PEOPLE'S AND DEMOCRATIC REPUBLIC OF ALGERIA

MINISTRY OF HIGHER EDUCATION AND SCIENTIFIC RESEARCH

UNIVERSITY YAHIA FARES, MEDEA



Faculty of Technology

Dissertation Submitted in Partial Fulfilment

of the Requirements for the Degree of Master

Sector: Department of Electrical Engineering

Specialty: telecommunication systems

Adaptive Filters Applied for the Detection of Radar Signals

Submitted by:

Mr. AHZI Haithem
Mr. BENKESSIRAT Othmane

Under the Supervision of:

Dr. LAIDI Kamel

Promotion 2020

DEDICATION

I dedicate this work to my dear parents who sacrificed their lives for my success and their encouragement throughout my school career, to my sisters, my brother to the whole BENKESSIRAT family, without forgetting all my teachers who contributed to my training since primary school to date, to my friends and brothers also to all those who helped me to realize this dissertation. Finally, to all those I love, and who love me.

BENKESSIRAT OTHMANE

DEDICATION

I dedicate this work to my dear parents who sacrificed their lives for my success and their encouragement throughout my school career, to my sisters, my brothers to the whole AHZI family, without forgetting all my teachers who contributed to my training since primary school to date, to my friends and brothers also to all those who helped me to realize this dissertation. Finally, to all those I love, and who love me.

AHZI HAITHEM

ملخص

يعمل الرادار على إرسال وإعادة استقبال الإشارة. كما يستعمل الرادار مجال كبير للترددات،لذلك عليه استعمال مجال واسع لرصدها،لهذا نجد أن كمية التشويش عالية على مستوى الإشارات القادمة وفي كثير من الأحيان لا يمكن رصد الإشارة تقريبا لذلك يجب علينا تصفية إشارات الرادار، ولكن في حال ما لم نكن نعرف تردد الرادار أو كان لدينا تردد متغير بدلالة الزمن فلن نستطيع القيام بالتصفية من بين الحلول المقترحة هي التصفية التكيفية.

الهدف من هذا العمل هو كشف إشارات الرادار و تصفيتها عن طريق المرشحات التكيفية ،و العمل على تحسين نسبة الإشارة بالنسبة لكمية الضوضاء،كما سنقوم باستعمال خوارزميتين للمرشحات التكيفية LMS و RLS

ABSTRACT

The radar transmits a signal and detects the received echo. Due that the radar signal has a wide band of frequencies, a wide bandwidth is needed in order to detect all possible radar signals. However, this would result in an increase in the power of noise. Consequently, filtering the signal to reduce the noise is mandatory. Unfortunately in some cases we don't know the frequency of the received signal or we have a variable frequency. For this reason, an adaptive filters is required to adapts its band-pass to the received radar signal.

In this work our aim is to extract or detect the radar signal embedded in the noise using an adaptive filtering, and ensuring a high SNR that through which we can know how well the adaptive filter reduces the noise, we will use two adaptive algorithms called LMS and RLS.

RESUME

Le radar transmet un signal et reçoit son écho. Les radars d'aujourd'hui ont de larges bandes de fréquences, donc nous avons besoin de grande bande passante pour détecter tous signaux radar possibles. Une grande bande passante a de mal effet, parce que la puissance de bruit sera très grande, par conséquent un filtrage du signal est obligatoire. Malheureusement, dans le cas des signaux à fréquences variables ou dans le cas ou nous ne connaissons pas la fréquence du signal on ne peut pas faire un filtrage classique. La solution de ce problème est d'applique le filtrage adaptatif.

Le but de ce travail est d'appliquer un filtrage adaptatif (deux algorithmes LMS et RLS) pour détecter ou extraire un signal radar noyé dans un bruit, tout en assurant un bon rapport signal sur bruit (SNR).

CONTENTS

DEDICATION I
ABSTRACT III
LIST OF FIGURES VII
LIST OF TABLES IX
ABBREVIATIONS AND ACRONYM X
GENERAL INTRODUCTION 1

CHAPTER I : RADAR SYSTEM

I.1 INTRODUCTION 4
I.2 HISTORY 4
I.3 DEFINITION 6
I.4 TECHNOLOGY RADAR 7
I.4.1 MONOSTATIC VERSUS BISTATIC 7
I.4.2 BISTATIC AND MULTISTATIC RADAR 8
I.5 THE RADAR EQUATION [6] 8
I.6 RADARS CLASSIFICATION 13
I.6.1 IMAGING AND NON-IMAGING RADAR 13
I.6.2 PRIMARY RADAR 14
I.6.3 SECONDARY RADAR 14
I.6.4 CONTINUOUS WAVE VERSUS PULSED 14
I.6.4.1 CONTINUOUS WAVE WAVEFORM 14
I.6.4.2 PULSED WAVEFORM [6] 15
I.6.5 NONCOHERENT VERSUS COHERENT 18
I.6.6 THE DOPPLER SHIFT [6] 19
I.6.7 UNAMBIGUOUS DOPPLER SHIFT MEASUREMENT 20
I.7 RADAR APPLICATIONS 21
I.8 RADAR SIGNALS 21
I.8.1 PULSES WITH A FIXED FREQUENCY [5] 21
I.8.2 LINEAR CHIRP PULSES [5] 22
I.8.3 BINARY PHASED CODED PULSES [5] 23
I.8.4 RADAR SIGNALS EXPLICATION [5] 24
I.9 CONCLUSION 25

CHAPTER II : ADAPTIVE FILTERS

II.1 INTRODUCTION 27
II.2 ADAPTIVE SIGNAL PROCESSING 28
II.2.1 ADAPTIVE FILTER STRUCTURE 28
II.2.2 APPLICATION 28
II.2.3 ALGORITHM 29
II.2.4 TYPE OF APPLICATION 29
II.3 SIGNAL REPRESENTATION 30
II.3.1 DETERMINISTIC SIGNALS [1] 30
II.3.2 RANDOM SIGNALS [1] 31
II.4 THE CORRELATION MATRIX [1] 35
II.5 DIGITAL FILTERING[2] 37
II.5.1 SIGNAL FREQUENCY (SPECTRUM) ANALYSIS 38
II.6 FIR AND IIR[3] 39
II.6.1 FIR FILTERS 39
II.6.1.1 TRANSFER FUNCTION 40
II.6.1.2 KEY ATTRIBUTES 40
II.6.2 IIR FILTERS 40
II.6.2.1 KEY ATTRIBUTES 41
II.6.3 REALIZATION OF DIGITAL FILTERS [4] 41
II.6.3.1 DIRECT-FORM I REALIZATION [4] 42
II.6.3.2 DIRECT-FORM II REALIZATION [4] 43
II.6.3. 3 CASCADE (SERIES) REALIZATION 43
II.6.3.4 PARALLEL REALIZATION 44
II.7 WIENER FILTER [1] 45
II.8 NEWTON ALGORITHM 48
II.9 ADAPTIVE FILTERS 48
II.9.1 LMS ALGORITHM (LEAST MEAN SQUARES) 48
II.9.1.1 INTRODUCTION 48
II.9.1.2 THE LMS ALGORITHM 49
II.9.2 RLS ALGORITHM 51
II.9.2.1 INTRODUCTION 51
II.9.2.2 THE RECURSIVE LEAST-SQUARES ALGORITHM 51
II.10 CONCLUSION 54

CHAPTER III : SIMULATION

III.1 INTRODUCTION 56
III.2 SIGNAL DATA 56
III.2.1 RADAR SIGNALS 56
III.3 RADAR SIGNALS WITH FIXED FREQUENCY COHERENT PULSED RF 57
III.4 RADAR SIGNALS WITH VARYING FREQUENCY COHERENT PULSED RF 58
III.5 RADAR SIGNALS WITH PHASE CODED PULSES 60
III.6 CALCULATION OF SNR 61
III.6.1 SNR OF LMS 61
III.6.1.1 SNR FOR VARIABLE FREQUENCY 62
III.6.1.2 SNR FOR FIXED FREQUENCY PULSE 63
III.6.2 SNR OF RLS 64
III.6.2.1 SNR FOR FIXED FREQUENCY PULSE 64
III.6.2.2 SNR FOR VARIABLE FREQUENCY PULSE 65
III.7 TIME DOMAIN SIMULATIONS 66
III.7.1 FIXED FREQUENCY 67
III.7.1.1 FIXED FREQUENCY USING LMS 67
III.7.1.2 FIXED FREQUENCY USING RLS 70
III.7.2 CHIRPED PULSES 73
III.7.2.1 CHIRPED PULSES USING LMS 73
III.7.2.2 CHIRPED PULSES USING RLS 76
III.8 BINARY PHASE CODED 79
III.9 CONCLUSION 83
GENERAL CONCLUSION 84
REFERENCES 85

LIST OF FIGURES

Figure I.1 Major elements of the radar transmission/reception process 6
Figure I.2 components of a radar 7
Figure 1.3 Power density range R from the radar transmitter for an isotropic antenna 9
Figure I.4 Power density at range R given transmit antenna gain G_t 10
Figure I.5 Power density Q_r back at the radar receive antenna 11
Figure I.6 Radar Classification 13
Figure I.7 Pulsed radar waveform 15
Figure I.8 Pulsed radar waveform showing ADC clock pulses 16
Figure I.9 Pulsed radar range ambiguity 16
Figure I.10 Coherent system local oscillator, transmit, and received signals 19
Figure I.11 A sinusoid with a 180 degrees phase shift ..... .23
Figure I.12 Barker 7 code. A difference between +1 and -1 (or -1 and +1) is phase shift of180 degrees 23
Figure II.1 General adaptive filter configuration 27
Figure II.2 system identification 29
Figure 1I.3 channel equalization 30
Figure II.4 signal enhancement 30
Figure II.5 digital filtering. 37
Figure II.6 noisy signal before and after filtering 38
Figure II.7 Audio signals and their spectrums. 38
Figure II.8 FIR filter structure 39
Figure II.9 IIR filter structure 40
Figure II.10(A) Direct-form I realization.(B) Direct-form I realization with M = 2. 42
Figure II.11 (A) Direct-form II realization. (B) Direct-form II realization with M = 2. 44
Figure II.12 Cascade realization 44
Figure II.13 a) Linear combiner;**b)** Adaptive FIR filter 45
Figure 1I.14 LMS adaptive FIR filter 50
Figure II.15 Adaptive FIR filter 53
Figure III.1 coherent pulsed RF signal 57
Figure III.2 radar signals with fixed frequency 58
Figure 1II.3 radar signal with variable frequency 59
Figure III.4 radar signal with low frequency 59
Figure III.5 phase coded pulse 60

LIST OF FIGURES

Figure III.6 simulation scheme 66

Figure III.7 radar signal with fixed frequency 67

Figure III.8 Additive white Gaussian noise picked by signal 68

Figure III.9 Radar signal with fixed frequency pulses merged with additive white Gaussian noise 68

Figure III.10 The radar signal with fixed frequency before and after the adaptive filter using LMS algorithm. 69

Figure III.11 Radar signal with fixed frequency 70

Figure III.12 Additive white Gaussian noise picked by signal 71

Figure III.13 Radar signal with fixed frequency pulses merged with additive white Gaussian noise 71

Figure III.14 The radar signal with fixed frequency before and after the adaptive filter using RLS algorithm 72

Figure 1II.15 Radar signal with variable frequency 73

Figure III.16 Additive white Gaussian noise picked by signal 74

Figure III.17 Radar signal with variable frequency pulses merged with additive white Gaussian noise 74

Figure III.18 The radar signal with variable frequency before and after the adaptive filter using LMS algorithm 75

Figure III.19 Radar signal with variable frequency 76

Figure III.20 Additive white Gaussian noise picked by signal 77

Figure III.21 Radar signal with variable frequency pulses merged with additive white Gaussian noise 77

Figure III.22 The radar signal with variable frequency before and after the adaptive filter using RLS algorithm 78

Figure III.23 phase coded pulse barker code 79

Figure III.24 Additive white Gaussian noise picked by signal 80

Figure III.25 Phase coded pulse and additive white Gaussian noise and the superposition between them 80

Figure III.26 The radar phase coded pulse before and after using the adaptive filter with LMS algorithm. 81

Figure III.27 The radar phase coded pulse before and after using the adaptive filter with RLS algorithm. 82

LIST OF TABLES

Table III.1 Signal parameters for a fixed pulsed radar signal. 57
Table III.2 Signal parameters for a chirped pulsed radar signal 58
Table III.3 Signal parameters for a phase coded pulsed radar signal. 60
Table III.4 SNR gain and convergence time for a variable frequency. 62
Table III.5 SNR gain and convergence time for a fixed frequency 63
Table III.6 SNR gain and convergence time for a fixed frequency. 65
Table III.7 SNR gain and convergence time for a variable frequency 65

ABBREVIATIONS AND ACRONYM

RADAR: Radio Detection And Ranging

LIDAR: Light Detection And Ranging ou « laser detection and ranging »

GPS: Global Positioning System

RCS : radar cross section

GSM : Global System for Mobile

CW: continuous wave

FM: frequency modulated

EM: Electromagnetic

PRI: pulse repetition interval

IPP: inter pulse period

PRF: Pulse Repetition Frequency

ADC: Analog & Digital Systems

LO: local oscillator

AWGN: Additive Gaussian White Noise

IIR: infinite impulse response

FIR: finite impulse response

MSE: Minimum square error

WSS: Wide sense stationary

FFT: Fast Fourier Transform

DSP: digital signal processing

LMS: least-mean-square

RLS: recursive least-squares

SNR : signal to noise ratio

RWR: radar warning receiver

GENERAL INTRODUCTION

The most important things in telecommunication are sending and receiving information with working on protecting them, the information can take forms and properties, one of the main technologies in telecommunication are radars. Radar is stands for Radio Detection and Ranging, it is a system that uses electromagnetic waves to detect objects and determine their range, altitude and speed. The main idea behind radars is to transmit electromagnetic wave pulses in predetermined directions. When these wave pulses come in contact with an object they are usually reflected and scattered in different directions. Hopefully some part of the transmitted wave pulses are reflected or scattered back to the radar system. The radar system tries to listen to these weak echoes and also tries to extract useful information out of them, in other words, radar send pulses or waveform and detect the echo to determine the information

Problem description that we have. when we use radar we must have a wide instantaneous bandwidth in order to detect different radar signals, this means that the noise power will be high in the wide open receiver. Therefore the signal-to-noise ratio (SNR) will be low. The radar signals will be hard to detect if a strong noise is present. It would be better to reduce the noise to be able to detect weak radar signals .A common way to reduce noise from signals is by introduce a filter that just covers the incident radar signal bandwidth The filter will then capture only the noise within the filter bandwidth and the SNR will increase, but the problem is that in some cases we can not know the frequency of the incident radar signal, example for that is radar warning receiver (RWR) is a device, usually used by aircrafts, with the purpose to detect when the aircraft is illuminated by enemy radar signals. It measures the pulse characteristics and may identify the threat by using pre-stored radar signature information. An RWR must also try to localize the threat so it can present it to the pilot from the correct direction. Airborne RWRs also has to work in real time, because they have to alert the pilot at once, so the pilot may decide to do something about the detected threat. The pilot may decide to maneuver away from the threat, and in another case we use varying frequency in order not to be tracked by enemies so the solution would be to introduce an adaptive filter, which adapts its band-pass to the incident radar signal, So the goal of this work is to apply adaptive filters to receive radar signals to improve the SNR, The adaptive filter changes its filter coefficients by an adaptive algorithm, the most common algorithms are LMS and RLS

GENERAL INTRODUCTION

In this thesis we will talk about radars, covering some details about them. We will also introduce the adaptive filtering technology, tackling the way it works and the necessary algorithms.

Finally, we will simulate many forms of radar signals in the simulation process under the objective of reducing thermal noise in received radar signals to be able to detect the weak radar signals. The technique of estimating signals corrupted by noise using adaptive filtering is called adaptive noise cancellation.

CHAPTER I

RADAR SYSTEM

I.1 INTRODUCTION

Radar is an electronic device for the detection and location of objects. It operates by transmitting a particular type of waveform, a pulse-modulated sine wave for example, and detects the nature of the echo signal. Radar is used to extend the capability of man's senses for observing his environment, especially the sense of vision. The value of radar lies not in being a substitute for the eye, but in doing what the eye cannot do .Radar cannot resolve detail as well as the eye, nor is it yet capable of recognizing the "colour" of objects to the degree of sophistication of which the eye is capable. However, radar can be designed to see through those conditions impervious to normal human vision, such as darkness, haze, fog, rain, and snow. In addition, radar has the advantage of being able to measure the distance or range to the object. This is probably its most important attribute.

I.2 HISTORY [7]

British physicist James Clerk Maxwell developed equations governing the behaviour of electromagnetic waves in 1864. Inherent in Maxwell's equations are the laws of radio-wave reflection, and these principles were first demonstrated in 1886 in experiments by the German physicist Heinrich Hertz. Some years later a German engineer Chistian Huelsmeyer proposed the use of radio echoes in a detecting device designed to avoid collisions in marine navigation.

The first successful radio range-finding experiment occurred in 1924, when the British physicist Sir Edward Victor Appleton used radio echoes to determine the height of the ionosphere, an ionized layer of the upper atmosphere that reflects longer radio waves.

The first practical radar system was produced in 1935 by the British physicist Sir Robert Watson-Watt, and by 1939 England had established a chain of radar stations along its south and east coasts to detect aggressors in the air or on the sea.

In 1935 Watson-Watt wrote a paper entitled "The Detection of Aircraft by Radio Methods". This was presented to Henry Tizard, the chairman of the Committee for the Scientific Survey of Air Defence. Tizard was impressed with the idea and on 26th February 1935, Watson-Watt demonstrated his ideas at Daventry. His idea was based on the bouncing of a radio wave against an object and measuring its travel to provide targeting information. It

was called radar (radio detection and ranging). As a result he was appointed head of the Bawdsey Research Station in Felixstowe.

By the outbreak of the Second World War in September 1939, Watson-Watt had designed and installed a chain of radar stations along the East and South coast of England. In the same year two British scientists were responsible for the most important advance made in the technology of radar during World War II. The physicist Henry Boot and biophysicist John T. Randall invented an electron tube called the resonant-cavity magnetron. This type of tube is capable of generating high-frequency radio pulses with large amounts of power, thus permitting the development of microwave radar, which operates in the very short wavelength band of less than 1cm, using lasers. Microwave radar, also called LIDAR (Light Detection and Ranging) is used in the present day for communications and to measure atmospheric pollution. During the Battle of Britain these stations were able to detect enemy aircraft at any time of day and in any weather conditions.

Radar was also used by ships and aircraft during the war. Germany was using radar by 1940 but Japan never used it effectively. The United States had a good radar system and it was able to predict the attack on Pearl Harbor an hour before it happened.

Britain tended to have the best radar system during the early stages of the war and in 1940 the invention of the Magnetron cavity resonator enabled more centimetric waves to be transmitted. It also enabled more compact high-frequency sets to be used by aircraft in the Royal Air Force .

I.3 DEFINITION

Radar (radio detection and range) is a system That uses electromagnetic waves to determine the position and speed of objects such as << aircraft, ships, submarines >> and also is used to detect and track rockets.

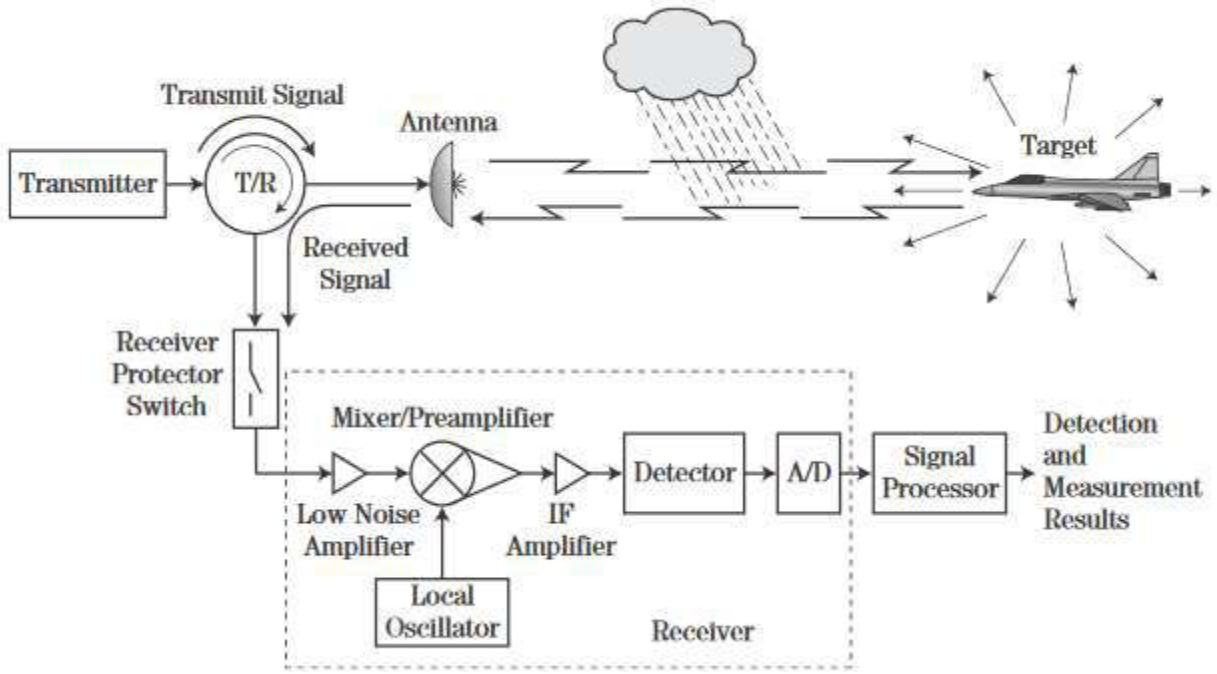


Figure I.1 Major elements of the radar transmission/reception process

The first shape of the radar is formed as shown in Figure I-1 from the transmitting antenna, the electromagnetic wave pulses resulting from oscillators of some kind, and the wave pulses are intercepted by the medium of an object, so they are reflected and spread and are broadcasted in all directions The parts of the pulses of the wave sent to the incoming system again and the radar system try to listen to weak echoes wherever they are and are processed to detect the presence of the target and extract location information Radar has different types, and its frequencies differ from one band to another. These frequencies extend from 0.5 GHz to 18 GHz and are divided into two parts [5]

- Low frequency search radar 0.5GHz – 6 GHz
- Radar search for a frequency higher than 6GHz – 18 GHz

I.4 TECHNOLOGY RADAR

In most cases, the radar transmitter and receiver share electronics and a common antenna. We then speak of monostatic radar. However, nothing prevents us from considering a radar device where the transmitter and the receiver are split; we then speak of biostatic radar, or even of multistate configuration, if we have a transmitter and several different receivers. Both configurations have advantages and disadvantages:

I.4.1 MONOSTATIC VERSUS BISTATIC

There are two basic antenna configurations of radar systems: monostatic and bistatic Figure I-2. In the monostatic configuration, one antenna serves both the transmitter and receiver. In the bistatic configuration, there are separate antennas for the transmit and receive radar functions. [6]

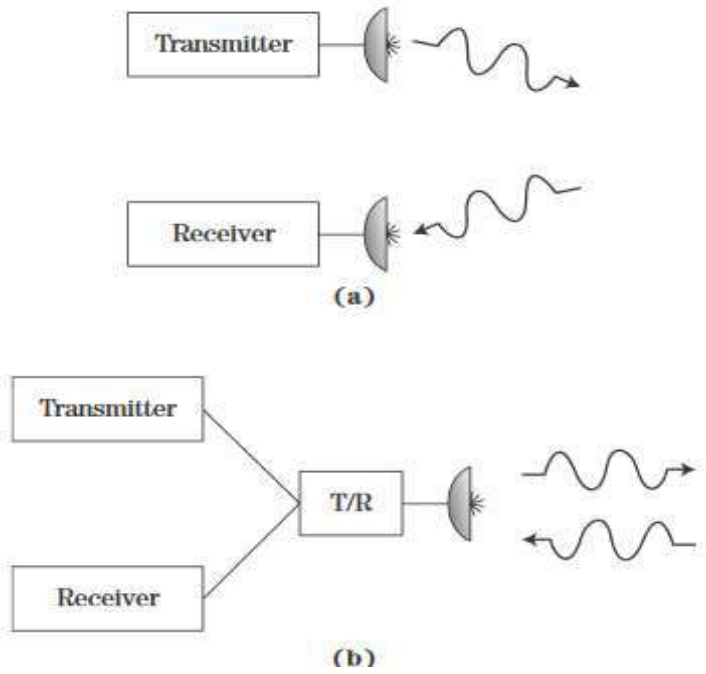


Figure I.2 components of a radar

Use of two antennas alone does not determine whether a system is monostatic or bistatic. If the two antennas are very close together, say, on the same structure, then the system is considered to be monostatic. The system is considered to be bistatic only if there is sufficient separation between the two antennas such that ". . . the angles or ranges to the target are sufficiently different [2] (modern radar)

I.4.2 BISTATIC AND MULTISTATIC RADAR

In a bistatic configuration, the receiver is different from the transmitter and is completely passive, therefore less easily detectable by a potential enemy. In addition to specialized radar transmitters, it is also envisaged to use transmitters called opportunity such as GSM relay antennas, or television, or GPS satellites whose signal is diverted from their primary use to perform at lower cost and discreetly a measurement work generally left to radars. Finally, the possibility of positioning the transmitter and the receiver at will makes it possible to explore other reflection configurations making it possible to increase the volume of information available on the target. In return, the use of a bistatic configuration requires good synchronization between the transmitter and the receiver, and the use of less trivial acquisition geometry.

When we talk about bistatic radar, we implicitly assume that the transmitter and the receiver are really split (either from a distance point of view, or from an angular point of view). If the transmitter and the receiver are physically different (different antennas) but located almost at the same place, the received signal is qualitatively close to a monostatic signal. We are talking about highly bistatic or weakly bistatic configurations to integrate these two possibilities [7]

I.5 THE RADAR EQUATION [6]

The radar range equation is not formally derived here from first principles, it is informative to develop the equation heuristically in several steps. The total peak power (watts) developed by the radar transmitter,p_t , is applied to the antenna system. If the antenna had an isotropic or omnidirectional radiation pattern, the power density Q_i(wattsper square meter) at a distance R(meters) from the radiating antenna would be the total power divided by the surface area of a sphere of radius R,

$$Q_i = \frac{P_t}{4\Pi R^2} \qquad \text{(I.1)}$$

All radar systems use an antenna that has a directional beam pattern rather than an isotropic beam pattern. This means that the transmitted power is concentrated in to a finite angular extent, usually having a width of several degrees in both the azimuthally and elevation planes. In this case, the power density at the centre of the antenna beam pattern is higher than that from an isotropic antenna, because the transmit power is concentrated onto a smaller area on the surface of the sphere, as depicted in Figure I.4 The power density in the

gray ellipse depicting the antenna beam is increased from that of an isotropic antenna. The ratio between the power density for a lossless directional antenna and a hypothetical

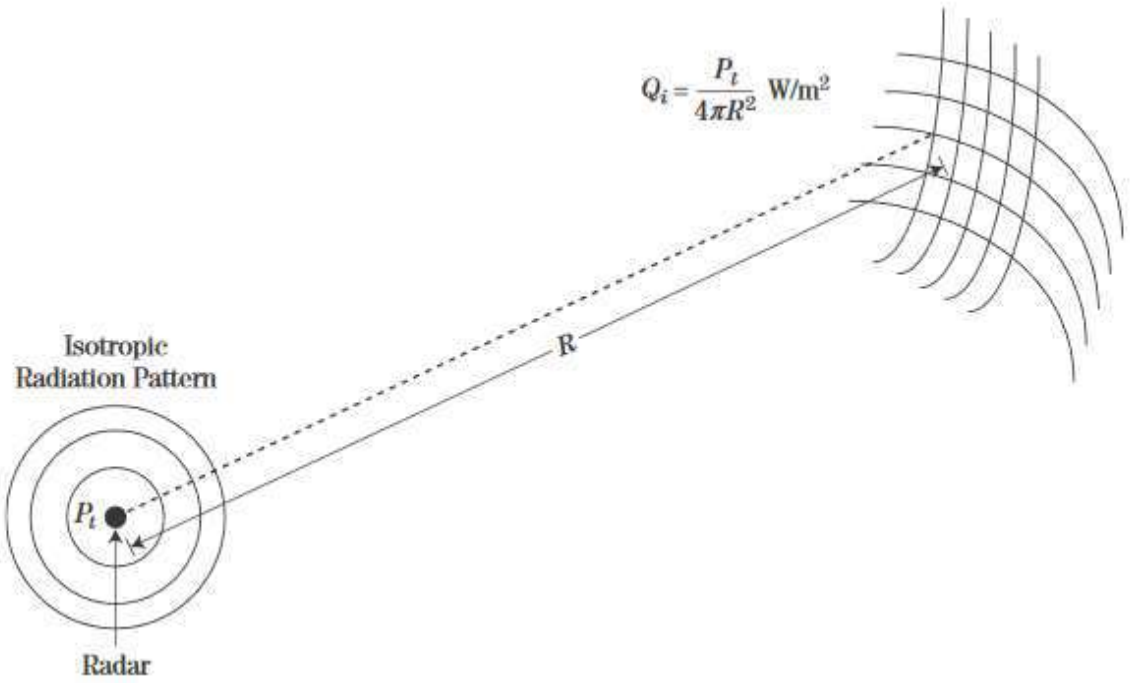


Figure I.3 Power density at range *R* from the radar transmitter for an isotropic antenna.

Isotropic antenna is termed the directivity. The gain, G, of an antenna is the directivity reduced by the losses the signal encounters as it travels from the input port to the point at which it is "launched" into the atmosphere . The subscript is used to denote a transmit antenna, so the transmit antenna gain isG_t.Given G_t, the increased power density due touse of a directional antenna is

$$Q_i = \frac{P_t G_t}{4\pi R^2} W/m^2 \quad \text{(I.2)}$$

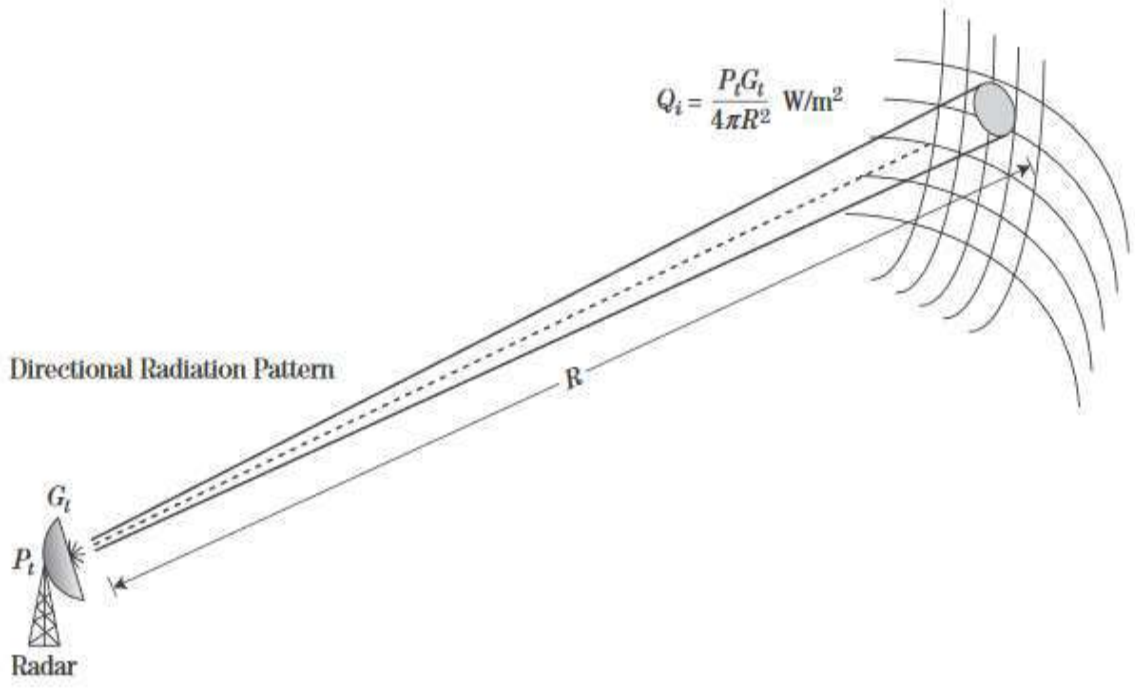


Figure I.4 Power density at range *R* given transmit antenna gainG_t

Next, consider a radar "target" at range R, illuminated by the signal from a radiating antenna. The incident transmitted signal is reflected in a variety of directions, as depicted in Figure I.5. The expression for the power reflected back toward the radar ,P_{refl} from the target is:

$$P_{refl} = Q_i \sigma = \frac{P_t G_t \sigma}{4\pi R^2} \quad \text{(I.3)}$$

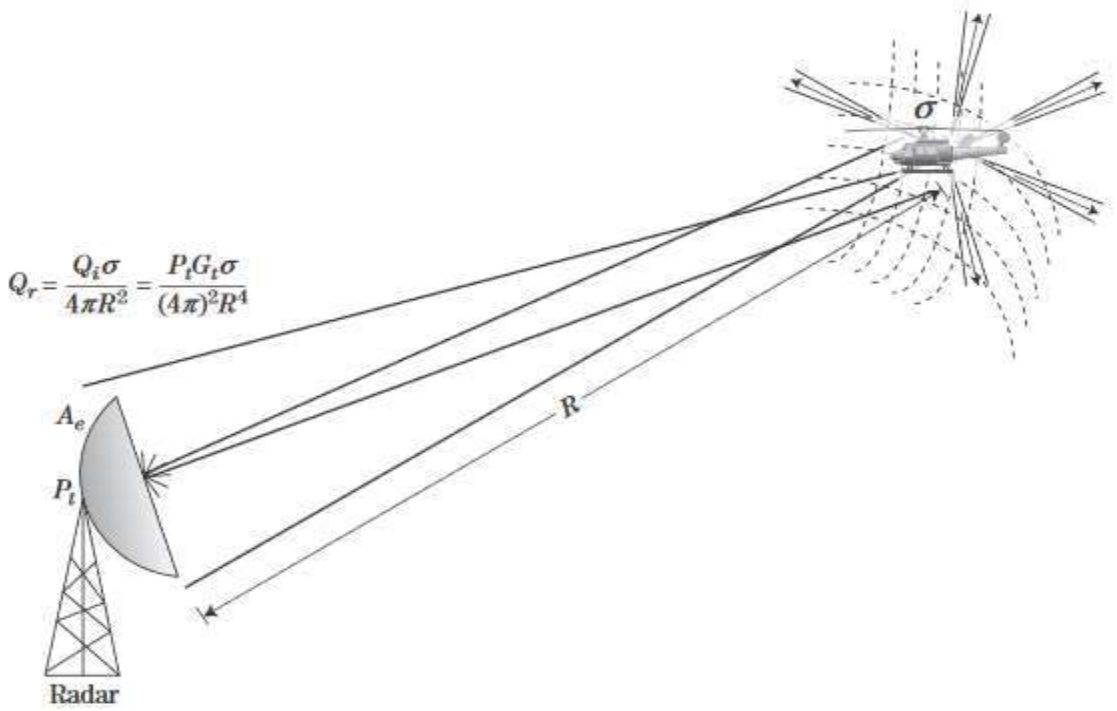


Figure I.5: Power densityQ_r back at the radar receive antenna.

The signal reflected from the target propagates back toward the radar system over a distance R so that the power density back at the radar receiver antenna,Q_r ,is

$$Q_r = \frac{P_{refl}}{4\pi R^2} \tag{I.4}$$

Combining equations (I.3) and (I.4), the power density of the radio wave received back at the radar receive antenna is given by

$$Q_r = \frac{Q_i\sigma}{4\pi R^2} = \frac{P_t G_t \sigma}{(4\pi)^2 R^4} \tag{I.5}$$

The radar wave reflected from the target, which has propagated through a distance R and results in the power density given by equation (I.5), is received (gathered) by a radar receive antenna having an effective antenna area of A e. The power receivedP_r, (watts) from a target at range R at a receiving antenna of effective area of A e is found as the power density at the antenna times the effective area of the antenna:

$$P_r = Q_r A_e = \frac{P_t G_t A_e}{(4\pi)^2 R^4} \tag{I.6}$$

It is customary to replace the effective antenna area term A e with the value of receive antenna gain G_rth at is produced by that area. Also, because of the effects of tapering and losses, the effective area of an antenna is somewhat less than the physical area, A. As discussed in Chapter 9 as well as in many standard antenna texts such as [1], the relationship between an antenna gain G and its effective are a A e is given by [6]:

$$G=\frac{4\pi\eta aA}{\lambda^2}=\frac{4\pi A_e}{\lambda^2} \quad (I.7)$$

Where "ηa" is the antenna efficiency. Antenna efficiency is a value between 0 and 1; however, it is seldom below 0.5 and seldom above 0.8.Solving (2.7) for "Ae" and substituting into equation (I.6), the following expression for the received power,p_r results [6]:

$$P_r=\frac{P_t G_t G_r \lambda^2 \sigma}{(4\pi)^3 R^4}\ G^2 \quad (I.8)$$

In this expression,

p_t is the peak transmitted power in watts.

G_t is the gain of the transmit antenna.

G_t is the gain of the receive antenna.

λ is the carrier wavelength in meters.

σ is the mean RCS of the target in square meters.

R is the range from the radar to the target in meters

This form is found in many existing standard radar texts, including [2–6].For many monostatic radar systems, particularly those using mechanically scanned antennas, the transmit and receive antennas gains are the same, so in those cases the two gain terms in (2.8) are replaced by G^2. However, for bistatic systems and in many modern radar systems, particularly those that employ electronically scanned antennas, the two gains are generally different, in which case the preferred form of the radar range equation is that shown in (2.8), allowing for different values for transmit and receive gain .For a bistatic radar, one for which the receive antenna is not collocated with the transmit antenna, the range between the transmitter and target,R_t may be different from the range between the target and the receiver, R_r In this case, the two different range values must be independently specified, leading to the bistatic form of the equation [6]:

$$P_r \frac{P_t G_t G_r \lambda^2 \sigma_{biastatic}}{(4\pi)^3 R_t^2 R_r^2} \quad \text{(I.9)}$$

Though in the following discussions the monostatic form of the radar equation is described, a similar bistatic form can be developed by separating the range terms and using the bistatic radar cross section, $\sigma_{biastatic}$, of the target

I.6 RADARS CLASSIFICATION

The classification based on the main function of the Radar is shown in the following figure

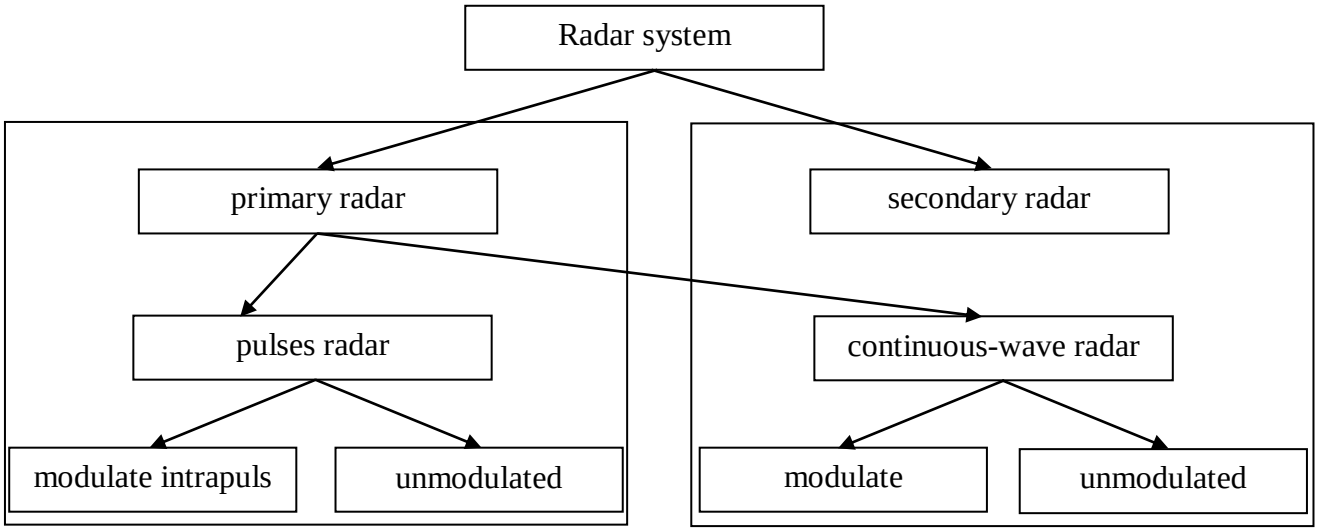


Figure I.6 Radar Classification

I.6.1 IMAGING AND NON-IMAGING RADAR

An imaging radar allows the presentation of an image of the object (or area) being observed. Imaging radars are used to map the earth, other planets, asteroids and other celestial objects. They provide military systems with a target classification capability. Typical examples of non-imaging radar are radar range finders (small, roadside...) and radio altimeters. This type of radar is also called scatter meters because it measures the reflection properties of the observed region or object

I.6.2 PRIMARY RADAR

A Primary Radar transmits high-frequency signals to targets. The transmitted pulses are reflected by the target and received by the same radar. The reflected energy or echoes are further processed to extract useful information [9].

I.6.3 SECONDARY RADAR

Secondary Radars operate with active response signals. In addition to the primary Radar, this type of Radar uses a transponder (Transmitter Answering Device) on the target where it will respond to the Radar interrogation by generating a coded signal. This response can contain much more information than a Primary Radar can collect (e.g., altitude, an identification code, or an on-board problem report such as a total radio failure

I.6.4 CONTINUOUS WAVE VERSUS PULSED

I.6.4.1 CONTINUOUS WAVE WAVEFORM

Radar waveforms can be divided into two general classes: *continuous wave* (CW) and pulsed. With the CW waveform the transmitter is continually transmitting a signal, usually without interruption, all the time the radar transmitter is operating. The receiver continuously operates also. The pulsed waveform transmitter, on the other hand, emits a sequence of finite duration pulses, separated by times during which the transmitter is "off." While the transmitter is off, the receiver is on so that target signals can be detected. Continuous wave radars often employ the bistatic configuration to effect transmitter/ receiver isolation. Since the isolation between the transmitter and receiver is not perfect, there is some competing signal due to the leakage, relegating CW systems to relatively low power and hence short-range applications. Since a CW radar is continuously transmitting, determination of the transmitted EM wave's round-trip time and, thus, target range, must be accomplished by changing the characteristics of the wave (e.g., changing the wave's *frequency* over time). This frequency modulated (FM) technique effectively puts a timing.

Mark on the EM wave, thus allowing for target range determination. Though there are relatively complex CW systems employed as illuminators in fire control systems, semi active missiles, and trackers, CW radars tend to be simple radars and are used for such applications as police speed-timing radars, altimeters, and proximity fuses. [6]

I.6.4.2 PULSED WAVEFORM [6]

Pulsed radars transmit EM waves during a very short time duration, or *pulse width* τ , typically 0.1 to 10 microseconds (μs), but sometimes as little as a few nanoseconds (10^{-9}seconds) or as long as a millsecond. During this time, the receiver is isolated from the antenna, or *blanked*, thus protecting its sensitive components from the transmitter's high-power EM waves. No received signals can be detected during this time. In addition to the isolation provided by the T/R device shown in Figure I-1, further protection is offered by the receiver protection switch, not shown in the figure. During the time between transmitted pulses, typically from 1 microsecond to tens of milliseconds, the receiver is connected to the antenna, allowing it to receive any EM waves (echoes) that may have been reflected from objects in the environment. This "listening" time plus the pulse width represents one pulsed radar cycle time, normally called the *inter pulse period* (IPP) or *pulse repetition interval* (*PRI*). The pulsed waveform is depicted in Figure (I - 7) [6]

Pulse Repetition Frequency (PRF) The number of transmit/receive cycles the radar completes per second is called the *pulse repetition frequency* (PRF), which is properly measured in pulses per second (PPS) but is often expressed in hertz (cycles per second).The PRF and PRI are related according to.

$$\text{PRF} = \frac{1}{PRI} \tag{I.11}$$

Pulse Width and Duty Cycle The fraction of time the transmitter is transmitting during one radar cycle is called the transmit *duty factor* (or *duty cycle*), d_t, and from Figure I .7 is given by [6:]

$$d_t = \frac{\tau}{PRI} = \tau . PRF \tag{I.12}$$

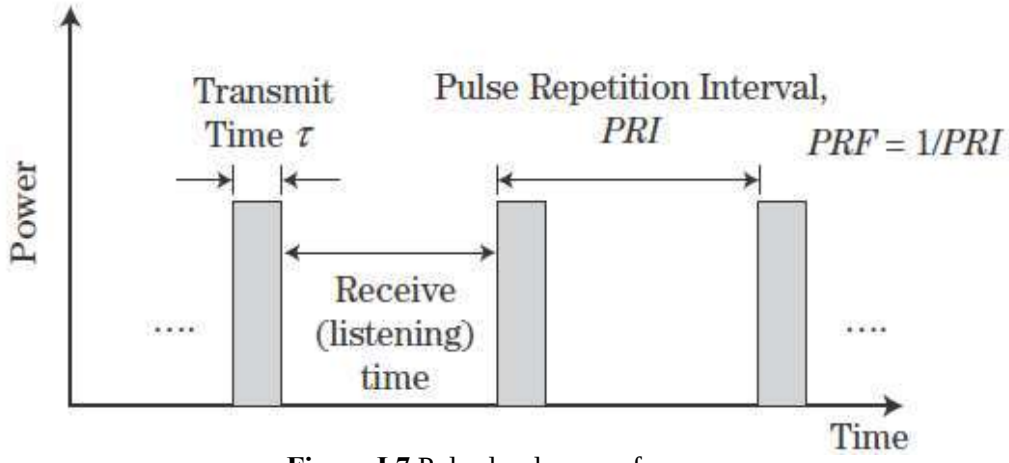


Figure I.7 Pulsed radar waveform.

The average power, p_{avg} of the transmitted EM wave is given by the product of the peak transmitted power, p_t , and the transmit duty factor [6]

$$p_{\text{avg}} = p_t . d_t = p_t . \tau . PRF \tag{I.13}$$

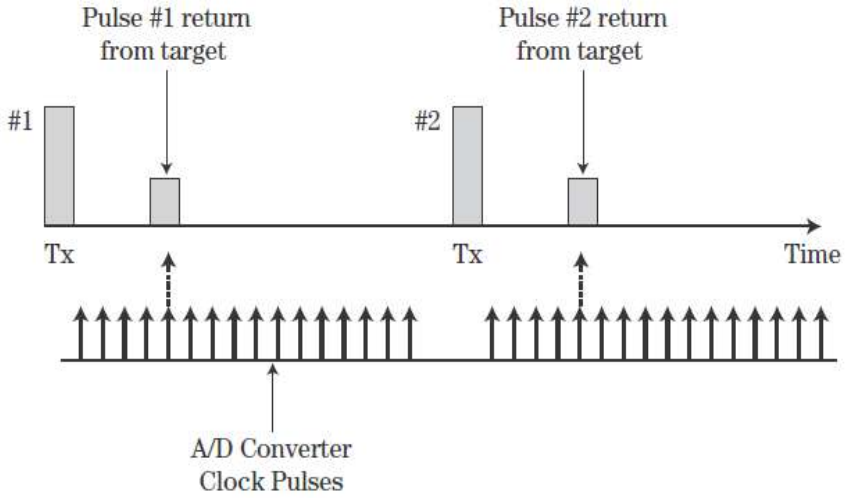


Figure I.8 Pulsed radar waveform showing ADC clock pulses.

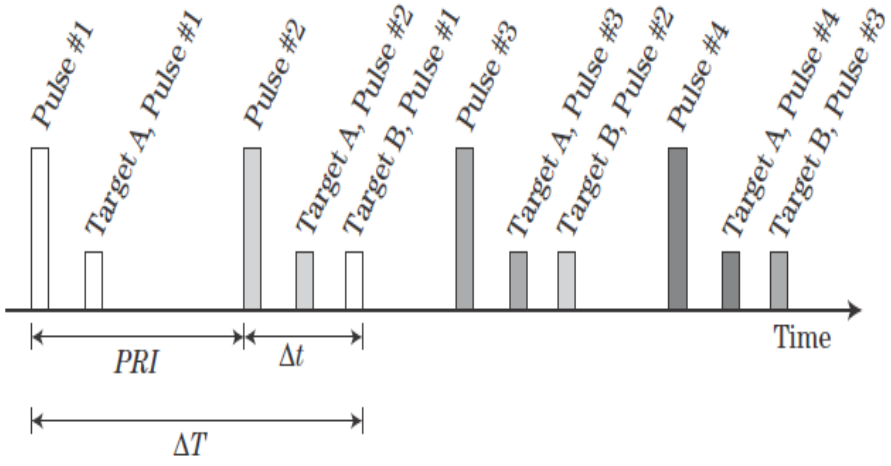


Figure I.9 Pulsed radar range ambiguity

Range Sampling Figure I.8 depicts a sequence of two transmit pulses and adds a hypothetical target echo signal. Because the time scale is continuous, a target signal can arrive at the radar receiver at any arbitrary time, with infinitesimal time resolution. In a modern radar system, the received signal is normally sampled at discrete time intervals, using an ADC, which quantizes the signal in time and amplitude. The time quantization corresponds to the ADC sample times, and the amplitude quantization depends on the number of ADC "bits" and the full-scale voltage. To achieve detection, the time between samples must be no more than a

pulse width; for example, for a 1 μs transmit pulse, the received signal must be sampled at intervals of no more than a microsecond. Usually, to achieve improved detection, oversampling is used; for example, there would be two samples for a given pulse width. A 1 μs pulse width would suggest a 0.5 μs sample period.

Unambiguous Range Measurement Recall that target range is determined by measuring the delay time from transmission of a pulse to reception of the reflected signal. Problems can occur in a pulsed radar when determining the range to targets if the pulse round-trip travel time, *_T* , between the radar and the distant target is greater than the inter pulse period, *IPP*. In this case, the EM wave in a given pulse will not return to the radar's receiver before the next pulse is transmitted, resulting in a time ambiguity and related *range ambiguity*. The received pulse could be a reflection of the pulse that was just transmitted and, thus, a reflection from a close-in target, or it could be a reflection resulting from a previously transmitted pulse and, thus, a reflection from a distant target. This situation is illustrated in Figure I9. The tall rectangles represent transmitted pulses; the shorter rectangles represent the received echoes from two targets. The shading of the target echoes matches the shading of the pulse from which they originated. The time delay to target A and back is less than the interpulse period, so the echo from target A from a given pulse is received before the next pulse is transmitted. The time delay *_T* to target B is greater than the *PRI*; specifically, suppose*_T = PRI +_t*. Then the reflection from target B due to pulse #1 occurs *_t* seconds after pulse #2, as shown in the figure. Consequently, it is unclear if this echo is from a short-range target *_t* seconds away or a longer-range target *_T* seconds away range ambiguities can be avoided by ensuring that the interpulse period, *PRI*, is long enough or, equivalently, the pulse repetition frequency *PRF* is low enough, such that all echoes of interest from a given pulse return to the radar receiver before the next pulse is transmitted .by [6]:

$$\Delta t = \frac{2R}{c} \tag{I.14}$$

Thus, to prevent range ambiguities, the following condition must be satisfied

$$\text{PRI} \geq \Delta T_{max} = \frac{2R_{max}}{c} \; or \; R_{max} \leq \frac{c.PRI}{2} = \frac{c}{2PRF} \tag{I.15}$$

where $R_{max}$is the maximum target range of interest. Conversely, the *unambiguous range*, R_{ua}, is the maximum range at which the range to a target can be measured unambiguously by the radar. It is given by

$$R_{ua} = \frac{c}{2PRF} \tag{I.16}$$

It should be noted that not all radars satisfy this condition. Some systems cannot avoid an ambiguous range condition, due to other conflicting requirements, as is seen in the following section.

I.6.5 NONCOHERENT VERSUS COHERENT

Radar systems can be configured to be noncoherent or coherent. Whereas a noncoherent system detects only the amplitude of the received signal, the coherent system detects the amplitude and the phase, treating the received signal as a vector. Noncoherent systems are often used to provide a two-dimensional display of target location in a ground map background. The amplitude of the signal at any instant in time will determine the brightness of the corresponding area of the display face. Noncoherent radars can be used in cases in which it is known that the desired target signal will exceed any competing clutter signal. All early radars were noncoherent; target detection depended on operator skill in discerning targets from the surrounding environment. For a coherent system, measurement of the phase of the received signal provides the ability to determine if the phase is changing, which can provide target motion characteristics and the ability to image a target. Though there are still applications for which noncoherent radar technology is appropriate, most modern radar systems are coherent. A pulsed coherent system measures the phase of the received signal on a pulse-to pulse basis. This reference sinusoid is usually implemented in the form of a local oscillator (LO) signal used to produce the transmit signal that also serves as the reference for the received signal. This process is depicted in Figure I-10. The top line is the local oscillator signal; the solid segments represent the transmit pulse times, and the dashed segments represent “listening” times between transmit pulses. If the local oscillator signal is a fixed frequency, it can serve as a reference for measuring the phase of the received signal. The expanded “balloon” shows the phase relationship for a single transmit/receive pulse pair. The ability to measure the phase of the received signal depends on the stability of the LOs, [6]

I.6.6 THE DOPPLER SHIFT [6]

If there is relative motion between the radar and the target, then the frequency of the EM wave reflected from the target and received by the radar will be different from the frequency of the wave transmitted from the radar. This is the *Doppler effect*, common to all wave phenomena and originally identified as an acoustic (sound wave) phenomenon. The Doppler frequency shift, f_d, or "Doppler" for short, is the difference between the frequency of the received wave and that of the transmitted wave and is approximately given by

$$f_d = \frac{2u_r}{\lambda} \tag{I.17}$$

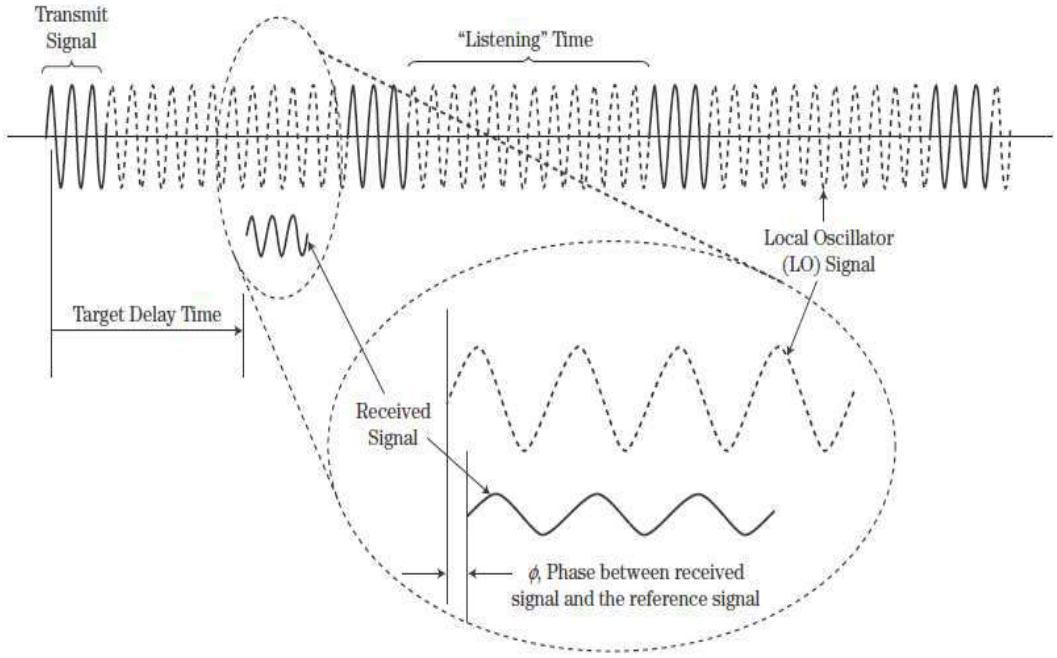


Figure I.10 Coherent system local oscillator, transmit, and received signals.

where *vr* is the radial component of the target's velocity vector toward the radar, and λ is the wavelength of the transmitted EM wave. The approximation is excellent as long as the radial component of velocity of the target is much less than the speed of light. The negative of the radial velocity is often called the *range rate*. This radial velocity component, u_r, is positive (and, thus, f_d is positive) for targets approaching the radar and negative ($f_d$negative) for targets receding from the radar.

I.6.7 UNAMBIGUOUS DOPPLER SHIFT MEASUREMENT

Clearly from equation (I.16), lowering the PRF of the radar will increase the radar's unambiguous range. However, lowering the radar's PRF also has a negative consequence. Most modern radars measure the Doppler frequency shift of the received EM wave. A pulsed radar samples the Doppler frequency shift at the pulse repetition frequency. This can lead to Doppler frequency ambiguities if the sampling rate (PRF) is not high enough, sampled at the radar's PRF; thus, the maximum range of Doppler shift frequencies that can be unambiguously measured is[6]

$$f_{d_{max}} = \pm PRF/2 \text{ or } PRF_{min} = 2f_{d_{max}} = \frac{4u_{r_{max}}}{\lambda} \quad \text{(I.18)}$$

While maximizing unambiguous range leads to lower PRFs, maximizing unambiguous Doppler shift leads to higher PRFs. In many systems, no single PRF can meet both of these opposing requirements. Fortunately, some signal processing techniques such as staggered PRFs allow radars to unambiguously measure range and Doppler shift at almost any PRF. This conflict leads to the definition of three different *PRF regimes*: low PRF, medium PRF, and high PRF. A *low PRF* system is one that is unambiguous in range, for all target ranges of interest. Though there is no specific range of PRF values that define such a system, the PRF ranges from as low as 100 Hz to as high as 4 kHz. Of course, there may be lower or higher PRFs for low PRF systems, but a large majority of low PRF systems fall into these limits. At the other extreme, a *high PRF* system is defined as one for which the Doppler shift measurement is always unambiguous. That is, the Nyquist sampling criterion is satisfied for the fastest target of interest. Typical values of PRF for these systems are from 10 kHz to 100 kHz (or sometimes much more).

In between these two conditions lies the *medium PRF* regime, for which both range ambiguities and Doppler ambiguities will exist .Typical values for medium PRF waveforms are from 8 kHz to 30 kHz or so. For radar systems operating in the HF, VHF, and UHF regions, a different set of conditions apply to the definition for medium PRF. If the radar system operates in these regions it is possible that the PRF required to satisfy the Nyquist sampling criterion will be also sufficient to measure the range to the farthest target of interest unambiguously. In this case, a medium PRF system will be unambiguous in both range and Doppler. [6]

I.7 RADAR APPLICATIONS

The applications of Radar are many and varied. They are either military, such as Airborne and Ground Based Detection and Surveillance Radars, Radar jammers, Earth Observation Radar satellites, or civil, such as aeronautics, where one can find Navigation Radars, Air Traffic Control Radars, and Airport Approach Guidance Radars, as well as in maritime, meteorological and traffic and road safety applications, such as Speed Control Radars for cars

I.8 RADAR SIGNALS

We will now introduce the fundamentals of the signal models that will be used in this thesis work. All signals we deal with will be complex discrete-time signals. The signals are assumed to be obtained by the complex sampling theorem. The complex sampling theorem says that we can sample all signals correctly up to the sampling frequency . We start by defining the pulse shapes and then construct a complete radar signal.

I.8.1 PULSES WITH A FIXED FREQUENCY [5]

A pulse with a constant frequency f_1 can be modelled by a complex sinusoid with real amplitude A_1 and phase φ_1, see Equation (I.19)

$$x_1(t) = A_1 e^{j2\pi f_1 t + \varphi_1} \qquad 0 \le t \le t_{pw} \tag{I.19}$$

The most of the signal processing now days are digitalized. Therefore the received radar signals are sampled by an analog to digital converter (ADC). The discretetime version of the pulse, given by Equation (I.19), sampled with frequency f_s is given by Equation (I.20). Here n represent a specific sample and N is the total number of samples for the pulse.

$$x_1[n] = A_1 e^{j2\pi f_1 \frac{n}{f_s} + \varphi_1} \qquad 0 \le n \le f_s t_{pw} = N \tag{I.20}$$

Equation (I.20) holds as long as the condition $0 \le f_1 \le f_s$ is satisfied due to the complex sampling theorem.

I.8.2 LINEAR CHIRP PULSES [5]

A chirp pulse has a varying frequency with respect to time. In a linear chirp pulse the frequency varies linearly with the time during the pulse, see Equation (I.21)

$$f(t) = f_0 + kt \tag{I.21}$$

$$k = \frac{f_1 - f_0}{t_1 - t_0} \tag{I.22}$$

The constantst_0, t_1 are the start time and stop time respectively. The constantsf_0, f_1 are the start frequency and stop frequency for the chirped pulse. In our case we set $t_0 = 0$ and $t_1 = t_{pw}$ and yield Equation (I.23).

$$k = \frac{f_1 - f_0}{t_{pw}} \tag{I.23}$$

A model of a complex chirp pulse is given in Equation (I.24) where $\emptyset(t)$ represent the phase, i.e. the frequency variation.

$$x_2(t) = A_2 e^{j2\emptyset(t)} \quad 0 \le t \le t_{pw} \tag{I.24}$$

We have that,

$$\emptyset(t) = 2\pi f(t) = w(t) \tag{I.25}$$

By integrating both sides of Equation (I.25) with respect of time and using Equation (I.21) we obtain Equation (I.26).

$$\emptyset(t) = 2\pi \int_0^t (f_0 + kt) d\tau = 2\pi \left(f_0 t + \frac{k}{2} t^2 \right) \tag{I.26}$$

Inserting Equation (I.26) into Equation (I.24) gives us Equation (I.27).

$$x_2(t) = A_2 e^{j2\pi \left(f_0 t + \frac{k}{2} t^2 \right)} \quad 0 \le t \le t_{pw} \tag{I.27}$$

By sampling the continuous chirp pulse with sampling frequency f_s , with the same assumptions as for the fixed pulse, we obtain the time-discrete version, see Equation (I.28). Equation (I.28) holds for the frequencies in the range $0 \le f \le f_s$

$$x_2[n] = A_2 e^{j2\pi \left(f_0 \frac{n}{f_s} + \frac{k}{2} (\frac{n}{f_s})^2 \right)} \quad 0 \le n \le f_s t_{pw} = N] \tag{I.28}$$

I.8.3 BINARY PHASED CODED PULSES [5]

A binary phase coded pulse change phase 180 degrees at certain time of the pulse. A phase shift can be seen in Figure I.11.

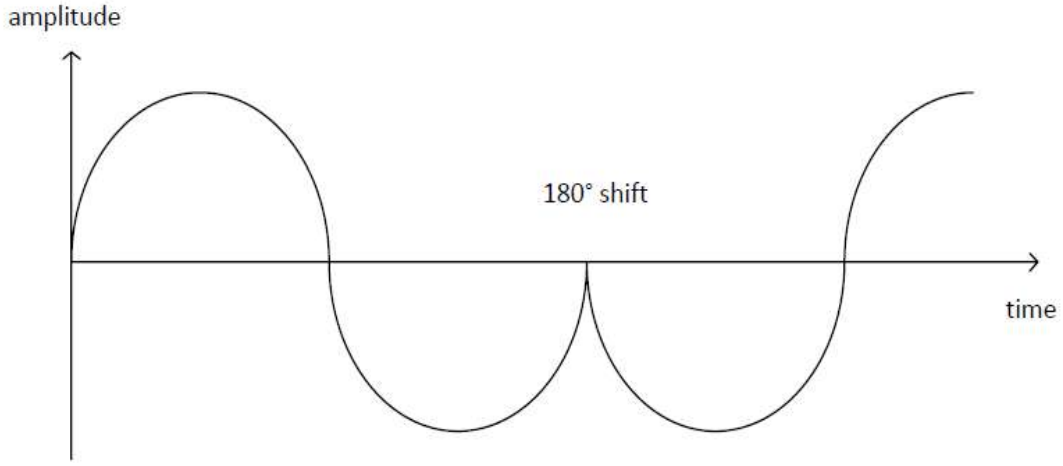


Figure I.11 A sinusoid with a 180 degrees phase shift.

One set of binary phased codes called Barker codes are used in radar and will be described here. We will consider the Barker 7 code. In Barker 7 code each pulse are divided into 7 equal segments in time, see Figure (I.12). Each difference between +1 and -1 (or -1 and +1) represent a 180 degrees phase shift. For a sinusoid a 180 degree phase shift is the same as multiplying the amplitude.by-1

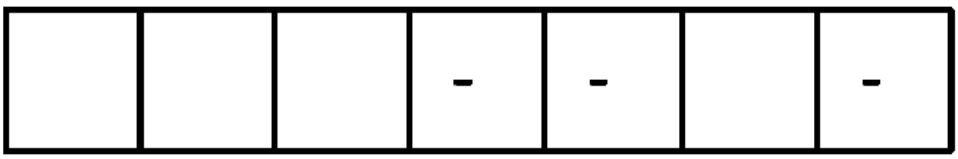


Figure I.12 Barker 7 code. A difference between +1 and -1 (or -1 and +1) is a phase shift of180 degrees.

The binary phase coded pulse can be described by Equation (I.29)

$$x_3(t) = A_3(t)e^{j2\pi f_3 t+\varphi_3} \quad \text{(I.29)}$$

The amplitude $A_3(t)$ is defined by Equation (I.30) for the Barker 7 codes.

$$A_{3(t)} = \begin{cases} A & 0 \le t \le 3T \\ -A & 3T < t \le 5T \\ A & 5T < t \le 6T \\ -A & 6T < t \le 7T \end{cases} \quad \text{(I.30)}$$

For the discrete-time case we obtain, see Equation (I.31)

$$x_3[n] = A_3 e^{j2\pi f_3 \frac{n}{f_3} + \varphi_3} \quad \text{(I.31)}$$

I.8.4 RADAR SIGNALS EXPLICATION [5]

A radar signal consists of a train of pulses. To get an easier view of how a pulse train is composed we divided it into small parts in time, which we later add on after the order. Each divided part is described from the beginning of one pulse until next pulse beginning, i.e. the pulse repetition interval t_{PRI} Each part begins with a pulse that lasts for the time $T_{PW}$and then equals zero until it reacht_{PRI}. This is described by Equation (I.32). The signal $x_P(t)$is some pulsed signal where the sub index p represents the pulse shapes derived in previous sections.

$$x(t) = \begin{cases} x_p(t) & 0 \le t \le t_{pw} \\ 0 & t_{pw} < t < t_{PRI} \end{cases} \quad \text{(I.32)}$$

By looping this procedure and add all parts one after the other we obtain a simulated radar signal. The discrete-time version of Equation (I.32) is given by Equation (I.33).

$$x[n] = \begin{cases} x_p[n] & 0 \le n \le f_s t_{pw} \\ 0 & f_s t_{pw} < n < f_s t_{PRI} \end{cases} \quad \text{(I.33)}$$

We have now described an ideal radar signal, but they rarely appear in such away in reality. In reality received radar signals are corrupted by noise. Noise is a random signal that usually is unwanted.

Thermal noise is generated from random motions of electrons in conductive materials. The thermal noise is almost constant for the whole spectrum, exists in every frequency and has an approximate normal distribution. Thus the thermal noise is commonly assumed to be additive white Gaussian noise, AWGN, in radar and communication theory. Therefore AWGN will be used to model the thermal noise in our simulations.

AWGN is represented by a series of complex-valued outputs $y_n$which are Gaussian distributed with mean value zero and variance σ^2[3] see Equation (I.34)

$$y_n = N(0, \sigma^2) \tag{I.34}$$

An AWGN signal can be created by generating independent Gaussian samples and in MATLAB it can be done by using the function **randn.**

I.9 CONCLUSION

We had a general vision about radar system and we had also took a look about their difference equations ,after this we saw the different forms of radar signal and how they work finally we introduce some concept how we can generate the radar signals and pulses

CHAPTER II

ADAPTIVE FILTERS

II.1 INTRODUCTION

The design of digital filters with fixed coefficients requires well-defined prescribed specifications. However, there are situations where the specifications are not available, or are time-varying. The solution in these cases is to employ a digital filter with adaptive coefficients, known as adaptive filters since no specifications are available, the adaptive algorithm that determines the updating of the filter coefficients requires extra information that is usually given in the form of a signal. This signal is in general called a desired or reference signal, whose choice is normally a tricky task that depends on the application. Adaptive filters are considered nonlinear systems; therefore, their behavior analysis is more complicated than for fixed filters. On the other hand, because the adaptive filters are self-designing filters, from the practitioner's point of view their design can be considered less involved than in the case of digital filters with fixed coefficients .The general form of an adaptive filtering is illustrated in Figure II.1, where (k) is the iteration number , $x(k)$ denotes the input signal, $y(k)$ is the adaptive filter output signal, and d(k)defines the desired signal. The error signal $e(k)$ is calculated as $d(k) - y(k)$. The error signal is then used to form a performance (or objective) function that is required by the adaptation algorithm in order to determine the appropriate updating of the filter coefficients. The minimization of the objective function implies that the adaptive filter output signal is matching the desired signal in some sense. The complete specification of an adaptive system, as shown in Figure II.1

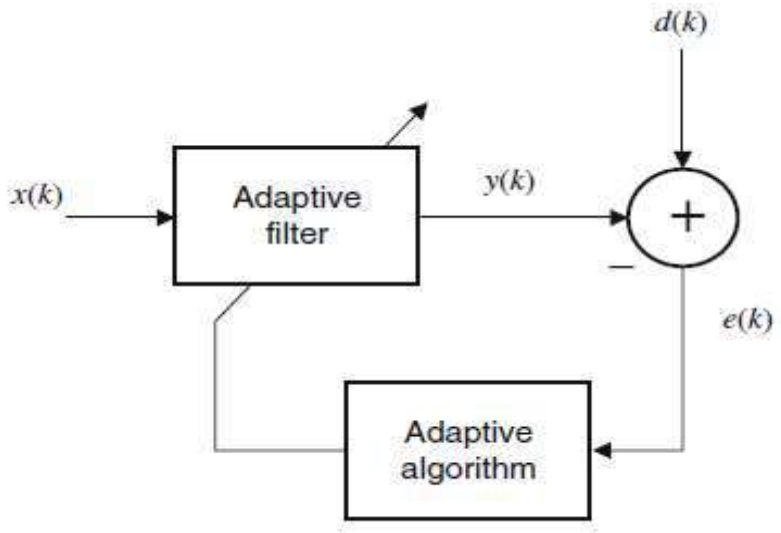


Figure II.1 General adaptive filter configuration

II.2 ADAPTIVE SIGNAL PROCESSING

II.2.1 ADAPTIVE FILTER STRUCTURE

The adaptive filter can be implemented in a number of different structures or realizations. The choice of the structure can influence the computational complexity (amount of arithmetic operations per iteration) of the process and also the necessary number of iterations to achieve a desired performance level. Basically, there are two major classes of adaptive digital filter realizations, distinguished by the form of the impulse response, namely, the finite-duration impulse response (FIR) filter and the infinite-duration impulse response (IIR) filters. FIR filters are usually implemented with nonre cursive structures, whereas IIR filters utilize recursive realizations.

•Adaptive FIR filter realizations: The most widely used adaptive FIR filter structure is the transversal filter, also called tapped delay line, that implements an all-zero transfer function with a canonic direct-form realization without feedback .For this realization, the output signal $y(k)$ is a linear combination of the filter coefficients, which yields a quadratic mean-square error ($MSE = E[|e(k)|2]$) function with a unique optimal solution. Other alternative adaptive FIR realizations are also used in order to obtain improvements as compared to the transversal filter structure, in terms of computational complexity, speed of convergence, and finite word length properties

•Adaptive IIR filter realizations: The most widely used realization of adaptive IIR filters is the canonic direct-form realization, due to its simple implementation and analysis. However, there are some inherent problems related tore cursive adaptive filters which are structure dependent, such as pole-stability monitoring requirement and slow speed of convergence [1]

II.2.2 APPLICATION

There are many applications for the adaptive filtering The type of application is defined by the choice of the signals acquired from the environment to be the input and desired-output signals. The number of different applications in which adaptive techniques are being successfully used has increased enormously during the last two decades. Some examples are echo cancellation, equalization of dispersive channels, system identification, signal enhancement, adaptive beam forming, noise cancelling, and control [1].

II.2.3 ALGORITHM

The algorithm is the procedure used to adjust the adaptive filter coefficients in or de to minimize a prescribed criterion. The algorithm is determined by defining the search method (or minimization algorithm), the objective function, and the error signal nature. The choice of the algorithm determines several crucial aspects of the overall adaptive process, such as existence of sub-optimal solutions, biased optimal solution, and computational complexity [1]

II.2.4 TYPE OF APPLICATION

As we discuss previously we said there is many type of application in this section, we discuss some possible choices for the input and desired signals and how these choices are related to the applications. Some of the classical applications of adaptive filtering are system identification, channel equalization, signal enhancement, and prediction.

First In the system identification application, the desired signal is the output of the unknown system when excited by a broadband signal, in most cases a white-noise signal. The broadband signal is also used as input for the adaptive filter as illustrated in Figure.2.2. When the output MSE is minimized, the adaptive filter represents a model for the unknown system. [1]

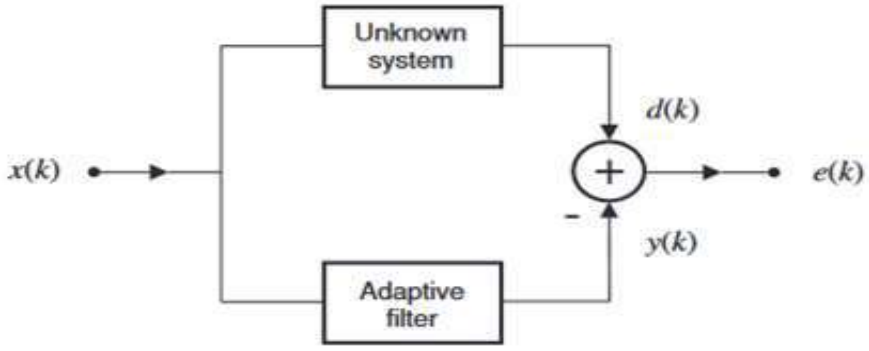


Figure II.2 system identification

Secondly in The channel equalization scheme consists of applying the originally transmitted signal distorted by the channel plus environment noise as the input signal to an adaptive filter, whereas the desired signal is a delayed version of the original signal as depicted in Figure. II.3. This delayed version of the input signal is in general available at the receiver in a form of standard training signal. In a noiseless case ,the minimization of the

MSE indicates that the adaptive filter represents an inverse model (equalizer) of the channel.[1]

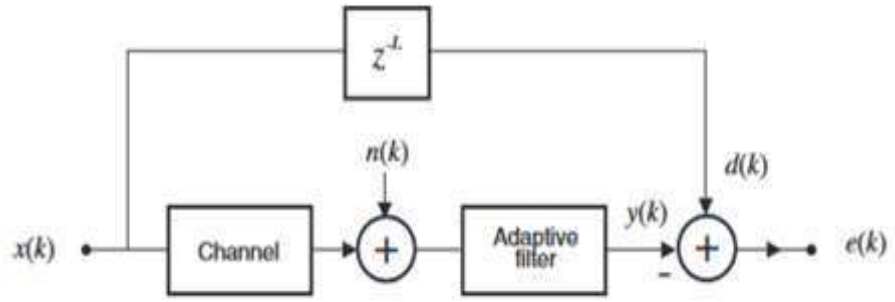


Figure II.3 channel equalization

In the signal enhancement case, a signal $x(k)$ is corrupted by noise $n_1(k)$, and a signal $n_2(k)$correlated to the noise is available (measurable). If $n_2(k)$is used as an input to the adaptive filter with the signal corrupted by noise playing the role of the desired signal, after convergence the output [1]

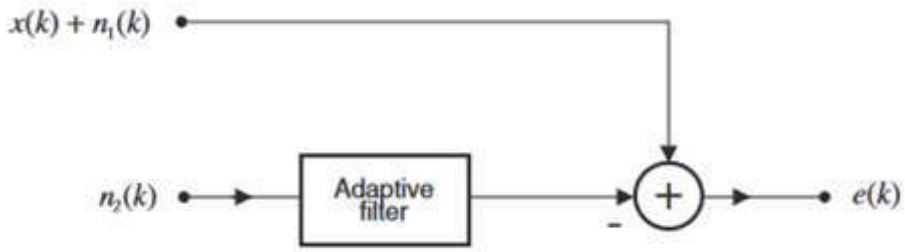


Figure II.4 signal enhancement

II.3 SIGNAL REPRESENTATION

In this section, we briefly review some concepts related to deterministic and random discrete-time signals. Only specific result essential to the understanding of adaptive filtering are reviewed. For further details on signals and digital signal processing,

II.3.1 DETERMINISTIC SIGNALS [1]

Deterministic discrete-time signal is characterized by a defined mathematical function of the time index k, with k=0,±1,±2,±3,....

An example of a deterministic signal (or sequence) is:

$$x(k) = e^{-\propto k}\cos(wk) + u(k) \quad \text{(II.1)}$$

In this case $u(k)$ is the unit step sequence. The response of a linear time-invariant filter to an input $x(k)$ is given by the convolution summation, as follows:

$$y(k) = x(k) * h(k) = \sum_{n=-\infty}^{\infty} x(n)h(k-n) = \sum_{n=-\infty}^{\infty} h(n)x(k-n) = h(k) * x(k) \quad \text{(II.2)}$$

and h(k)is the impulse response of the filter.

The Z-transform of a given sequence x(k) is defined as:

$$Z\{x(k)\} = X(z) = \sum_{k=-\infty}^{\infty} x(k)z^{-k} \quad \text{(II.3)}$$

For regions in the Z-plane such that this summation converges. If the Z-transform is defined for a given region of the Z-plane ,in other words the above summation converges in that region, the convolution operation can be replaced by a product of the Z-transforms as follows:

$$Y(z) = H(z)X(z) \quad \text{(II.4)}$$

Where $Y(z), X(z)$, and $H(z)$are the Z-transforms of $y(k), x(k)$, and $h(k)$, respectively. Considering only waveforms that start at an instant $k \geq 0$ and have finite power, their Z-transforms will always be defined outside the unit circle. For finite-energy waveforms, it is convenient to use the discrete-time Fourier transform defined as:

$$f\{x(k)\} = x(e^{j\omega}) = \sum_{k=-\infty}^{\infty} x(k)e^{-j\omega k} \quad \text{(II.5)}$$

Although the discrete-time Fourier transform does not exist for a signal with infinite energy, if the signal has finite power, agene ralized discrete-time Fourier transform exists and is largely used for deterministic signals.

II.3.2 RANDOM SIGNALS [1]

Random variable X is a function that assigns a number to every outcome, denoted by ϱ, of a given experiment. A stochastic process is a rule to describe the time evolution of the random variable depending on. In this section , $x(k)$ represents a random signal .Random signals do not have a precise description of their waveforms. What is possible is to characterize them via measured statistics or through a probabilistic model. For random signals, the first- and second-order statistics are most of the time sufficient for characterization of the stochastic

process. The first- and second-order statistics are also convenient form measurements. In addition, the effect on these statistics caused by linear filtering can be easily accounted for as shown below. Let's consider for the time being that the random signals are real. We start to introduce some tools to deal with random signals by defining the distribution function of a random variable as

$$Px\ (k)(y) \triangleq \text{probability of } x(k) \text{ being smaller or equal to y}$$

Or

$$P_{x(k)}(y) = \int_{-\infty}^{y} p(x)(z)dz \tag{II.6}$$

The derivative of the distribution function is the probability density function (pdf)

$$P_{x(k)}(y) = \frac{dp_{x(k)}(y)}{dy} \tag{II.7}$$

The expected value, or mean value, of the process is defined by

$$m_x(k) = E[x(k)] \tag{II.8}$$

The definition of the expected value is expressed as

$$E[x(k)] = \int_{-\infty}^{\infty} y\, P_x(k)(y)dy \tag{II.9}$$

Where is$p_{x(k)}(y)$ the PDF of $x(k)$at the pointy .The autocorrelation function of the process $x(k)$ is defined by :

$$r_x(k,l) = E(k)x(l) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} y\, z p_{x(k).x(l)}(y,z)dydz \tag{II.10}$$

Where $p_{x(k)x(l)}(y,z)$ is the joint probability density of the random variables x(k) and x(l) defined as:

$$P_{x(k)x(l)}(y,z) = \frac{\partial^2 p_{x(k)x(l)}(y,z)}{\partial y \partial z} \tag{II.11}$$

Where:

$$P_{x(k)x(l)}(y,z) \triangleq \text{probabilit } y \text{ of}\{x(k) \leq y \text{ and } x(l) \leq z\}$$

The autoco variance function is defined as:

$$\sigma_x^2(k,l) = E\{[x(k) - m_x(k)][x(l) - m_x(l)]\} = r_x(k,l) - m_x(k)m_x(l) \tag{II.12}$$

Where the second equality follows from the definitions of mean value and autocorrelation.

For $k = l, \sigma_x^2(k,l) = \sigma_x^2(k)$ which is the variance of $x(k)$.The most important specific example of probability density function is the Gaussian density function, also known as normal density function The Gaussian pdf is defined by:

$$P(k) = \frac{1}{\sqrt{2\pi\sigma_x^2(k)}} e^{\frac{(y-m_x(k))^2}{2\sigma(k)}} \quad \text{(II.13)}$$

Where m_x and σ_x^2 (k) are the mean and variance of $x(k)$, respectively. One justification for the importance of the Gaussian distribution is the central limit theorem. Given a random variable composed of the sum of n independent random variables x_i as follows:

$$x = \sum_{i=1}^{n} x_i \quad \text{(II.14)}$$

The central limit theorem states that under certain general conditions, the probability density function of x approaches a Gaussian density function for largen. The mean and variance of x are given, respectively, by:

$$m_x = \sum_{i=1}^{n} m_{xi} \quad \text{(II.15)}$$

$$\sigma_x^2 = \sum_{i=1}^{n} x_i^2 \quad \text{(II.16)}$$

Considering that the values of the mean and variance of x can grow, define

$$x' = \frac{x-m_x}{\sigma_x} \quad \text{(II.17)}$$

In this case, for $n \to \infty$ it follows that

$$P = \frac{1}{\sqrt{2\pi}} e^{-\frac{y^2}{2}} \quad \text{(II.18)}$$

In a number of situations we require the calculation of conditional distributions, where the probability of a certain event to occur is calculated assuming that another event B has occurred. In this case, we define :

$$p_{x(k)}(y\backslash B) = \frac{p(\{x(k) \le y\}) \cap B}{p(B)} \triangleq \text{probability of } x(k) \le y \text{ assuming B has occurred} \quad \text{(II.19)}$$

This joint event consists of all out comes $_{\varrho}\in$ B such that $x(k) = x(k,_{\varrho}) \leq y$. The definition of the conditional mean is given by:

$$m_{x\backslash B}(\mathrm{k}) = E\,[x(k)/B] = \int_{-\infty}^{\infty} y p_{x(k)}\,(y\backslash B)dy \qquad \text{(II.20)}$$

Where $\mathrm{p_{x(k)}}(\mathrm{y}\backslash \mathrm{B})$ is the pdf of x(k) conditioned on B. The conditional variance is defined as:

$$\sigma^2_{x(k)}(k) = E\{[x(k) - m_{x\backslash B}(k)]^2 \backslash \mathrm{B}\} = \int_{-\infty}^{\infty}[y - m_{x\backslash B}\,(k)]^{\,2} p_{x(k)}(y\backslash B)dy \qquad \text{(II.21)}$$

There are processes for which the mean and autocorrelation functions are shift (or time) invariant, i.e.,

$$\mathrm{m_x}(\mathrm{y} - \mathrm{i}) = \mathrm{m_x}(\mathrm{k}) = \mathrm{E}[\mathrm{x}(\mathrm{k})] = \mathrm{m_x} \qquad \text{(II.22)}$$

$$\mathrm{r_x}(\mathrm{k}, \mathrm{i}) = \mathrm{E}[\mathrm{x}(\mathrm{k} - \mathrm{j})\mathrm{x}(\mathrm{i} - \mathrm{j})] = \mathrm{r_x}(\mathrm{k} - \mathrm{i}) = \mathrm{r_x}(\mathrm{l}) \qquad \text{(II.23)}$$

and as a consequence :

$$\sigma_x^2(l) = r_x(l) - \mathrm{m_x^2} \qquad \text{(II.24)}$$

These processes are said to be wide-sense stationary (WSS). If the nth-order statistics of a process is shift invariant, the process is said to be nth-order stationary. Also if the process is n the-order stationary for any value of n, the process is stationary in strict sense .Two processes are considered jointly WSS if and only if any linear combination of them is also WSS. This is equivalent to state that

$$y(k) = k_1\, x_1(k) + k_2\, x_2(k) \qquad \text{(II.25)}$$

must be WSS, for any constants k_1 and k_2,if x_1(k) and x_2(k) are jointly WSS. This property implies that both x_1(k)andx_2(k)have shift-invariant means and autocorrelations, and that their cross-correlation is also shift in variant.

For complex signals where $x(k) = x_r(k) + Jx_i(k)$,y = $y_r + Jy_i$ and z = $z_r + Jz_i$,

We have the following definition of the expected value:

$$\mathrm{E}[\mathrm{x}(\mathrm{k})] = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} y p_{x_r(k),x_i(k)}\,(y_r\,, y_i)dy_r dy_i \qquad \text{(II.26)}$$

Where $p_{x_r(k),x_i(k)}(dy_r dy_i)$ is the joint probability density function (pdf) of $x_r(k)$ and.$x_i(k)$ The autocorrelation function of the complex random signal x(k)is defined by:

$$r_x(k,l) = E[x(k)x*(l)]$$

$$= \int_{-\infty}^{\infty}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} yz * p_{x_r(k),x_i(k),x_r(l)}(y_r,y_i,z_r,z_i)dy_r\, dy_i dz_r\, dz_i \quad \text{(II.27)}$$

Where $p_{x_r(k),x_i(k)}(dy_r dy_i)$ denotes complex conjugate, since we assume for now that we are dealing with complex signals, and p x_r(k),x_i(k),x_r (l),x_i (l)(y_r,y_i,z_r,z_i) is the joint probability density function of the random variables *x(k)* and *x(l)*.For complex signals, the autoco variance function is defined as:

$$\sigma_x^2(k,l) = E\{[x(k) - m_x(k)][x(k)]^*\} = r_x(k,l) - m_x(k)m_x^*(l) \quad \text{(II.28)}$$

II.4 THE CORRELATION MATRIX [1]

Usually, adaptive filters utilize the available input signals at instant in their updating equations. These inputs are the elements of the input signal vector denoted by

$$x(k) = [x_0(k)x_1(k) \ldots\ldots x_N(k)]^T \quad \text{(II.29)}$$

The correlation matrix is defined as **R** = $E[x(k)x^H(k)]$ where $x^H(k)$ is the Hermitian transposition of ***x(k)***, that means transposition followed by complex conjugation or vice versa. As will be noted, the characteristics of the correlation matrix play a key role in the understanding of properties of most adaptive filtering algorithms. As a consequence, it is important to examine the main properties of the matrix **R**. Some properties of the correlation matrix come from the statistical nature of the adaptive filtering problem, whereas other properties derive from the linear algebra theory.

For a given input vector, the correlation matrix is given by:

$$R = \begin{bmatrix} E[|x_0(k)|]^2 & E[x_0(k)x_1^*(k)] & \dots & E[x_0(k)x_N^*(k)] \\ E[x_1(k)x_0^*(k) & E[|x_1(k)|]^2 & \cdots & E[x_1(k)x_N^*(k)] \\ \vdots & \vdots & \ddots & \vdots \\ E[x_N(k)x_0^*(k) & E[x_N(k)x_1^*(k) & \cdots & E[|x_N(k)|]^2 \end{bmatrix}$$

$$= E[x(k)x^H(k)] \qquad \text{(II.30)}$$

The main properties of the R matrix are the matrix R is positive semi definite.

Proof Given an arbitrary complex weight vector w, we can form a signal given by:

$$y(k) = w^H x(k)$$

The magnitude squared of $y(k)$ is:

$$y(k)y^* = |y(k)|^2 = w^H x(k) x^H(k) \geq 0$$

The mean-square (MS) value of y(k) is then given by:

$$MS[y(k)] = E[|y(k)|^2] = w^H E[x(k)x^H(k)]w = w^H R w \geq 0$$

Therefore, the matrix R is positive semi definite. Usually, the matrix R is positive definite, unless the signals that compose the input vector are linearly dependent. Linear-dependent signals are rarely found in practice.

1. The matrix R is Hermitan, i.e:

$$R = R^H \qquad \text{(II.31)}$$

Proof:

$$R^H = E\{[x(k)x^H(k)]^H\} = E[x(k)x^H(k)] = R^H$$

2. A matrix is To eplitz if the elements of the main diagonal and of any secondary diagonal are equal. When the input signal vector is composed of delayed versions of the same signal *(i.e., xi(k) = x0(k−i),for i=1,2,...,N*) taken from a WSS process, matrix R is Toeplitz .

Proof:

For the delayed signal input vector, with x(k)WSS, matrix R has the following form:

$$R = \begin{bmatrix} r_x(0) & r_x(1) & \cdots & r_x(N) \\ r_x(-1) & r_x(0) & \cdots & r_x(N-1) \\ \vdots & \vdots & \ddots & \vdots \\ r_x(-N) & r_x(-N+1) & \cdots & r_x(0) \end{bmatrix} \quad \text{(II.32)}$$

II.5 DIGITAL FILTERING [2]

In signal processing, a digital filter is a system that performs mathematical operations on a sampled, discrete-time signal to reduce or enhance certain aspects of that signal and in this section we will see why we need filtering From the situation shown in Figure II.5, depicting a digitized noisy signal obtained from digitizing analog voltages (sensor output) containing a useful low-frequency signal and noise that occupies all of the frequency range. After ADC, the digitized noisy signal x(n), where is the sample number ,can be enhanced using digital filtering. Since our useful signal contains the low-frequency component, the high-frequency components above that of our useful signal are considered as noise, which can be removed by using a digital low pass filter. We set up the DSP block in Figure II.5 to operate as a simple digital low pass filter. After processing the digitized noisy signal x(n), the digital low pass filter produces a clean digital signal y(n). We can apply the cleaned signal y(n) to another DSP algorithm for a different application or convert it to the analog signal via DAC and the recon-struction filter. The digitized noisy signal and clean digital signal, respectively, are plotted in Figure II.6, where the top plot shows the digitized noisy signal, while the bottom plot demonstrates the clean digital signal obtained by applying the digital low-pass filter. Typical applications of noise filtering include acquisition of clean

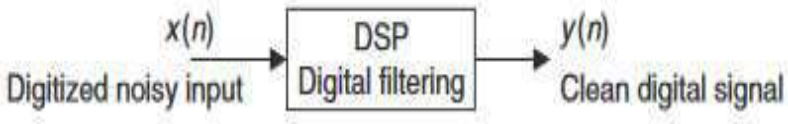


Figure II.5 digital filtering

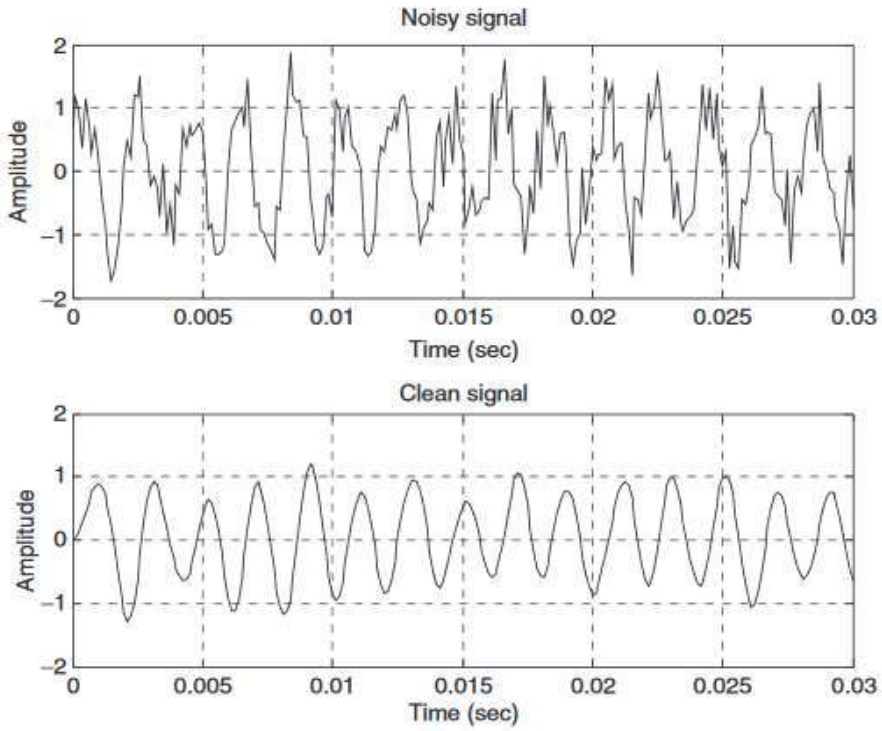


Figure II.6 noisy signal before and after filtering

II.5.1 SIGNAL FREQUENCY (SPECTRUM) ANALYSIS

Spectral analysis studies the frequency spectrum contained in discrete, uniformly sampled data. The Fourier transform is a tool that reveals frequency components of a time- or space-based signal by representing it in frequency space. A digitized audio signal and its calculated signal spectrum (frequency content), defined as the signal amplitude versus its corresponding frequency for the time being via a DSP algorithm, called fast Fourier transform (FFT) [2]

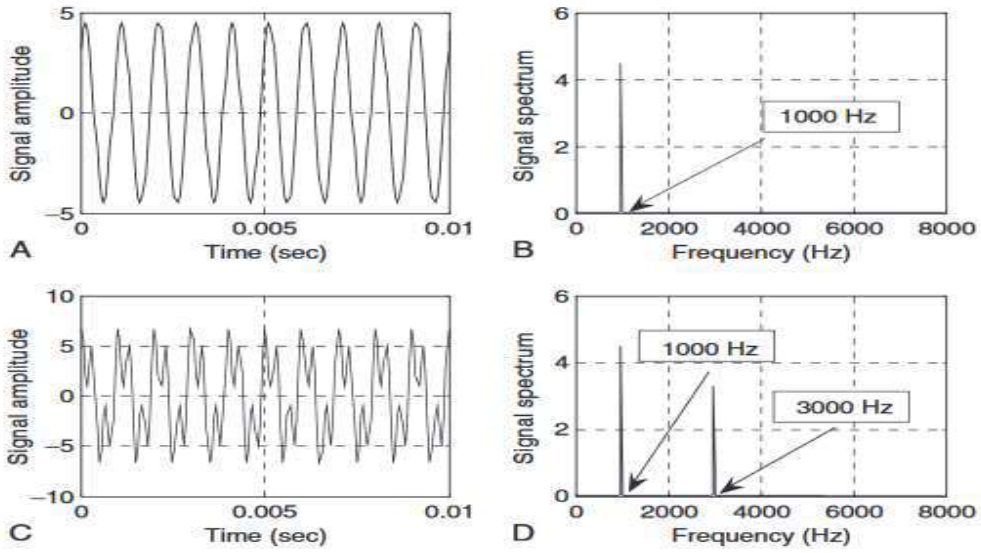


Figure II.7 Audio signals and their spectrums.

As show in figure above plot (a) is a time domain display of the recorded audio signal with a frequency of 1,000 Hz and plot (b) displays the calculated signal spectrum versus frequencies, in which the peak amplitude is clearly located at 1,000 Hz.

From the plot (c) we see a noisy signal and if we want to remove the noise we can take from calculated signal spectrum that shown in Plot (d) we have two locations (1,000 Hz and 3,000 Hz) so we can use for example a low pass filter to reduce the noise.

II.6 FIR AND IIR[3]

II.6.1 FIR FILTERS

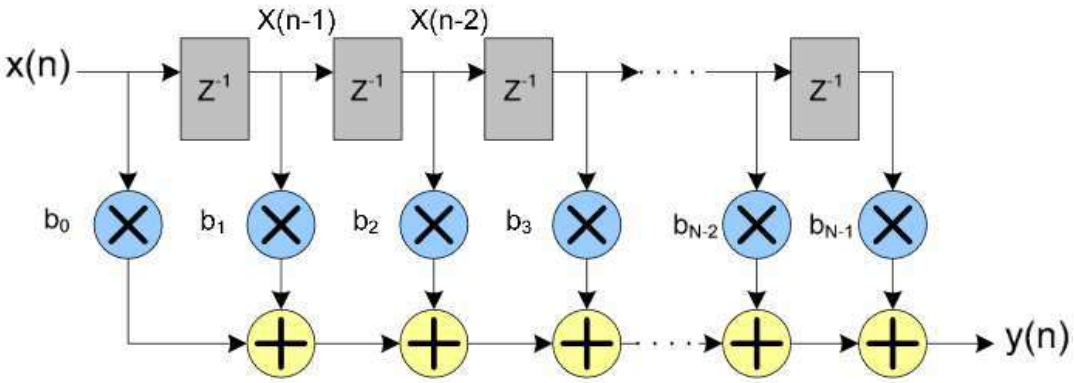


Figure II.8 FIR filter structure

The difference equation for the FIR filter is as follows:

$$Y(n) = \sum_{i=0}^{p} b_i x(n-i) \qquad \text{(II.33)}$$

$y(n)$ = output sample at time n

$x(n)$ = input sample at time n

P = order of the filter (# of delay elements) = # of taps -1

b_i= filter coefficients

II.6.1.1 TRANSFER FUNCTION

The transfer function can define by the equation below:

$$H(z)=\sum_{i=0}^{p} b_i z^{-1} \quad \text{(II.34)}$$

II.6.1.2 KEY ATTRIBUTES

The key attributes of an FIR filter are as follows:

- FIR filters have no analog equivalent.
- FIR filters can only be implemented as an “all-zero” filter, since the FIR has no poles.
- FIR filters are therefore inherently stable, since their poles are located at the origin in the z-plane.
- FIR filters have a linear phase response if their filter taps are symmetrical about the center tap position. This results in zero phase distortion in the filter output.
- FIR filters can achieve very high roll-off rates when a large number of taps are used. More taps increase the steepness of the filter roll-off while also increasing calculation time (delay) and for high order filters, limiting bandwidth.
- FIR filters are insensitive to coefficient quantization errors since they are non-recursive.
- FIR filters have no limit cycle issues.
- FIR filters are easy to design and can be implemented using fractional coefficients, which makes fixed point calculations easier.

II.6.2 IIR FILTERS

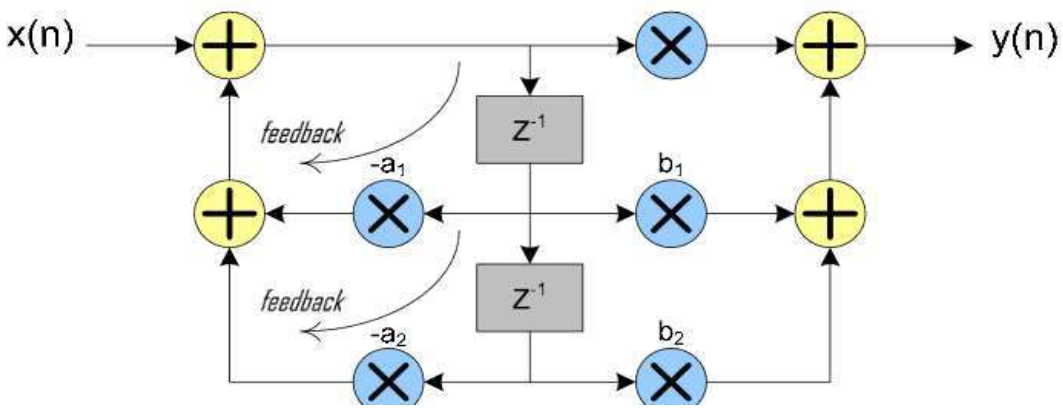


Figure II.9 IIR filter structure

$$Y(n)=\sum_{i=0}^{p} b_i x(n-i) + \sum_{k=1}^{q} a_k y(n-k) \quad \text{(II.35)}$$

The transfer function in the Z domain for the IIR filter is as follows:

$$H(z)=\frac{\sum_{i=0}^{p} b_i z^{-1}}{1-\sum_{k=1}^{q} a_k z^{-k}} \quad \text{(II.36)}$$

II.6.2.1 KEY ATTRIBUTES

The key attributes of an IIR filter are as follows:

- IIR filters are typically implemented as a digital equivalent of a classical analog filter such as Butterworth, Chebyshev, Bessel, or Elliptical.
- IIR filters can be implemented as an “all-pole” or “pole-zero” filter. The location of the poles determines the stability in IIR filters. (i.e. must be within the Z plane unit circle to be stable)
- IIR filters usually have poor phase responses that are very non-linear at the edge of the bands
- IIR filters can achieve high roll-off rates with a minimum number of taps due to feedback.
- IIR filters are high speed due to the small number of MAC cycles that are required.
- IIR filters are difficult to design for high orders (8 max) due to stability issues that arise from the effects of finite precision math.
- IIR filters are very sensitive to coefficient quantization errors that occur due to using a finite number of bits to represent the filter coefficients
- IIR filters are very sensitive to rounding effects introduced by finite precision math operations, which could result in limit cycles, which are never-ending low amplitude oscillations in the output value of the filter.
  - IIR filter latency = 1 sample period

II.6.3 REALIZATION OF DIGITAL FILTERS [4]

In this section, basic realization methods for digital filters are discussed. Digital filters described by the transfer function H(z) may be generally realized in the following forms:

- Direct form I
- Direct form II
- Cascade

- Parallel.

II.6.3.1 DIRECT-FORM I REALIZATION [4]

As we know, a digital filter transfer function, $H(z)$, is given by

$$\mathrm{H(z)} = \frac{\mathrm{B(Z)}}{\mathrm{A(Z)}} = \frac{\mathrm{b_0 + b_1 Z^{-1} + \cdots + b_M Z^{-M}}}{\mathrm{1 + a_1 Z^{-1} + \cdots + a_N z^{-N}}} \quad \text{(II.37)}$$

Let *x(n)* and *y(n)* be the digital filter input and output, respectively. We can express the relationship in z-transform domain as

$$\mathrm{Y(Z) = H(z).X(z)} \quad \text{(II.38)}$$

where $X(z)$ and $Y(z)$ are the z-transforms of $x(n)$ and $y(n)$, respectively. If we substitute Equation (II.37) into $H(z)$ in Equation (II.38), we have

$$\mathrm{Y(z)} = \left(\frac{\mathrm{b_0 + b_1 Z^{-1} + \cdots + b_M Z^{-M}}}{\mathrm{1 + a_1 Z^{-1} + \cdots + a_N z^{-N}}}\right).\mathrm{X(z)} \quad \text{(II.39)}$$

Taking the inverse of the z-transform of Equation (II.39), we yield the relationship between input *x(n)* and output *y(n)* in time domain, as follows:

$$\mathrm{y(n) = b_0 x(n) + b_1 x(n-1) + \cdots + b_M x(n-M) - a_1 y(n-1) - a_2 y(n-2) - \cdots - a_M y(n-N)} \quad \text{(II.40)}$$

This difference equation thus can be implemented by a direct-form I realization shown in Figure II.10 (a). Figure II.10 (b) illustrates the realization of the second-order IIR filter

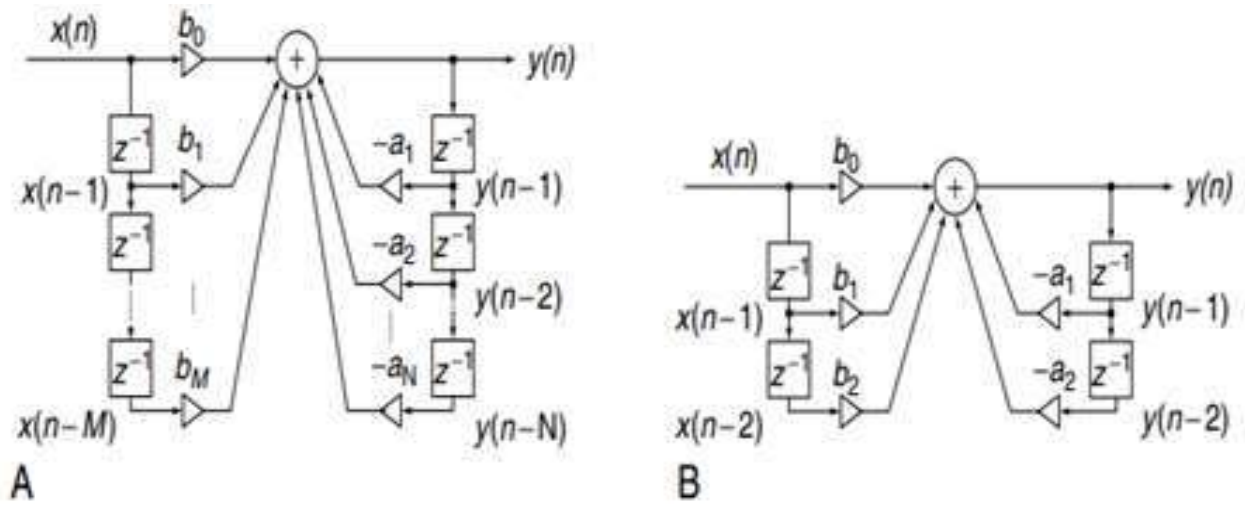


Figure II.10(A) Direct-form I realization.(B) Direct-form I realization with M = 2.

II.6.3.2 DIRECT-FORM II REALIZATION [4]

Considering Equations (II.37) and (II.38) with N = M, we can express

$$Y(z) = H(z)X(z) = \frac{B(z)}{A(z)}X(z) = B(z)\left(\frac{X(z)}{A(z)}\right)$$

$$= (b_0 + b_1 z^{-1} + \cdots + b_M z^{-M})\left(\frac{X(z)}{1+a_1 Z^{-1}+\cdots+a_M z^{-M}}\right) \quad \text{(II.41)}$$

Also, defining a new z-transform function as

$$w(z) = \frac{X(z)}{1+a_1 Z^{-1}+\cdots+a_M z^{-M'}} \quad \text{(II. 42)}$$

we have

$$Y(z) = (b_0 + b_1 z^{-1} + \cdots + b_M z^{-M})W(z) \quad \text{(II. 43)}$$

The corresponding difference equations for Equations (II.42) and (II.43), respectively, become

$$w(n) = x(n) - a_1 w(n-1) - a_2 w(n-2) - \cdots - a_M w(n-M) \quad \text{(II.44)}$$

and

$$y(n) = b_0 w(n) + b_1 w(n-1) + \cdots + b_M w(n-M) \quad \text{(II. 45)}$$

The realization of Equations (II.44) and (II.45) becomes another direct-form II realization, which is demonstrated in Figure II.11(a). Again, the corresponding realization of the second-order IIR filter is described in Figure II. (b). Note that in Figure II.(a), the variables *w(n), w(n − 1), w(n − 2), ... , w(n − M)* are different from the filter inputs *x(n −1), x(n − 2), ... , x(n − M).*

II.6.3. 3 CASCADE (SERIES) REALIZATION

An alternate way to filter realization is to cascade the factorized H(z) in the following form:

$$H(z) = H_1(z)H_2(z) \ldots H_k(z) \quad \text{(II.46)}$$

where $H_k(z)$ is chosen to be the first- or second-order transfer function (section), which is defined by:

$$H_k(z) = \frac{b_{k0}+b_{k1}z^{-1}}{1+a_{k1}z^{-1}} \quad \text{(II.47)}$$

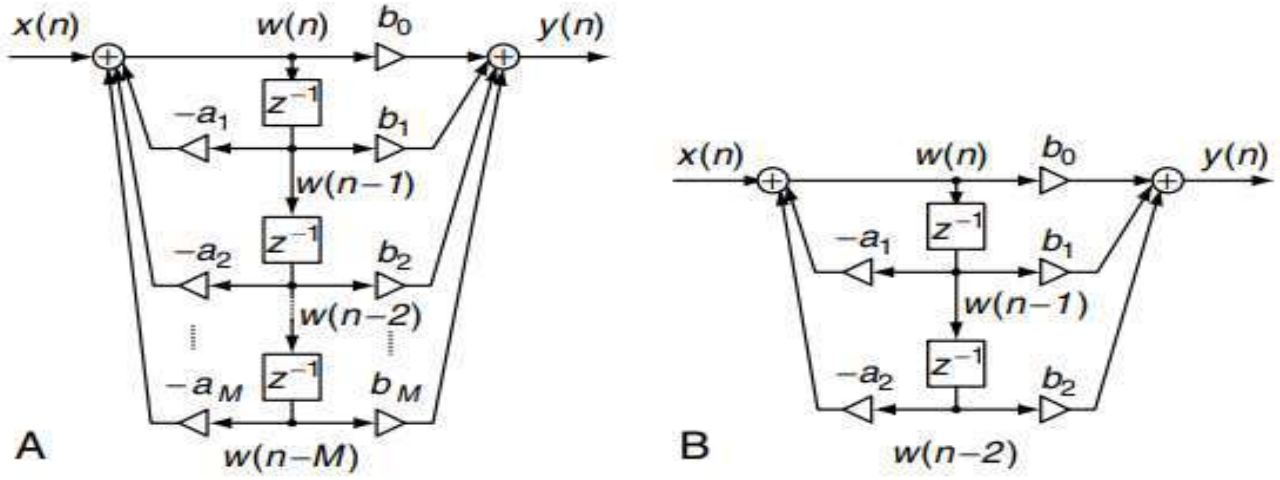


Figure II.11 (A) Direct-form II realization. (B) Direct-form II realization with M = 2.

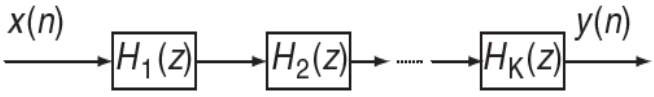


Figure II.12 Cascade realization.

Or:

$$H_k(z) = \frac{b_{k0}+b_{k1}z^{-1}+b_{k2}z^{-2}}{1+a_{k1}z^{-1}+a_{k2}z^{-2}} \quad \text{(II.48)}$$

respectively. The block diagram of the cascade, or series, realization is depicted in Figure II. 12.

II.6.3.4 PARALLEL REALIZATION

Now we convert H(z) into the following form:

$$H(z) = H_1(z) + H_2(z) + \cdots + H_k(z) \quad \text{(II.49)}$$

Where Hk(z) is defined as the first- or second-order transfer function (section) given by

$$H_k(z) = \frac{b_{k0}}{1+a_{k1}z^{-1}} \quad \text{(II.50)}$$

Or

$$H_k(z) = \frac{b_{k0}+b_{k1}z^{-1}}{1+a_{k1}z^{-1}+a_{k2}z^{-2}} \quad \text{(II. 51)}$$

II.7 WIENER FILTER [1]

One of the most widely used objective functions in adaptive filtering is the MSE defined as:

$$F\,[e(k)] = \xi(k) = E[e^2(k)] = E[d^2(k) - 2d(k)y(k) + y^2(k) \quad \text{(II.52)}$$

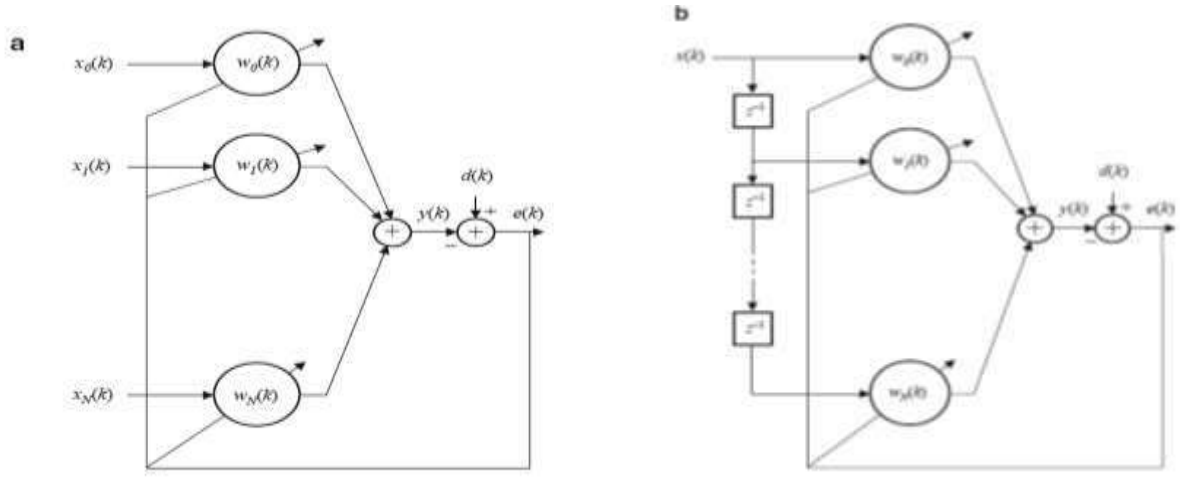


Figure II.13 a) Linear combiner; **b)** Adaptive FIR filter

where *d(k)* is the reference signal as illustrated.

Suppose the adaptive filter consists of a linear combiner, i.e., the output signal is composed of a linear combination of signals coming from an array as depicted in Figuer. II.13 In this case,

$$y(k)=N\sum_{i=0}^{N} = w_i(k)x_i(k) = w^T(k)x(k) \quad \text{(II.53)}$$

where $x(k) = [x_0(k)x_1(k) \dots x_N(k)]^T$ and $w(k) = [w_0(k)w_1(k) \dots w_N(k)]^T$ are the input signal and the adaptive filter coefficient vectors, respective

Many applications, each element of the input signal vector consists of a delayed version of the same signal, that is $x_0(k) = x(k), x_1(k) = x(k-1), \dots, x_N(k) = x(k-N)$. Note that in this case the signal y(k)is the result of applying an FIR filter to the input signal *x(k)*.

The most straightforward realization for the adaptive filter is through the direct-form FIR structure as illustrated in Figuer II.13, with the output given by:

$$y(k)=N\sum_{i=0}^{N} w_i(k)x(k-i) = w^T(k)x(k) \quad \text{(II.54)}$$

where $x(k) = [x(k)x(k-1) \dots x(k-N)$ it's the input vector representing a tapped-delay line, and $w(k) = [w_0(k)w_1(k) \dots w_N(k)]^T$ is the tap-weight vector .In both the linear combiner and FIR filter cases, the objective function can be rewritten as

$$E[e^2(k)] = \xi(k$$

$$= E[d^2(k) - 2d(k)w^Tx(k) + w^Tx(k) + x^T(k)w(k)$$

$$= E[d^2(k)] - 2E[d(k)w^T(k)x(k)] + E[w^T(k)x(k)x^T(k)w(k)] \quad \text{(II.55)}$$

For a filter with fixed coefficients, the MSE function in a stationary environment is given by

$$\xi = E[d^2(k)] - 2w^TE[d(k)x(k)] + w^TE[x(k)x^T(k)]w$$

$$= E[d^2(k) - 2w^T\mathbf{p} + w^T\mathbf{R}\mathbf{w} \quad \text{(II.56)}$$

the cross-correlation vector between the desired and input signals, and$R = E[x(k)x^T(k)]$is the input signal correlation matrix. As can be noted, the objective function ξ is a quadratic function of the tap-weight coefficient s which would allow a straightforward solution for w that minimizes ξ , if vector p and matrix are known. Note that matrix R corresponds to the Hessian matrix of the objective function .The gradient vector of the MSE function related to the filter tap-weight coefficients is given by

$$g_w = \frac{\partial \xi}{\partial w}\left[\frac{\partial \xi}{\partial w0} \quad \frac{\partial \xi}{\partial w1} \quad \frac{\partial \xi}{\partial wN}\right]^T = -2\mathbf{p} + 2\mathbf{R}\mathbf{w} \quad \text{(II.57)}$$

By equating the gradient vector to zero and assuming R is nonsingular, the optimal values for the tap-weight coefficients that minimize the objective function can be evaluated as follows:

$$Wo = R^{-1}P \quad \text{(II.58)}$$

This solution is called the Wiener solution. Unfortunately, in practice, precise estimations of Rand p are not available. When the input and the desired signals are ergodic, one is able to use time averages to estimate Rand p, what is implicitly performed by most adaptive algorithms.

If we replace the optimal solution for **w** in the MSE expression, we can calculate the minimum MSE provided by the Wiener solution

$$\xi_{min}= E[d^2(k)] -2w_0^T p+w_0^T RR^{-1}p \quad = E[d^2(k)]- \ w_0^T p \tag{II.59}$$

The above equation indicates that the optimal set of parameters removes part of the power of the desired signal through the cross-correlation between *x(k)* and *d(k)*, assuming both signals stationary. If the reference signal and the input signal are orthogonal, the optimal coefficients are equal to zero and the minimum MSE is $E[d^2(k)]$. This result is expected since nothing can be done with the parameters in order to minimize the MSE if the input signal carries no information about the desired signal. In this case, if any of the taps is nonzero, it would only increase the MSE.

An important property of the Wiener filter can be deduced if we analyze the gradient of the error surface at the optimal solution. The gradient vector can be expressed as follows:

$$g_w= \frac{\partial E[e2(k)]}{\partial w} = E[2_e(k)\frac{\partial e(k)}{\partial w} = -E[2_e(k)x(k)] \tag{II.60}$$

With the coefficients set at their optimal values, i.e., at the Wiener solution, the gradient vector is equal to zero, implying that

$$E[e(k)x(k)] = 0 \tag{II.61}$$

Or:

$$E[e(k)x(k-1)] = 0 \tag{II.62}$$

For $i = 0, 1, \ldots, N$. This means that the error signal is orthogonal to the elements of the input signal vector. In case either the error or the input signal has zero mean, the orthogonality property implies that *e(k)* and *x(k)* are uncorrelated.

The orthogonality principle also applies to the correlation between the output signal *y(k)* and the error *e(k)*, when the tap weights are given by $\boldsymbol{w = w_0}$. By pre multi plying (2.61) by w_0^T the desired result follows:

$$E[e(k)\, w_0^T x(k)] = E[e(k)y(k)] = 0 \tag{II.63}$$

The gradient with respect to a complex parameter has not been defined. For our purposes, the complex gradient vector can be defined as:

$$g_{w(k)} = \{F(e(k))\} = \frac{1}{2}\left\{\frac{\partial F[e(k)}{\partial re[w(k)]} - j\,\frac{\partial F[e(k)]}{\partial im[w(k)]}\right\}$$

where re[·] and im[·] indicate real and imaginary parts of [·], respectively. Note that the partial derivatives are calculated for each element of **w***(k)*.

For the complex case, the error signal and the MSE are, respectively, described by:

$$e(k) = d(k) - w^H(k)x(k) \qquad \text{(II.64)}$$

and

$$\begin{aligned}\xi &= E[|e(k)|^2] \\ &= E[|d(k)|2] - 2re\{w^H E[d^*(k)x(k)]\} + w^H E[x(k)x^H(k)]W \\ &= E[|d(k)|2] - 2re\{w^H p] + w^H Rw \qquad \text{(II.65)}\end{aligned}$$

Where $p = E[d^*(k)x(k)]$ is the cross-correlation vector between the desired and input signals, and $R = E[x(k)x^H(k)]$ is the input signal correlation matrix.

II.8 NEWTON ALGORITHM

In the context of the MSE minimization discussed in the previous section, the coefficient-vector updating using the Newton method is performed as follows:

$$W(k+1) = w(k) - \mu R^{-1} g_w(k) \qquad \text{(II.66)}$$

II.9 ADAPTIVE FILTERS

II.9.1 LMS ALGORITHM (LEAST MEAN SQUARES)

II.9.1.1 INTRODUCTION

The least-mean-square (LMS) is a search algorithm in which a simplification of the gradient vector computation is made possible by appropriately modifying the objective function The review explains the history behind the early proposal of the LMS algorithm, whereas places into perspective the importance of this algorithm.

The LMS algorithm, as well as others related to it, is widely used in various applications of adaptive filtering due to its computational simplicity. The convergence characteristics of the LMS algorithm are examined in order to establish a range for the convergence factor that will guarantee stability. The convergence speed of the LMS is shown to be dependent on the eigen value spread of the input signal correlation matrix.

II.9.1.2 THE LMS ALGORITHM

The optimal solution for the parameters of the adaptive filter implemented through a linear combiner, which corresponds to the case of multiple input signals. This solution leads to the minimum mean-square error in estimating the reference signal *d(k)*. The optimal (Wiener) solution is given by:

$$w_0 = R^{-1} p \qquad \text{(II.67)}$$

where p = E [x(k) x^T(k)] and p = E [d(k) x(k)], assuming that d(k) and **x**(k) are jointly WSS. If good estimates of matrix ***R***, denoted by $\hat{\mathbf{p}}(k)$, and of vector **p**, denoted by $\hat{\mathbf{p}}$ *(k)*, are available, a steepest-descent-based algorithm can be used to search the Wiener solution of (II.67) as follows:

$$W(k) = w(k) - \mu \hat{g}_w(k) \qquad = w(k) + 2\mu(\hat{p}(k) - \hat{R}(k)w(k)) \qquad \text{(II.68)}$$

for $k = 0, 1, 2, \ldots$, where $\hat{g}\mathbf{w}(k)$ represents an estimate of the gradient vector of the objective function with respect to the filter coefficients. One possible solution is to estimate the gradient vector by employing instantaneous estimates for **R** and **p** as follows:

$$\hat{R}(k) = x(k)x^T(k)$$
$$\hat{P}(k) = d(k)x(k) \qquad \text{(II.69)}$$

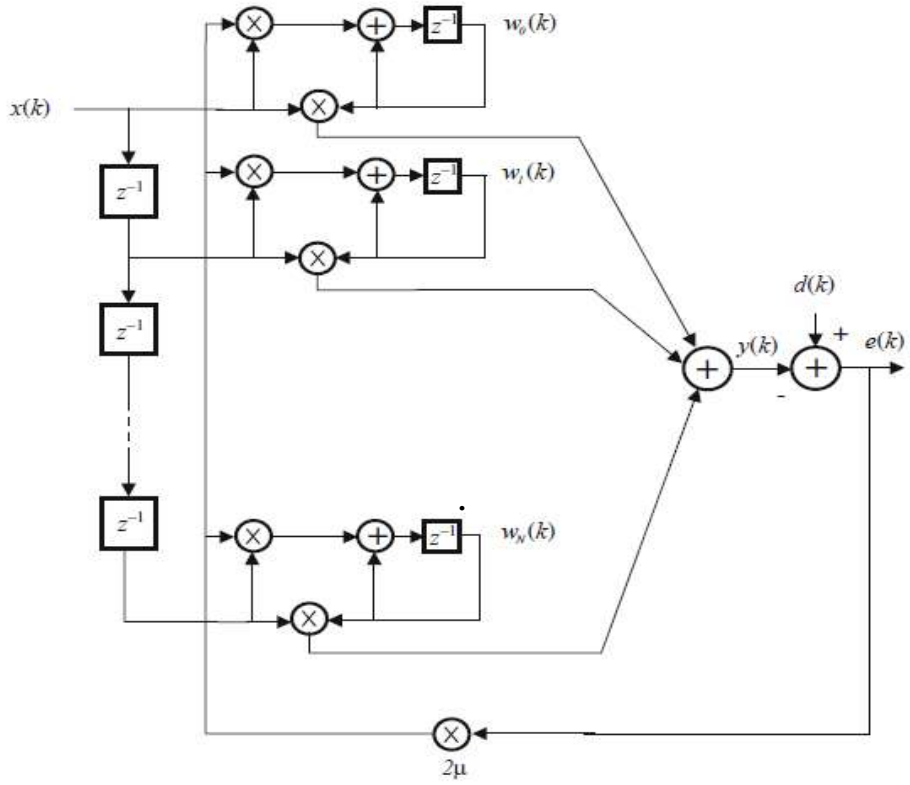


Figure II.14 LMS adaptive FIR filter

The resulting gradient estimate is given by

$$\hat{g}_w = -2d(k)x(k) + 2x(k)x^T(k)w(k) = 2x(k)(-d(k) + x^T(k)w(k) = 2e(k)x(k) \quad \text{(II.70)}$$

Note that if the objective function is replaced by the instantaneous square error $e^2(k)$, instead of the MSE, the above gradient estimate represents the true gradient vector since:

$$\frac{\partial e^2(k)}{\partial w} = [2e(k)\frac{\partial e(k)}{\partial w_0}\ 2e(k)\frac{\partial e(k)}{\partial w_1} \ldots \ldots 2e(k)\frac{\partial e(k)}{\partial w_N(k)}]^T = -2e(k)x(k) = \hat{g}_w(k \quad \text{(II.71)}$$

The resulting gradient-based algorithm is known as the least-mean-square (LMS) algorithm, whose updating equation is:

$$W(k+1) = w(k) + 2\mu e(k)x(k) \quad \text{(II.72)}$$

II.9.2 RLS ALGORITHM

II.9.2.1 INTRODUCTION

Least-squares algorithms aim at the minimization of the sum of the squares of the difference between the desired signal and the model filter output. When new samples of the incoming signals are received at every iteration, the solution for the least-squares problem can be computed in recursive form resulting in the recursive least-squares (RLS) algorithms.
The RLS algorithms are known to pursue fast convergence even when the eigen value spread of the input signal correlation matrix is large. These algorithms might have competitive performance when working in time-varying environments, depending on the unknown parameters model

II.9.2.2 THE RECURSIVE LEAST-SQUARES ALGORITHM

The objective here is to choose the coefficients of the adaptive filter such that the output signal *y(k)*, during the period of observation, will match the desired signal as closely as possible in the least-squares sense. The minimization process requires the information of the input signal available so far. Also, the objective function we seek to minimize is deterministic. The generic FIR adaptive filter realized in the direct form is shown in Figuer. II.15.The input signal information vector at a given instant *k* is given by

$$x(k) = [x(k)x(k-1)\ldots\ldots x(k-N)]^T \qquad \text{(II.73)}$$

Where *N* is the order of the filter. The coefficients *wj (k)*, for $j = 0, 1, \ldots, N$, are adapted aiming at the minimization of a given objective function. In the case of least-squares algorithms, the objective function is deterministic and is given by

$$\xi^d(k) = \sum_{i=0}^{k} \lambda^{k-i}\, \varepsilon^2(i) \qquad = \sum_{i=0}^{k} \lambda^{k-i}\, [d(i) - x^T(i)w(k)]^T \qquad \text{(II.74)}$$

Where $\mathbf{w}(k) = [\, w_0(k)\, w_1(k)\ldots\ldots\, w_N(k)]^T$ is the adaptive filter coefficient vector and $\varepsilon(i)$ is the a posteriori output error at instant i . The parameter λ is an exponential weighting factor that should be chosen in the range $0 \ll \lambda \leq 1$ This parameter is also called forgetting factor since the information of the distant past has an increasingly negligible effect on the coefficient updating.

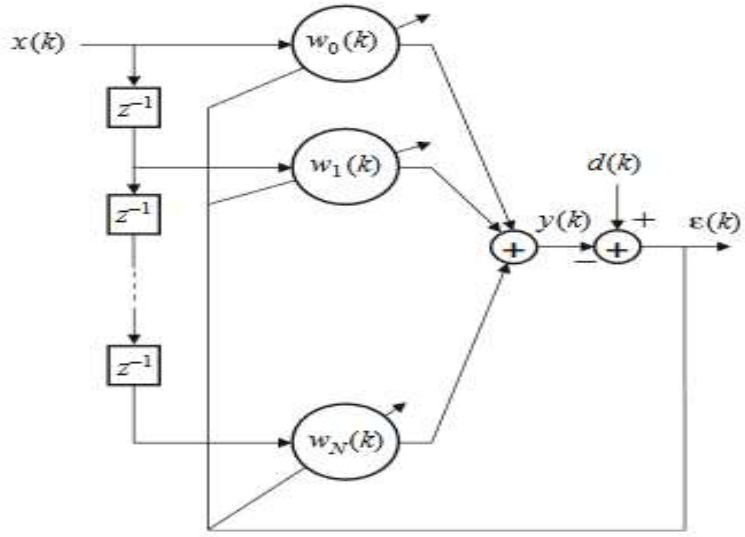


Figure II.15 Adaptive FIR filter

It should be noticed that in the development of the LMS and LMS-based algorithms, we utilized the a priori error. In the RLS algorithms, ε(k)is used to denote the a posterior error where ease(k)denotes the a priori error. The a posterior error will be our first choice in the development of the RLS-based algorithms .As can be noted, each error consists of the difference between the desired signal and the filter output, using the most recent coefficients w(k). By differentiating ξ d(k)with respect tow(k) , it follows that:

$$\frac{\partial \xi^{d}(k)}{\partial w(k)} = -2\sum_{i=0}^{k}\lambda^{k-i}\,x(i)\,[\,d(i) - x^{T}(i)w(k)] \qquad \text{(II.75)}$$

By equating the result to zero, it is possible to find the optimal vector w(k)that minimizes the least-squares error, through the following relation

$$-\sum_{i=0}^{k}\lambda^{k-i}x(i)x^{T}(i)w(k) + \sum_{i=0}^{k}\lambda^{k-i}\,x(i)d(i) = \begin{matrix}0\\0\\0\end{matrix} \qquad \text{(II.76)}$$

The resulting expression for the optimal coefficient vector w(k)is given by

$$w(k)=[\,\sum_{i=0}^{k}\lambda^{k-i}x(i)x^{T}(i)]^{-1}\sum_{i=0}^{k}[\lambda^{k-i}x(i)d(i)] = R_{D}^{-1}(k)P_{D}(k) \qquad \text{(II.77)}$$

The straightforward computation of the inverse of $R_D(k)$ results in an algorithm with computational complexity of O[N3].In the conventional RLS algorithm, the computation of the inverse matrix is avoided through the use of the matrix inversion lemma [1], first presented in the previous chapter for the LMS–Newton algorithm. Using the matrix inversion

lemma, the inverse of the deterministic correlation matrix can then be calculated in the following form

$$S_D(\mathrm{k}) = R_d^{-1}(\mathrm{k}) = \frac{1}{\lambda}[S_D\ (\mathrm{k}-1) - \frac{D(k-1)x(k)xT(k)SD(k-1)}{\lambda+xT(k)SD(k-1)x(k)}]$$

The complex RLS algorithm that we use is given below.

$$\left[\sum_{i=0}^{k} \lambda^{k-i} x(i)x^T(i)\right] \mathrm{w(k)} = \lambda\left[\sum_{i=0}^{k-1} \lambda^{k-i-1} x(i)d(i)\right] + x(k)d(k) \qquad \text{(II.78)}$$

By considering that $R_D(k-1)w(k-1) = P_D(k-1)$, it follows that:

$$\left[\sum_{i=0}^{k} \lambda^{k-i} x(i)x^T(i)\right] \mathrm{w(k)} = \lambda P_D(k-1) + x(k)d(k)$$

$$= \lambda R_D(K-1)w(k-1)x(k)d(k)$$

$$= \left[\sum_{i=0}^{k} \lambda^{k-i} x(i)x^T(i) - x(k)x^T(k)\right]\mathrm{w(k\text{-}1)} + x(k)d(k) \qquad \text{(II.79)}$$

Where in the last equality the matrix $\mathrm{x(k)}x^T(k)$ was added and subtracted inside square bracket on the right side of (2.84). Now, define the a priori error as

$$\mathrm{e(k)} = d(k) - x^T(k)w(k-1) \qquad \text{(II.80)}$$

By expressing *d(k)* as a function of the a priori error and replacing the result in (2.84), after few manipulations, it can be shown that

$$\mathrm{w(k)} = \mathrm{w(k-1)} + \mathrm{e(k)S_D(k)x(k)} \qquad \text{(II.81)}$$

With (2.86), it is straightforward to generate an alternative conventional RLS algorithm as shown in Algorithm 2.79. In Algorithm 2.79, ***ψ(k)*** is an auxiliary vector required to reduce the computational burden defined by

$$\psi(\mathrm{k}) = \mathrm{S_D(k-1)x(k)} \qquad \text{(II.82)}$$

Further reduction in the number of divisions is possible if an additional auxiliary vector is used, defined as

$$\Phi(k) = \frac{\psi(k)}{\lambda + \psi^T(k)x(k)} \quad \text{(II.83)}$$

This vector can be used to update $S_D(k)$as follows:

$$S_D(k) = \frac{1}{\lambda}\left[S_D(k-1) - \psi(k)\,\Phi^T(k)\right] \quad \text{(II.84)}$$

II.10 CONCLUSION

In this chapter we saw some concept about signal processing to let us be able to understand what digital filters means secondly we took a look about the difference between FIR and IIR filters we introduced some concept about adaptive filters the winner solution, Newton algorithm and the two different algorithm LMS and RLS

CHAPTER III

SIMULATION

III.1 INTRODUCTION

In this section we studied how we can receive different forms of radar signals/pulses and filter them with adaptive filters also we investigate the performance of the adaptive filters.

From the simulated radar signals we can understand which adaptive algorithm we can use in real signal radar.

III.2 SIGNAL DATA

In this simulation we use MATLAB to generate the radar signal/pulses we generating three different form of signal first we generate a radar pulses with fixed frequency secondly we generate chirped pulse with varying frequency, finally we use a phase coded pulses called barker code with fixed frequency

However to understand the idea of how simulated radar signals they look like, we give some examples of different radar signals in time domain

III.2.1 RADAR SIGNALS

CW radar transmits an unmodulated sinusoidal RF signal. Although this type of radar can detect the presence of a target and, using the Doppler shift, determine its radial velocity, it cannot determine the range of the target. The reason for this is because there is never any change or “marker” in the signal that allows the radar to measure the round-trip transit time of the signal. In order to allow the radar to determine the range of targets, some periodic change must occur in the transmitted signal. The simplest and most common technique is to transmit pulses of RF energy, rather than a continuous wave

Here the method of generating the pulsed RF signals in the transmitter. A CW RF signal is generated and is subsequently amplitude modulated by a baseband pulse signal. The result consists of pulses of RF energy. Each pulse may contain thousands of cycles of the sinusoidal waveform. Note that the RF pulses are, in a sense, “cut out” of a continuous sinusoidal signal. As a result, the phase relationship of the pulse signal with respect to the CW signal is stable. This type of pulsed RF signal is said to be coherent. [8]

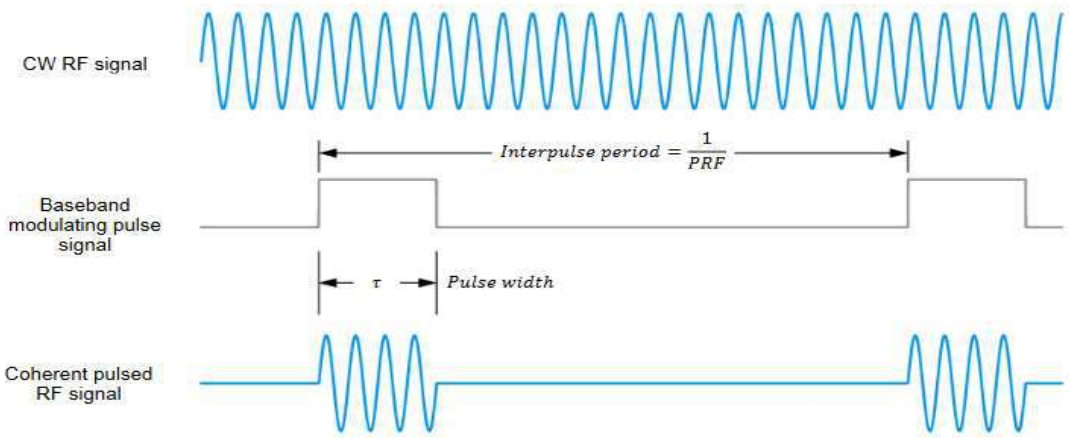


Figure III.1 coherent pulsed RF signal

III.3 RADAR SIGNALS WITH FIXED FREQUENCY COHERENT PULSED RF

We have a radar Coherent pulsed RF in form of signal sinusoidal plus square wave in Figure III.2 we see their representation in time domain, the signal parameters are given in Table III.1. The simulation time, the pulse width and the pulse-repetition-interval

Table III.1 Signal parameters for a fixed pulsed radar signal.

Signal parameter	**Value**
frequency for the pulse	500 MHz
Sampling frequency	1280 MHZ
Amplitude	1
Pulse width	2 us
Pulse-repetition-interval	20 us
Simulation time	100 us

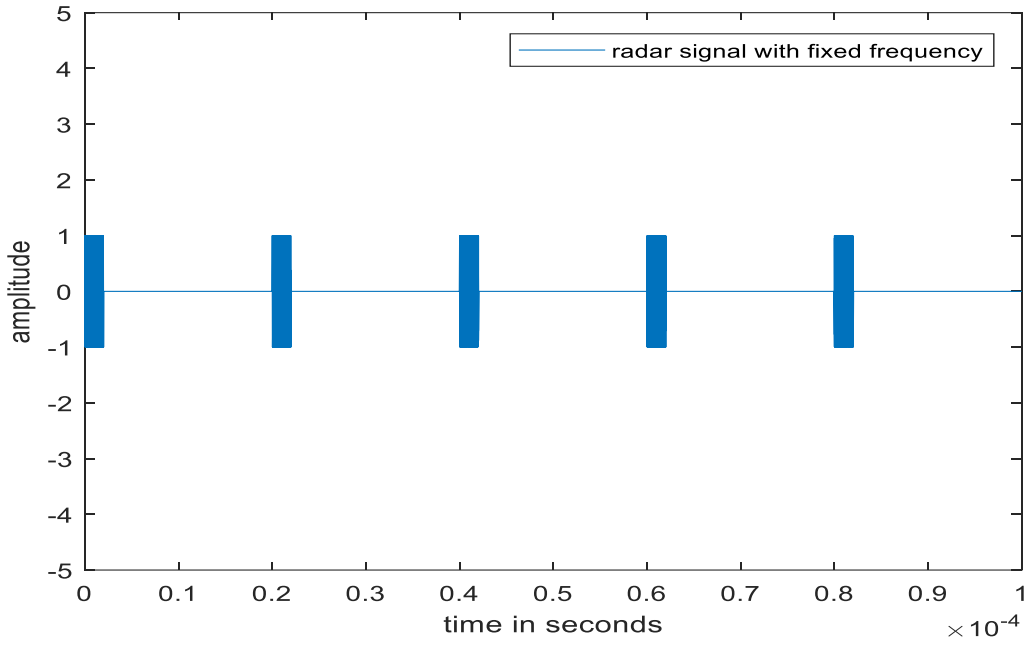


Figure III.2 Radar signals with fixed frequency

III.4 RADAR SIGNALS WITH VARYING FREQUENCY COHERENT PULSED RF

We have a radar Coherent pulsed RF in form of signal sinusoidal plus square wave in Figure III.3 we see their representation in time domain, the signal parameters are given in Table III.2. The simulation time, the pulse width and the pulse-repetition-interval

Table III.2 Signal parameters for a chirped pulsed radar signal.

Signal parameter	**Value**
Start frequency for the pulse	500 MHz
Stop frequency for the pulse	530 MHz
Sampling frequency	1280 MHz
Amplitude	1
Pulse width	2us
Pulse-repetition-interval	20 us
Simulation time	100 us

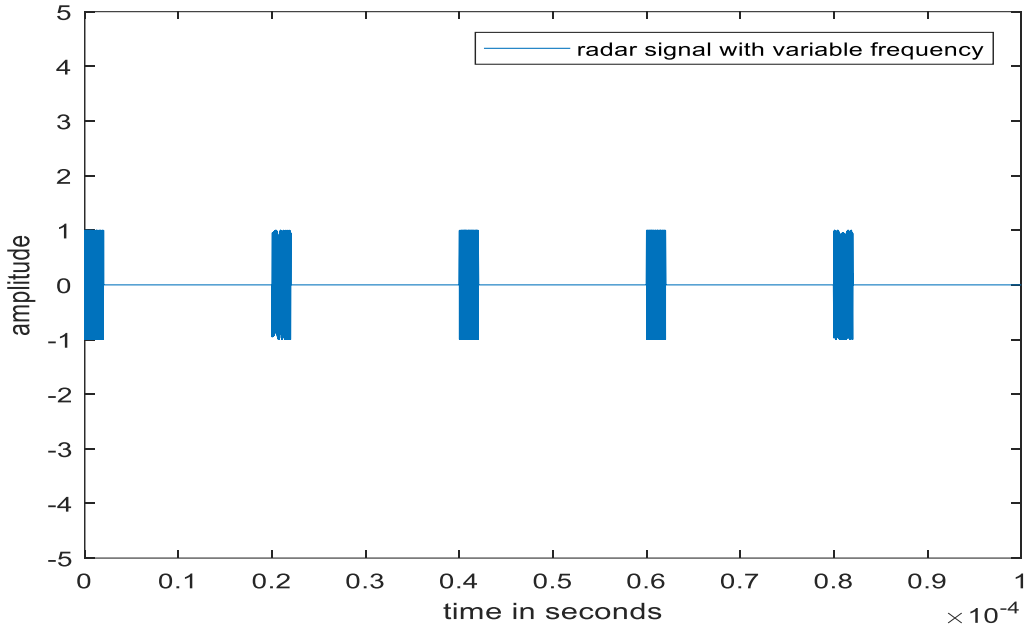


Figure III.3 Radar signal with variable frequency

Because of the highest frequencies that we had we can't see the varying of frequency but if we took an example with low frequencies we can see the variation

The figure below represent radar signal with low varying frequency between 90-360 Hz

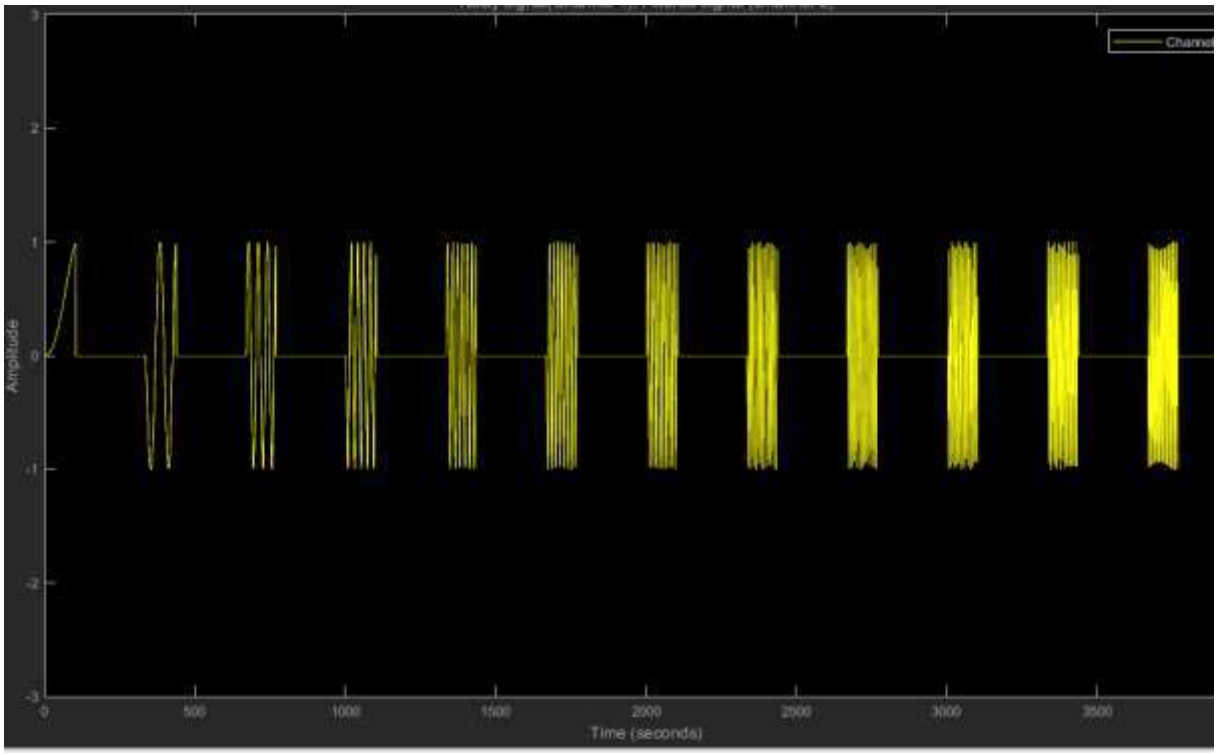


Figure III.4 radar signal with low frequency

III.5 RADAR SIGNALS WITH PHASE CODED PULSES

We have generating a radar signal in form of phased coded pulses we see their representation in time domain in Figure III.5 and the simulation time, the pulse width and the pulse-repetition-interval can easily be verified from table III.3

Table III.3 Signal parameters for a phase coded pulsed radar signal.

Signal parameter	**Value**
frequency for the pulse	25 kHz
Sampling frequency	50 kHz
Amplitude	1
Pulse width	10 ms
Pulse-repetition-interval	20 ms
Simulation time	50 ms

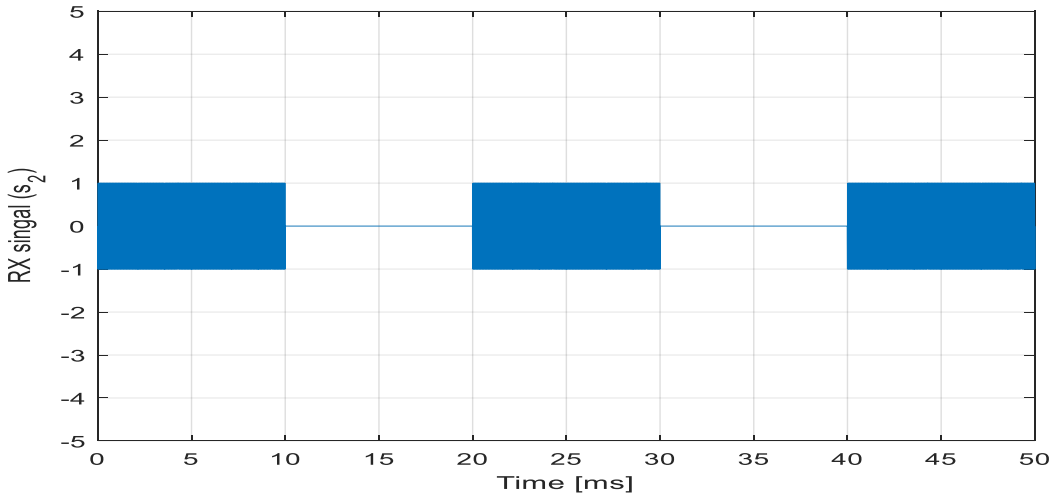


Figure III.5 phase coded pulse

III.6 CALCULATION OF SNR

The SNR is Signal to noise ratio (SNR) is a measurement that compares the power level of a desired signal to the power level of background noise. It is defined in Equation below.

$$\text{SNR}=\frac{P_{SIGNAL}}{P_{NOISE}}$$

If we want the value in decibel it would be

$$SNR_{dB} = 10\log(SNR)$$

As we see to obtain the SNR we must know the value of the power of signal and noise so the method is

By calculating the mean value of the maximum value of the FFT of signals and when we talk about the power of noise It is estimated by taking the average of the magnitude in some frequency bins from the FFT which consists of only noise

In this chapter we calculate the SNR to know how good the adaptive filter can suppress noise. We introduce SNR gain that is defined as the SNR of the signal after the adaptive filter divided by the SNR of the signal before the adaptive filter, The SNR gain in decibel dB is given in Equation below

$$SNR_{gain} = \frac{SNR_{after}}{SNR_{befor}}$$

The SNR gain in decibel

$$SNR_g = SNR_{after} - SNR_{befor}$$

In this simulation we use two different algorithm LMS and RLS and we want to have a perfect SNR gain after the using the adaptive filtering we will start to investigate the filters performance on continuous waves, a single radar pulse.

III.6.1 SNR OF LMS

For the LMS algorithm we have two major factors first step size, small step size results in that the changes of the filter parameters in each time step is small and the steps towards the minimum of the performance surface are short. The filter length L is important to

obtain SNR gain but will also affect the convergence time. The filter length determines the best SNR performance of the adaptive filter can achieve. Just a few filter coefficients will result in a filter not able to give much SNR gain. On the other hand, a long filter requires more samples of the pulse before the adaptive filter will work and converge correctly. Below are table of the SNR gain and the convergence time for different kinds of pulses. The SNR gain and the convergence time depend on the filter length L and the step size. The filter length is going from 10-60. The step size is varied between 0.01, 0.03and 0.05

III.6.1.1 SNR FOR VARIABLE FREQUENCY

The variable frequency pulse signal parameters are given in Table III.2 we look in Table III.4 and choose step size and filter length for which the SNR gain is the highest. We get a maximum SNR gain of approximate 2.7492 dB for a filter length of 10 and a step size 0.03

Table III.4 SNR gain and convergence time for a variable frequency

Filter length	Step size	SNR gain	Computing time
10	0.01	2.7414	0.5313
20	0.01	2.6432	0.2500
30	0.01	2.6134	0.2344
40	0.01	2.5272	0.2188
50	0.01	2.5180	0.2188
60	0.01	2.4710	0.2344

Filter length	Step size	SNR gain	Computing time
10	0.03	2.7492	0.2188
20	0.03	2.7073	0.2500
30	0.03	2.7469	0.2500
40	0.03	2.6735	0.2969

Filter length	Step size	SNR gain	Computing time
50	0.03	2.6805	0.2500
60	0.03	2.6730	0.2500

Filter length	Step size	SNR gain	Computing time
10	0.05	2.7487	0.2188
20	0.05	2.7011	0.2188
30	0.05	2.6937	0.2813
40	0.05	2.7194	0.2656
50	0.05	2.7061	0.2969
60	0.05	2.6767	0.2813

III.6.1.2 SNR FOR FIXED FREQUENCY PULSE

The fixed frequency pulse signal parameters are given in Table III.1 we look in Table III.5 and choose step size and filter length for which the SNR gain is the highest. We get a maximum SNR gain of approximate 2.8398 for a filter length of 10 and a step size 0.03

Table III.5 SNR gain and convergence time for a fixed frequency

Filter length	Step size	SNR gain	Computing time
10	0.01	2.7314	0.2344
20	0.01	2.6832	0.2188
30	0.01	2.6394	0.2500
40	0.01	2.5473	0.2656
50	0.01	2.4880	0.2188
60	0.01	2.4552	0.2656

Filter length	Step size	SNR gain	Computing time
10	0.03	2.8398	0.2188
20	0.03	2.7777	0.2420
30	0.03	2.7569	0.2500
40	0.03	2.6945	0.2659
50	0.03	2.6855	0.2800
60	0.03	2.6740	0.2840

Filter length	Step size	SNR gain	Computing time
10	0.05	2.7787	0.2188
20	0.05	2.7011	0.2288
30	0.05	2.6937	0.2613
40	0.05	2.7297	0.2756
50	0.05	2.7161	0.3069
60	0.05	2.6967	0.3113

III.6.2 SNR OF RLS

for the RLS algorithm we have also two factors that use to study the performance of filter, the length filter and forgetting factor in this part we will use a different value of length from 10 to 60 and we use a fixed value for the forting factor that is “1” the result below for the fixed radar pulse and variable radar pulses

III.6.2.1 SNR FOR FIXED FREQUENCY PULSE

The fixed frequency pulse signal parameters are given in Table III.1 we look in Table III.6 and choose step size and filter length for which the SNR gain is the highest. We get a maximum SNR gain of approximate 2.7876 dB for a filter length of 10 and forgetting factor of 1

Table III.6 SNR gain and convergence time for a fixed frequency

Filter length	Forgetting factor	SNR gain	Computing time
10	1	2.7876	3.0313
20	1	2.7525	3.4844
30	1	2.7551	5.0313
40	1	2.6564	3.6719
50	1	2.7078	3.8750
60	1	2.6681	4.1719

III.6.2.2 SNR FOR VARIABLE FREQUENCY PULSE

The variable frequency pulse signal parameters are given in Table III.2 we look in Table III.7 and choose step size and filter length for which the SNR gain is the highest. We get a maximum SNR gain of approximate 2.7755 dB for a filter length of 10 and forgetting factor of 1

Table III.7 SNR gain and convergence time for a variable frequency

Filter length	Forgetting factor	SNR gain	Computing time
10	1	2.7755	3.5375
20	1	2.7452	3.1875
30	1	2.7181	3.5938
40	1	2.7374	3.5000
50	1	2.7054	3.8594
60	1	2.6724	4.0469

III.7 TIME DOMAIN SIMULATIONS

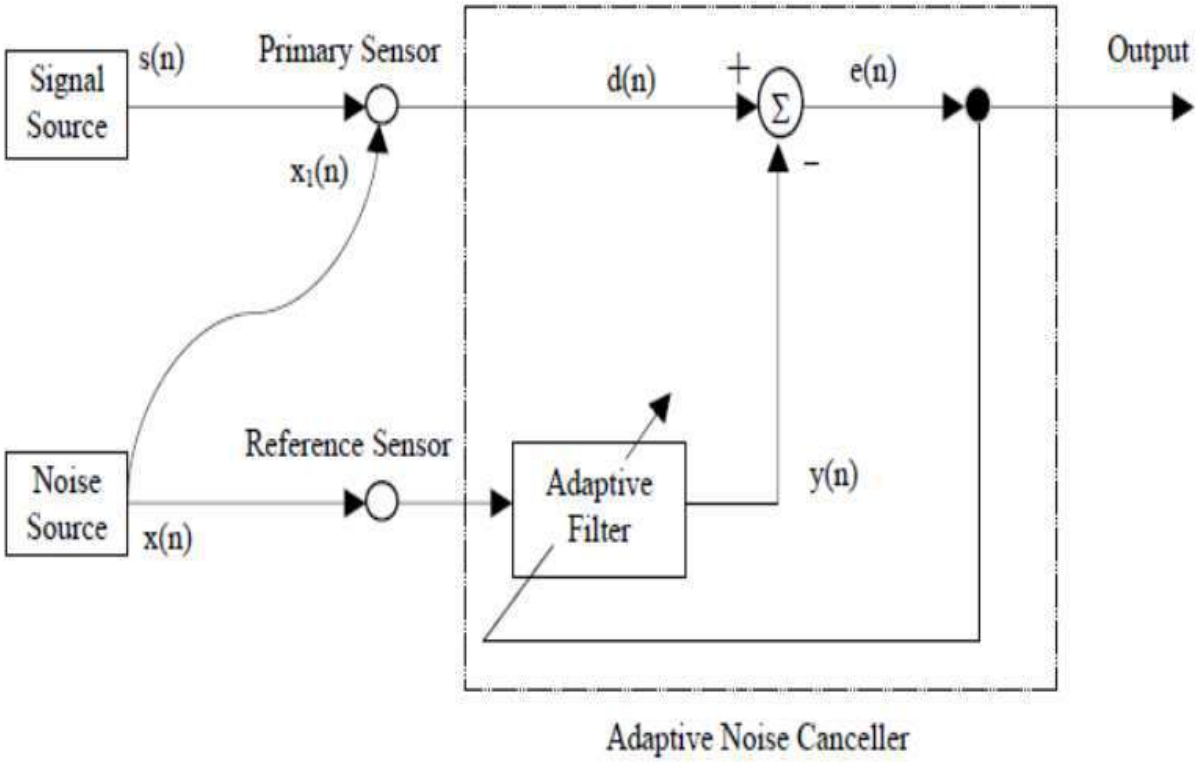


Figure III.6 simulation scheme

The figure above illustrates how our simulation work, This scheme represent the adaptive noise cancelation ,the signal source s(n) represented our radar signals ,we generate three different forms of radar signal with fixed frequency ,variable frequency and phase coded pulse called barker code next we have the noise source x(n) that's represent the noise picked by signal after we have the desired signal d(n) that is represent the radar signal plus the noise finally we have the block adaptive noise cancelation Through which we can understand how the adaptive filters work, the final result after filters the signals is the error signal e(n) that we can get it from the output

III.7.1 FIXED FREQUENCY

III.7.1.1 FIXED FREQUENCY USING LMS

We had used the Coherent pulsed RF signal defined in Table III.1 to construct a pulse train. In Figure III.7 we can see the radar signal in form of Coherent pulsed RF with a pulse width of 2 us and pulse-repetition-interval of 20 us. Next in figure III.8 we see additive white Gaussian noise, after in figure II.9 we see the superposition between the pure radar signal and the noise. We had filtered the radar signal though an adaptive filter using the LMS algorithm. The optimal values were to set the step size to 0.03 and the filter length to 10. The radar signals before and after the adaptive filter can be seen in Figure III.10

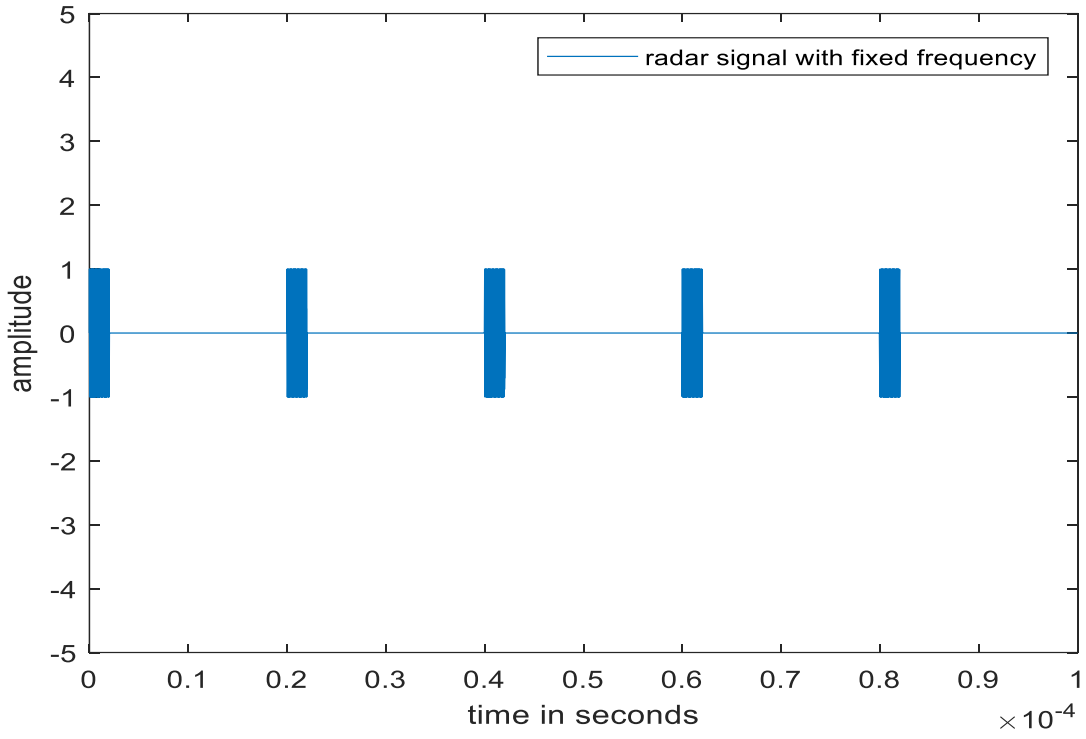


Figure II.7 radar signal with fixed frequency

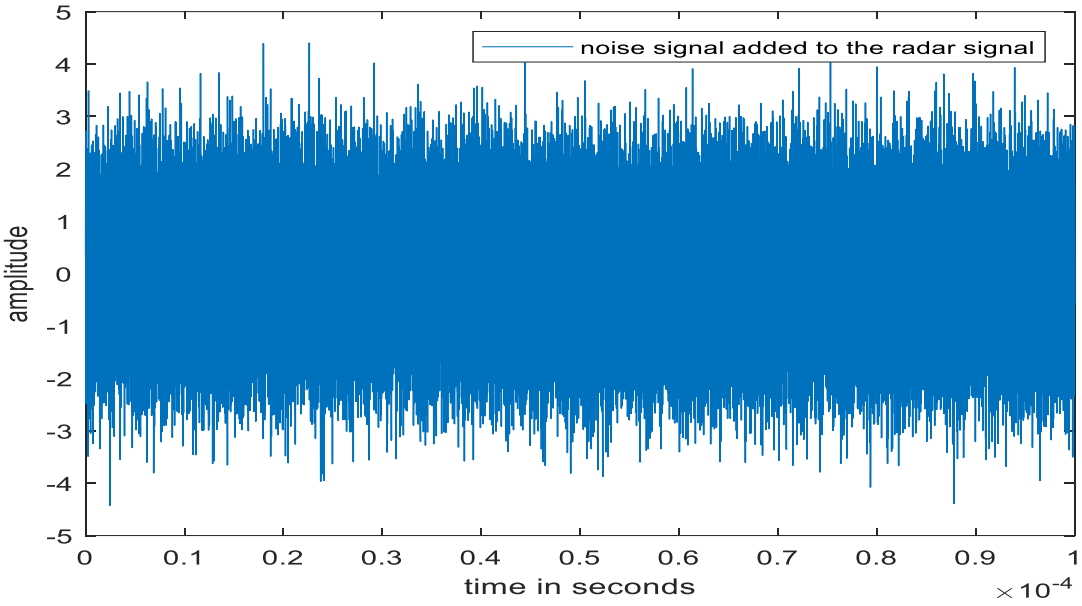


Figure III.8 Additive white Gaussian noise picked by signal

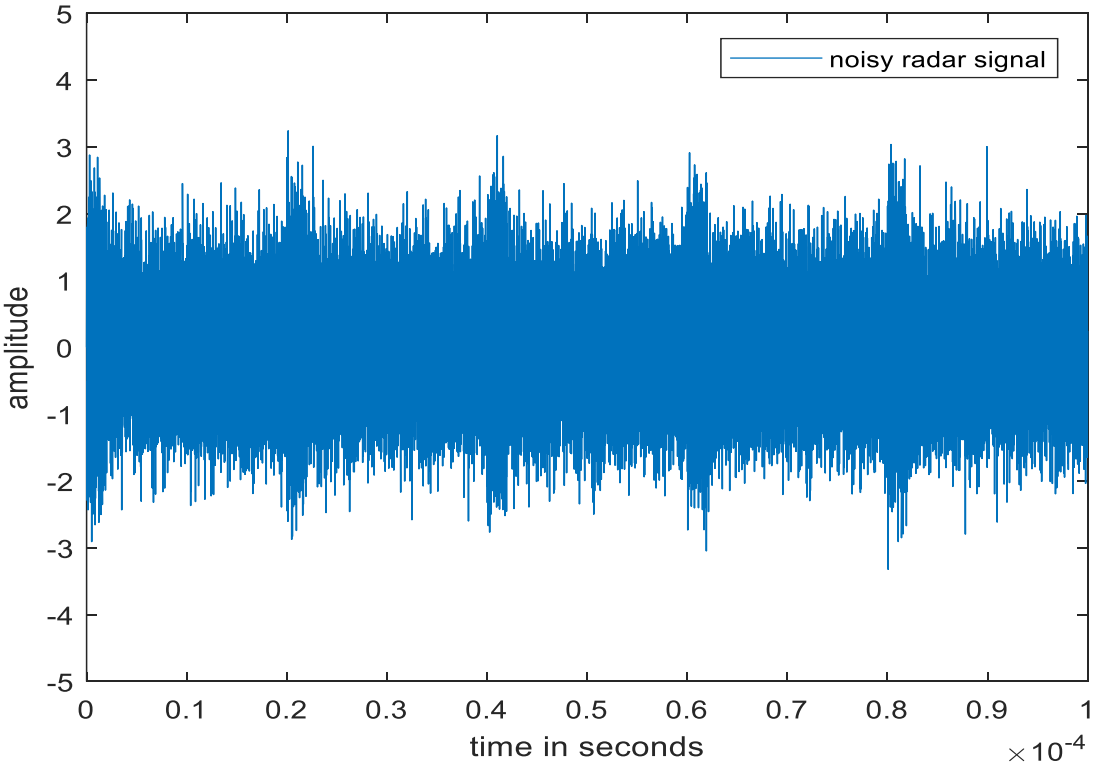
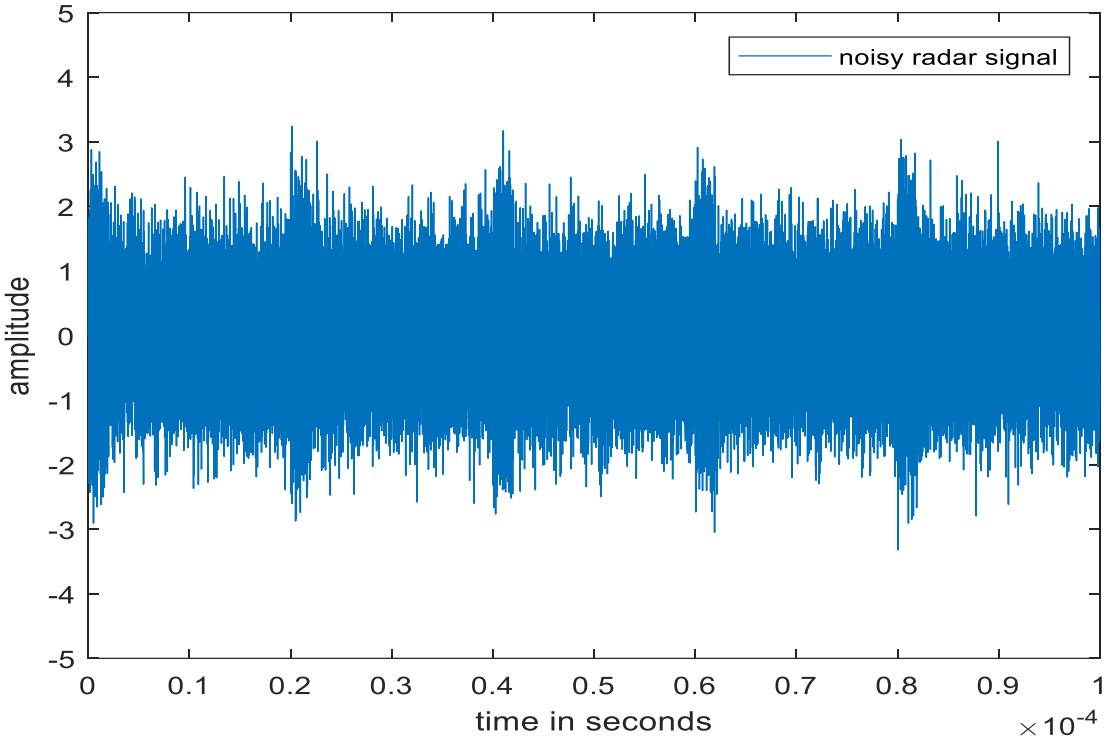


Figure III.9 Radar signal with fixed frequency pulses merged with additive white Gaussian noise

Before using adaptive filter



After the adaptive filter using LMS

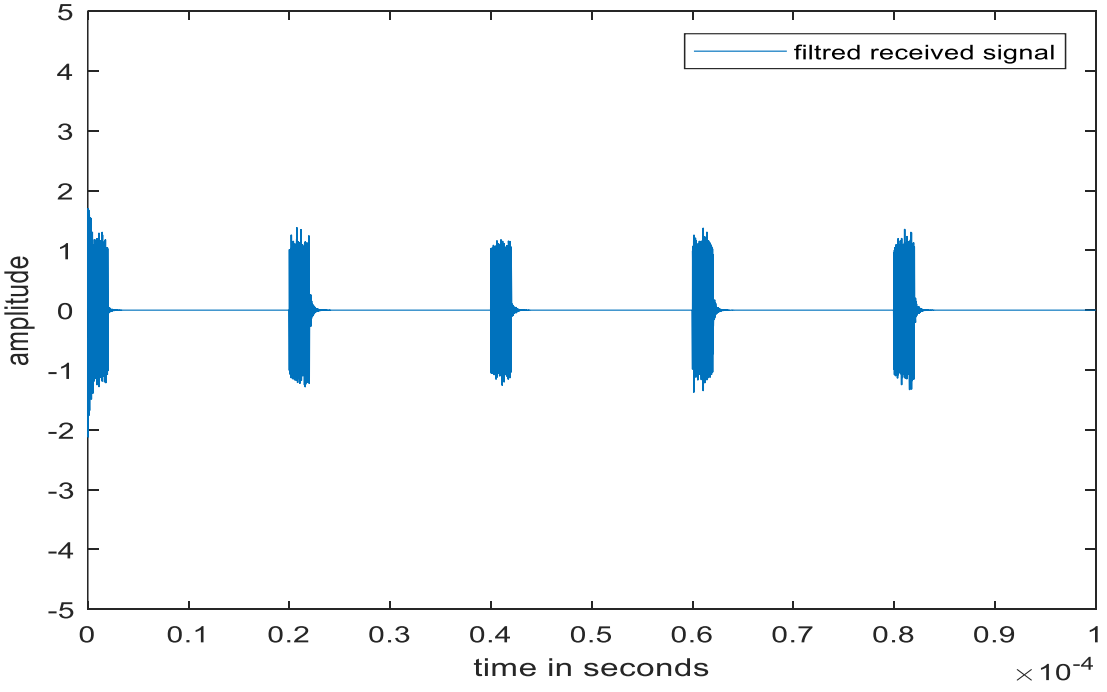


Figure III.10 The radar signal with fixed frequency before and after the adaptive filter using LMS algorithm.

III.7.1.2 FIXED FREQUENCY USING RLS

We had used the Coherent pulsed RF signal defined in Table III.1 to construct a pulse train. In Figure III.11 we can see the radar signal in form of Coherent pulsed RF with a pulse width of 2 us and pulse-repetition-interval of 20 us. Next in figure III.12 we see additive white Gaussian noise, after in figure III.13 we see the superposition between the pure radar signal and the noise. We have filtered the radar signal though an adaptive filter using the RLS algorithm. The optimal values were to set with value of 1 for the forgetting factor and the filter length to 10. The radar signals before and after the adaptive filter can be seen in Figure III.14.

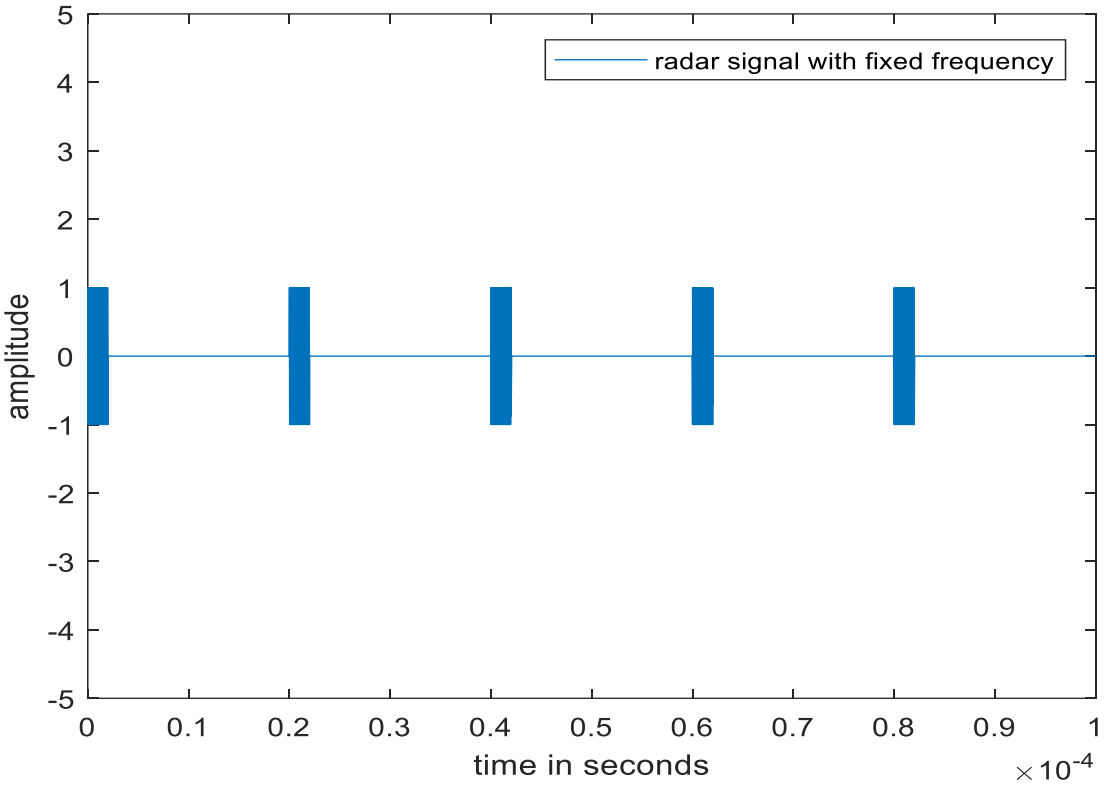


Figure III.11 Radar signal with fixed frequency

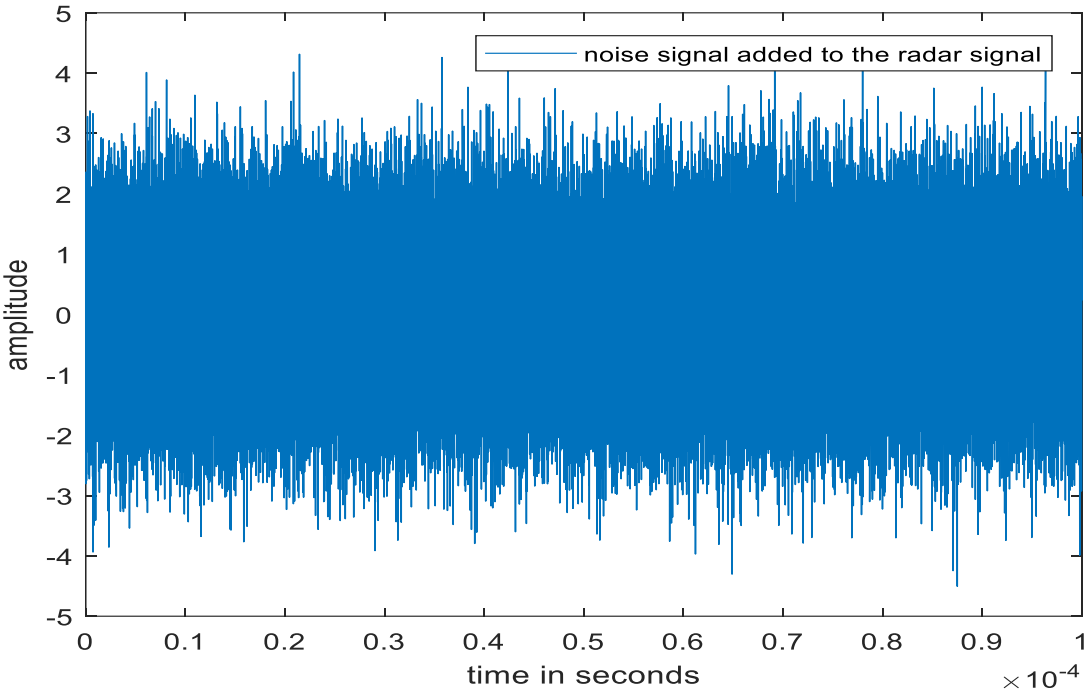


Figure III.12 Additive white Gaussian noise picked by signal

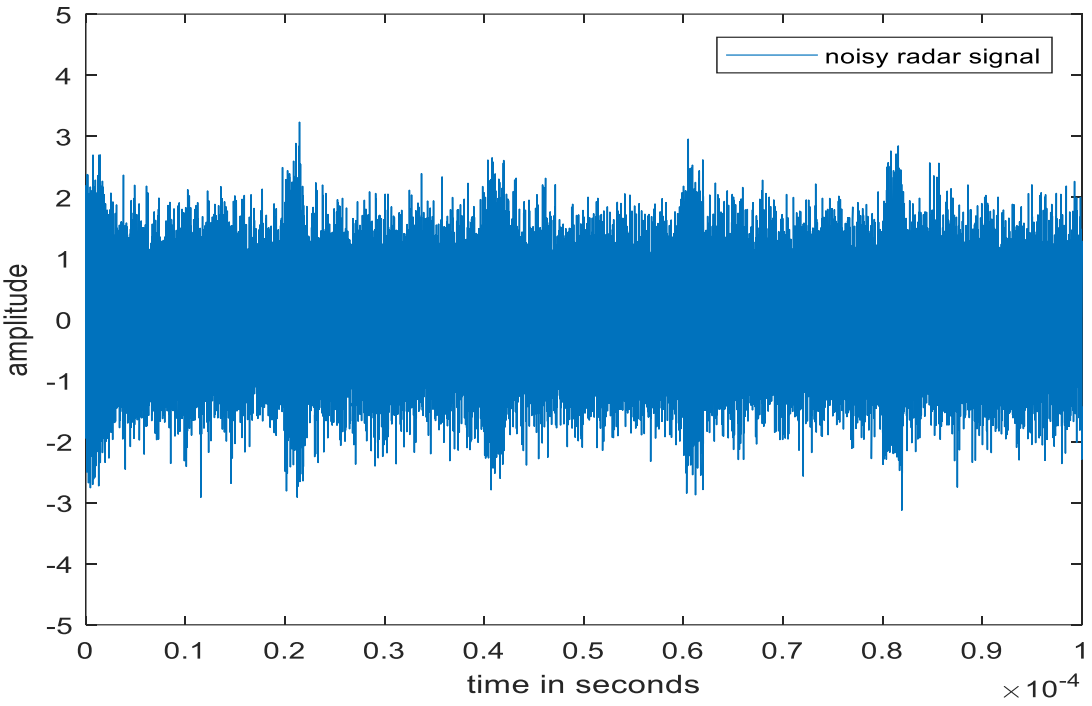
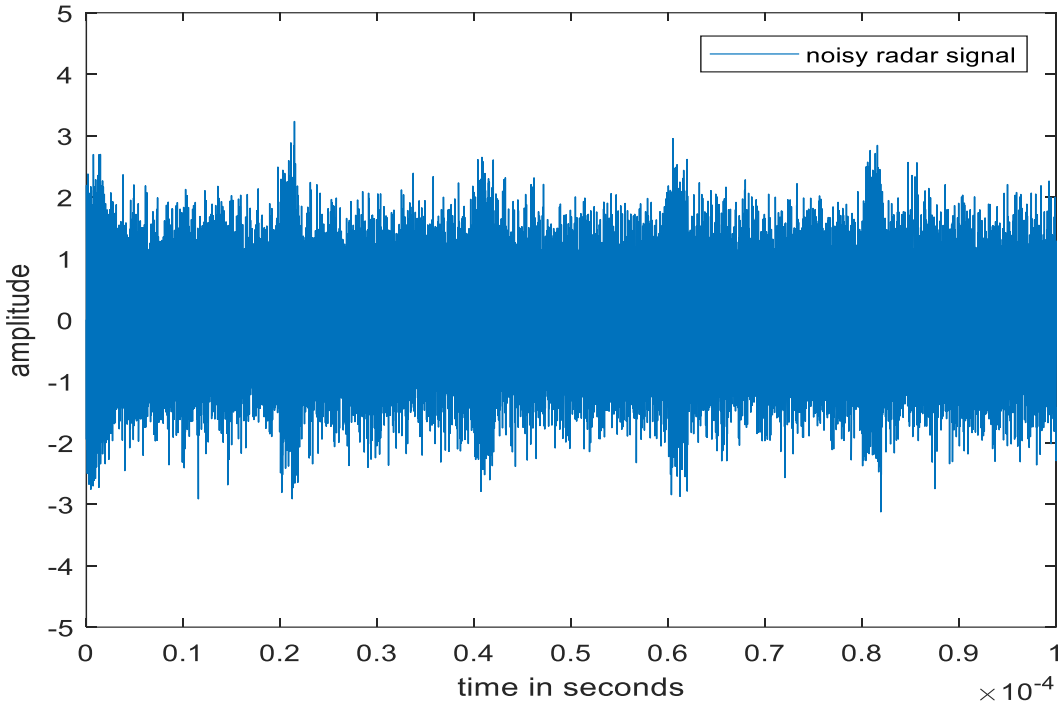


Figure III.13 Radar signal with fixed frequency pulses merged with additive white Gaussian noise

Before adaptive filter



After the adaptive filter with RLS

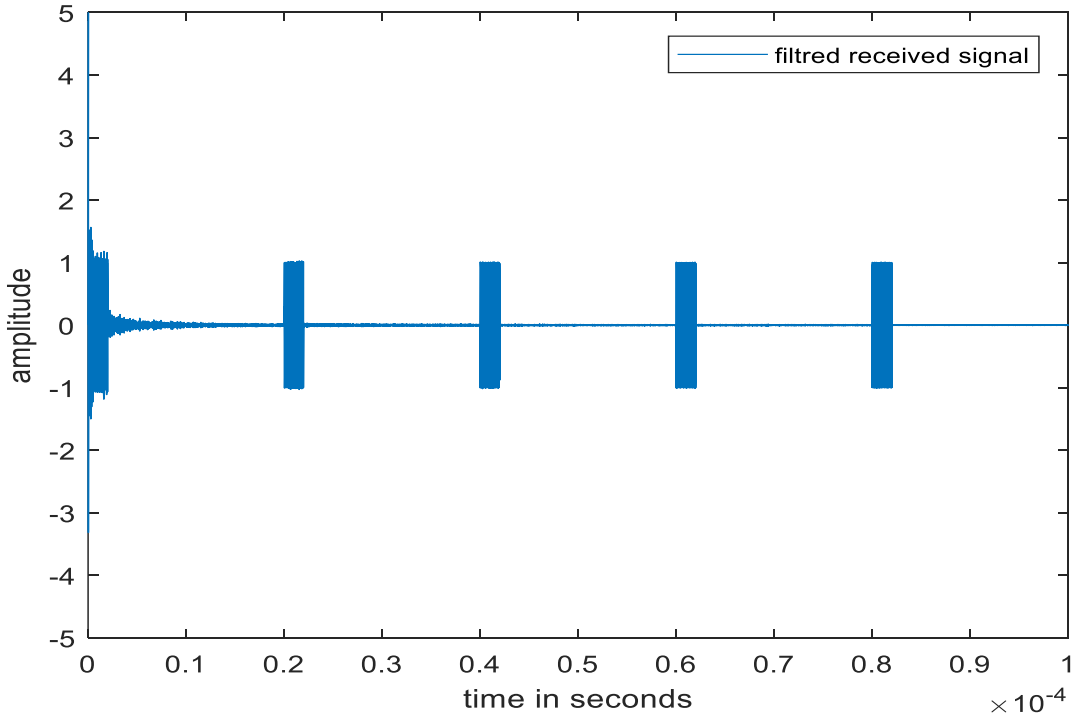


Figure III.14 The radar signal with fixed frequency before and after the adaptive filter using a RLS algorithm.

III.7.2 CHIRPED PULSES

III.7.2.1 CHIRPED PULSES USING LMS

We had used radar signal with varying frequency defined in Table III.2 to construct a pulse train. In Figure III.15 we can see the radar signal in form of Coherent pulsed RF with a pulse width of 2 us and pulse-repetition-interval of 20 us. Next in figure II.16 we see additive white Gaussian noise after in figure II.17 we see the superposition between the pure radar signal and the noise. We have filtered the radar signal though an adaptive filter using the LMS and RLS algorithm. The optimal values were to set the step size to 0.02 and the filter length to 10. The radar signals before and after the adaptive filter can be seen in Figure III.18.

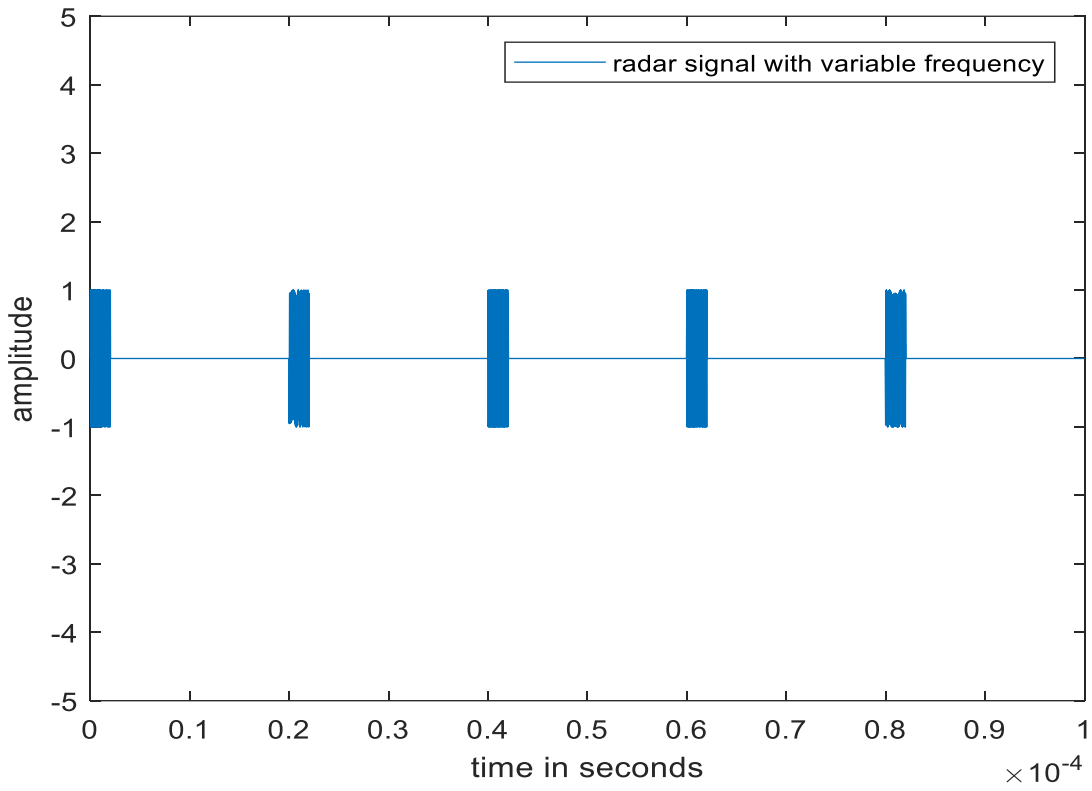


Figure III.15 Radar signal with varying frequency (chirped pulses)

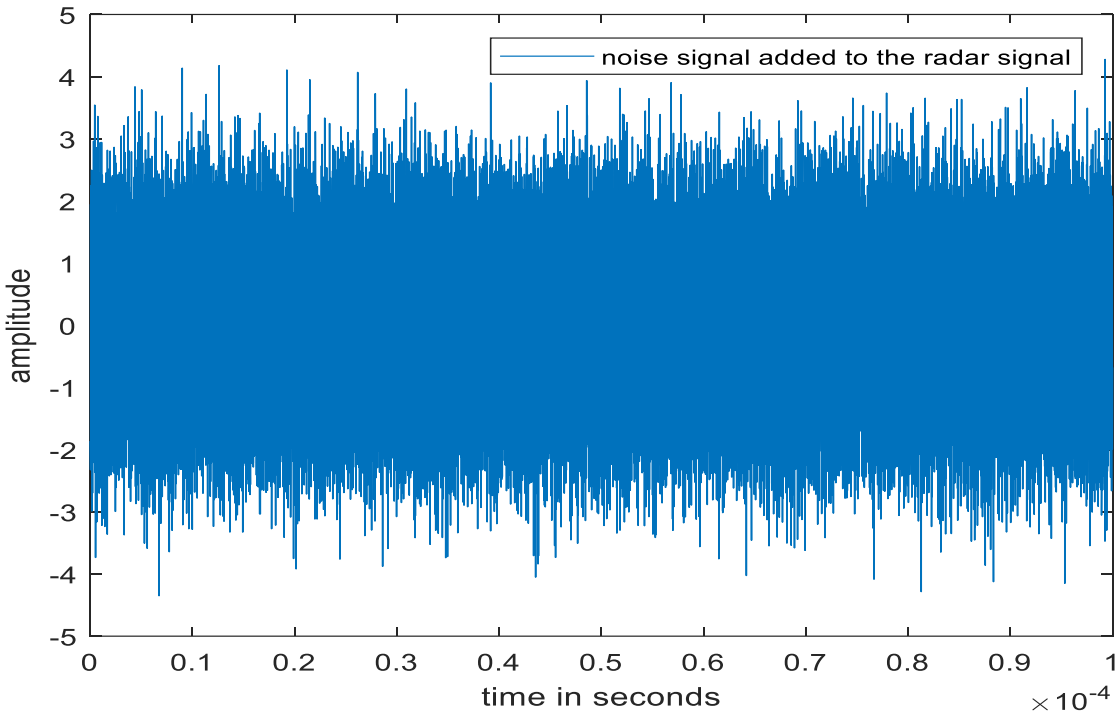


Figure III.16 Additive white Gaussian noise picked by signal

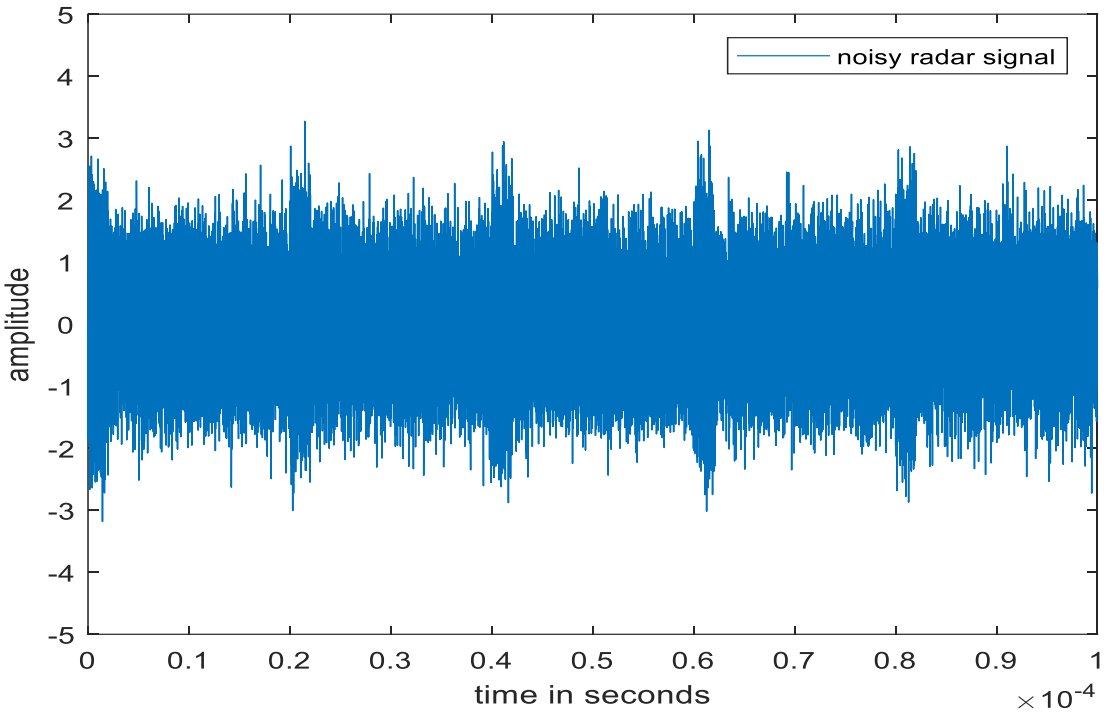
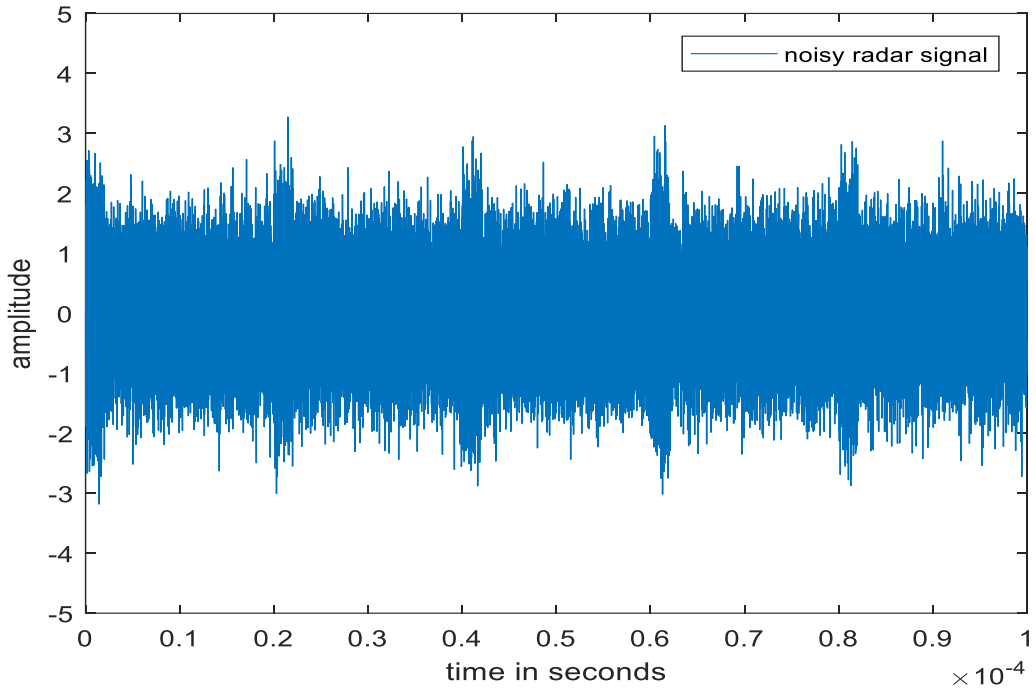


Figure III.17 Radar signal with varying frequency pulses merged with additive white Gaussian noise.

Before adaptive filter using LMS



After adaptive filter using LMS

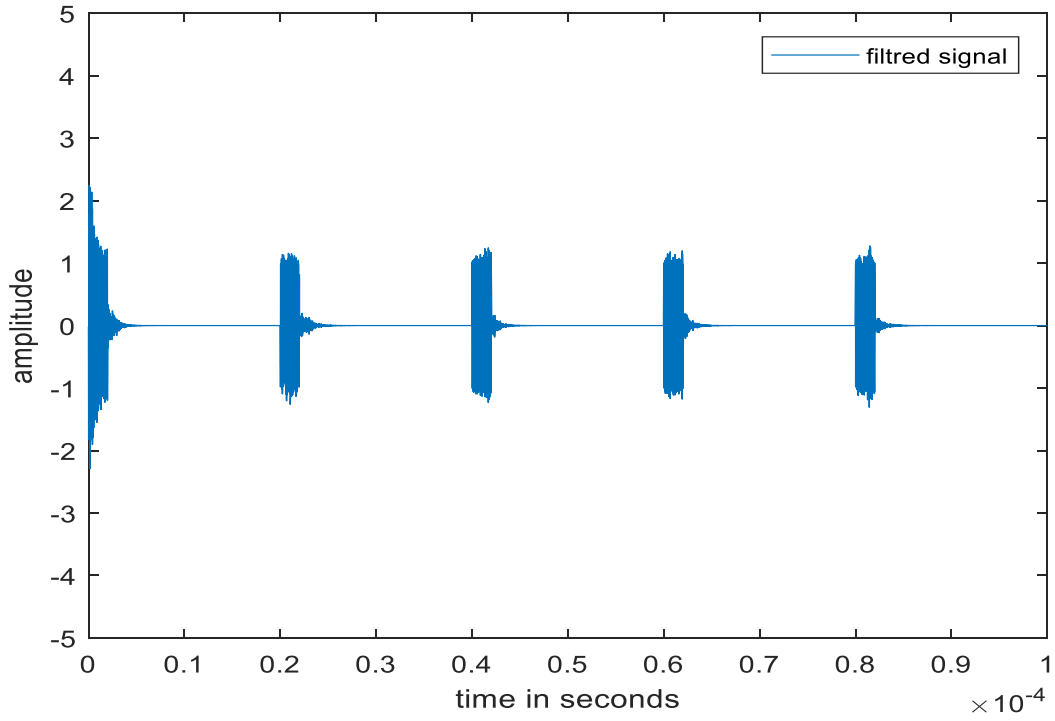


Figure III.18 Radar signal with varying frequency before and after the adaptive filter using a LMS algorithm.

III.7.2.2 CHIRPED PULSES USING RLS

We had used the Coherent pulsed RF signal defined in Table III.1 to construct a pulse train. In Figure III.19 we can see the radar signal in form of Coherent pulsed RF with a pulse width of 2 us and pulse-repetition-interval of 20 us. Next in figure III.20 we see additive white Gaussian noise after in figure III.21 we see the superposition between the pure radar signal and the noise. We have filtered the radar signal though an adaptive filter using the RLS algorithm. The optimal values were to set with value of 1 for the forgetting factor and the filter length to 10. The radar signals before and after the adaptive filter can be seen in Figure III.22.

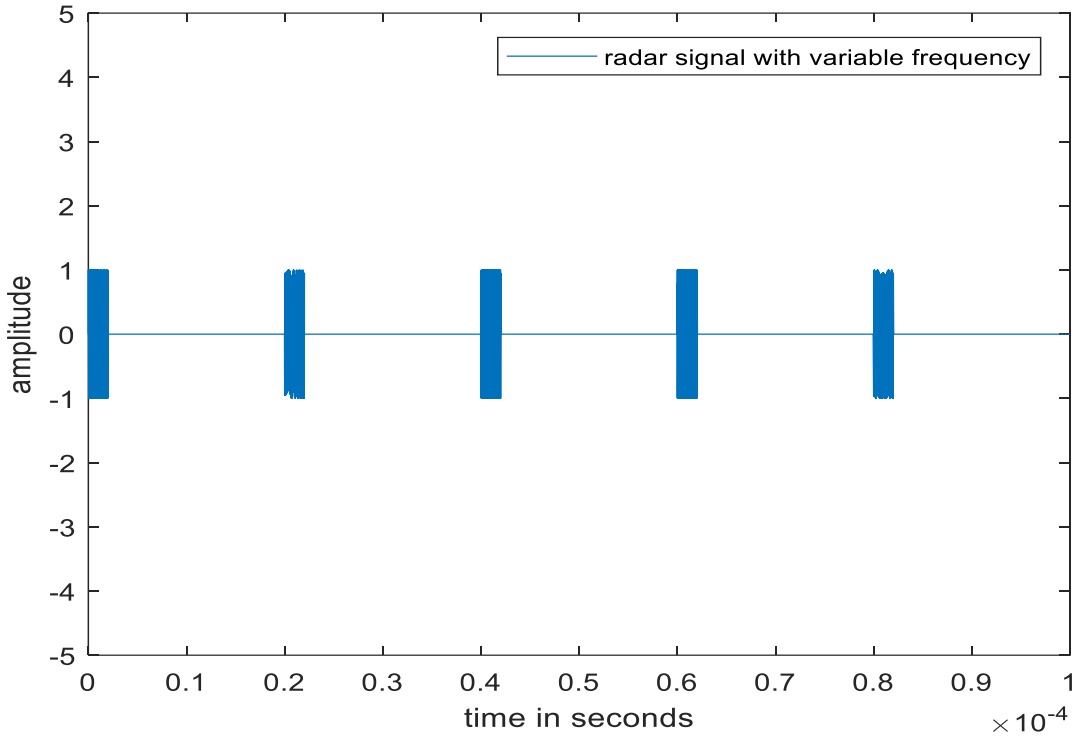


Figure III.19 Radar signal varying frequency (with Coherent pulsed RF)

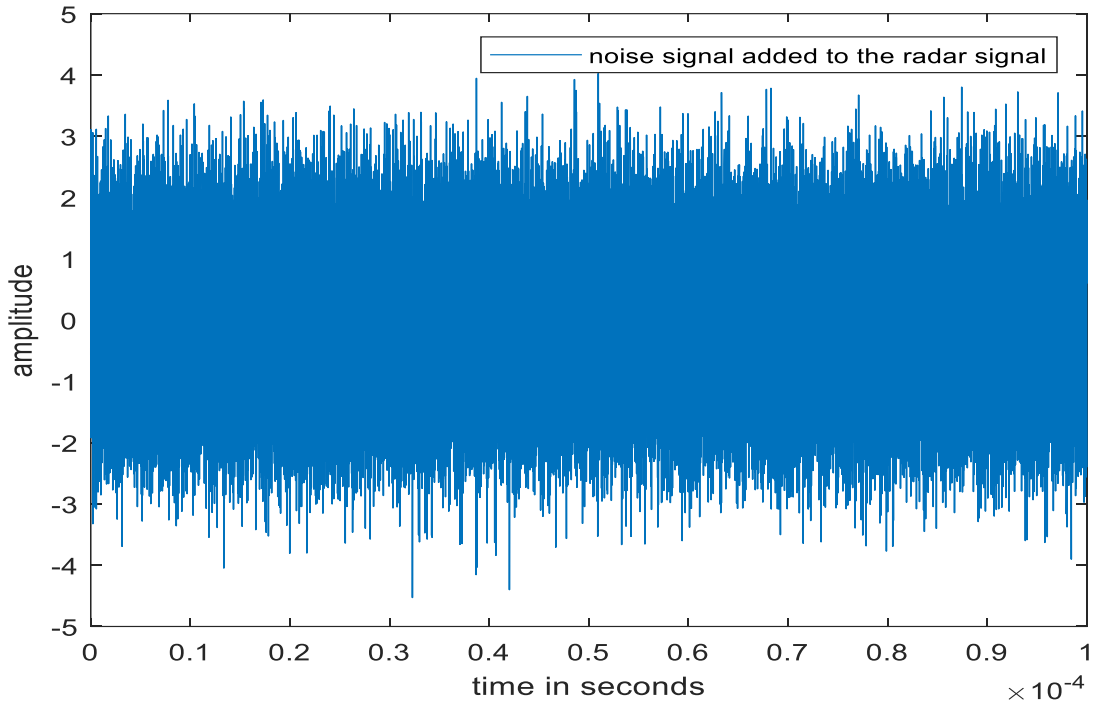


Figure III.20 additive white Gaussian noise picked by signal

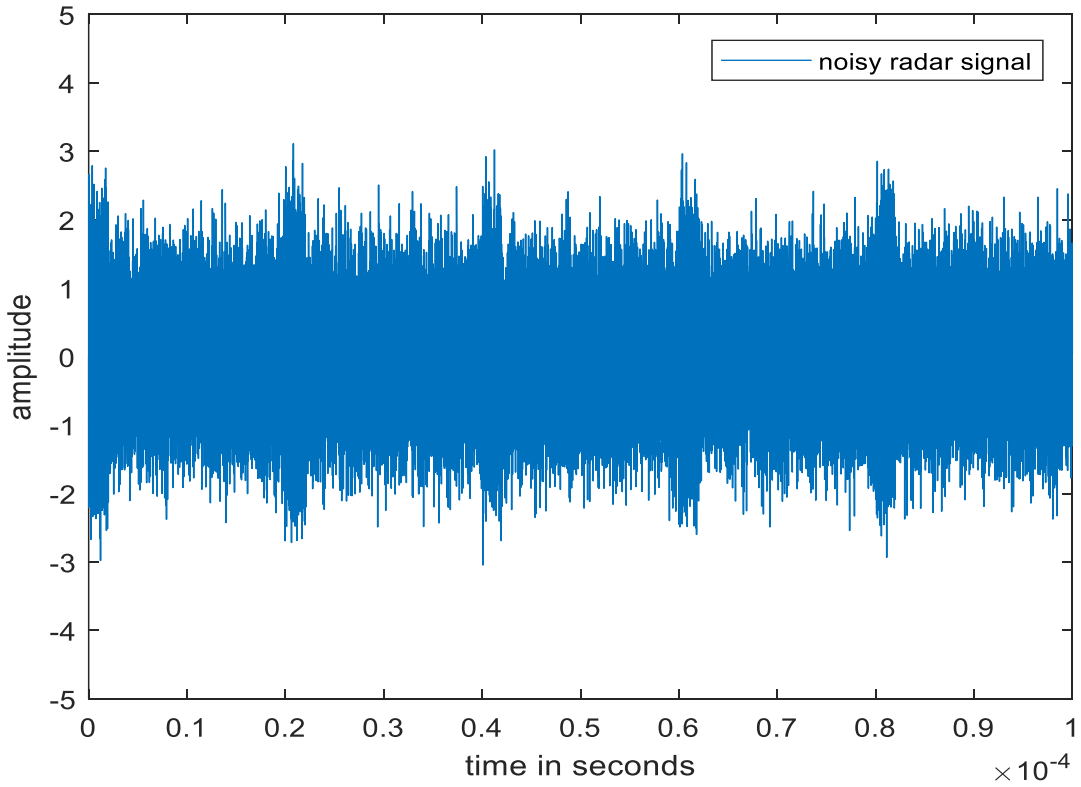
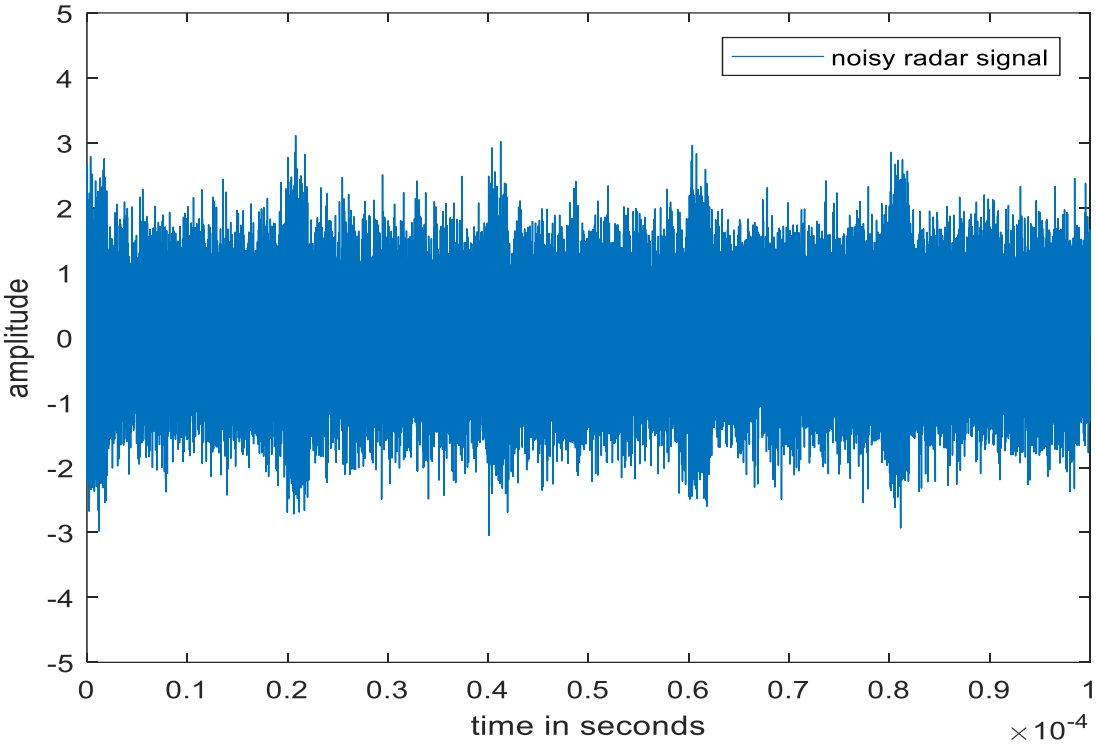


Figure III.21 Radar signal with varying frequency pulses merged additive white Gaussian noise.

Before adaptive filter using RLS



After adaptive filter using RLS

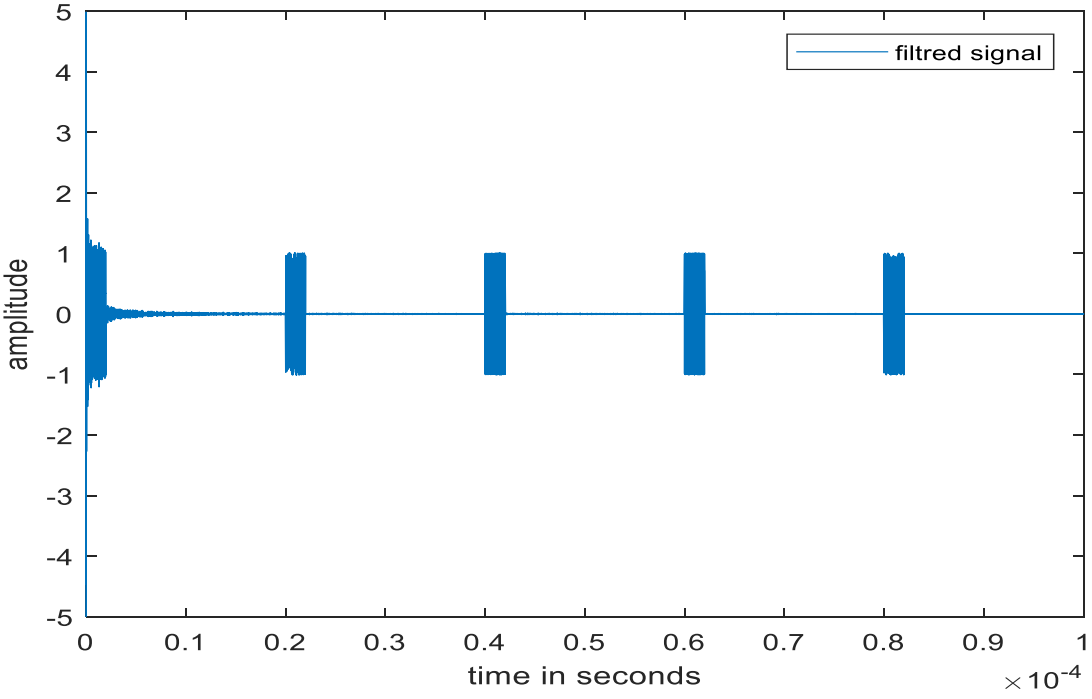


Figure III.22 Radar signal with varying frequency before and after the adaptive filter using a RLS algorithm.

III.8 BINARY PHASE CODED

We had used radar signal with varying frequency defined in Table III.3 to construct a phase coded pulse barker code 7. In Figure III.23 we can see the phase coded pulse in form of pulse width of 10 ms and pulse-repetition-interval of 20 ms. Next in figure II.24 we see additive white Gaussian noise after in figure II.25 we see the superposition between the pure radar signal and the noise. We have filtered the radar signal though an adaptive filter using the LMS and RLS algorithm. The radar signals before and after the adaptive filter can be seen in Figure III.26, III.27.

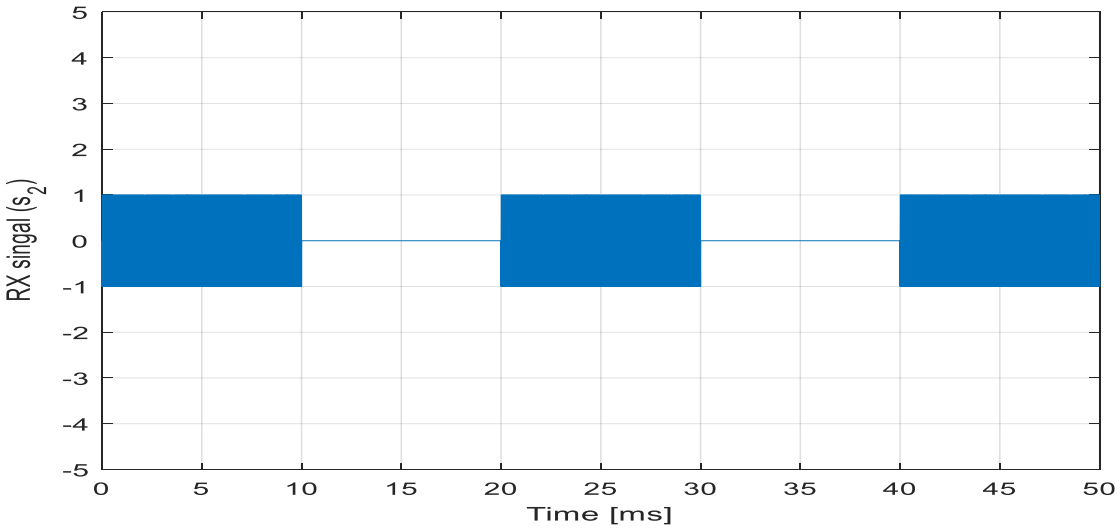


Figure III.23 phase coded pulse barker code

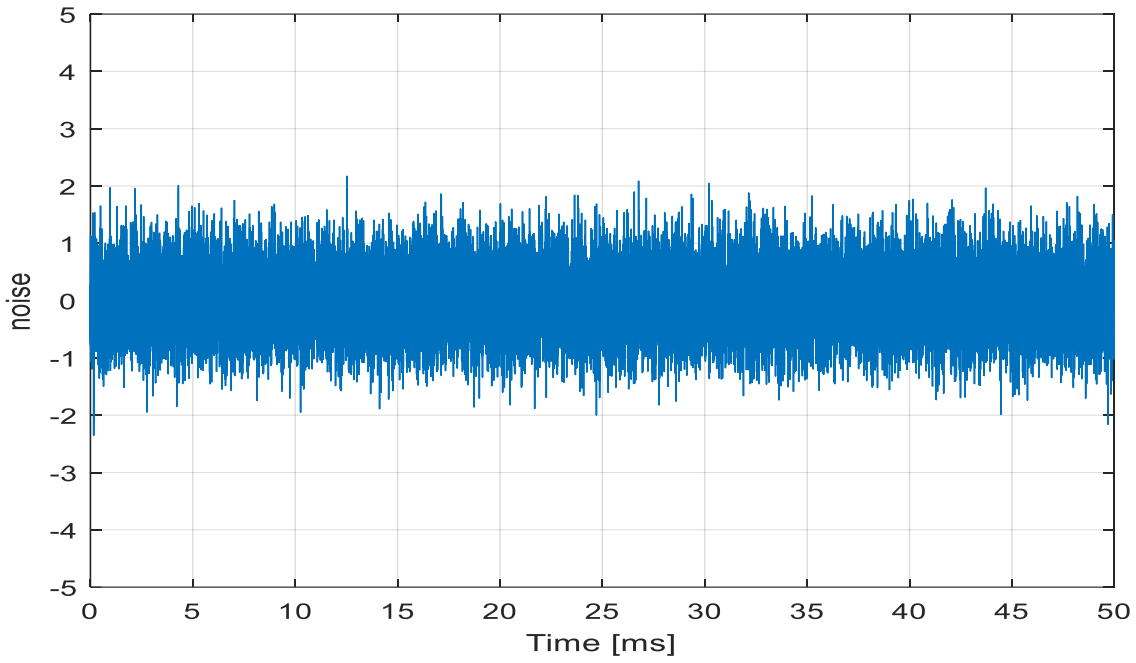


Figure III.24 Additive white Gaussian noise.

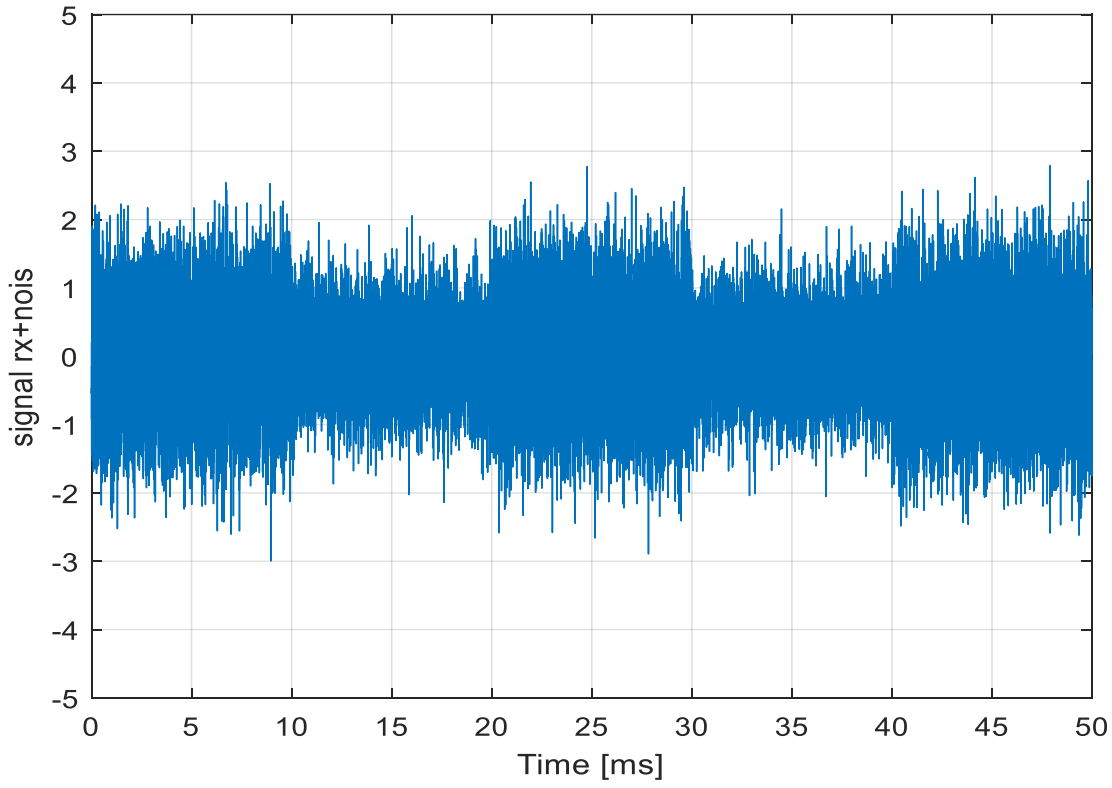
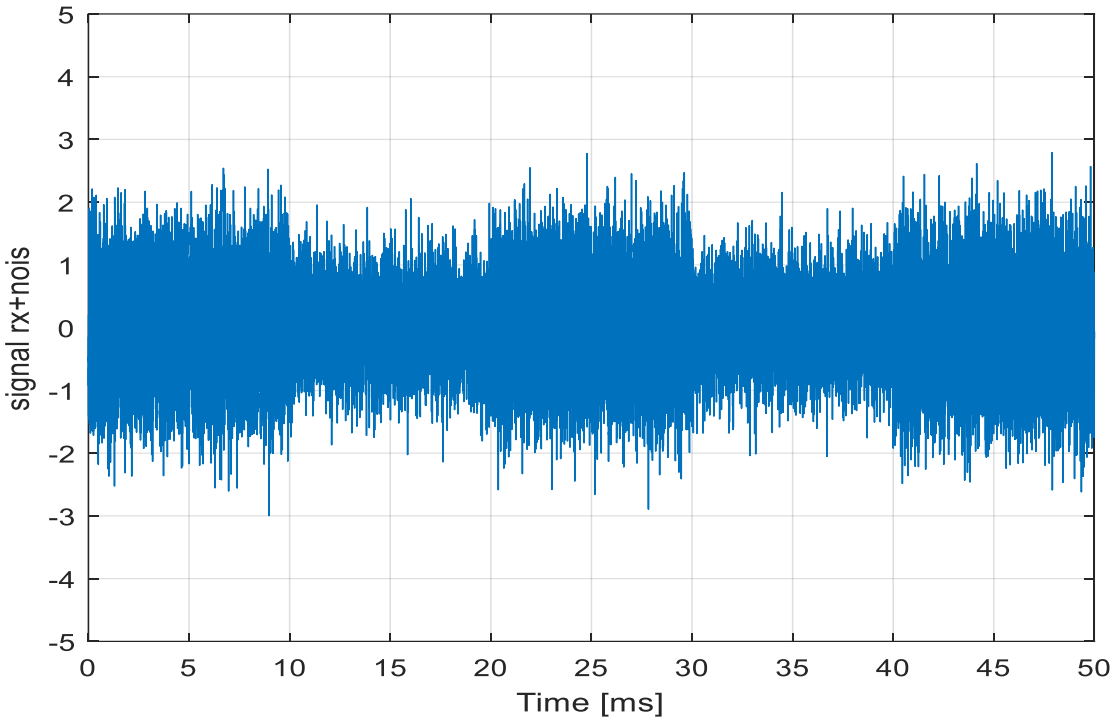


Figure III.25 Phase coded pulse and additive white Gaussian noise and the superposition between them

Before using the adaptive filter



After the adaptive filter using LMS

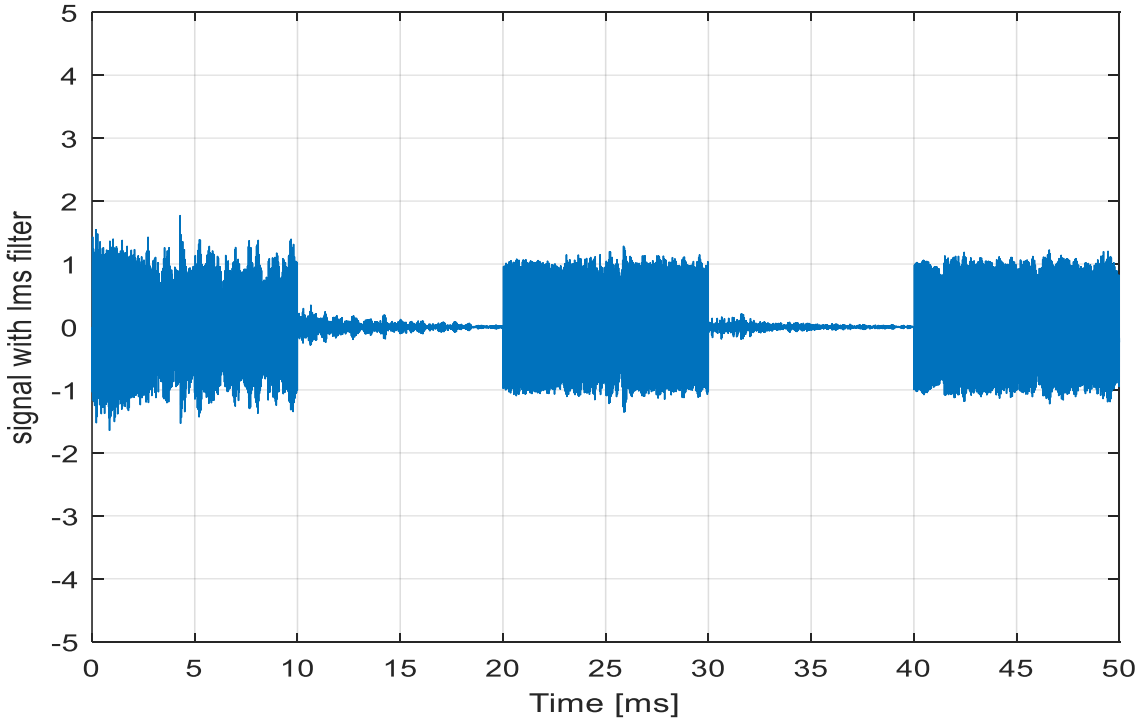
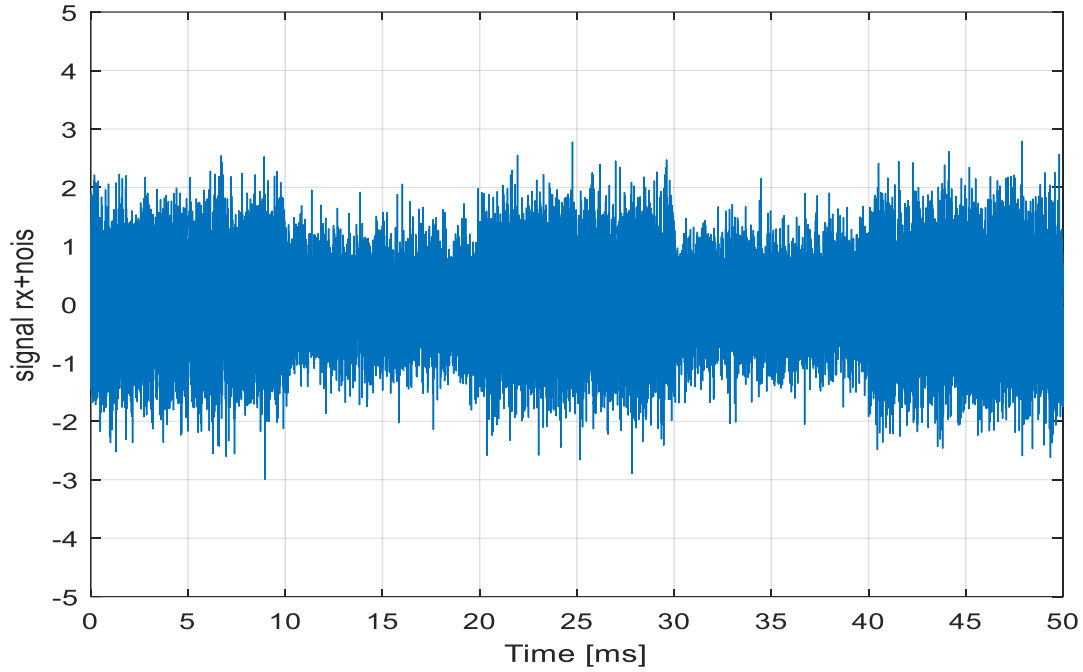


Figure III.26 The radar phase coded pulse before and after using the adaptive filter with LMS algorithm.

Before using the adaptive filter RLS



After using the adaptive filter RLS

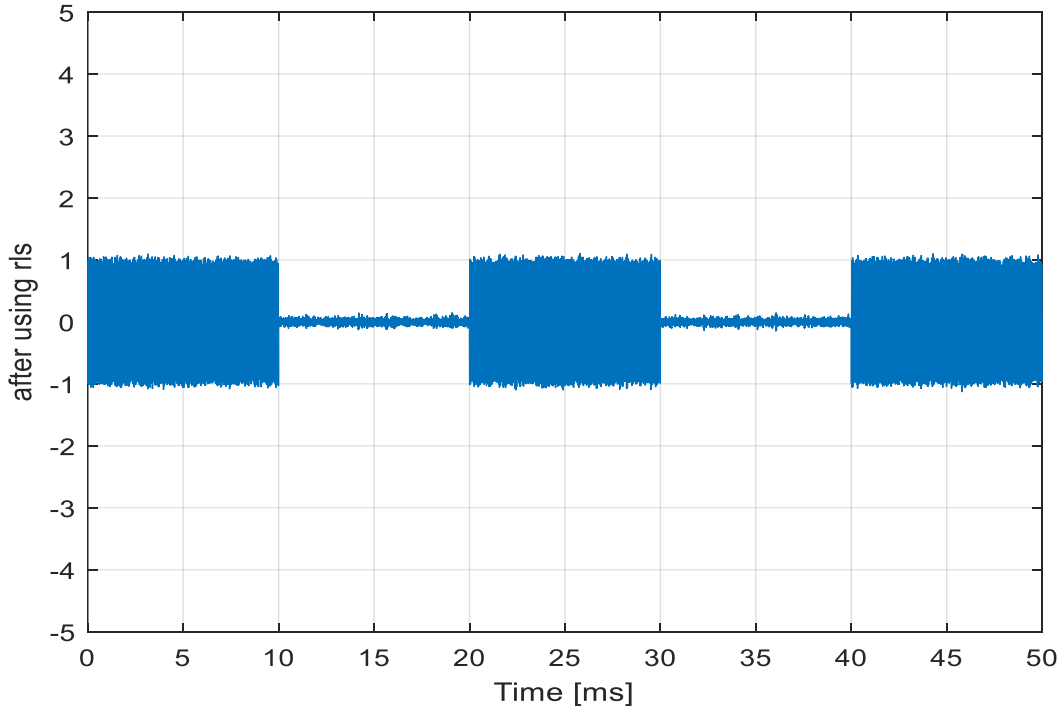


Figure III.27 The radar phase coded pulse before and after using the adaptive filter with RLS algorithm.

III.9 CONCLUSION

We did a simulation that through which we had applied adaptive filters on radar signal using MATLAB, we applied it on different forms of radar signal with fixed frequency, variable frequency and phase coded pulse we had using LMS and RLS algorithm to reduce the noise, we were able to extract the signal and filters the noise and we got a better SNR The best way to reduce the noise from signal with variable frequency is to introduce adaptive filters we conclude that LMS was simpler and easier to implement than RLS who had a computational complexity; LMS is the best algorithm in this section because it is faster than RLS, we can confirm this by reviewing the result above from the computing time

This conclusion is due to the results that we obtained from our simulation

GENERAL CONCLUSION

In this thesis, we introduced radar systems in chapter 1,we tackled some concepts about radar signals, their equation and how we can generate them, then in chapter 2 we introduced some concepts about adaptive filtering with taking a look on the two main adaptive algorithms LMS and RLS with mentioning some concepts and equations , the objective of this work is to receive and filter different forms of radar signals, in some cases we had a problem of varying frequency, however in other cases we had fixed frequency without being able to know the frequency in RWR for example and because a digital filter with fixed coefficients is designed according to some specifications depending on its application, in order to produce a desired output signal when the input signal has certain characteristics. However if those characteristics change over time, a digital filter with fixed coefficients would no longer produce the desired output. Thus in these cases it is necessary to use an adaptive filter, whose coefficients are adjusted at each time instant through an adaptive algorithm. Finally in chapter 3 we did a simulation to evaluate the performance of noise cancellation in radar signals using the LMS and RLS algorithms. Three different pulses shapes were investigated they were fixed frequency pulses, chirped pulses and binary phase coded pulses. We applied LMS and RLS algorithms to our simulated pulses and radar signal, we managed to get a good results illustrated in the figures presented in chapter 3 and from the values of the SNR gain

We concluded that LMS was simpler and easier to implement than RLS who had a computational complexity that is not suitable for real time applications in the stability regions the RLS and LMS algorithms gave us the same SNR gains, however LMS took much shorter running time than RLS, hence LMS is the best algorithm in this section because it is faster than RLS.

REFERENCES

[1] Paulo S. R. Diniz, Adaptive Filtering Algorithms and Practical Implementation, Fifth Edition, Universidade Federal do Rio de JaneiroNiterói, Rio de Janeiro, Brazil, 2020

[2] Li TanDeVry University Decatur, Georgia , Digital Signal Processing Fundamentals and Applications , ISBN: 978-0-12-374090-8

[3],Digital Filtering Alternatives for Embedded Designs Based on a paper presented at ESC-Boston, September 2006, 25 page, www.quickfiltertech.com

[4] Andreas Antoniou ,Digital Signal Processing signals systems and filters , University of Victoria British Columbia Canada , 2006

[5] Daniel Salminen, uppsala university, Adaptive filters applied on radar signals , master thesis, October 2013

[6] Mark A. James A. ScheerWilliam A. Holm, Principles of Modern Radar Volume I - Basic Principles, 2010, ISBN: 978-1-891121-52-4

[7] Wikipedia , ww.wikipedia.org/wiki/Radar

[8] By the staff of Festo Didactic, Telecommunications Radar Phase-Coded Pulse Compression Courseware Sample First Edition, Canada 2017, ISBN 978-2-89747-888-9

[9] Preeti Jain. Different Types of RADARs ,Engineers Garage …. Inspiring creations, February 23,2012.