aid in rapid transferal of signal information essential for emitter location using the coherent method. This compression scheme exploits the periodic nature of radar pulses. In the compression scheme, each pulse of the pulse train (signal data) is chopped to form the row of a matrix. Since the signal is periodic in nature, each row of the matrix is very similar to the others provided the signal is free of anomalies. This row-to-row similarity is what is being exploited by the two-dimensional adaptive prediction method to improve compression. The first several samples of the signal are sent uncoded and the rest are coded using linear prediction techniques. This receiver decodes the whole signal and reconstructs it. The reconstructed signal is cross-correlated with the signal received at this receiver to extract TDOA and FDOA information. The TDOA and FDOA accuracies achieved with and without compression are compared to evaluate the effect of compression.

This thesis is divided into six Chapters. Chapter 2 gives an overview of the system and its components. It also discusses in brief the basic methods used in extracting TDOA/FDOA estimates. Chapter 3 states the problem under consideration and gives a brief approach to solve the problem. Chapter 4 discusses Adaptive Prediction and Quantization in detail and how they are applied to the problem at hand. Chapter 5 presents the simulation results and Chapter 6 states the conclusion along with scope for future work.

CHAPTER 2. Background

In this section, we shall discuss the emitter location scenario and the methods employed to locate the emitter.

2.1 System Configuration

The scenario under consideration has a ground-based transmitter emitting a radar signal and at least three receivers collecting the received signal. The receivers can be moving or stationary. The system configuration is depicted in Figure 2.1.
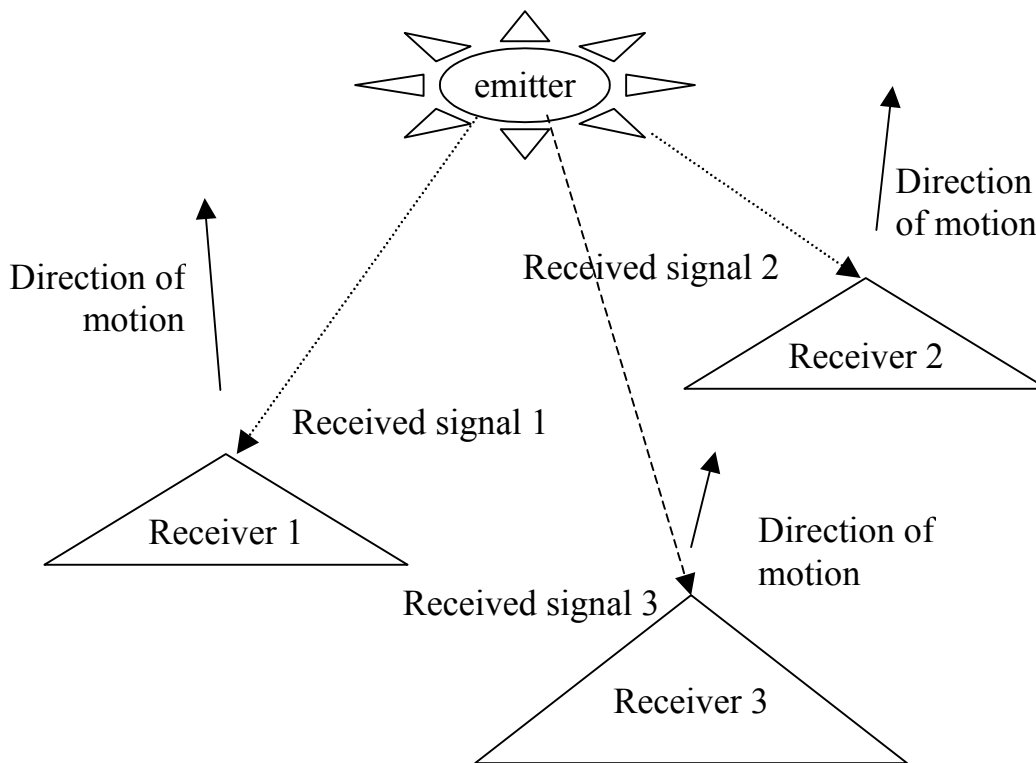

Figure 2.1 System configuration

2.1.1 Radar Transmitters and Receivers

Radar transmitters can be broadly classified as [3]:

1. Continuous Wave/Doppler Radar

2. Pulse-Doppler Radar

Continuous Wave/Doppler radar transmits a continuous signal, thus requiring a second dedicated antenna to receive the signals. This radar uses the relative Doppler shift between the aircraft and itself to determine the aircraft location. The biggest drawback of this radar is its inability to detect the aircraft when the relative motion of the aircraft toward or away from the transmitter is zero or negligible. Also, the probability that the radar detects the aircraft depends on the aircraft's angle to and physical distance from the radar.

Pulse-Doppler radar transmits pulses instead of a continuous signal. Most present day radars employ the pulse technology because it is much cheaper than the latter. For Pulse-Doppler radars, a single antenna emits a pulse train for a short duration and between the transmissions the same antenna picks up return signals. Thus a second antenna is not required to receive the return signals. This type of radar has a shorter range. For the simulations, we assume the signal is pulsed.

The receivers acquire the pulse trains emitted by various transmitters [2]. They then group the signal pertaining to the emitter (usually frequency) of interest into one or more subtrains, each having pulses from the same mode of operation. The pulses in the subtrain are very similar except for random phase shifts. The subtrain pulses are then gated and the inter-pulse samples are removed. The resulting series of pulses can be thought of as a pulse train with very short Pulse Repetition Interval (PRI). The subtrain is used for further processing to extract TDOA/FDOA information. For the simulations, we assume that the subtrain is available to us.

2.1.2 Radar Signals

Different types of signals are generated based on what modulation mode, carrier frequency and PRI modes are employed. The transmitter could generate a radio pulse of a particular modulation mode, carrier frequency and PRI mode and continue in the same mode. It could also shift between various modes thus making its detection difficult.

Radar Signals are pass-band signals. For our analysis and simulations, we model them as complex base-band signals.

2.2 Emitter Location Techniques

With the system configuration now explained, we can now discuss the means to estimate the location of the transmitter. There are three prevalent methods to locate the emitter [4].

1. Triangulation method

2. Azimuth/Elevation method

3. TDOA/FDOA

The Triangulation method typically employs a single aircraft to locate the emitter. It cannot process the location information in real time and is not very accurate. Azimuth/Elevation employs a single aircraft and can instantaneously estimate the location but its accuracy degrades with decreasing altitude. TDOA/FDOA estimates the transmitter location very precisely in real time but requires at least three receivers and a wide band data link.

We shall use the TDOA/FDOA method to estimate the emitter location because of its high precision and accuracy as compared to the other methods stated above.

TDOA is the time difference of arrival of the emitted pulse between two different receivers. If the pulse arrives at receiver 1, located at a distance of R_1 from the emitter, at t_1 seconds and the same pulse arrives at receiver 2, located at a distance of R_2 from the emitter, at t_2

seconds, the TDOA would be t_1-t_2. The time t_1 is directly proportional to R_1 and t_2 to R_2. This can be represented with equations as $t_1=k*R_1$ and $t_2=k*R_2$ which implies that t_1-$t_2=k*(R_1$-$R_2)$, that is, TDOA$=k*(R_1$-$R_2)$. This essentially means that the emitter lies on the locus of the curve where $k*R_1$-$k*R_2$ is a constant, which is a hyperbola. From this we can conclude that the emitter lies on the hyperboloid surface such that receiver 1 and receiver 2 are the foci. But one such hyperboloid curve will not provide us the exact 3-D location of the emitter (x_e,y_e,z_e). Therefore we need another TDOA curve that is obtained between the third aircraft and one of the first two aircrafts. This still will not provide us enough information for us to pin point the emitter location since we have two curves but three variables. We now could use another TDOA estimate from a fourth aircraft or FDOA estimates from the three aircraft to find the location of the emitter. We use the FDOA estimates to locate the emitter. Unfortunately, FDOA curve analysis is more complicated than the TDOA and doesn't simplify to any of the known curve forms. Moreover, the FDOA estimates would vary with the speed as well as direction of travel. Once the FDOA estimates are obtained, the emitter location can be found.

2.3 Ambiguity Function [5]

The ambiguity function is a very important tool to study, understand and analyze waveforms. It is a two dimensional function that is defined as a functional of the waveform. Every waveform can be analyzed using the ambiguity function, which gives an insight into waveform choice for radar design. It is also the tool used to estimate the TDOA/FDOA between two signals.

2.3.1 Cross-Ambiguity Function

There is the important concept of cross-ambiguity function, which is derived from the ambiguity function and is used extensively in TDOA/FDOA estimation. The cross-ambiguity

function measures the similarity of any two waveforms. For any two waveforms $s_1(t)$ and $s_2(t)$ the cross-ambiguity function is defined as

$$\chi_{12}(\tau,v) = \int_{-\infty}^{\infty} s_1(t + \frac{\tau}{2}) s_2^*(t - \frac{\tau}{2}) e^{-j2\pi vt} dt \tag{2.3.1}$$

If $s(t)e^{j2\pi f_o t}$ is the transmitted signal, then its delay and Doppler shifted version $v(t) = \lambda s(t - \tau_o) e^{-j2\pi v_o t} e^{-j2\pi \vartheta}$ where λ is the amplitude attenuation factor, τ_o the delay, v_o is the Doppler shift and ϑ is the phase shift. The similarity of $s(t)$ and $v(t)$ can be found using the cross-ambiguity function $\chi_{12}(\tau,v)$. The ambiguity surface, given by $|\chi_{12}(\tau,v)|$, would peak at delay shift τ_o and Doppler shift v_o and from the peak location we can compute TDOA/FDOA. This is the principle behind estimating the emitter location, which will be discussed in greater detail in Chapter 3.

2.4 Cramer-Rao Bound

The Cramer-Rao bound gives a bound on the accuracy with which TDOA/FDOA estimates can be made. They are given by [1]

$$\sigma_{TDOA} \geq \frac{1}{2\pi B_{rms} \sqrt{SNR_o}} \tag{2.4.1}$$

$$\sigma_{FDOA} \geq \frac{1}{2\pi D_{rms} \sqrt{SNR_o}} \tag{2.4.2}$$

where B_{rms} is the RMS signal bandwidth in Hz, D_{rms} is the RMS signal duration in seconds and SNR_o is the signal-to-noise ratio after cross-correlation which is given by

$$SNR_o = \frac{BT}{\frac{1}{SNR} + \frac{1}{DNR} + \frac{1}{SNR.DNR}} \tag{2.4.3}$$

where *SNR* is the signal-to-noise-ratio at one platform, *DNR* the signal-to-noise-ratio at the other platform and *BT* is the time-bandwidth product.

CHAPTER 3. Basic Concept

Our system consists of an emitter at an unknown remote location. We have three receivers mounted on aircraft that are geographically separated from each other. These receivers receive the emitted pulse trains and then two of the receivers send the collected pulse trains to the third receiver, which will also be referred to as the common platform, to estimate the emitter location.

A very common approach to locate emitter is to measure the time-difference-of-arrival (TDOA) and frequency-difference-of-arrival (FDOA) between pairs of signals received at geographically separated locations. To compute the TDOA and FDOA, the signal from the first receiver is transmitted across a data link, which is assumed to have a fixed data rate. Then the cross-ambiguity surface of the two signals (one from receiver 1 and the other from the common platform) is computed and its peak found to jointly estimate TDOA and FDOA; this processing is known as cross-correlation processing or coherent processing.

This is also done for the signal received from receiver 2 and that two TDOA/FDOA pairs from all three signals are used to locate the emitter. Because the data link provided for exchange of information between the receiver platforms is bandwidth limited, our problem is centered on the best way to transmit as little information as possible over the data link and still be able to estimate the TDOA and FDOA to a high degree of accuracy.

To overcome the bandwidth constraint, the signals need to be compressed and sent over the data link. The aircraft with the common platform would then receive the compressed signals, decompress and then cross-correlate them with the common platform signal to estimate the emitter location. Figure 3.1 and 3.2 illustrate the compression and decompression scheme.
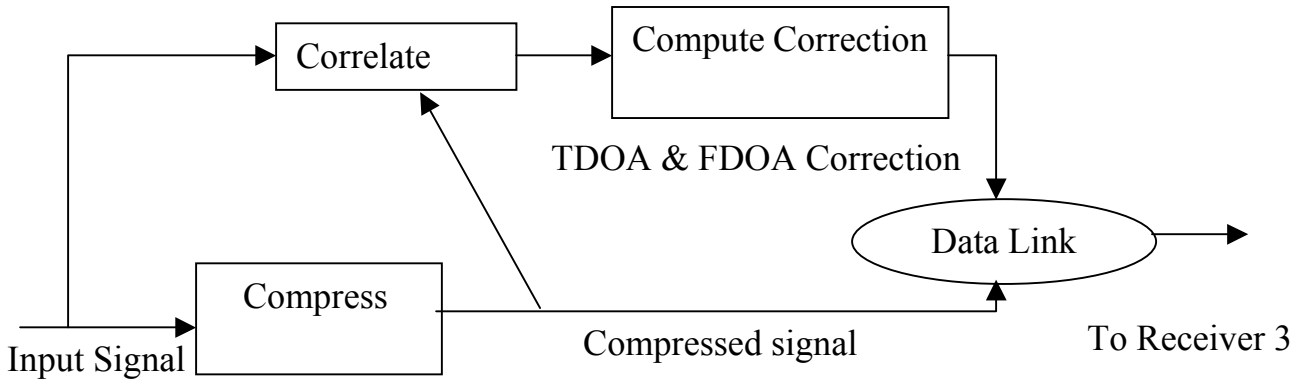
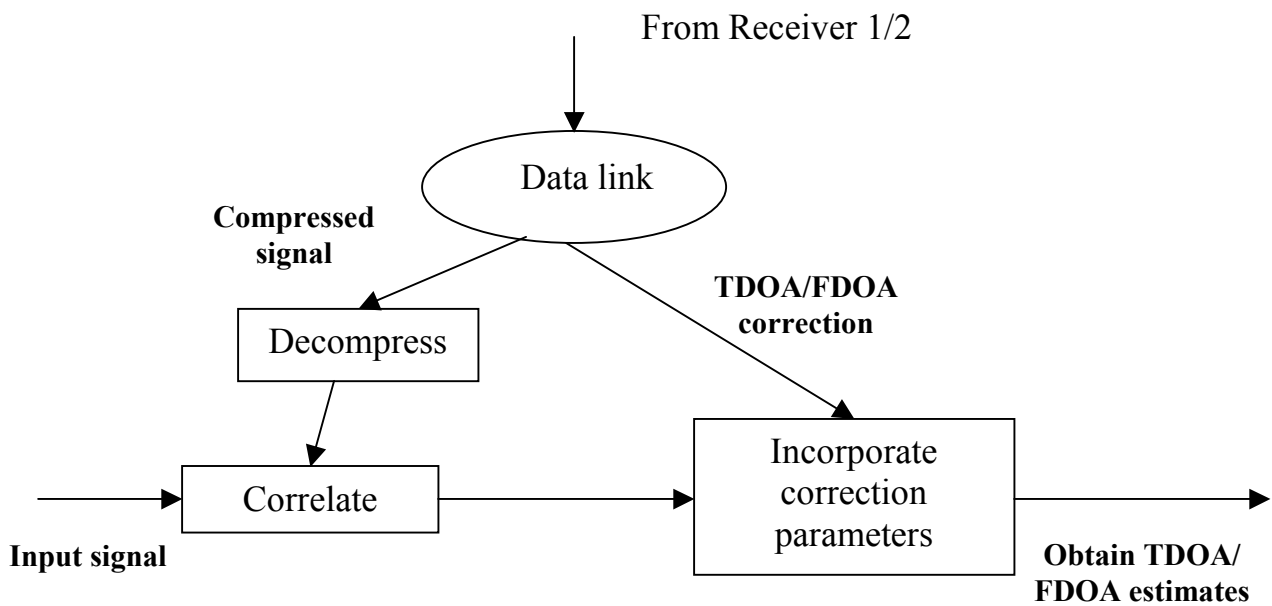**Figure 3.1 Signal Processing Operations at Receiver 1 and Receiver 2**

Figure 3.2 Signal Processing Operations at Receiver 3

In Figure 3.1, the received signal is compressed and cross-correlated with its uncompressed version to compute the correction [6]. The compressed signal along with the correction term is transmitted to Receiver 3. At Receiver 3, the signals are decompressed and correlated with the signal collected at Receiver 3 to obtain approximate TDOA/FDOA estimates

as shown in Figure 3.2. Better estimates of TDOA/FDOA are obtained by incorporating the correction parameters.

There are two basic methods to compress the signals: lossless and lossy. The lossless scheme involves no loss of information. There are many situations where we would want the reconstructed signal to look identical to the original. In those cases we use lossless compression. The compression ratio achieved using any of these schemes would be low. The lossy compression method involves some loss of information. This method would result in some distortion in the reconstructed signal and hence would achieve higher compression ratios.

The compression method that has been developed here is based on 2-D adaptive prediction, which is a lossy compression method. In this scheme, each pulse of the pulse train forms a row of a signal matrix. The first few signal values are sent uncoded. The rest of the signal values are predicted using linear and block prediction as the case may be, where the prediction is done from row-to-row whenever feasible to exploit the periodic nature of the signal. This approach is believed to be very robust because it is based on creating a signal model that captures the periodic nature of the signal but can adapt that model where needed to account for any anomalies in the pulse train. The signal model parameters are then transmitted along with the quantized prediction error and the initial signal sample points. The common platform can then recreate the signal as in standard differential compression-methods. Then signal processing operations are carried out to calculate the TDOA and FDOA estimates from which the emitter could be located. The compression scheme that we employ for this problem is illustrated in Figure 3.3.
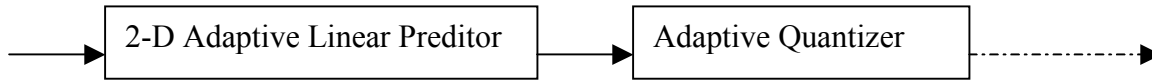
| 2-D Adaptive Linear Preditor | | Adaptive Quantizer | |

Figure 3.3 Model of the transmitter

The signal samples are predicted based on initial signal points using the 2-D adaptive linear predictor. The predictor coefficients are initialized using the least squares method. The next sets of coefficients are calculated using the adaptive prediction algorithm described in detail in the next section. The error between the actual signal samples and the predicted ones are then quantized using an adaptive quantizer that adjusts its step size for a specified fixed number of bits. This reduces the number of bits needed to be transmitted. The compressed error values, initial signal points and filter coefficients are encoded and then transmitted through the data link. The reconstruction process at the receiver is illustrated in Figure 3.4.
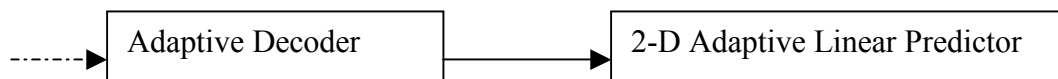
| Adaptive Decoder | 2-D Adaptive Linear Predictor |

Figure 3.4 Model of Receiver

The initial signal points and predictor coefficients are used to set the predictor to start predicting the rest of the signal points. The prediction error values are progressively added to the predicted signal points to reconstruct the entire signal. Using this technique, only the initial signal samples, initial predictor coefficients and the quantized error values need to be transmitted instead of the whole signal. This would reduce the data to a large extent. If entropy information

was available, entropy coding could also be used to further compress the signal information; this is not done here though. The next section discusses the compression scheme in detail.

CHAPTER 4. Prediction and Quantization Scheme

The concept applied here is very similar to Differential Pulse Code Modulation (DPCM). The current sample is predicted based on some set of previous data samples and the difference between the actual sample and the predicted one is quantized and transmitted over the data link. This reduces the data that needs to be transmitted over the link. The received bit stream is sent through a decoder to reconstruct the quantized error values, which are then added to the predicted signal sample to generate the reconstructed signal.

The first sub-section discusses adaptive filters and their application; the second sub-section describes application of an adaptive filter as a predictor. After that we'll discuss the type of adaptive filter chosen for the current application, its specifications and rationale for its use. The third sub-section discusses the adaptive quantizer, which will be followed by a sub-section on the type of quantizer used, its specification and the reason for its use.

4.1 Adaptive Filters [7]

An adaptive filter, as the name suggests, has the ability to satisfactorily adapt to an unknown and time varying environment according to some set performance criteria without any intervention from the user. The reason for the use of an adaptive filter would be clear if we compare its characteristics with that of the normal frequency selective digital filters. Frequency selective digital filters have fixed filter coefficients that are chosen to provide a desired frequency response to alter the input signal spectrum selectively. These filters are linear and time invariant. Their coefficients are chosen during the design phase and held constant during operation of the filter. However, there are situations where we may not have sufficient information to design a digital filter. Moreover, the design criteria may keep varying during the

operation of the filter. If the filter coefficients were fixed we would not be able to get the desired response. To overcome these limitations adaptive filters are used. The key feature of adaptive filters is their inherent ability to modify their response to improve performance during the operation without any user intervention.

4.1.1 Features of Adaptive Filters

Adaptive filter applications usually have a set of input signal samples and a desired response that may or may not be available to the adaptive filter. These signals collectively constitute the signal operating environment (SOE) of the adaptive filter. Every adaptive filter consists of three main modules: the filtering structure, the criterion of performance (COP) and the adaptation algorithm. The filtering structure is the filter, which filters the input signal samples. The filtering structure could be linear or non-linear, as fixed by the designer and its parameters adjusted by the adaptive algorithm. The output of the adaptive filter and the desired response, when available, are compared and processed by the COP to assess the filtering structure's performance with respect to the requirements of the application. The choice of the criterion is a compromise between what is acceptable to the application and what can possibly be used mathematically to derive an adaptive algorithm. Usually the COP uses some specific error reduction mechanism. The adaptive algorithm uses the value of the COP, the input signal and the desired response to modify the filter parameters.

The design of adaptive filters requires some knowledge of the SOE and an understanding of the application. This information is valuable in deciding the filtering structure and the COP. Unreliable a priori information and/or incorrect assumptions about the SOE can result in a poor design. So it is important to get access to reliable information about the SOE. If the SOE remains constant the adaptive filter finds the best parameters and then stops the adjustment. The filter

starts with an acquisition mode and then moves to the tracking mode. So depending on the SOE information available we determine the filter structure and the COP. This filter would have a tracking mode if the SOE were variable; otherwise it would only have the acquisition mode. Figure 4.1 below depicts the filtering structure.
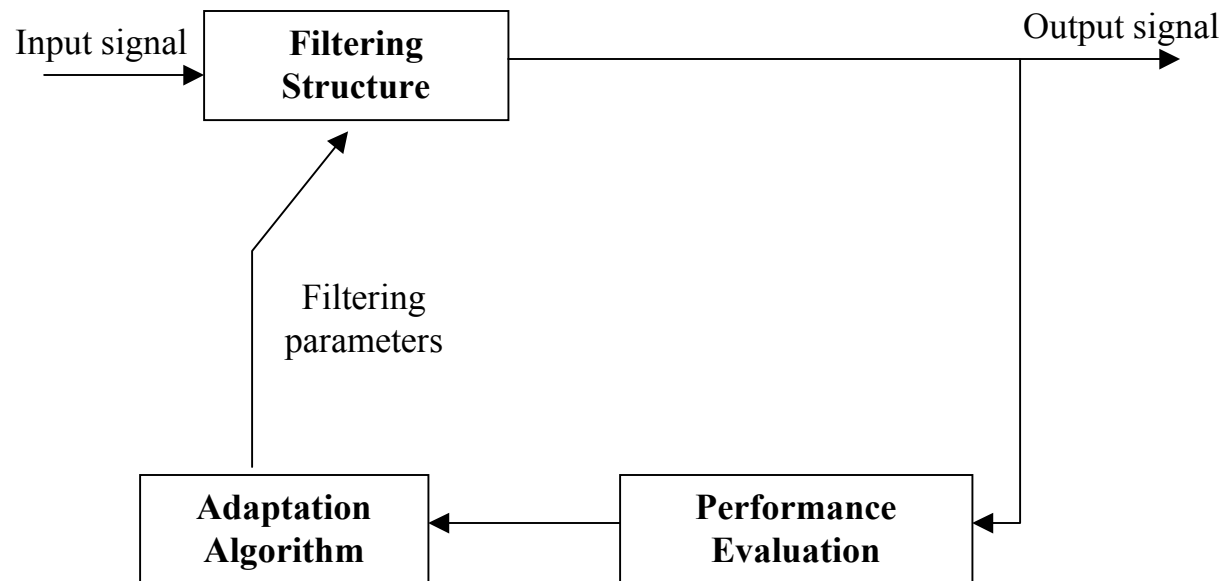

Figure 4.1 Basic Filtering structure

4.1.2 Applications of Adaptive Filters

There are wide ranges of applications for adaptive filters because of their self-adjusting property. A few of these applications are

1. Echo cancellation in communication systems

2. Equalization of data communication channels

3. Linear predictive coding

4. Noise cancellation

We will discuss the application of adaptive filters to Linear Predictive Coding in detail. This will help us in developing an adaptive predictor with relative ease. An efficient way of storage and transmission of analog signals using digital systems requires minimization of the number of bits necessary to represent the signal while maintaining the signal quality. The conversion of analog to digital involves two steps: sampling and quantization. Sampling converts the analog signal to a discrete time signal and quantization discretizes the amplitude. A code word is assigned to each representation level of the quantizer. One important property of quantization is used to develop the idea of linear predictive coding (LPC). For a fixed number of bits, decreasing the dynamic range of the signal reduces the required quantization step and hence the average quantization error. Alternatively, for a fixed quantization step (i.e. fixed quantization error) the dynamic range reduces the number of bits needed. If the signal samples are highly correlated, the variance of the difference between the adjacent samples is smaller than the variance of the original signal. This would mean a much lower quantization error or fewer bits. This differential quantization concept is exploited by the LPC scheme. LPC predicts the current input sample and takes the difference of this estimate from the actual current sample. This error is then quantized. The difference between the error and the quantized error is added to the estimated signal sample to generate the new input signal, which is then sent through the predictor. The predictor adaptively calculates the next estimate. This process goes on till the entire signal is coded and sent. The decoder does the reverse operation of reconstruction. Figure 4.2 and 4.3 illustrates the block diagram of the transmitter and the receiver. Using this knowledge we can analyze the prediction scheme developed in this thesis.
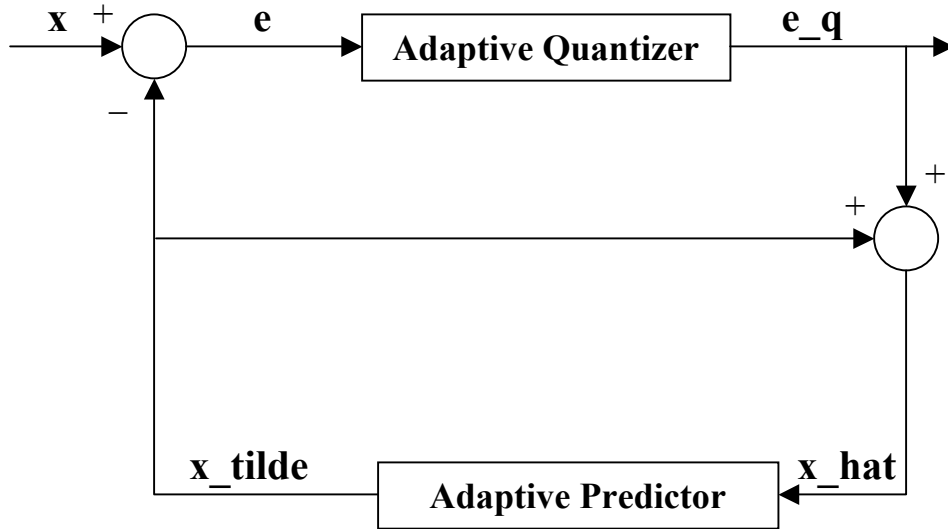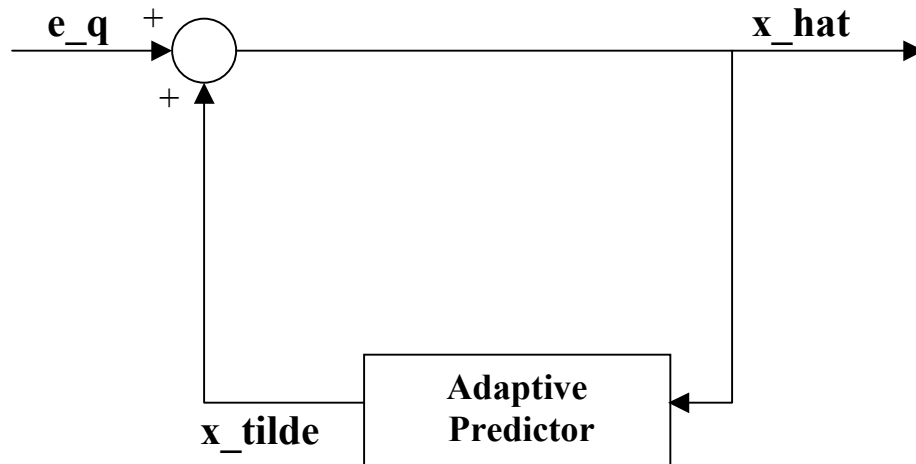
Figure 4.2 Model of the transmitter

Figure 4.3 Model of the receiver

18

4.1.3 Adaptation Algorithm

The key component of an adaptive filter is the adaptation algorithm, which is the method to determine the filter coefficients from the available data. The dependence of the filter coefficients on the input signal makes this filter non-linear. There are two different types of adaptation algorithms: a priori and a posteriori, which is based on the difference in coefficient updating methods. When the desired response is estimated using the previous coefficient matrix then it is called a priori. When the estimate is derived using the current coefficient matrix it is called a posteriori. We have used the a priori method for desired response prediction because it is more direct and easier to implement.

The adaptation algorithms can also be classified based on the adaptation method used. The most common algorithms are listed below

1. Steepest Descent (SD)

2. Least-Mean-Square (LMS)/Normalized Least-Mean-Square (NLMS)

3. Recursive Least-Squares (RLS)

NLMS is a slight variation of the LMS which allows easy choice of weighing factor in updating the predictor coefficients. We use NLMS algorithm for our prediction because NLMS doesn't require the autocorrelation matrix estimates unlike the SD and RLS. Moreover, NLMS is simple to implement and it is very robust to perturbations.

4.2 NLMS Algorithm

NLMS is widely used in practice due to its simplicity, computational efficiency and good performance under a variety of operating conditions. NLMS algorithm facilitates an easy choice of step-size increment parameter unlike the LMS algorithm. So NLMS algorithm is used in the

Adaptive Predictor. The design and initialization parameters along with the computation method are discussed below.

Design parameters:

x(n) : Input data vector at time n

y(n) : Desired response at time n

c(n) : Filter(Predictor) coefficient vector at time n

M : Number of coefficients

$\hat{y}(n)$: predicted response at time n

e(n) : prediction error at time n

μ : Step size parameter

Initialization:

We could initialize the filter coefficients to zero and start predicting the sample points based on the above initialization. In our simulation, we compute the filter coefficients based on Least Squares Principle [8].

Computation:

For $n =0,1,2…$ compute

$\hat{y}(n) = \mathbf{c}^{H}(n-1)\mathbf{x}(n)$ where superscript H denotes the Hermitian.

$e(n) = y(n) - \hat{y}(n)$

$\mathbf{c}(n) = \mathbf{c}(n-1) + \dfrac{\mu \mathbf{x}(n)e^{*}(n)}{E_{\mu}(n)}$ where the superscript * denotes the conjugate.

$E_{\mu}(n) = \| \mathbf{x}(n) \|^{2}$

and $0<\mu<1$

For the simulations the following predictors were used. The step sizes for different predictor (described below) are given here. These have been derived by experimentation. Predictors for unmodulated and linear frequency modulated signals are initialized differently. It is assumed that the receiver's front end processing detects the type of modulation used and provides us with this information.

Initialization parameters (for unmodulated signal):

μ 1 = 1e-6

μ 2 = 1e-4

μ 3 = 1e-3

Initialization parameters (for linear frequency modulated signal):

μ 1 = 1e-2

μ 2 = 1e-6

μ 3 = 1e-5

4.3 2-D Prediction Scheme

All the sample values are represented as points in the following figures. Sample values of a pulse occupy a single row, the bottom most row representing the first pulse in the input signal and the top most row representing the last pulse in the input signal.

The prediction scheme employed here consists of three stages of prediction. They are one-dimensional horizontal prediction (1DHP), one-dimensional vertical prediction (1DVP) and two-dimensional linear prediction (2DLP). The above schemes are schematically shown and described below.

1DHP:

The 1DHP scheme is used only for the first pulse of the input signal. Each sample point is predicted based on the previous sample points of the first pulse only. The prediction scheme is illustrated in Figure 4.4. The next sample value is predicted based on the previous 5 sample points, which is decided by the size of the predictor (where $l_1=5$ is the size of the predictor). Based on the prediction error between the predicted value and the actual value the predictor coefficients are updated. This process continues until the end of the first row.
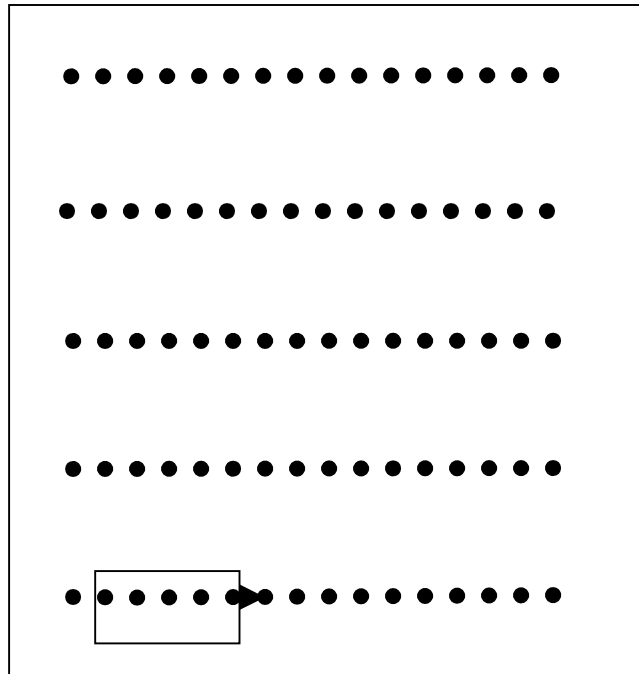
Figure 4.4 1DHP scheme

1DVP:

The 1DVP scheme predicts the sample point x (where x indexes to a column in the matrix) in pulse n (where n indexes a row in the matrix) from sample points x-$fix(l_1/2)$ to x+$fix(l_1/2)$ in pulse n-1 (fix is a MATLAB function which rounds the real number to it nearest

lower integer) only. It is computationally difficult to take identical sample points from pulses *1,2...n* for prediction because the size of the predictor keeps varying for every row predicted. Hence we predict the current pulse sample point with the sample points from the previous pulse only. This scheme is used to predict samples through l_2 rows after which 2DLP scheme would be used for prediction. In our algorithm, the block size/number of samples for 1DVP prediction in the above two schemes is chosen as 1 for unmodulated and 5 for linear frequency modulated case. This choice yielded very good results during the simulations. This scheme is shown in Figure 4.5.
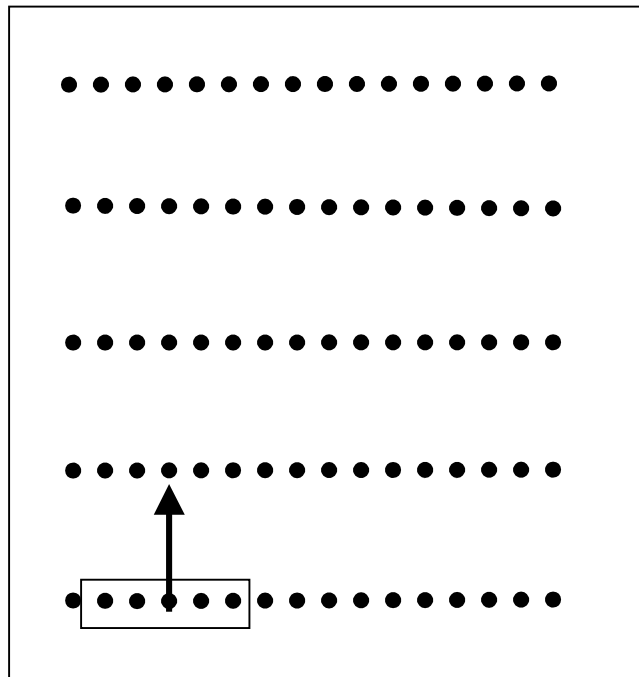
Figure 4.5 1DVP scheme

2DLP:

2DLP is a two-dimensional prediction scheme, where sample points are predicted using a block of signal points from the immediate earlier pulses. Here l_1 is the length of the block

23

predictor along the horizontal direction and l_2 refers to the length of the predictor in the vertical direction, that is the size of the block predictor is (l_1,l_2) matrix. To predict the sample point x in pulse n we use the sample points x-fix($l_1/2$) to x+fix($l_1/2$) in pulse n-1 , n-2..n-l_2. In our simulations l_2 is chosen to be 3. This choice proved to be good for both unmodulated and linear frequency modulated signals. This scheme is illustrated in Figure 4.6.
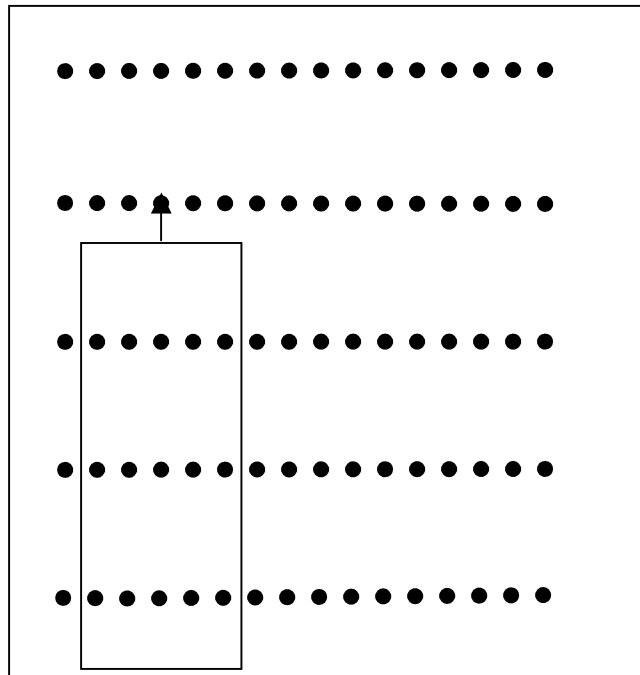

Figure 4.6 2DLP scheme

There are sample points on the left and right sides of the matrix that have not been predicted using any of the above schemes. So we need to specify a suitable scheme for those points. 1DVP would be the ideal scheme to use here but this scheme would result in variable size predictors for each and every point. This is very cumbersome to implement. So 1DHP scheme was chosen. The first few points in the rows (left side of the matrix) would be the rising edge of the pulse and the last few points in the rows (right side of the matrix) would be the falling edge

of the pulse. The sampled values of the rising edge and the falling edge of each pulse would be very similar so we could use the 1DHP scheme to a give a reasonable prediction because it uses the falling edge of the previous pulse to predict the rising edge of the current pulse. The over all compression scheme is illustrated in Figure 4.7.
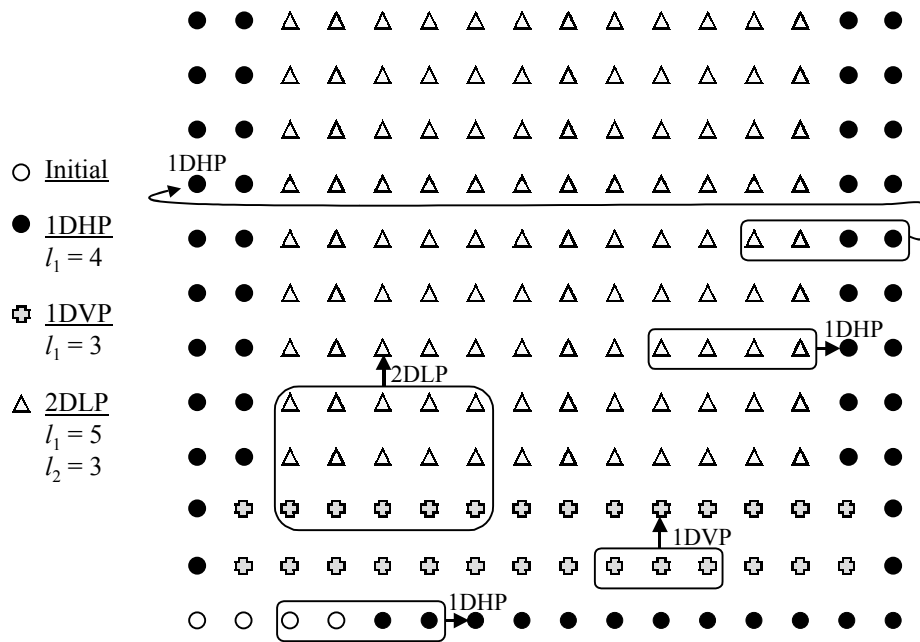
Initial

1DHP
$l_1 = 4$

1DVP
$l_1 = 3$

2DLP
$l_1 = 5$
$l_2 = 3$

1DHP 2DLP 1DHP 1DVP 1DHP

Figure 4.7 Compression Scheme

4.4 Adaptive Quantizer [9]

There are two basic approaches that can be used in quantization: adaptive and non-adaptive. We choose adaptive quantization (AQ) to provide robustness over a variety of signal types and conditions. AQ are robust to two types of mismatch :

1.   When the assumed distribution (used to design the quantizer) is identical to the actual distribution but the variance of the input is different from the assumed variance

2. When the actual distribution is different from the assumed distribution

An adaptive quantizer deals with the mismatch problems by changing the quantizer parameters based on the difference between the observed input statistics and the assumed statistics. There are two ways of performing AQ: forward adaptive approach and backward adaptive approach. We use the backward adaptive approach because then quantizer side information need not be transmitted to the receiver along with the compressed signal.

4.5 Quantization scheme

We use the Jayant quantizer [9,10] (JQ) as an AQ. The JQ adjusts the quantizer step size after each sample and the adjustment is based on observing a single output of the quantizer. If the input falls in the outer levels, the step size is expanded and if the input falls in the inner quantization levels, the step size is reduced. The expansions and contractions should be done in such a way that once the quantizer is matched to the input (assuming stationary input), the product of expansions and contractions must be unity. Below, the quatizer parameters are specified.

Initialization parameters:

Step size for real value of input signal = 0.3

Step size for imaginary value of output signal = 0.1

Multiplier constant for real part (Mr) of the signal = 1

Multiplier constant for imaginary part (Mi) of the signal = 1

The loop parameters vary for modulated and unmodulated signals. The front end system at the receiver specifies the type of signal being analyzed. The loop parameters are chosen based on that.

Loop parameters (for unmodulated signal):

Representation Level 1 Mr = 0.5

Representation Level 2 Mr = 0.9

Representation Level 3 Mr = 2.0

Representation Level 4 Mr = 3.5

Representation Level 1 Mi = 0.1

Representation Level 2 Mi = 0.5

Representation Level 3 Mi = 0.8

Representation Level 4 Mi = 1.0

Loop parameters (for linear frequency modulated signal):

Representation Level 1 Mr = 0.7

Representation Level 2 Mr = 0.9

Representation Level 3 Mr = 2.5

Representation Level 4 Mr = 3.6

Representation Level 1 Mi = 0.1

Representation Level 2 Mi = 0.5

Representation Level 3 Mi = 0.8

Representation Level 4 Mi = 1.0

These initialization and loop parameter values have been obtained by experimenting with different pulse types.

Compression ratios (CRs) of around 2.5 and 4 are achievable using the above JQ (3-bit and 2-bit quantizers). Better CRs can be obtained by decreasing the number of bits needed to represent the sample values. CRs of around 8 was observed too but for certain signal types this compression loses significant information required for further processing. So we restrict our analysis to a CR of 4.

CHAPTER 5. Simulation and Results

We have described the compression method used to compress the radar signal. Now we will assess its performance via simulation. The compressed signal along with the side information is transmitted via the bandwidth limited data link to the common platform, which already has acquired the signal emitted by the same emitter. The common platform decompresses the signal. Now we use the cross-ambiguity function to estimate TDOA/FDOA between the two signals: one that is received after compression and one that is collected at this receiver. Since these two signals were emitted by the same transmitter, assuming both the receivers were synchronized when they started acquiring the signal, one would be a delayed and Doppler shifted version of the other. The amount of delay and Doppler shift can be estimated by processing the cross-ambiguity surface as described in Chapter 2. The cross-ambiguity surface will have a peak at the delayed time and Doppler shifted frequency. Once we have the delay and Doppler we use it together with delay/Doppler estimated between other receiver pairs to locate the emitter. To efficiently compute the ambiguity function we use a processing algorithm proposed by Stein [1]. We do not discuss the algorithm here but mention it for completeness. Using all the information that is available to us we can now locate the emitter to a good degree of accuracy. The accuracy of location depends on the accuracy of the TDOA/FDOA estimates. Thus, we assess the performance of the compression algorithm by comparing the TDOA/FDOA estimates achieved with and without compression. Signal parameters for all simulations, except the one with real signal data, were: Pulse width=6.3e-6, PRI=8.4e-6, frequency deviation=2.1e-6, center frequency= 1e5 and sampling frequency=3.8e6. The compression ratio for all simulation cases were 4:1.
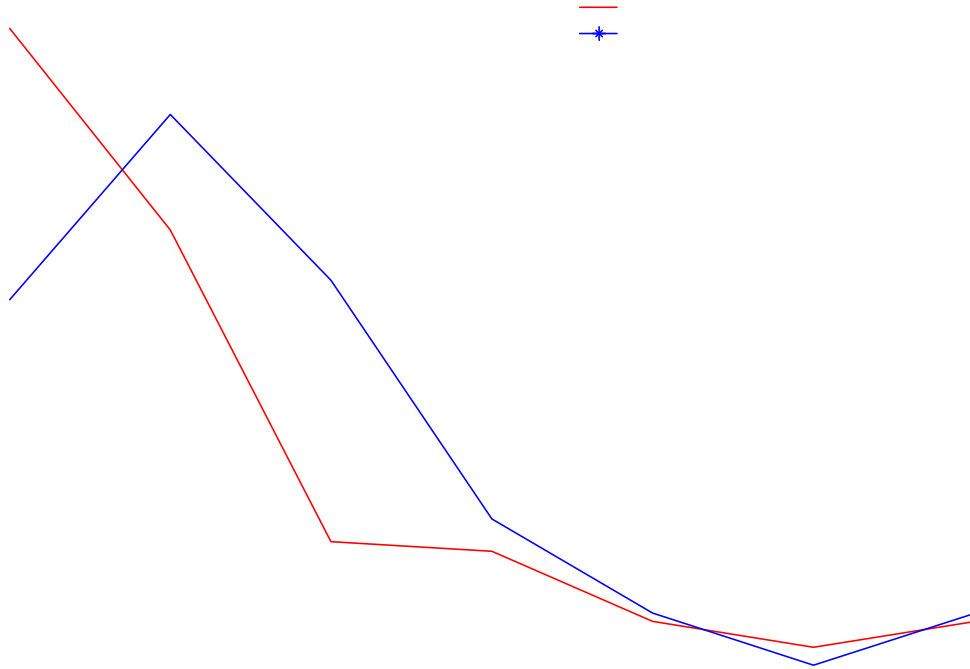
Figure 5.1 TDOA plot for a simulated noisy pulse train

Figure 5.1 shows the RMS delay error (in nanoseconds) versus the input SNR (in dB) for two noisy signals. The two signals are at different SNRs. Input SNR refers to the signal-to-noise ratio at the compressing receiver. The signal-to-noise ratio at the common platform is kept constant at 20 dB. It could be varied if required. The plot shows the RMS delay error without compression and with compression. Except at low SNRs the accuracy of compression is comparable to that without compression. This curve could be made smoother by running more Monte Carlo runs. The present curve was obtained for 5 Monte Carlo runs because of increased computation time.
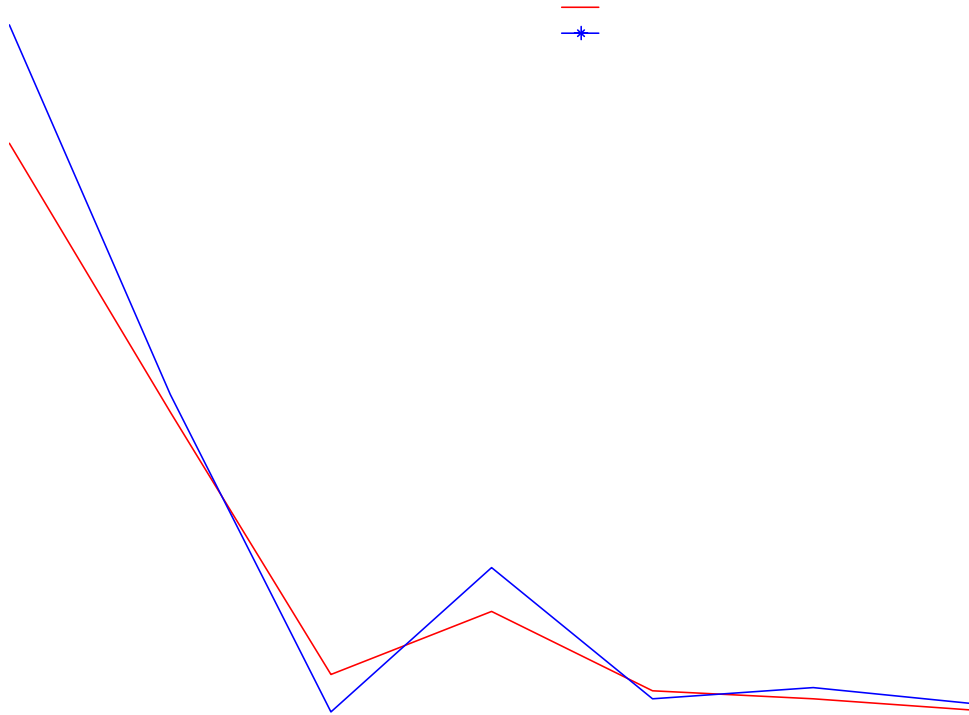
Figure 5.2 FDOA plot for a simulated noisy pulse train

Figure 5.2 shows the RMS Doppler error (in Hz) versus the input SNR (in dB) for two noisy signals. The signal-to-noise ratio at the other receiver is 20dB. The plot shows the RMS Doppler error without compression and with compression. This curve could be made smoother by running more Monte Carlo runs. The compressed FDOA plot seems to be following the uncompressed FDOA plot very closely.
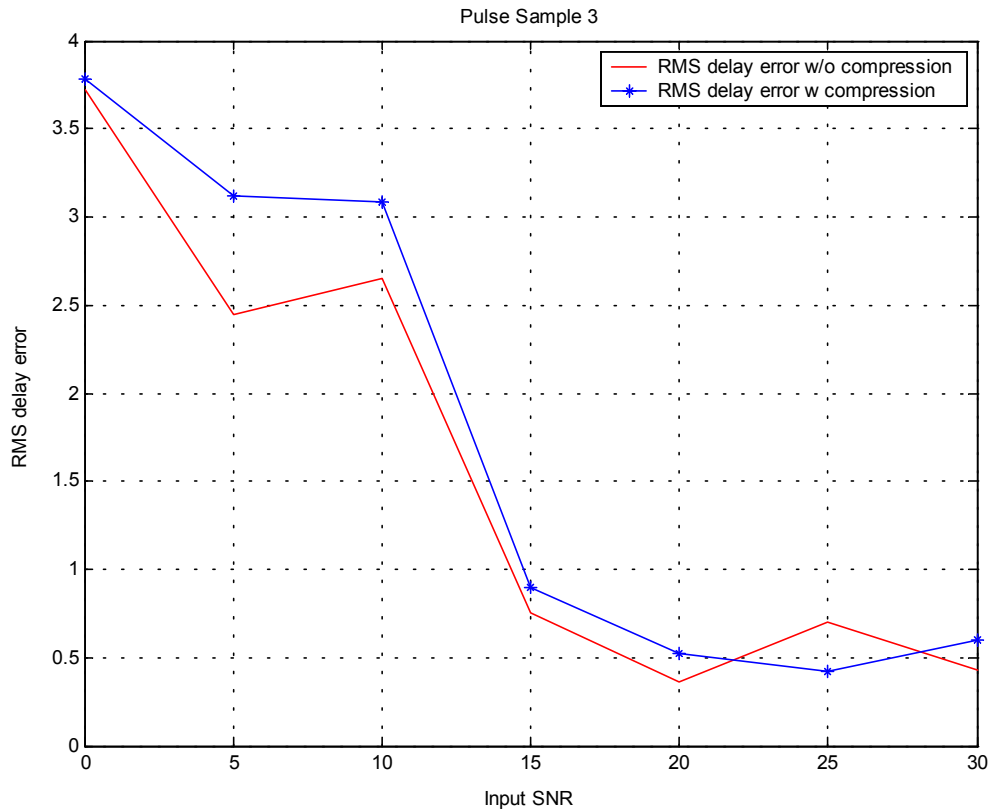
Figure 5.3 TDOA plot for a simulated noisy pulse train with perturbations

Figure 5.3 shows the RMS delay error (in nanoseconds) versus the input SNR (in dB) for two noisy signals each of them subject to perturbations in the form of bad pulses. The signal-to-noise ratio at the other receiver is 20dB. The plot shows the RMS delay error without compression and with compression. At high input SNRs, the accuracy with compression is comparable to that without compression. This curve could be made smoother by running more Monte Carlo runs (the present curve was obtained for 5 runs). On comparing Figures 5.1 and 5.3, it can be observed that adaptive prediction is capable of handling perturbations without significant loss in the TDOA accuracy.
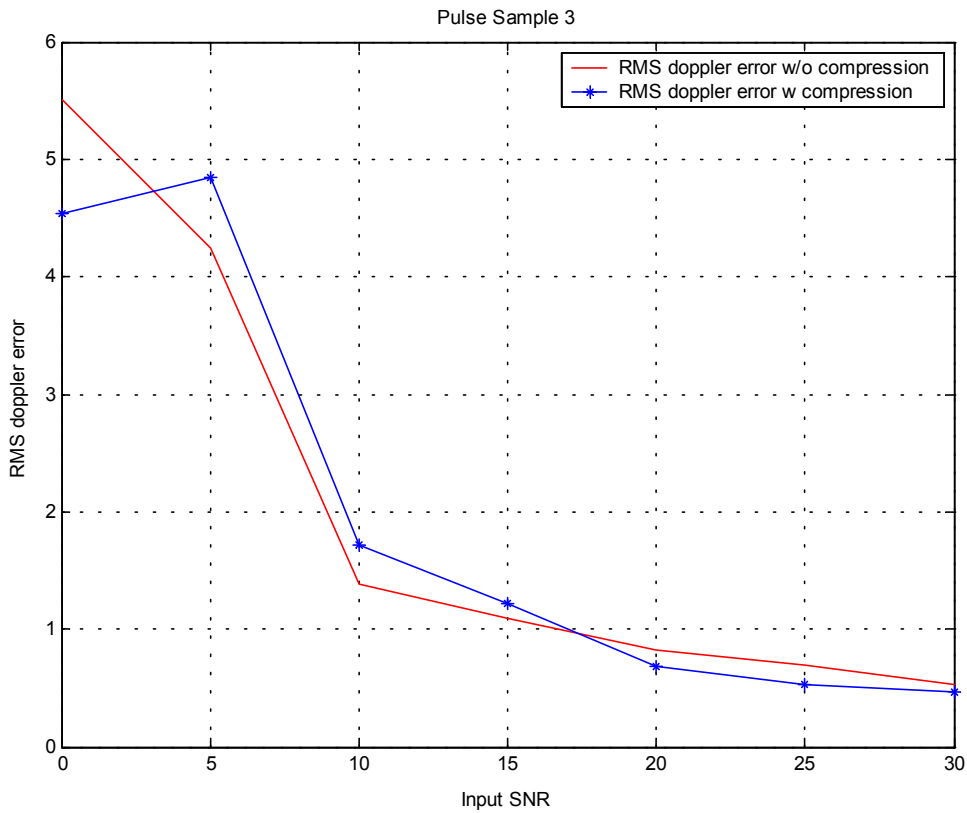
Figure 5.4 FDOA plot with a noisy simulated pulse train with perturbations

Figure 5.4 shows the RMS Doppler error (in Hz) versus the input SNR (in dB) for two noisy signals, each of them subject to perturbations. The signal-to-noise ratio at the other receiver is 20dB. The plot shows the RMS Doppler error without compression and with compression. At high input SNRs, the accuracy with compression is comparable to that without compression. This curve could be made smoother by running more Monte Carlo runs. On comparing Figures 5.2 and 5.4, it can be observed that adaptive prediction is capable of handling pertubations without significant loss in the FDOA accuracy.
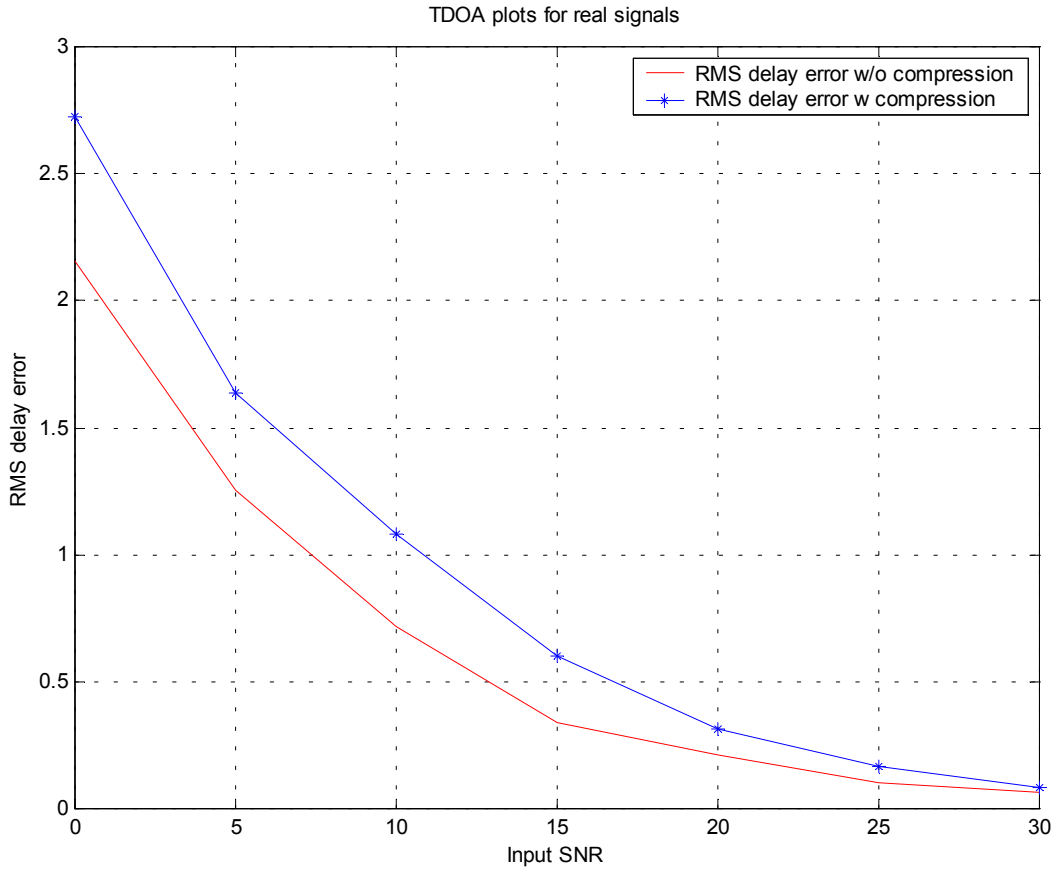
Figure 5.5 TDOA plot for real signal collected from the aircraft

Figure 5.5 shows the RMS delay error (in nanoseconds) versus the input SNR (in dB) for two real (real here refers to signals actually collected by receivers mounted on aircraft) signals collected from aircrafts. One of the signal was subject to delay and Doppler shifts apart from the one already embedded in it. Then for various noise processes the two signals were correlated for various SNR levels. The plot shows the RMS delay error without compression and with compression. The compressed signal TDOA plot seems to very closely follow the not compressed signal TDOA plot. This shows the applicability of the adaptive scheme to real signals.
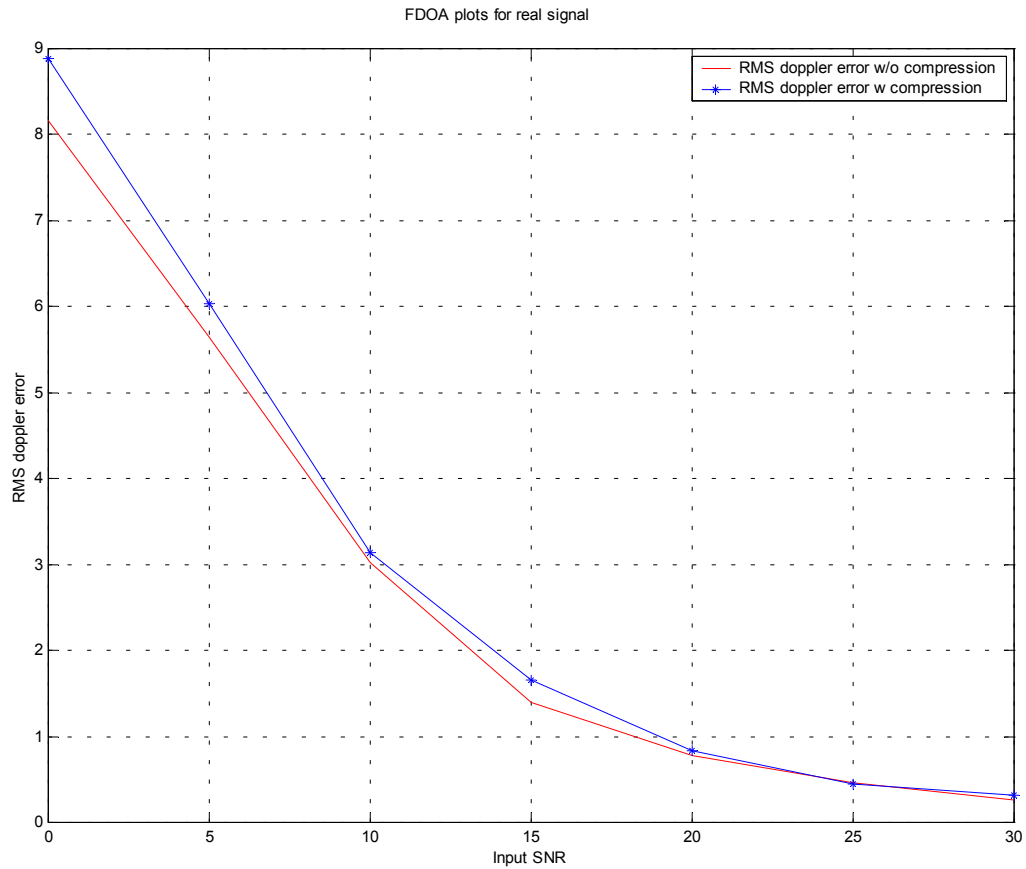
Figure 5.6 FDOA plot for a real signal collected from the aircraft

Figure 5.6 shows the RMS Doppler error (in Hz) versus the input SNR (in dB) for two real signals collected from aircrafts. The plot shows the RMS Doppler error without compression and with compression. The compressed signal FDOA plot seems to very closely follow the not compressed signal FDOA plot. This shows the applicability of the adaptive scheme to real signals.

CHAPTER 6. Conclusions and Discussion

In this thesis, 2-D adaptive prediction and adaptive quantization techniques were used to compress radar signals. Both the methods put together constitute a very powerful tool for compression. These methods give a reliable compression ratio of 4:1, which can be extended to 8:1 at the cost of losing a little accuracy in locating the emitter. Though this is not a great figure in the compression area, it has significant advantage over other methods with high compression ratios in that it is robust to perturbations in the signal train such as propagation effects and inclusion of pulses from other emitters and its compression ratio exceeds what the sponsor was hoping for a minimum. Receiver acquisition errors, filter errors, bad pulses over a small duration of time have negligible effect on this method.
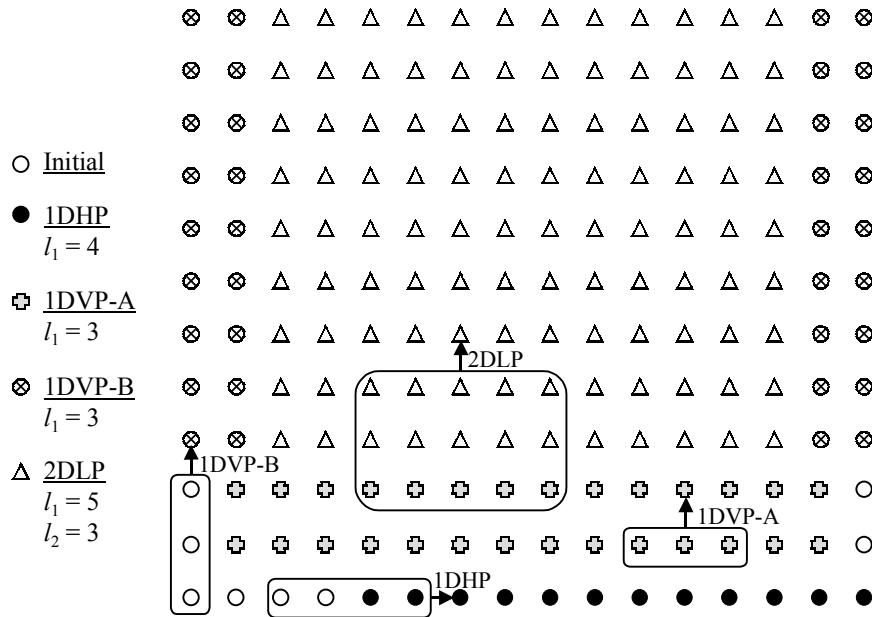

Figure 6.1 Compression Scheme II

This scheme could be augmented using a slight variant illustrated in Figure 6.1. Here we have one more version of 1DVP called 1DVP-B, which uses the sample points on the rising edge of the previous pulse to predict the sample points on the rising edge of the current pulse. This would be more appropriate than the method we discussed.

Vector Quantization could be used instead of scalar quantization to achieve higher compression ratios. Since in vector quantization fractional number of bits could be used to represent a set of signal values, compression ratios larger than eight can be achieved.

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