GENERATION OF BIPHASE CODED SEQUENCES USING PARTICLE SWARM OPTIMIZATION ALGORITHM

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CERTIFICATE

Date: April 22, 2016.

This is to certify that the Major Project Work entitled "**Generation of Biphase Coded Sequences using Particle Swarm Optimization Algorithm**" is a bonafide work carried out by

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in partial fulfillment of the requirements for the degree of **BACHELOR OF TECHNOLOGY** in **ELECTRONICS & COMMUNICATION ENGINEERING** by the Jawaharlal Nehru Technological University, Hyderabad during the academic year 2015-16.

The results embodied in this report have not been submitted to any other University or Institution for the award of any degree or diploma.

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Faculty Advisor/Liaison

Dr. S P Singh
Professor & Head

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Abstract

Pulse compression allows radar designers to use long pulse in order to obtain high energy for detection of targets at long ranges and simultaneously achieve the resolution of a short pulse by internal modulation of the long pulse. This technique can increase signal bandwidth through frequency or phase coding. In this connection, a good radar signal design for high performance radar applications demands good autocorrelation property – to have low sidelobe levels at the output of the matched filter. One of the basic types of pulse compression is binary phase coding which encodes the transmitted pulse with information that is compressed (decoded) in the receiver of the radar. The study of the Peak Sidelobe Level (PSL) binary sequences occurs as a classical problem of signal design for radar systems. In this project, we describe design of biphase codes for pulse compression radar systems, which improves resolution and detection probability of modern radar systems. The work presented here describes various types of Binary codes and their generation methods. Finally, an exhaustive search for minimum peak sidelobe level binary codes, using optimization technique. Particle Swarm Optimization Algorithm is used to optimize the biphase sequences for good auto-correlation property. This project tries to make a detailed analysis for optimizing signal lengths 60 to 69. For the code lengths 60 to 64 the PSL = 4 and code length 65 to 69 PSL value is achieved 5.

This work can be extended to a great extent by effective scaling biphase code to polyphase code which has huge number of applications

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OVERVIEW

1.1 INTRODUCTION

Radar applications require sequences with individually peaky autocorrelation. It is a combinatorial problem for obtaining such sequences. So designing a signal above referred is a challenging problem for which many global optimization algorithms like genetic algorithm, particle swarm optimization algorithm, simulated annealing, tunneling algorithm were reported in the literature. The project aims at the design of optimal set of Binary Sequences using Particle Swarm Optimization Algorithm.

Binary phase codes with good autocorrelation and low side lobe levels are useful in such diverse applications as radar pulse compression, communication systems, and theoretical physics. Knowledge of minimum achievable side lobe levels for given code lengths can help inform searches for low side lobe level codes. Sets of codes that achieve the minima can provide new dimensions to trade studies supporting code selection tasks. This project adds to advance the upper bound on code lengths for which the optimal PSL is known. This project tries to make a detailed analysis for signal lengths 60 to 69.

1.2 AIM OF THE PROJECT

The aim of this project is to generate best autocorrelation sequences for signal lengths from 60 to 69 using PSO (Particle Swarm Optimization) Algorithm.

1.3 METHODOLOGY

In this project, optimized biphase pulse compression codes (BPCC) with low peak side lobe (PSL) have been investigated. The robustness of genetic algorithm in solving optimization problems degrades simultaneously as the code length increases. So, we have adopted the Particle Swarm Optimization algorithm to generate the sequences. The Particle Swarm Optimization algorithm is a biologically-inspired algorithm motivated by a social analogy. Sometimes it is related to the Evolutionary Computation (EC) techniques, basically with Genetic Algorithms (GA) and Evolutionary Strategies (ES), but there are significant differences with those techniques.

The PSO algorithm is population-based: a set of potential solutions evolves to approach a convenient solution (or set of solutions) for a problem. Being an optimization method, the aim is finding the global optimum of a real-valued function (fitness function) defined in a given space (search space).

The algorithm and its concept of “Particle Swarm Optimization (PSO) were introduced by James Kennedy and Russel Ebhart in 1995. However, its origins go further backwards since the basic principle of optimization by swarm is inspired in previous attempts at reproducing observed behavior animals in their natural habitat, such as bird flocking or fish schooling, and thus ultimately its origins nature itself. These roots in natural processes of swarms lead to the categorization of the algorithm one of Swarm Intelligence and Artificial Life.

Our project mainly consists of three sections. The function of each section is as given below.

- **Section I:**
    - This section deals with reviewing the different phase coded sequences like the barker codes, nested barker codes and maximum length sequences. Carefully evaluated all the phase coded sequences.
- **Section II:**
    - This section introduces to particle swarm optimization algorithm. It offers a better mechanism of coding for the biphase of the pulse so that the side lobe factor (in vicinity of the center of the correlation function) is greatly reduced.
- **Section III:**
    - In this section, we deal with the generation of the Biphase coded pulse yielding the desired properties of the auto - correlation. To do this, the help of Matlab-10 is taken.

1.4 SIGNIFICANCE OF THE WORK

Biphase codes of longer sequences having low PSL and high MF are important research area in the field of radar signal processing. The significance of the project comes from the fact that the efficient code design using Particle swarm optimization technique (that converges to good auto-correlation) is proposed. We employed this method that synthesis Biphase codes having good auto-correlation that can be used in Pulse compression radars to achieve good range resolution.

In modern days, military radars are being more and more threatened by electronic counter measure (ECM) and anti-radiation missiles (ARM); thus Biphase coded signal with good coding agility can be used to achieve low probability of intercept.

This design procedure may be applied to other cases also where correlation properties of the radar system are away from the ideal auto correlation property, that is application based code design can also be made.

1.5 ORGANIZATION OF THE WORK

This project is mainly organized into 4 chapters

Chapter 1 deals with the project presenting the aim and methodology of the project. The significance and applications are also cited in this chapter.

Chapter 2 introduces the concepts related to fundamentals in radar systems and existing pulse compression technique. Is also discusses the limitations of these existing techniques.

Chapter 3 deals with biphase codes like barker codes, nested barker codes and maximum length sequences

Chapter 4 deals with Particle Swarm Optimization Algorithm which was used to obtain best biphase codes which has best auto-correlation property

Chapter 5 deals with the coding

Chapter 6 deals with the results

Chapter 7 deals with conclusion and future scope

CHAPTER 2

CHAPTER 2

2.1 INTRODUCTION

Radar (RAdio Detection And Ranging) is an electromagnetic system for the detection and location of reflecting objects such as aircraft, ships, spacecraft, vehicles, people and the natural environment. It operated by radiating energy into space and detecting the echo signal reflected from the object, or target. The reflected energy that is returned to the radar not only indicates the presence of the target, but by comparing the received echo signal with the signal that was transmitted, its location can be determined along with other target related information. Radar can perform its function at long or short distances and under condition impervious to optical and infrared sensors. It can operate in darkness, haze, fog, rain and snow. Its ability to measure distance with high accuracy and in all weather is one of its most important attributes.

Radar relies on the propagation and reverberation of signal. In an active system, a projecting transducer creates a signaling wave and receiving transducers receive echoes off objects in the surrounding environments. The reverberation signal carries three types of information.

- The round trip time from send to receive reveals the range of the object.
- The frequency shift of the signal reveals the relative velocity (Doppler) of the object.
- The strength and phase shift of the reverberation revelas the nature of the object.

To attain these values, there are two task performed by radar

- Target detection: It is accomplished by transmitting an electromagnetic signal via an antenna and detecting, in the unavoidable system noise, the wave reflected by the target.
- Parameter estimation: If the returned signal of adequate strength is received, it is further analyzed to determine target distance, velocity, shape of target, number of targets and so forth. This analysis is referred to as parameter estimation.

The real test of radar capability comes when detection and parameter estimation must be performed for several targets simultaneously. This is the problem of target resolution. Continuous Wave (CW) or Pulsed Radars (PR) CW radars are those that continuously emit electromagnetic energy, and use separate transmit and receive antennas. Unmodulated CW radars can accurately measure target radial velocity (Doppler shift) and angular position. Target range information cannot be extracted without utilizing some form of modulation. The primary use of unmodulated CW radars is in target velocity search and track, and in missile guidance. Pulsed radars use a train of pulsed waveforms (mainly with modulation). In this category, radar systems can be classified on the basis of the Pulse Repetition Frequency (PRF), as low PRF, medium PRF, and high PRF radars. Low PRF radars are primarily used for ranging where target velocity (Doppler shift) is not of interest. High PRF radars are mainly used to measure target velocity. Continuous wave as well as pulsed radars can measure both target range and radial velocity by utilizing different modulation schemes.

Letter Designation	Frequency (GHz)	New band designation (GHz)
HF	0.003 – 0.03	A
VHF	0.03 – 0.3	A<0.25; B>0.25
UHF	0.3 – 1.0	B<0.5; C>0.5
L-band	1.0 – 2.0	D
S-band	2.0 – 4.0	E<3.0; F>3.0
C-band	4.0 – 8.0	G<6.0; H>6.0
X-band	8.0 – 12.5	I<10.0; J>10.0
Ku-band	12.5 -18.0	J
K-band	18.0 – 26.5	J<20.0; K.20.0
Ka-band	26.5 – 40.0	K
MMW	Normally > 34.0	L<60.0; M>60.0

Table 2.1 Radar Frequency Bands

2.2 RANGE

Figure 2.1 shows a simplified pulsed radar block diagram. The time control box generates the synchronization timing signals required throughout the system. A modulated signal is generated and sent to the antenna by the modulator/transmitter block. Switching the antenna between the transmitting and receiving modes is controlled by the duplexer. The duplexer allows one antenna to be used to both transmit and receive. During transmission it directs the radar electromagnetic energy towards the antenna. Alternatively, on reception, it directs the received radar echoes to the receiver. The receiver amplifies the radar returns and prepares them for signal processing. Extraction of target information is performed by the signal processor block. The target's range, R, is computed by measuring the time delay, Δt; it takes a pulse to travel the two-way path between the radar and the target. Since electromagnetic waves travel at the speed of light, $c = 3X\ 10^8$ m/sec, then

$$R = \frac{c\Delta t}{2}$$

Where R is in meters and Δt is in seconds. The factor of ½ is needed to account for the two – way time delay.

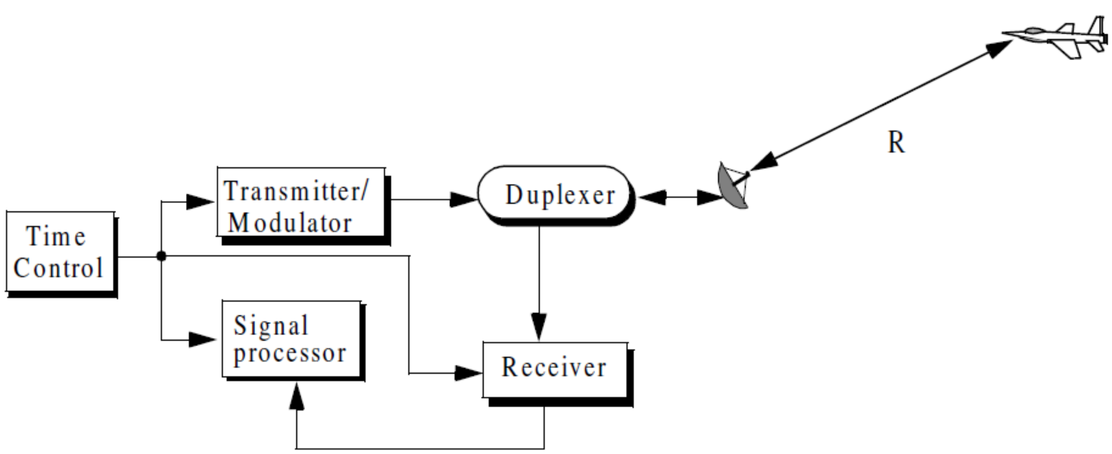

Figure 2.1 shows a Simplified Pulsed Radar Block Diagram

In general, pulsed radar transmits and receives a train of pulses, as illustrated by Figure 2.2. The Inter Pulse Period (IPP) is T, and the pulse width is τ. The IPP is often referred to as the Pulse Repetition Interval (PRI). The inverse of the PRI is the PRF, which is denoted by f_r

$$f_r = \frac{1}{PRI} = \frac{1}{T}$$

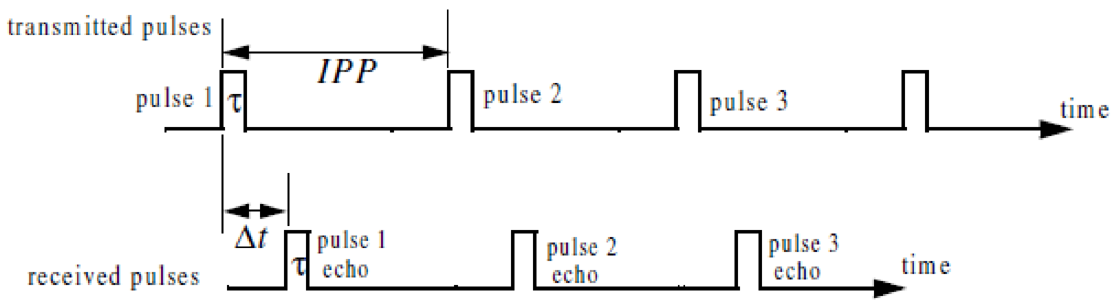

Figure 2.2 shows that Train of Transmitted and Received Pulses

During each PRI the radar radiates energy only for τ seconds and listens for target returns for the rest of the PRI. The radar transmitting duty cycle (factor) d_t is defined as the ratio $d_t = \tau/T$. The radar average transmitted power is

$$P_{av} = P_t \times d_t$$

Where P_t denotes the radar peak transmitted power.

The pulse energy is $E_p = P_t\tau = P_{av}T = P_{av}/f_r$.

The range corresponding to the two-way time delay T is known as the radar unambiguous range, R_u. Consider the case show in in Figure 2.3. Echo 1 represents the radar return from a target at range $R_1 = c\Delta t/ 2$ due to pulse 1. Echo 2 could be interpreted as the return from the same target due to pulse 2, or it may be the return from a faraway target at range R_2 due to pulse 1 again. In this case,

$$R_2 = \frac{c\Delta t}{2} \qquad or \qquad R_2 = \frac{c(T + \Delta t)}{2}$$

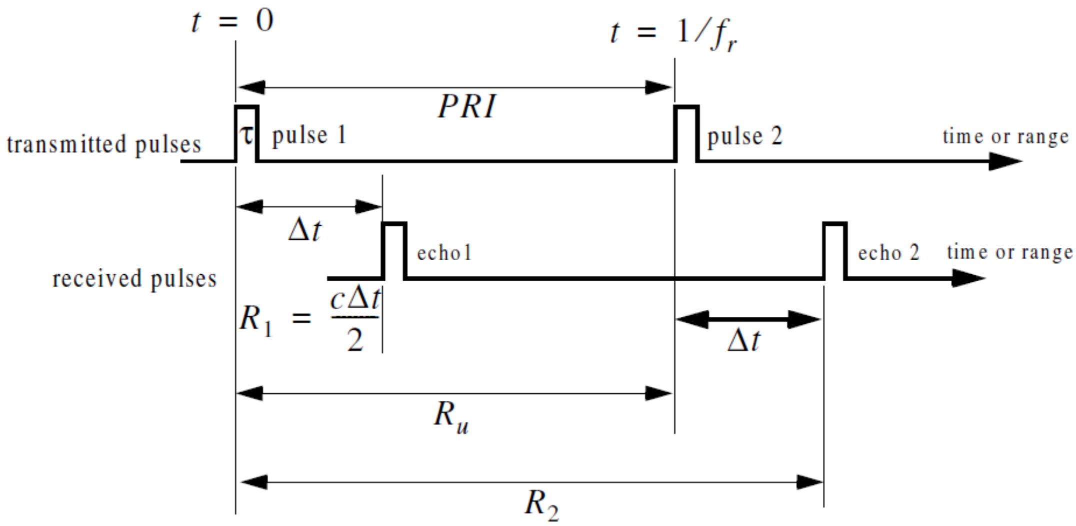

Figure 2.3 shows that Illustration of Range Ambiguity

Clearly, range ambiguity is associated with echo 2. Therefore, once a pulse is transmitted the radar must wait a sufficient length of time so that returns from targets at maximum range are back before the next pulse is emitted. It follows that the maximum unambiguous range must correspond to half of the PRI,

$$R_u = c\frac{T}{2} = \frac{c}{2f_r}$$

2.3 RESOLUTION

Range resolution, denoted as ΔR, is radar metric at describes its ability to detect targets in close proximity to each other as distinct objects. Radar systems are normally designed to operate between a minimum range R_{min}, and maximum range R_{max}. The distance between R_{min} and R_{max} is divided into M range bins (gates), each of width ΔR.

$$M = \frac{R_{max} - R_{min}}{\Delta R}$$

Targets separated by at least ΔR will be completely resolved in range as illustrated in Figure 2.4. Targets within the same range bin can be resolved in cross range (azimuth) utilizing signal processing techniques.

Consider two targets located at ranges R1 and R2, corresponding to time delays t1 and t2, respectively. Denote the difference between those two ranges as ΔR:

$$\Delta R = R_2 - R_1 = c\frac{(t_2 - t_1)}{2} = c\frac{\delta t}{2}$$

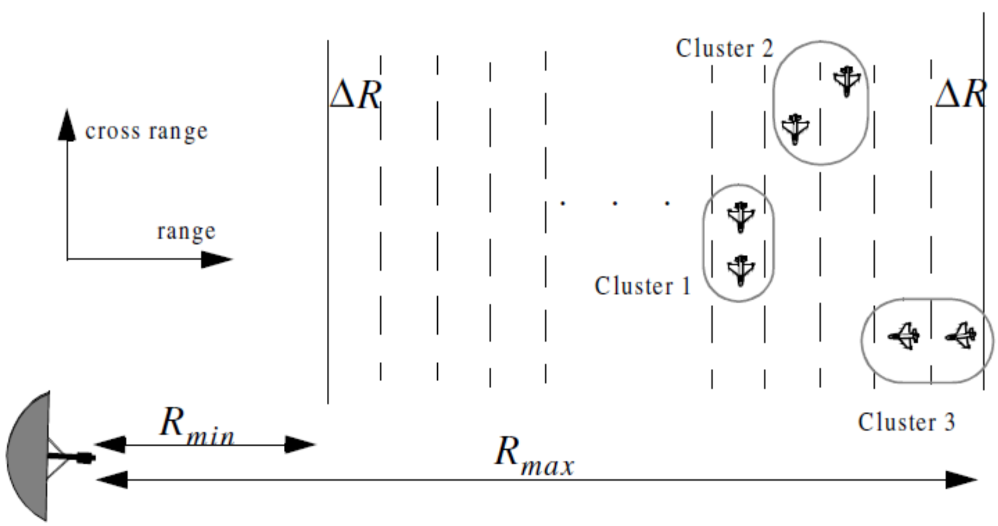

Figure 2.4 shows Resolving Targets in Range and Cross Range

2.4 DOPPLER FREQUENCY

Radars use Doppler frequency to extract target radial velocity (range rate), as well as to distinguish between moving and stationary targets or objects such as clutter. The Doppler phenomenon describes the shift in the center frequency of an incident waveform due to the target motion with respect to the source of radiation. Depending on the direction of the target's motion this frequency shift may be positive or negative. A waveform incident on a target has equiphase wavefronts separated by λ, the wavelength. A closing target will cause the reflected equiphase wavefronts to get closer to each other (smaller wavelength). Alternatively, an opening or receding target (moving away from the radar) will cause the reflected equiphase wavefronts to expand (larger wavelength), as illustrated in Figure 2.5

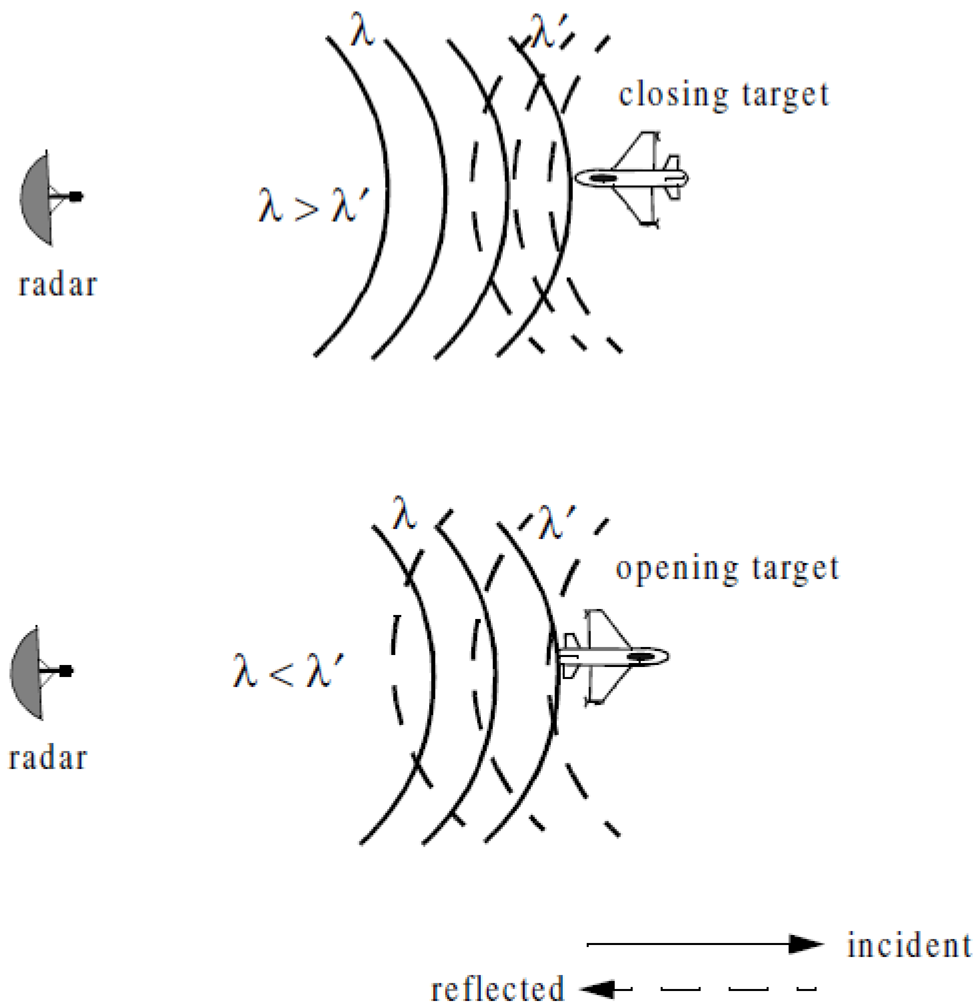

Figure 2.5 shows Doppler Frequency

2.5 RADAR EQUATION

Consider radar with an omni-directional antenna (one that radiates energy equally in all directions). Since these kinds of antennas have a spherical radiation pattern, we can define the peak power density (power per unit area) at any point in space as

$$P_D = \frac{Peak\ transmitted\ power}{area\ of\ a\ sphere} \qquad \frac{watts}{m^2}$$

The power density at range R away from the radar (assuming a lossless propagation medium) is

$$P_D = \frac{P_t}{4\pi R^2}$$

Where P_t is the peak transmitted power and $4\pi R^2$ is the surface area of a sphere of radius R. Radar systems utilize directional antennas in order to increase the power density in a certain direction. Directional antennas are usually characterised by the antenna gain G and the antenna effective aperture A_e. They are related by

$$A_e = \frac{G\lambda^2}{4\pi}$$

Where λ is the wavelength. The relationship between the antenna's effective aperture Ae and the physical aperture A is

$$A_e = \rho A$$
$$0 \le \rho \le 1$$

From calculations we can say that maximum Radar Range is

$$R_{max} = \left(\frac{P_t G^2 \lambda^2 \sigma}{(4\pi)^3 S_{min}}\right)^{1/4}$$

2.6 MATCHED FILTER

For good detection, radar needs a large peak signal power to average noise power ratio (So/No) at the time of the target's return signal. Hence, at the initial stages of the receiver, a matched filter is used to

- Increase the received the signal power to average noise power ratio (So/No)
- Obtain the information carried by the matched filtering of reverberation signal

The output of the matched filter is the cross correlation between

- The received signal plus noise and
- A replica of the transmitted signal

The frequency response of the linear time-invariant filter that maximizes the output peak SNR is

$H(f) = G_oS^*(f)\exp(-j2\pi ftm)$

And the output peak SNR from this matched filter is

$(SNR)_{max} \leq 2E/N$

This means that the matched filter output depends only on the total energy of the received signal and the noise power per unit spectral bandwidth. The matched filter has the interesting property that no matter what the shape, duration, or bandwidth of the input signal waveform, the maximum ratio of the output peak SNR is simply twice the energy E contained in the received signal divided by the noise power per unit bandwidth No.

When the SNR received is large (as it must be for detection), the output of the matched filter can usually be approximated by the auto correlation function of the transmitted signal; i.e. noise is ignored. This assumes that there is no Doppler shift so that received echo signal has the same frequency as the transmitted signal, which might not be the case in many radar systems.

Hence, the output of matched filter is reconsidered as the cross correlation between the

- Doppler-shifted received signal and
- The transmitted signal, with the noise being ignored

The shape of the projected signal acts the filter's ability to recognize the return. For example, if the signal resembles a time shifted version of itself, the filter might incorrectly determine the range of the object. If multiple signals are at the surrounding at the same time, the filter must reject all no-matched signals.

Hence, we can say that the filter's ability to reject a non-matched waveform depends on how little the non-matched waveform resembles time and frequency shifts of the filter's matched signal.

2.7 PULSE COMPRESSION

The maximum detection range depends upon the strength of the received echo. To get high strength reflected echo the transmitted pulse should have more energy for long distance transmission since it gets attenuated during the course of transmission. The energy content in the pulse is proportional to the duration as well as the peak power of the pulse. The product of peak power and duration of the pulse gives an estimate of the energy of the signal. A low peak power pulse with long duration provides the same energy as achieved in case of high peak power and short duration pulse. Shorter duration pulses achieve better range resolution. The range resolution r_{res} is expressed as

$$r_{res} = \frac{c}{2B}$$

Where B is the bandwidth of the pulse.

For unmodulated pulse the time duration is inversely proportional to the bandwidth. If the bandwidth is high, then the duration of the pulse is short and hence this offers a superior range resolution. Practically, the pulse duration cannot be reduced indefinitely. According to Fourier theory a signal with bandwidth B cannot have duration shorter than 1/B i.e. its time-bandwidth (TB) product cannot be less than unity. A very short pulse requires high peak power to get adequate energy for large distance transmission. However, to handle high peak power the radar equipment become heavier, bigger and hence cost of this system increases. Therefore peak power of the pulse is always limited by the transmitter. A pulse having low peak power and longer duration is required at the transmitter for long range detection. At the output of the receiver, the pulse should have short width and high peak power to get better range resolution. Figure 6 illustrates two pulses having same energy with different pulse width and peak power. To get the advantages of larger range detection ability of long pulse and better range resolution ability of short pulse, pulse compression techniques are used in radar systems.

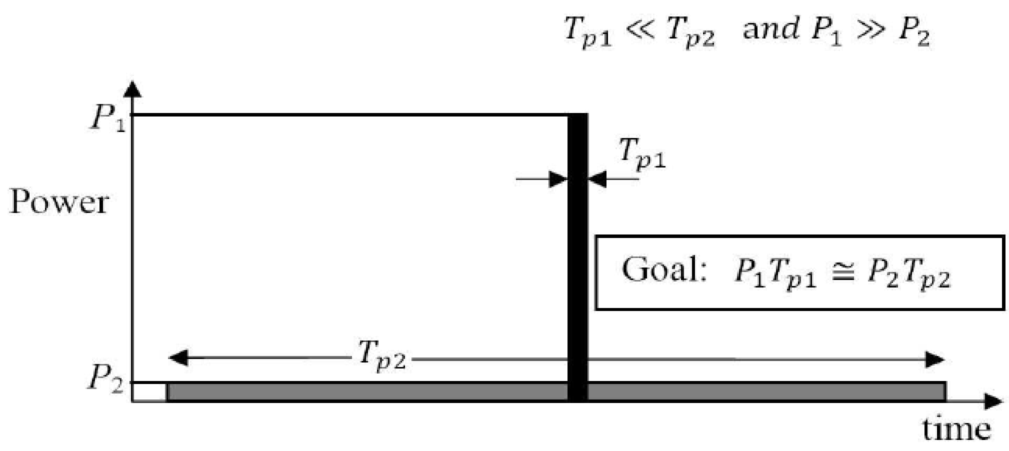

Figure 2.6 shows that Transmitter and Receiver Ultimate Signals

The range resolution depends on the bandwidth of a pulse but not necessarily on the duration of the pulse. Some modulation techniques such as frequency and phase modulation are used to increase the bandwidth of a long duration pulse to get high range resolution having limited peak power. In pulse compression technique a pulse having long duration and low peak power is modulated either in frequency or phase before transmission and the received signal is passed through a filter to accumulate the energy in a short pulse. The pulse compression ratio (PCR) is defined as

$$PCR = \frac{\text{width of the pulse before compression}}{\text{width of the pulse after compression}}$$

The block diagram of a pulse compression radar system is shown in Figure 7. The transmitted pulse is either frequency or phase modulated to increase the bandwidth. Transreceiver (TR) is a switching unit helps to use the same antenna as transmitter and receiver. The pulse compression filter is usually a matched filter whose frequency response matches with the spectrum of the transmitted waveform. The filter performs a correlation between the transmitted and the received pulses. The received pulses with similar characteristics to the transmitted pulses are picked up by the matched filter whereas other received signals are comparatively ignored by the receiver.

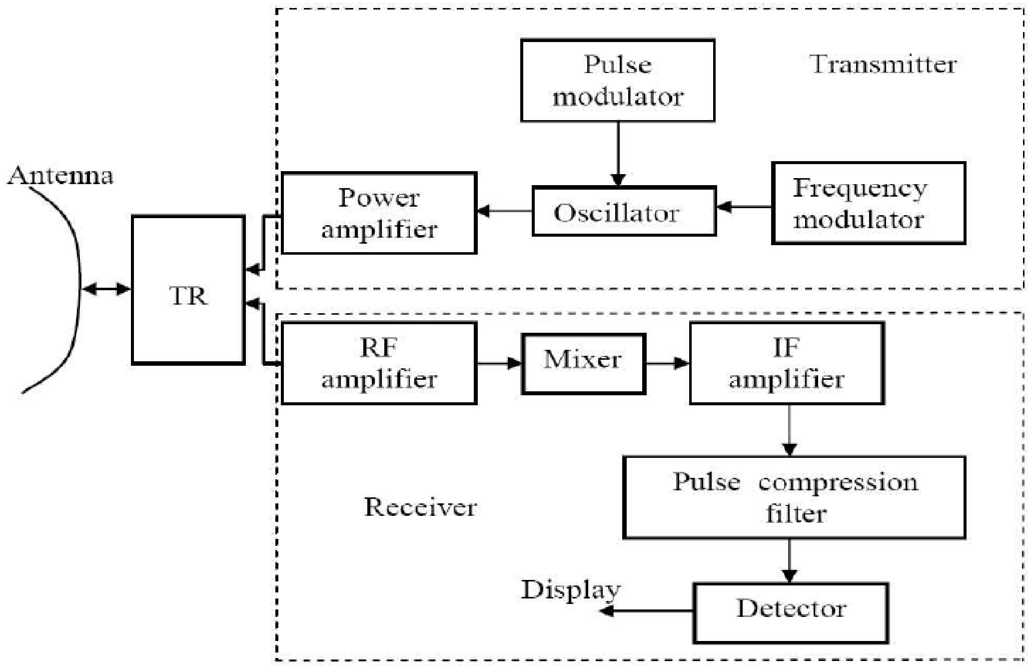

Figure 2.7 shows Block diagram of a pulse compression radar system

2.7.1 RANGE RESOLUTION WITH SHORTH PULSE RADAR

High range resolution as might be obtained with the short pulse, is important for many radar applications which are listed below.

a) Range resolution: Usually easier to separate (resolve) multiple targets in range than in angle.

b) Range accuracy: Radar capable of good range resolution is also capable of good range accuracy.

c) Clutter reduction: Increased target-to-clutter ratio is obtained by reducing the amount of distributed clutter with which the target echo signal must compete.

d) Inter-clutter visibility: With some types of "patchy" land and sea clutter, high resolution radar can detect moving targets in the clear areas between the clutter patches.

e) Glint reduction: Angle and range tracking errors introduced by a complex target with multiple scatters are reduced when high range-resolution is employed to isolate (resolve) the individual scatters that make up the target.

f) Multipath resolution: Range resolution permits the separation of the desired target echo from the echoes that arrive at the radar via scattering from longer propagation paths, or multipath.

g) Multipath height-finding: When multipath due to scattering of radar energy from the earth's surface can be separated from the direct-path signal by high range resolution, target height can be determined without a direct measurement of elevation angle.

h) Target classification: The range, or radial, profile of a target in some cases can provide a measure of target size in the radial dimension. From the range profile one might be able to sort one type of target from another based on size or distinctive profile, especially if the cross-range profile is also available.

i) Doppler tolerance: With a short -pulse waveform, the Doppler-frequency shift from moving target will be small compared to the receiver bandwidth. Hence, only a single matched filter is needed for detection, rather than a bank of matched filter search tuned for a different Doppler shift.

j) ECCM: Short-pulse radar can negate the effects of certain electronic countermeasures such as range-gate stealers, repeaters jammers and decoys. The wide bandwidth of the short-pulse radar can, in principle, provide some reduction in the effects of broadband noise jamming and reduce the effectiveness of some electronic warfare receivers and their associated signal processing.

k) Minimum range: A short pulse allows the radar to operate with a short minimum range. It also allows reduction of blind zones (eclipsing) in high PRF radars.

There can be limitations. However, to the use of a short pulse. They are,

a) Since the spectral bandwidth of a pulse is inversely proportional to its width, the bandwidth of a short pulse is large. Large bandwidth can increase system complexity, make greater demands on the signal processing, and increase the likelihood of interference to and from other users of the electromagnetic spectrum.

b) In some high-resolution radar the limited number of resolution cells available with conventional displays might result in overlap of nearby echoes when displayed, which results in a collapsing loss if an operator makes the detection decision.

c) Wide bandwidth can also mean less dynamic range in the receiver because receiver noise power is proportional to bandwidth.

d) A short-pulse waveform provides less accurate radial velocity measurement than if obtained from the Doppler-frequency shift. In spite of such limitations, the short pulse waveform is used because of the important capabilities it provides.

e) A serious limitation to achieving long ranges with short-duration pulses is that a high peak power radar can be subject to voltage breakdown (arc discharge), especially at the higher frequencies where wave guide dimensions are small.

If the peak power is limited by breakdown, the pulse might not have sufficient energy.

Now that, the detect ability requirements can be achieved by the use of the matched filter, we now proceed to the pulse compression coding to achieve range resolution conditions.

High-resolution can be obtained by the short pulse, but there can he limitations to the use of short pulse as discussed above.

A short pulse has a wide spectral bandwidth. A long pulse can have the same spectral bandwidth as a short if the long pulse is modulated in frequency or phase. The modulated long pulse with its increased bandwidth B is compressed by the matched filter of the receiver to a width equal to 1/B. this process is called 'pulse compression'.

The pulse compression can be described as the use of a long pulse of width I to obtain the resolution of a short pulse by modulating the long pulse to achieve a bandwidth B(>>1/T), and processing the modulated long pulse in a matched filter to obtain a pulse width approximately equal to 1/B.

Dividing a longer pulse into 'N' number of sub-pulses and then doing the phase or frequency modulation of the sub-pulses to achieve the pulse compression. It helps us maintain the pulse width unchanged decides increasing the bandwidth. This increase in the bandwidth as a result of pulse compression is defined as 'pulse compression ratio'. The pulse compression ratio is defined as the ratio of the long pulse width 1' to the compressed pulse width T, or T/τ. It can also be written as B_T (which cannot be used when amplitude weighting is used on the received signal).

The receiver gain depends proportionally on this time-bandwidth product of the received waveform. In the case of the uncompressed pulse transmission, the receiver gain is unity because of the fact that there is no pulse compression and consequently time, bandwidth is inversely proportional to each other. But when the pulse compression is done it results in an improved receiver gain more than unity is obtained because the pulse compression factor of order N_2 (where N is the number of sub pulses) can be achieved. In practical radar system, pulse compression ratio might be as small as 10 or even greater than 10^5. However, typically pulse compression ratio values can be in the range of 100 to 300.

2.7.2 PULSE COMPRESSION TECHNIQUES

As it was already mentioned, the pulse Compression is done either by phase or frequency modulation of the longer pulse which is divided into 'N' sub pulses. There are two general classes of the pulse-compression techniques:

- Phase-Coding techniques
- Frequency-Coding techniques

In the phase coding techniques, changes in phase are used to increase the signal bandwidth of a long pulse for the pulse compression. A long pulse of duration T is divided into N sub-pulses each of width T. An increase in bandwidth is achieved by changing the phase of each sub-pulse. Under phase-coding techniques, few of the common forms of coding can be listed as

- Binary-Phase Coding
- Barker Coding
- Linear Recursive Coding
- Poly-Phase Coding

In Binary Coding, the phase of each sub-pulse is selected to be either zero or π radians according to some specified criterion. If the selections of the zero, π phases are made at random, the waveform approximates a noise-modulated signal and has ideal characteristics. The matched filter output will be a compressed pulse of width r and will have the peak N times greater than that of the long pulse. The pulse compression ratio equals the number of sub-pulses N. the expected maximum (power) side lobe is about 2/N below the peak of the compressed pulse.

In Barker coding, all the time-side lobes of the compressed pulse are equal. This coding is nothing but the (0, π*)* binary coding that results in equal time-side lobes. The auto correlation function, which is the output of the matched filter, will have a peak M^2 times greater than that of the long pulse. The greatest pulse compression ratio for a barker code is 13.

In Linear Recursive coding, a set of random-like phase codes is obtained by employing a shift register with feedback and modulo-2 addition that generates a pseudorandom sequence of 0's and 1's of length 2n-1, where n is the number of stages in the shift register. An n-stage shift register consists of 'n' consecutive two-state memory units controlled by a single clock. The two states considered here are o and 1 corresponding to 0 and π phases. At each clock pulse, the state of each stage is shifted to the next stage in line. When the output sequence of an n-stage shift register is of period 2^n-1, it is called a maximal length sequence, or m-sequence. This type of waveform is also known as a linear recursive sequence (LRS). The highest (power) side lobe can be about 1/2N that of the maximum compressed-pulse power. The pulse compression ratio can be at the maximum 'N', the number of side-pulses

In the poly-phase coding, other than the levels of binary phases (0,π), other phases are also used in phase coding. The phase of each element is defined as each of the numbers in an M X N matrix multiplied by a phase equal to 2π/M. the poly-phase coding starts at the upper left-hand corner of the matrix, and a sequence will be of length $M^2 = N$, the total number of sub-pulses.

The peak of the matched filter output is $(N/2)^2$ times greater than that of the sidelobe. However, the width of the compressed pulse is doubled so that pulse compression is reduced to N/2.

Hence to avoid this disadvantage of the lower pulse compression in phase modulation, frequency hopping mechanism was introduced which does the hopping of different frequencies among different sub-pulses. This was guaranteed with a pulse compression ratio as 10^5 (orN^2).

2.7.3 PULSE COMPRESSION CODING CHARACTERIZING PROPERTIES

The pulse compression techniques can be characterized on the basis of their auto and cross- correlation properties. These properties assist the user in prioritizing the one coding to the other on the basis of the area of application.

The auto-correlation property deals the relation between the un-shifted frequency version of the transmitted frequency signal and the transmitted signal itself. The auto-correlation is good when the received signal is exactly the same as the transmitted without any related delay. It gives a measure of the range or delay factor.

The cross-correlation deals the relation between the transmitted signal and the frequency shifted version of it or the relation between the transmitted signal and the difference received signal (other system's echo). It gives a measure of the Doppler or the radial velocity factor.

At the receiver end these correlations need to be well-bounded for better resolution and accuracy at the receiver. In most of the cases the upper bounds of the auto and cross-correlation are converse in nature, i.e., can be good cross-correlation but poor auto correlation or the converse case. Often it is suggested to take a better comprise between the two depending on the field of application.

2.7.4 ADVANTAGES AND LIMITATIONS OF PULSE COMPRESSION CODING

The advantages offered by the pulse compression coding can be written as

a) More efficient use of average power available at the radar transmitter and, in some cases, avoidance of peak power problems in the high power sections of the radar transmitter.

b) Transmission of long pulse using average power capability of system

c) Average power may be increased without increasing the PRF. Hence it decreases range ambiguity.

d) Reduction of vulnerability to certain types of interfering signals that don't have some properties as that of the coded waveform

e) Increased system resolving capability, both in range and velocity. In the case of range resolution, the generation of extremely fast rise time and peak power signals is bypassed using pulse compression techniques.

f) Good range accuracy,

The pulse compression not only offers advantages but also has got the limitations that it has the range side lobes which might be taken mistakenly as true signal and also can missed the weak echo signal from target.

CHAPTER 3

CHAPTER 3

PHASE CODED SIGNAL

3.1 INTRODUCTION

The increase in bandwidth can also be achieved by phase modulation. In this case a long pulse width T_p is divided into a number of sub pulses each of width t_b as shown in Figure 3.1. Each sub pulse is assigned with a phase value φ_i, where i = 1, 2, ...N. The received echo is passed through a filter to get a single output peak. The most popular phase coding is biphase or binary coding. A biphase code consists of a sequence of +1 and -1. The phases of the transmitted waveform are 0^0 for +1 and 180^0 for -1. The coded signal is discontinuous at the point of phase reversal. The matched filter response of a randomly assigned 10-bit biphase code ([1 -1 1 -1 1 -1 -1 1 1 -1]) is shown in Figure 3.4. It is evident from the figure that phase coded signals are also associated with the sidelobes. The PCR of phase coded pulse is obtained as

$$PCR = \frac{T_p}{t_b}$$

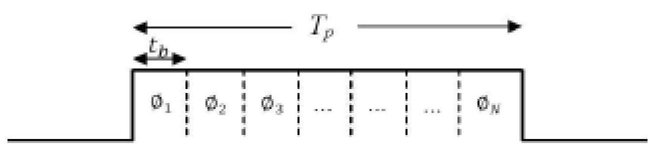

Figure 3.1 shows Phase Modulated Waveform

Figures 3.2, 3.3 & 3.4 shows that the modulated signals provide better range resolution as compared to unmodulated signals but the matched filter output of the modulated signals suffer from the sidelobes. These sidelobes may hide the small targets or ma cause false target detection. The sidelobe having largest amplitude is called peak side lobe. The lower the peak sidelobe level (PSL) the better is the code. To quantify the waveform characteristics peak to sidelobe ratio (PSR) and integrated sidelobe ratio (ISR) are used as measures of performance in radar systems. These are defined as

$$PSR = 10\,log_{10}\frac{\text{peak sidelobe power}}{\text{mainlobe power}}$$
$$ISR = 10\,log_{10}\frac{\text{total power in sidelobes}}{\text{mainlobe power}}$$

In biphase codes the selection of random phase 0 or π is a difficult task. The phases are selected so that the matched filter output of the code has lower sidelobes. If the pulse is allowed to take more than two values, it is known as a polyphase code. The phases of the polyphase code are chosen in such way that its ACF should have lower sidelobes. However the polyphase codes are sensitive to Doppler shift. To overcome this problem the polyphase codes are derived from the phase history of the frequency modulated pulses.

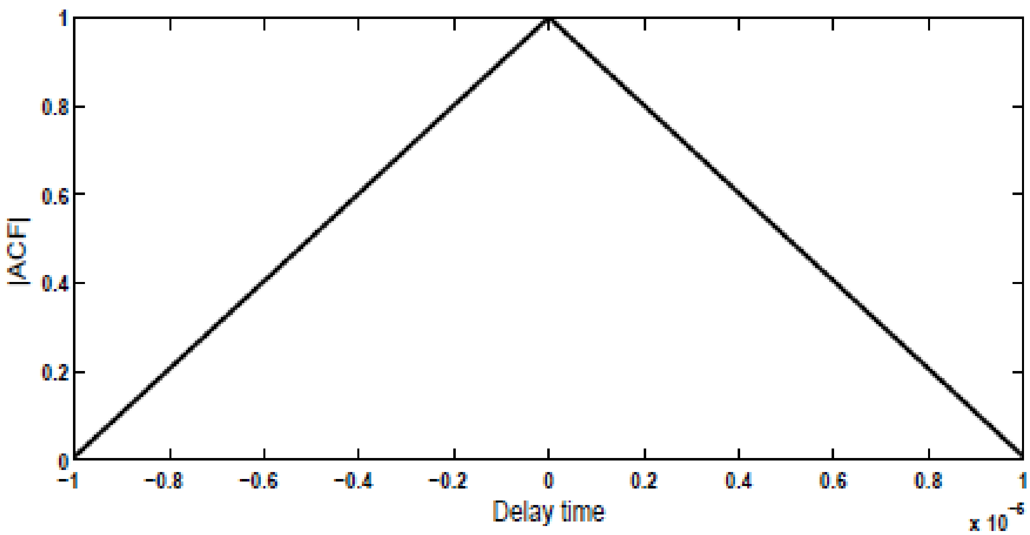

Figure 3.2 shows Matched filter response for unmodulated pulse

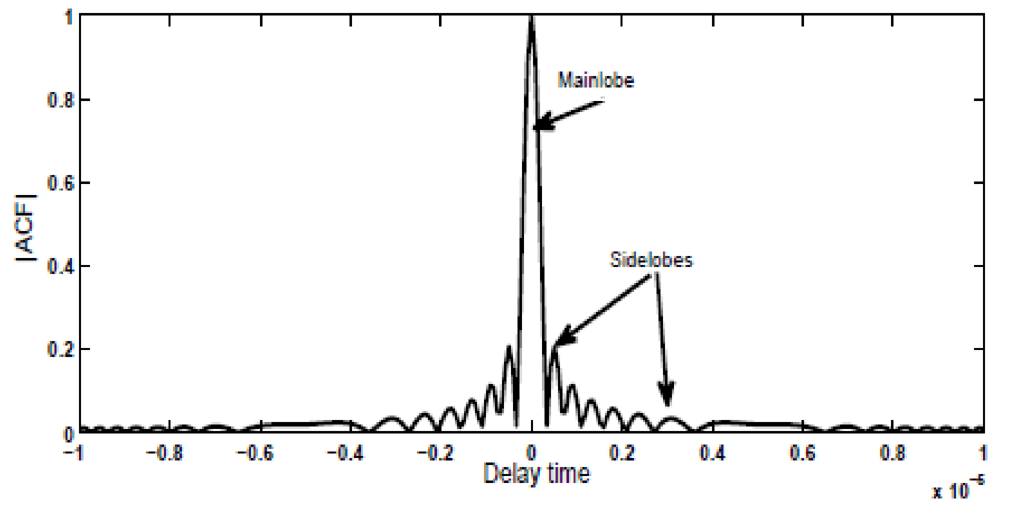

Figure 3.3 shows Matched filter response for frequency modulated pulse (T B = 30)

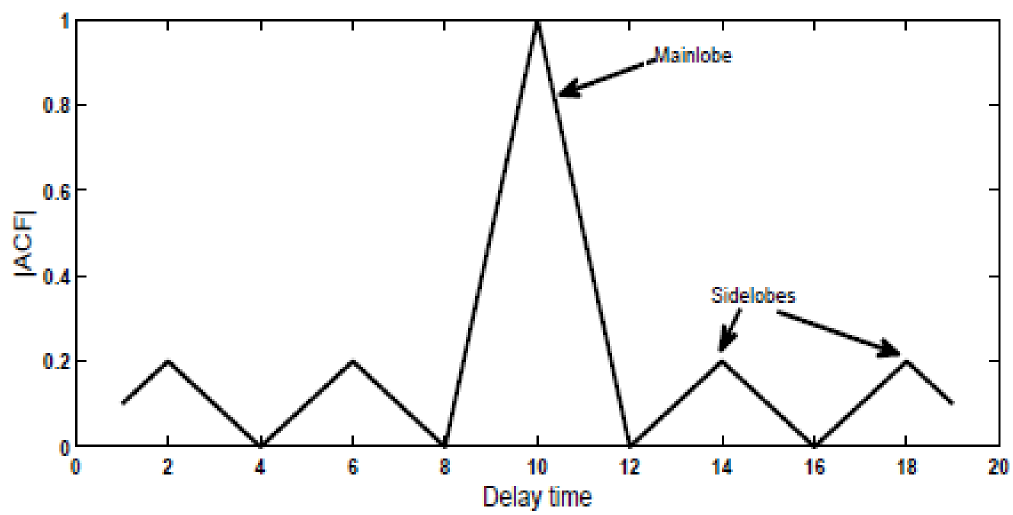

Figure 3.4 shows Matched filter output of different signals

3.2 BARKER CODES

Barker codes are the special type of binary codes having sidelobes of unity magnitude. Exhaustive computer based search reveals that the Barker codes are available for the length of 2, 3, 4, 5, 7, 11 and 13 only. The Barker codes along with their PSR values are listed in Table 2. The Barker code have maximum compression ratio is 13 and highest PSR magnitude is 22.3 dB.

A **Barker code** or **Barker sequence** is a finite sequence of*N* values of +1 and −1,

a_j for $j = 1, 2, \ldots, N$

With the ideal autocorrelation property, such that the off-peak (noncyclic) autocorrelation coefficients

$$c_v = \sum_{j=1}^{N-v} a_j a_{j+v}$$

Are as small as possible:

$$|c_v| \le 1$$

For all $1 \le v < N$

Only nine Barker sequences are known, all of length N at most 13. Barker's 1953 paper asked for sequences with the stronger condition

$$c_v \in \{-1, 0\}$$

Only four such sequences are known up to now.

The table of all known Barker codes is given below, where negations and reversals of the codes have been omitted. A Barker code has a maximum autocorrelation sequence which has sidelobes no larger than 1. It is generally accepted that no other perfect binary phase codes exist (It has been proven that there are no further odd-length codes, nor even-length codes of $N < 10^{22}$)

Code Length	Coded Signal	PSR in dB
2	1 -1,-1 1	-6
3	1 1 -1	-9.5
4	1 1 -1 1, 1 1 1 -1	-12
5	1 1 1 -1 1	-14
7	1 1 1 -1 -1 1 -1	-16.9

11	1 1 1 -1 -1 -1 1 -1 -1 1 -1	-20.8
13	1 1 1 1 1 -1 -1 1 1 -1 1 -1 1	-22.3

Table 3.1 Barker Codes

Barker codes of length *N* equal to 11 and 13 are used in direct-sequence spread spectrum and pulse compression radar systems because of their low autocorrelation properties (The sidelobe level of amplitude of the Barker codes is 1/N that of the peak signal). A Barker code resembles a discrete version of a continuous chirp, another low-autocorrelation signal used in other pulse compression radars.

The positive and negative amplitudes of the pulses forming the Barker codes imply the use of biphase modulation or binary phase-shift keying; that is, the change of phase in the carrier wave is 180 degrees.

Similar to the Barker codes are the complementary sequences, which cancel sidelobes exactly when summed; the even-length Barker code pairs are also complementary pairs. There is a simple constructive method to create arbitrarily long complementary sequences.

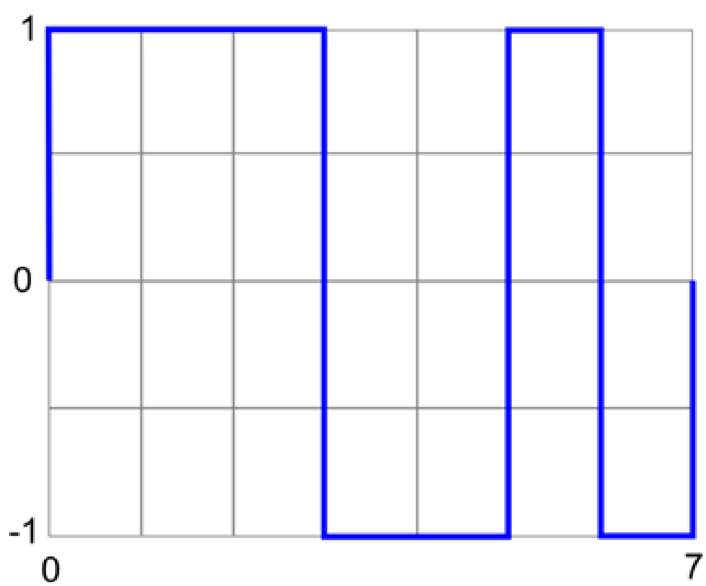

Figure 3.5 shows Graphical representation of a Barker 7 Code

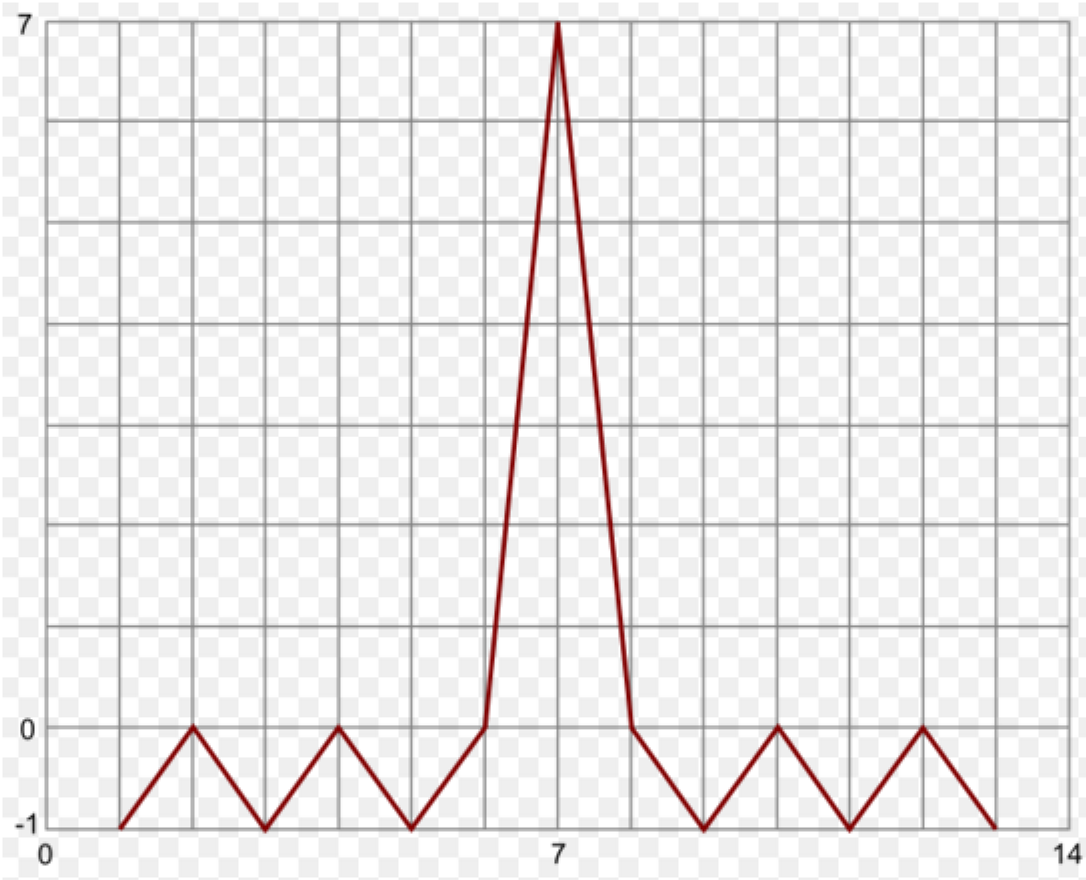

Figure 3.6 shows Autocorrelation function of a Barker-7 code

For the case of cyclic autocorrelation, other sequences have the same property of having perfect (and uniform) sidelobes, such as prime-length Legendre sequences and $2^n - 1$ maximum length sequences (MLS). Arbitrarily long cyclic sequences can be constructed.

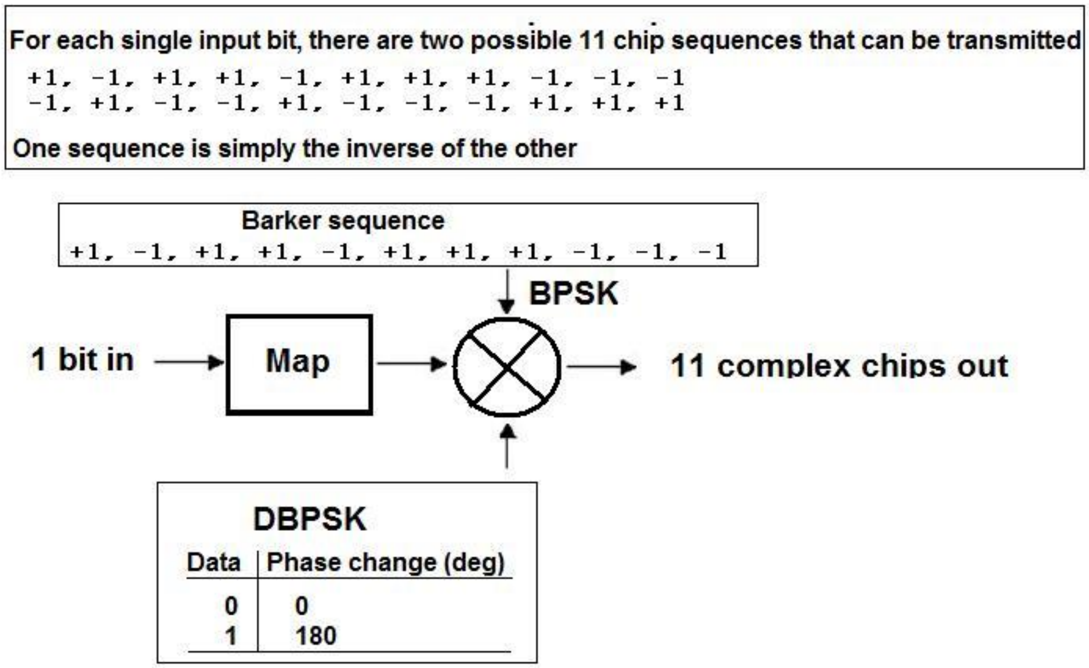

Figure 3.7 shows Barker code used in BPSK modulation

In wireless communications, sequences are usually chosen for their spectral properties and for low cross correlation with other sequences likely to interfere. In the 802.11b standard, an 11-chip Barker sequence is used for the 1 and 2 Mbit/sec rates. The value of the autocorrelation function for the Barker sequence is 0 or −1 at all offsets except zero, where it is +11. This makes for a more uniform spectrum, and better performance in the receivers. The codes those yield minimum peak sidelobe level but do not meet the Barker condition (i.e. maximum PSL is unity) are called minimum peak sidelobe (MPS) level codes.

3.3 NESTED BARKER CODES

A longer code is required for many radar applications to achieve high pulse compression ratio. One way to obtain a longer code having lower sidelobe level is by nesting two Barker codes using Kronecker product. This type of code is called compound Barker code. If one Barker code has length l1 and that of other is l2, then the compound Barker code is of length l1l2 and the compression ratio is l1l2. For example a 35-bit compound Barker code is generated by taking the Kronecker tensor product of 5-bit and 7-bit Barker codes and the resultant code is [1 1 1 -1 -1 1 -1 1 1 1 -1 -1 1 -1 1 1 1 -1 -1 1 -1 -1 -1 -1 1 1 -1 1 1 1 1 -1 -1 1 -1]. Although a larger compression ratio is achieved by compound Barker code, the peak sidelobes are not proportionally decreased.

Barker codes are the only biphase codes with smallest achievable sidelobes. However, the longest Barker code of odd length is proven to be of 13 and considered to be major disadvantage. There is also a strong conjecture that Barker codes of length 2 and 4 are the only ones of even length. The code of length 13 achieves a mainlobe to peak side lobe ratio of only 22.8 dB which is less than the practical requirement of at least 30dB. In literature mismatched filters are proposed to improve this ratio. In this paper Nested binary codes are considered and these have an improvement in PSLR compared to the Barker codes. Nested binary codes can be obtained by using the Kronecker product of two Barker codes whose initial matched filter response is good. If an N-bit Barker code is denoted by BN, and another BM , then an MN bit code can be constructed as BN⊗BM. The Kronecker product is simply the BM code repeated N times, with each repetition multiplied by the corresponding element of the BN code. For example, a 65 bit code can be constructed as the product B13⊗B5. These codes have a peak sidelobe greater than 1.

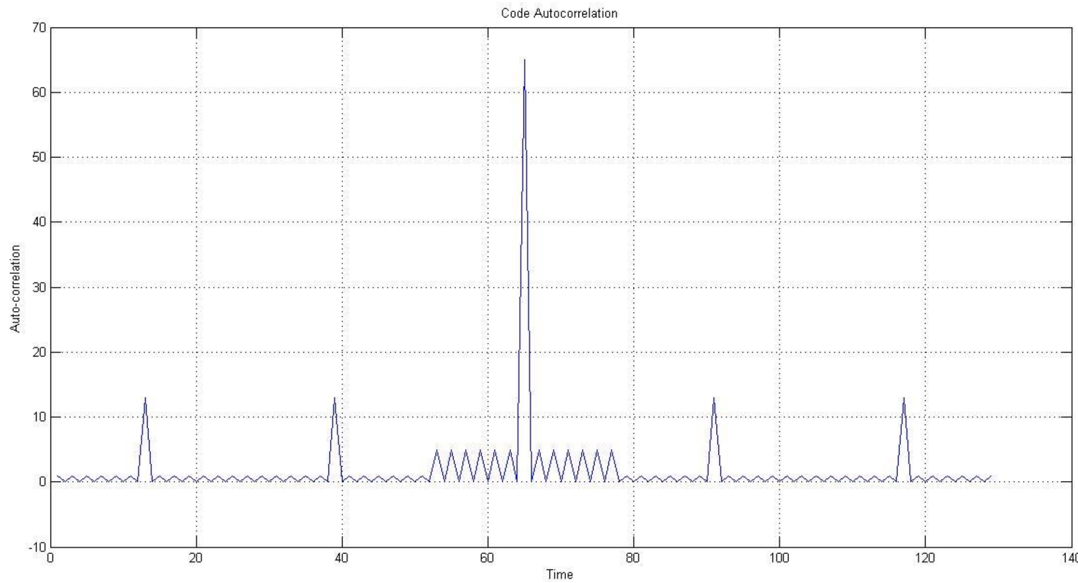

Figure 3.8 shows Auto Correlation Function of Nested Binary Code of Length 65

3.4 MAXIMUM LENGTH SEQUENCE (MLS)

A maximum length sequence (MLS) is a type of pseudorandom binary sequence. They are bit sequences generated using maximal linear feedback shift registers and are so called because they are periodic and reproduce every binary sequence (except the zero vector) that can be represented by the shift registers (i.e., for length-m registers they produce a sequence of length $2^m - 1$). An MLS is also sometimes called an n-sequence or an m sequence. MLSs are spectrally flat, with the exception of a near-zero DC term. These sequences may be represented as coefficients of irreducible polynomials in a polynomial ring over Z/2Z.

Practical applications for MLS include measuring impulse responses (e.g., of room reverberation). They are also used as a basis for deriving pseudo-random sequences in digital communication systems that employ direct-sequence spread spectrum and frequency-hopping spread spectrum transmission systems, and in the efficient design of some fMRI experiments.

3.4.1 GENERATION OF MAXIMUM LENGTH SEQUENCES

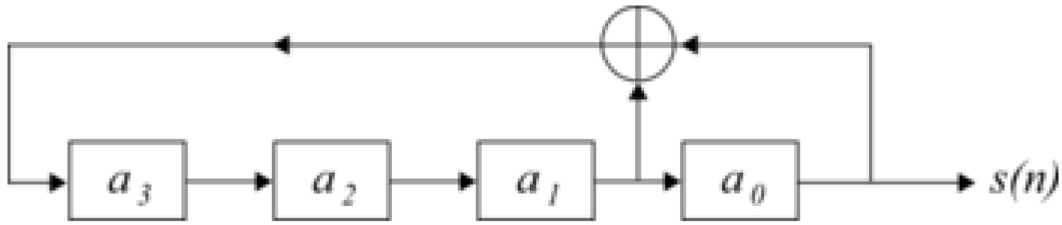

Figure 3.9 shows Shift Registers

Figure 3.9 shows the next value of register a_3 in a feedback shift register of length 4 is determined by the modulo-2 sum of a_0 and a_1.

MLS are generated using maximal linear feedback shift registers. An MLS-generating system with a shift register of length 4 is shown in Fig16. It can be expressed using the following recursive relation:

$$\begin{cases} a_3[n+1] = a_0[n] + a_1[n] \\ a_2[n+1] = a_3[n] \\ a_1[n+1] = a_2[n] \\ a_0[n+1] = a_1[n] \end{cases}$$

Where n is the time index and $+$ represents modulo-2 addition.

As MLS are periodic and shift registers cycle through every possible binary value (with the exception of the zero vector), registers can be initialized to any state, with the exception of the zero vector.

3.4.2 POLYNOMIAL INTERPRETATION

A polynomial over GF(2) can be associated with the linear feedback shift register. It has degree of the length of the shift register, and has coefficients that are either 0 or 1, corresponding to the taps of the register that feed the xor gate. For example, the polynomial corresponding to Figure 1 is $x^4 + x + 1$.

A necessary and sufficient condition for the sequence generated by a LFSR to be maximal length is that its corresponding polynomial be primitive.

3.4.3 IMPLEMENTATION

MLS are inexpensive to implement in hardware or software, and relatively low-order feedback shift registers can generate long sequences; a sequence generated using a shift register of length 20 is $2^{20} - 1$ samples long (1,048,575 samples).

3.4.4 PROPERTIES OF MAXIMUM LENGTH SEQUENCE

MLS have the following properties, as formulated by Solomon Golomb.

a) Balance Property

The occurrence of 0 and 1 in the sequence should be approximately the same. More precisely, in a maximum length sequence of length $2^n - 1$ there are 2^{n-1} ones and $2^{n-1} - 1$ zeros. The number of ones equals the number of zeros plus one, since the state containing only zeros cannot occur.

b) Run Property

Of all the "runs" in the sequence of each type (i.e. runs consisting of "1"s and runs consisting of "0"s):

- One half of the runs are of length 1.
- One quarter of the runs are of length 2.
- One eighth of the runs are of length 3.
- ... etc. ...

A "run" is a sub-sequence of "1"s or "0"s within the MLS concerned. The number of runs is the number of such sub-sequences.

c) Correlation Property

The autocorrelation function of an MLS is a very close approximation to a strain of Kronecker delta function.

3.4.5 EXTRACTION OF IMPULSE RESPONSES

If a linear time invariant (LTI) system's impulse response is to be measured using a MLS, the response can be extracted from the measured system output $y[n]$ by taking its circular cross-correlation with the MLS. This is because the autocorrelation of a

MLS is 1 for zero-lag, and nearly zero ($-1/N$ where $N$is the sequence length) for all other lags; in other words, the autocorrelation of the MLS can be said to approach unit impulse function as MLS length increases.

If the impulse response of a system is $h[n]$ and the MLS is $s[n]$, then

$$y[n] = (h * s)[n].$$

Taking the cross-correlation with respect to $s[n]$ of both sides,

$$\phi_{sy} = h[n] * \phi_{ss}$$

and assuming that φ_{ss} is an impulse (valid for long sequences)

$$h[n] = \phi_{sy}.$$

The maximal-length sequences are of particular interest. They are the maximum-length sequences that can be obtained from linear-feedback shift-register generators. They have a structure similar to random sequences and therefore possess desirable autocorrelation functions. They are often called pseudorandom (PR) or pseudonoise (PN) sequences. A typical shift-register generator is shown in Fig. 10.9. The n stages of the shift register are initially set to all Is or to combinations of Os and Is. The special case of all Os is not allowed, since this results in an all-zero sequence. The outputs from specific individual stages of the shift register are summed by modulo-2 addition to form the input. Modulo-2 addition depends only on the number of Is being added. If the number of Is is odd, the sum is 1; otherwise, the sum is O. The shift register is pulsed at the clock-frequency, or shift-frequency, rate. The output of any stage is then a binary sequence. When the feedback connections are properly chosen, the output is a sequence of maximal length. This is the maximum length of a sequence of Is and Os that can be formed before the sequence is repeated. The length of the maximal sequence is N = 2n — 1, where n is the number of stages in the shift-register generator. The total number M of maximum-length sequences that may be obtained from an n-stage generator is where p{ are the prime factors of N. The fact that a number of different sequences exist for a given value of n is important for applications where different sequences of the same length are required. The feedback connections that provide the maximal-length sequences may be determined from a study of primitive and irreducible polynomials. An extensive list of these polynomials is given by Peterson and Weldon

$$M = \frac{N}{n}\Pi\left(1 - \frac{1}{p_i}\right)$$

Table 3 lists the length and number of maximal-length sequences obtainable from shift-register generators consisting of various numbers of stages. A feedback connection for generating one of the maximal-length sequences is also given for each. For a seven-stage generator, the modulo-2 sum of stages 6 and 7 is fed back to the input. For an eight-stage generator, the modulo-2 sum of stages 4, 5, 6, and 8 is fed back to the input. The length N of the maximal-length sequence is equal to the number of subpulses in the sequence and is also equal to the time bandwidth product of the radar system. Large time-bandwidth products can be obtained from registers having a small number of stages. The bandwidth of the system is determined by the clock rate. Changing both the clock rate and the feedback connections permits the generation of waveforms of various pulse lengths, bandwidths, and time-bandwidth products. The number of zero crossings, i.e., transitions from 1 to O or from O to 1, in a maximal-length sequence is 2"-1 . Periodic waveforms are obtained when the shift-register generator is left in continuous operation. They are sometimes used in CW radars. Aperiodic waveforms are obtained when the generator output is truncated after one complete sequence. They are often used in pulsed radars. The autocorrelation functions for these two cases differ with respect to the sidelobe structure. Figure 10.10 gives the autocorrelation functions for the periodic and aperiodic cases for a typical 15-element maximal-length code obtained from a four-stage shiftregister generator. The sidelobe level for the periodic case is constant at a value of — 1. The periodic autocorrelation function is repetitive with a period of NT and a peak value of N9 where N is the number of subpulses in the sequence and T is the time duration of each subpulse. Hence the peak-sidelobe-voltage ratio is AT1 . For the aperiodic case, the average sidelobe level along the time axis is - 1 A. The sidelobe structure of each half of the autocorrelation function has odd symmetry about this value. The periodic autocorrelation function may be viewed as being constructed by the superposition of successive aperiodic autocorrelation functions, each displaced in time by AfT units.

The odd symmetry exhibited by the aperiodic function causes the sidelobe structure for the periodic function to have a constant value of — 1. When the periodic waveform is truncated to one complete sequence, this constant sidelobe property is destroyed. For large N the peak-sidelobe-voltage ratio is approximately AT"172 for the aperiodic case. Maximal-length sequences have characteristics which approach the three randomness characteristics ascribed to truly random sequences,27 namely, that (1) the number of Is is approximately equal to the number of Os; (2) runs of consecutive Is and Os occur with about half of the runs having a length of 1, a quarter of length 2, an eighth of length 3, etc.; and (3) the autocorrelation function is thumbtack in nature, i.e., peaked at the center and approaching zero elsewhere. Maximal-length sequences are of odd length. In many radar systems it is desirable to use sequence lengths of some power of 2. A common procedure is to insert an extra O in a maximal-length sequence. This degrades the autocorrelation function sidelobes somewhat. An examination of sequences with an inserted O will yield the sequence with the best autocorrelation characteristics.

Number of stages, n	Length of maximal sequence, N	Number of maximal sequences, M	Feedback-stage connection
2	3	1	2,1
3	7	2	3,2
4	15	2	4,3
5	31	6	5,3
6	63	6	6,5
7	127	18	7,6
8	255	16	8,6,5,4
9	511	48	9,5
10	1,023	60	10,7
11	2,047	176	11,9
12	4,095	144	12,11,8,6
13	8,191	630	13,12,10,9

14	16,383	756	14,13,8,4
15	32,767	1,800	15,14
16	65,535	2,048	16,15,13,4
17	131,071	7,710	17,14
18	262,143	7,776	18,11
19	524,287	27,594	19,18,17,14
20	1,048,575	24,000	20,17

Table 3.2 Maximal Length Sequences

CHAPTER 4

CHAPTER 4

BIPHASE CODES HAVING GOOD AUTO CORRELATION PROPERTY USING PARTICLE SWARM OPTIMIZATION

4.1 BASIC PSO ALGORITHM

The Particle Swarm Optimization algorithm is a biologically-inspired algorithm motivated by a social analogy. Sometimes it is related to the Evolutionary Computation (EC) techniques, basically with Genetic Algorithms (GA) and Evolutionary Strategies (ES), but there are significant differences with those techniques.

The PSO algorithm is population-based: a set of potential solutions evolves to approach a convenient solution (or set of solutions) for a problem. Being an optimization method, the aim is finding the global optimum of a real-valued function (fitness function) defined in a given space (search space).

The algorithm and its concept of "Particle Swarm Optimization (PSO) were introduced by James Kennedy and Russel Ebhart in 1995. However, its origins go further backwards since the basic principle of optimization by swarm is inspired in previous attempts at reproducing observed behaviour animals in their natural habitat, such as bird flocking or fish schooling, and thus ultimately its origins nature itself. These roots in natural processes of swarms lead to the categorization of the algorithm one of Swarm Intelligence and Artificial Life.

The social metaphor that led to this algorithm can be summarized as follows: the individuals that are part of a society hold an opinion that is part of a "belief space" (the search space) shared by every possible individual. Individuals may modify this "opinion state" based on three factors:

- The knowledge of the environment (its fitness value)
- The individual's previous history of states (its memory)
- The previous history of states of the individual's neighbourhood

An individual's neighbourhood may be defined in several ways, configuring somehow the "social network" of the individual. Several neighbourhood topologies exist (full, ring, star, etc.) depending on whether an individual interacts with all, some, or only one of the rest of the population.

Following certain rules of interaction, the individuals in the population adapt their scheme of belief to the ones that are more successful among their social network. Over the time, a culture arises, in which the individuals hold opinions that are closely related.

In the PSO algorithm each individual is called a "particle", and is subject to a movement in a multidimensional space that represents the belief space. Particles have memory, thus retaining part of their previous state. There is no restriction for particles to share the same point in belief space, but in any case their individuality is preserved. Each particle's movement is the composition of an initial random velocity and two randomly weighted influences: individuality, the tendency to return to the particle's best previous position, and sociality, the tendency to move towards the neighbourhood's best previous position.

4.2 WORKING OF THE ALGORITHM

Formally, let f: $R^n \rightarrow R$ be the cost function which must be minimized. The function takes a candidate solution as argument in the form of a vector of real numbers and produces a real number as output which indicates the objective function value of the given candidate solution. The gradient of f is not known. The goal is to find a solution **a** for which $f(\mathbf{a}) \leq f(\mathbf{b})$ for all **b** in the search-space, which would mean a is the global minimum. Maximization can be performed by considering the function $h = -f$ instead.

Let S be the number of particles in the swarm, each having a position $\mathbf{x}_i \in \mathbb{R}^n$ in the search-space and a velocity $\mathbf{v}_i \in \mathbb{R}^n$. Let $\mathbf{p}_i$ be the best known position of particle i and let **g** be the best known position of the entire swarm. A basic PSO algorithm is then:

- For each particle $i = 1, ..., S$ do:

- Initialize the particle's position with a uniformly distributed random vector: $\mathbf{x}_i \sim U(\mathbf{b_{lo}}, \mathbf{b_{up}})$, where $\mathbf{b_{lo}}$ and $\mathbf{b_{up}}$ are the lower and upper boundaries of the search-space.

- Initialize the particle's best known position to its initial position: $\mathbf{p}_i \leftarrow \mathbf{x}_i$

- If $(f(\mathbf{p}_i) < f(\mathbf{g}))$ update the swarm's best known position: $\mathbf{g} \leftarrow \mathbf{p}_i$

- Initialize the particle's velocity: $\mathbf{v}_i \sim U(-|\mathbf{b_{up}}-\mathbf{b_{lo}}|, |\mathbf{b_{up}}-\mathbf{b_{lo}}|)$

➢ Until a termination criterion is met (e.g. number of iterations performed, or a solution with adequate objective function value is found), repeat:

- For each particle $i = 1, ..., S$ do:

  ✓ For each dimension $d = 1, ..., n$ do:

  ❖ Pick random numbers: $r_p, r_g \sim U(0,1)$

  ❖ Update the particle's velocity: $\mathbf{v}_{i,d} \leftarrow \omega\, \mathbf{v}_{i,d} + \varphi_p\, r_p\, (\mathbf{p}_{i,d}-\mathbf{x}_{i,d}) + \varphi_g\, r_g\, (\mathbf{g}_d-\mathbf{x}_{i,d})$

  ✓ Update the particle's position: $\mathbf{x}_i \leftarrow \mathbf{x}_i + \mathbf{v}_i$

  ✓ If $(f(\mathbf{x}_i) < f(\mathbf{p}_i))$ do:

  ❖ Update the particle's best known position: $\mathbf{p}_i \leftarrow \mathbf{x}_i$

  ❖ If $(f(\mathbf{p}_i) < f(\mathbf{g}))$ update the swarm's best known position: $\mathbf{g} \leftarrow \mathbf{p}_i$

➢ Now **g** holds the best found solution.

The parameters ω, φ_p, and φ_g are selected by the practitioner and control the behaviour and efficacy of the PSO method.

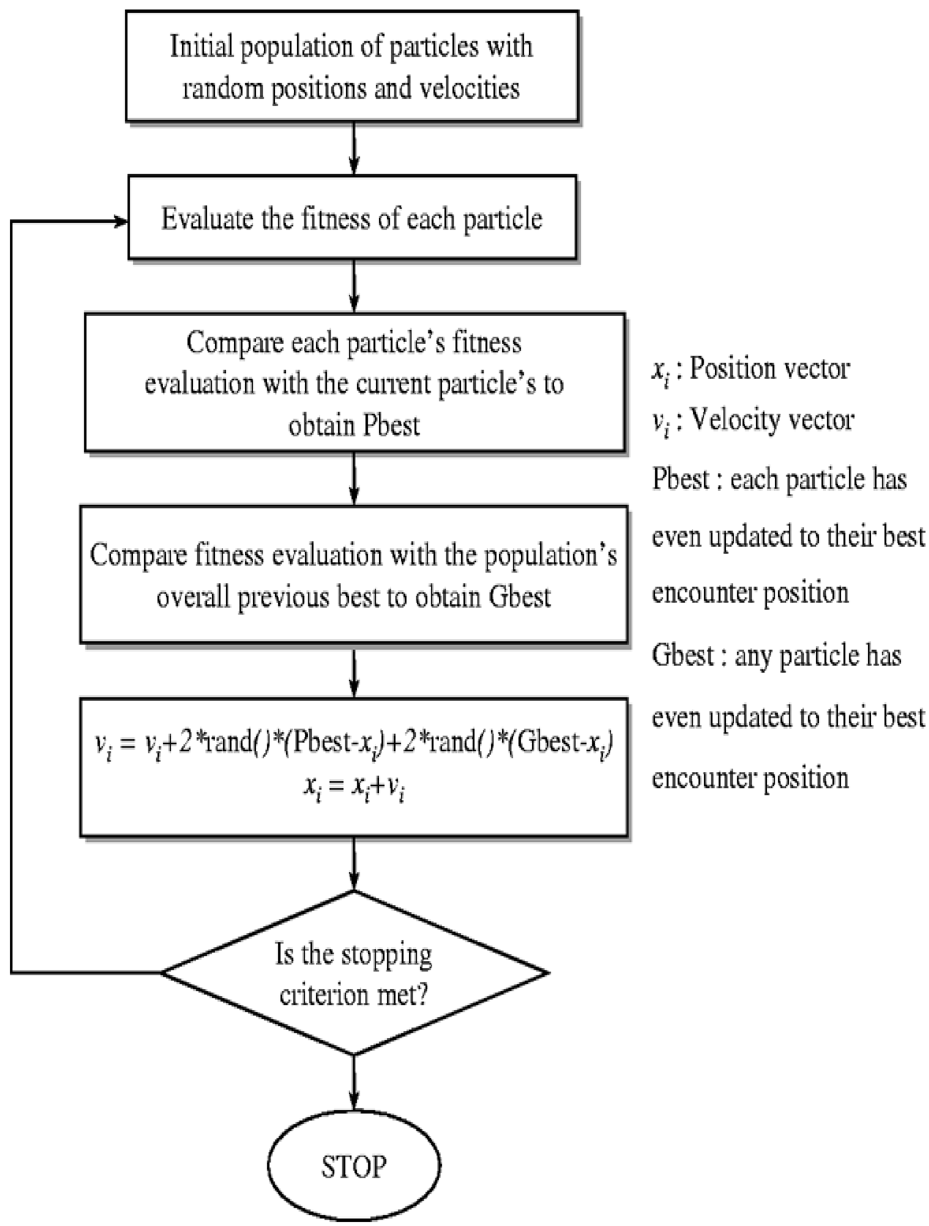

Fig 4.1shows Working of PSO Algorithm

4.3 BIPHASE CODES HAVING GOOD AUTO CORRELATION PROPERTY

The PSO algorithm here is used to obtain biphase codes which are having good auto-correlation property. According to the algorithm initially position best and global best are assigned and the velocity equation is modified. According to the velocity the particles move and finally best sequence order is extracted.

The below figure gives the equations used in PSO Algorithm:

$$x_{i,d}(it+1) = x_{i,d}(it) + v_{i,d}(it+1) \quad (1)$$

$$\begin{aligned} v_{i,d}(it+1) &= v_{i,d}(it) \\ &+ C_1 * Rnd(0,1) * [pb_{i,d}(it) - x_{i,d}(it)] \\ &+ C_2 * Rnd(0,1) * [gb_d(it) - x_{i,d}(it)] \end{aligned} \quad (2)$$

Caption:

i particle's index, used as a particle identifier;

d dimension being considered, each particle has a position and a velocity for each dimension;

it iteration number, the algorithm is iterative;

$\boldsymbol{x_{i,d}}$ position of particle i in dimension d;

$\boldsymbol{v_{i,d}}$ velocity of particle i in dimension d;

$\boldsymbol{C_1}$ acceleration constant for the cognitive component;

Rnd stochastic component of the algorithm, a random value between 0 and 1;

$\boldsymbol{pb_{i,d}}$ the location in dimension d with the best fitness of all the visited locations in that dimension of particle i;

$\boldsymbol{C_2}$ acceleration constant for the social component;

Fig 4.2 shows Figure showing equations involved in PSO Algorithm

The parameters are selected as suggested by the paper "The particle swarm optimization algorithm: convergence analysis and parameter selection" by Ioan Cristian Trelea.i.e., $C_1 = 1.494$, $C_2 = 1.494$ and the random value selected is 0.5

The velocity component is used or even multiplied by a W (inertial weight) factor the particle will tend to explore new areas of the search space since it cannot easily change its velocity towards the best solutions. It must first "counteract" the momentum previously gained, in doing so it enables the exploration of new areas with the time "spend counteracting" the previous momentum. This variation is achieved by multiplying the previous velocity component with weight value, W. in order to obtain good ratio between performance improvement and the algorithm's success in finding a desired solution, the w value should be between [0.9,1.2].

```
//initialize all particles
Initialize
repeat
  for each particle i in S do
    //update the particle's best position
    if f(x_i) < f(pb_i) then
      pb_i = x_i
    end if
    //update the global best position
    if f(pb_i) < f(gb) then
      gb = pb_i
    end if
  end for

  //update particle's velocity and position
  for each particle i in S do
    for each dimension d in D do
      v_{i,d} = v_{i,d} + C_1 * Rnd(0,1) * [pb_{i,d} - x_{i,d}] + C_2 * Rnd(0,1) * [gb_d - x_{i,d}]
      x_{i,d} = x_{i,d} + v_{i,d}
    end for
  end for

  //advance iteration
  it = it + 1
until it > MAX_ITERATIONS
```

Fig 4.3: PSO ALGORITHM

4.4 SOME APPLICATIONS OF PSO ALGORITHM

Since its initial development has had an exponential increase in applications (either in the algorithm's original form or in an improved or differently parameterized fashion). A first look into the applications of this algorithm was presented by one of its creators Eberhart and Shi in 2001 focusing on application areas such as: Aritificial Neutral Networks Training (for Parkinson Diagnostic), Control Strategy determination (for electricity management) and Ingredient Mix Optimization (for microorganisms strains growth). Later in 2007 a survey by Riccardo poli reported the exponential growth in applications and identified around 700 documented works on PSO. He also categorized the areas of applications in 26 categories being those most researched (with around or more than 6% of the works reviewed by Poli):

- Antennas - especially in its optimal control and array design. Aside from there are many others like failure correction and miniaturization.
- Control - especially in PI (Proportional Integral) and PID (Proportional Integral Derivative) controllers. These systems control a process based on its current output and its desired value (the difference between this two is its current error, P), past errors (I) and a prediction of future errors (D);
- Distribution Networks - especially in design/restructuring and load dispatching in electricity networks.
- Electronics and Electromagnetics - here the application are very disperse, but some of the main applications are: on-chip inductors, fuel cells, generic design and optimization in electomagnetics, semi-conductors optimization.
- Image and Video - this area is the one with most documented works in a wide range of applications, some examples are: face detection and recognition, image segmentation, image retrieval, image fusion, microwave imaging, contrast enhancement, body posture tracking.
- Power Systems and Plants - especially focused are power control and optimization. However, other specific applications are: load forecasting, photovoltaic systems control and power loss minimization.
- Scheduling - especially focused are flow shop scheduling, task scheduling in distributed computer systems, job-shop scheduling and holonic manufacturing systems. But other scheduling problems are addressed such as assembly, production, train and project.

The other categories identified are: Biomedical, Communication Networks, Clustering and Classification, Combinational Optimization, Design, Engines and Motors, Entertainment, Faults, Financial, Fuzzy and Neuro-fuzzy, Graphics and Visualization, Metallurgy, Modelling, Neural Networks, Prediction and Forecasting, Robotics, Security and Military, Sensor Networks, Signal Processing.

4.5 MATLAB CODE

4.5.1 MAIN PROGRAM

```
%Code prepared for Project Work
%Author: Datta Sainath D.
%Choose signal length at sig_len
%choose iteration according to your need for fine tuning
%more the no. of iterations more is the tuning

clc;
close all;
clear all;
particles =100000;
sig_len = 13;
iteration =50;


%initialize the random sequences for n particles
%more the random sequences gives us more scope for searching various
%random sequences
%increase the number of particles for better results
%initialize the random velocites for n particles
for i = 1:particles
    ranseq(i,:) = random('Normal',0,1,1,sig_len);
    vel(i,:) = random('Normal',0,1,1,sig_len);
end


%Randomly generated sequences consists of real numbers between -1 and 1
%Converting the random sequence to either 1 or -1
```

```
for i = 1:particles
    for j = 1:sig_len
        if(ranseq(i,j)>=0)
            ranseq(i,j)=1;
        end
        if(ranseq(i,j)<0)
            ranseq(i,j)=-1;
        end
    end
end

%Finding the discriminatory factor for all the random sequences generated
for lp = 1:1:particles
    st = xcorr(ranseq(lp,:));
    mainlobe = max(st);
    sidelobe = max(st(1:sig_len-1));
    df = mainlobe/sidelobe;
    ranseqmf(lp,:) = df;
end



%finding the maximum discriminatory factor from all the discriminatory
%factors of random sequences generated
%initializing p1 as local best
%initialzing p2 as global best
%initialzing a for iteration
%initialzing b1 and b2 according to PSO algorithm
[max_p1 ind] = max(ranseqmf);
p1 = ranseq(ind,:);
p2 = p1;
a = linspace(0.9,1.2, iteration);
```

```
b1 = 1.494;
b2 = 1.494;

%PSO algorithm
for t=1:iteration
for j = 1:particles
    vel(j,:) = a(t)*vel(j,:)+b1*0.5*(p1-ranseq(j,:)) + b2*0.5*(p2-ranseq(j,:));
    rass(j,:) = ranseq(j,:) + vel(j,:);
    bse = rass(j,:);
    x2 = limited(bse);
    v_ranseq(j,:) = x2;

    %calculating the discriminatory factory for the newly formed sequence
    v_st = xcorr(v_ranseq(j,:));
    v_mainlobe = max(v_st);
    v_sidelobe = max(v_st(1:sig_len-1));
    v_df = v_mainlobe/v_sidelobe;
    v_disc(j,:) = v_df;
end

%finding the maximum discriminatory function
[max_vdisc ind1]=max(v_disc);

%interchanging the old local best with the new local best if this
%discriminatory factor is greater than previous local best
if (max_vdisc>=max_p1)
    bes_disc = max_vdisc;
    best = v_ranseq(ind1,:);
else
    bes_disc = max_p1;
    best = p1;
```

```
end

%doing necessary changes for the local best and global best
p2 = best;
b_seq(t,:) = best;
b_disc(t,:) = bes_disc;
end

%finding the maximum discriminatory factor among all the iterations
[best_disc ind2] = max(b_disc);
best_seq = b_seq(ind2,:);
b_disc
x=best_seq

%plotting the autocorrelation plot
z=xcorr(x,x);
plot(z);
xlabel('n');
ylabel('z(n)');
title('auto correlation of input sequence');
```

4.5.2 LIMITED PROGRAM

```
%Limited Function
function [bse] = limited(bse)
sequ = bse;
n = length(sequ);
for i =1:1:n
   if(sequ(i)>=0)
      sequ(i) = 1;
   end
   if(sequ(i)<0)
      sequ(i) = -1;
   end
end
x2 = round(sequ);
seq = x2;
bse = seq;
end
```

4.5.3 MAXIMUM LENGTH SEQUECES

```
%Generation of Binary maximum length sequence code
% maxlength.m
Clear all;
clc;


%code length and feed back (m=2-7; 9-11)
m= input ('length =');
a= m-1;
if m==5;a=3;end;
if m==6;a=5;end;
if m==7;a=6;end
if m==9;a=5;end;
if m==10;a=7;end;
if m==11;a=9;end;

l=2^m-1;


%start sequence
x=eye(1,m);
z=x;


%generate sequence of zero-ones
 for j=1:l;
    for i=2:m; x(i)=z(i-1); x(1) =z(a)+z(m); end;
    if x(1)==2; x(1)=0;end;
    Y(j)=z(m); z=x; end;


%Convert to sequence of 1,-1
for i=1:l;
    if Y(i)==0; Y(i)=-1; end;
end;

t=1:2*l-1; zz=xcorr(Y);
plot(t,abs(zz)); grid;
xlabel('Time');
ylabel('Auto-correlation');
title(['Binary Code Autocorrelation']);
zz=xcorr(Y);


% Estimate the cross correlation
```

```
zz =xcorr(Y)
zz=20*log10(abs(xcorr(Y))+eps);
zz=zz-max(zz);
zz=max(zz,-60);
figure
plot(zz);
title('Auto-correlation Function');
xlabel('{\it\tau}/\itt_b');
ylabel('Autocorrelation [dB]');
grid;


%Display sequence
b=input('Display Sequence Yes=1; No=0; ');
if b==1; disp(Y); end;
```

CHAPTER 5

Chapter 5

5.1 Results

We used in optimization algorithm to eliminate the computational difficulty in constructing codes and also to eliminate the restriction on length of code. Using Particle Swarm Optimization technique we can even construct codes for higher lengths i.e., n = 105. By observing the results obtained we can see how see how the sides lobes are minimised to exhibit the best auto-correlation property.

Since the project is related to the design of biphase codes, it is achieved using the Particle Swarm Optimization technique for different lengths. The results are followed showing the phases of the length sequence.

The results shown below are for different lengths i.e., for n = 60, 61, 62, 63, 64, 65, 66, 67, 68, 69 & 70. We generated maximum length sequences for lengths 31, 63 and 127. We also tried to generate a code for nested barker code of length 65. To achieve this Matlab-10 software is used.

5.1.1 NESTED BARKER CODES

For Signal Length: 65

Peak Lobe: 65

Side Lobe: 13

Discrimination Factor: 5

Side lobe attenuation: 13.979dB

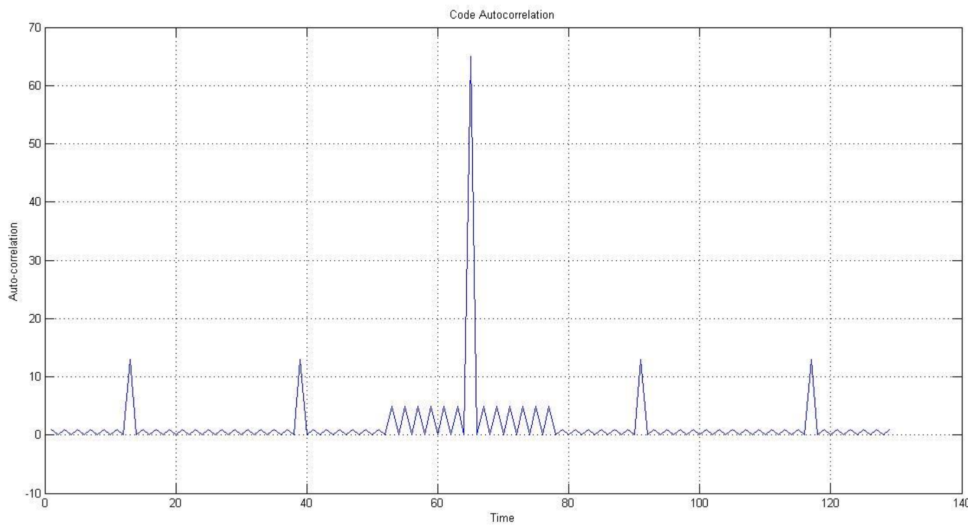

Figure 5.1 shows the auto correlation of signal length of 65

5.1.2 MAXIMUM LLENGTH SEQUENCES:

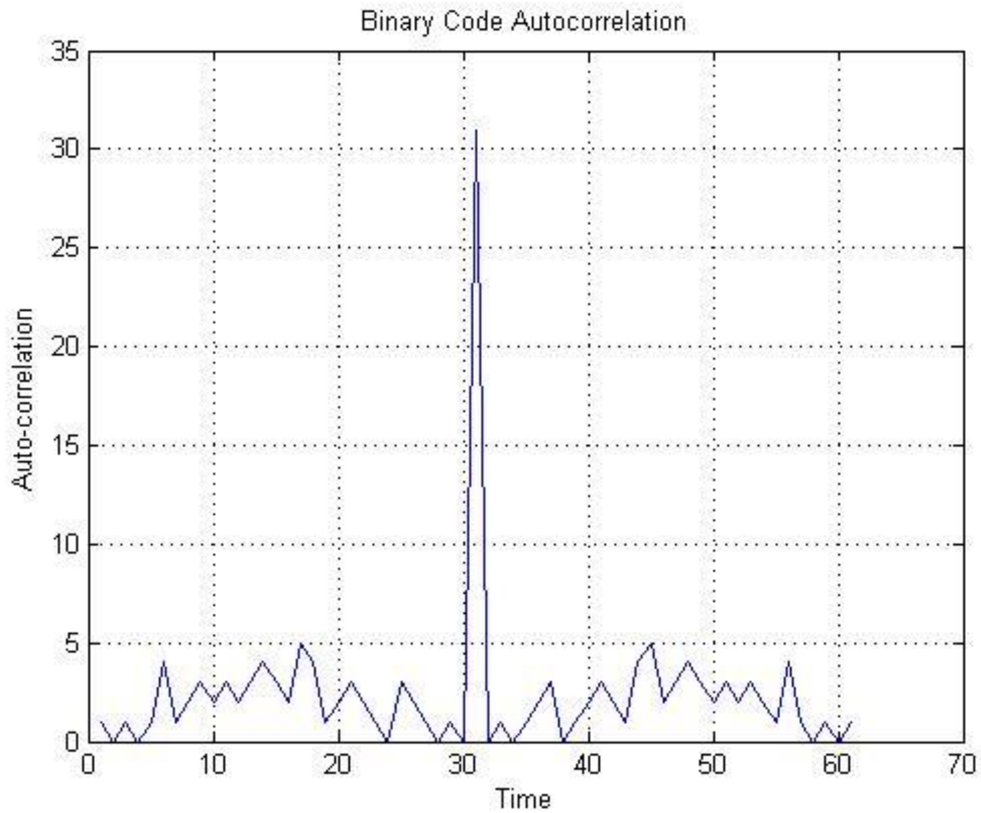

Figure 5.2 shows the auto correlation of maximum length sequence of 31

Main Lobe: 31

Side Lobe: 5

Discrimination Factor: 6.2

Side lobe Attenuation: -15.848

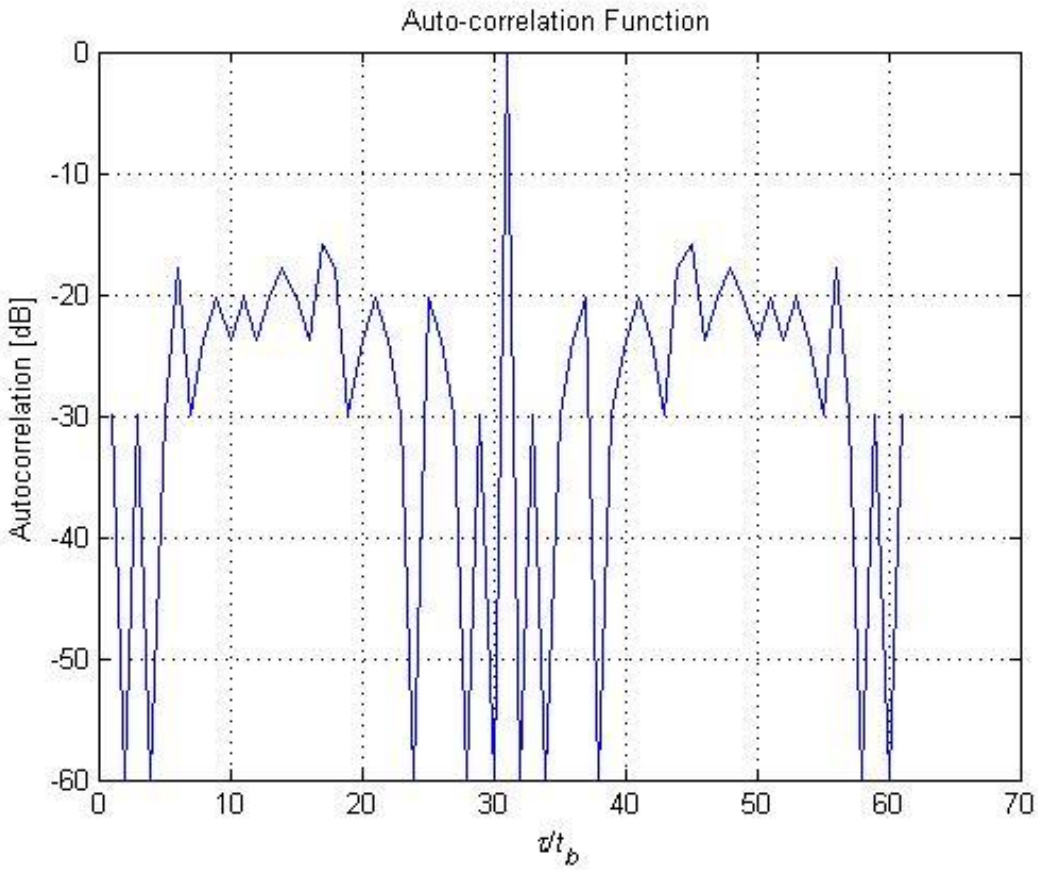

Figure 5.3 shows the auto correlation of maximum length sequence of 31 in dB.

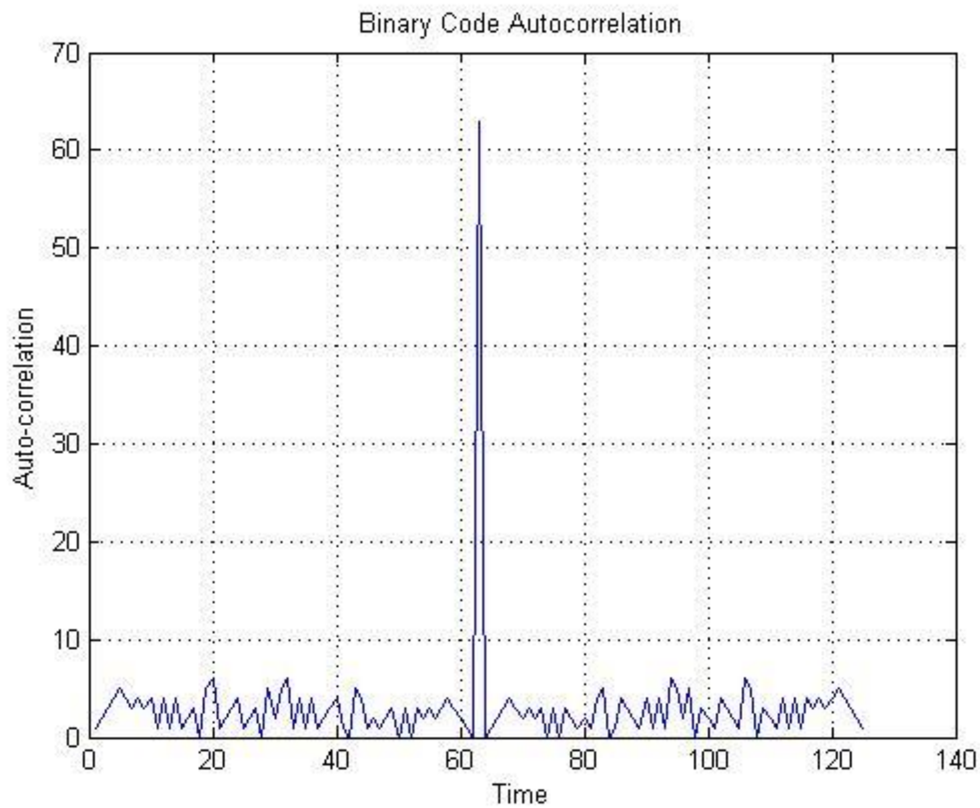

Figure 5.4 shows the auto correlation of maximum length sequence of 63

Main lobe: 63

Side lobe: 6

Discrimination Factor: 10.5

Side lobe attenuation: 20.424dB

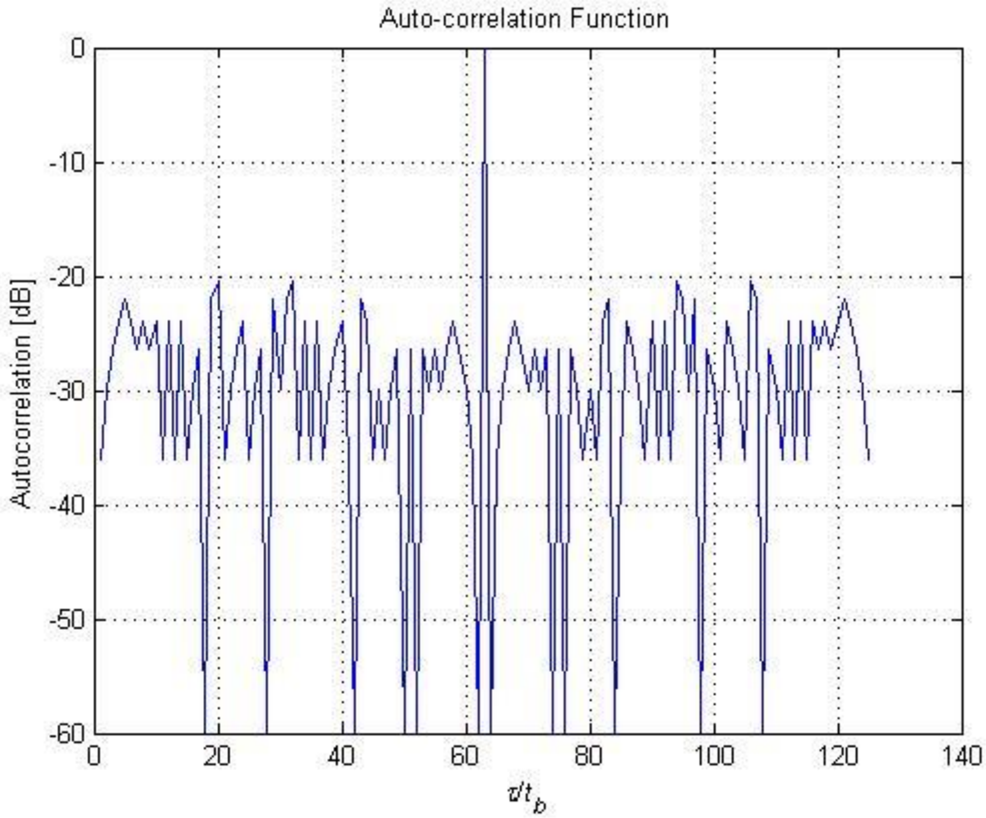

Figure 5.5 shows the auto correlation of maximum length sequence of 63 in dB

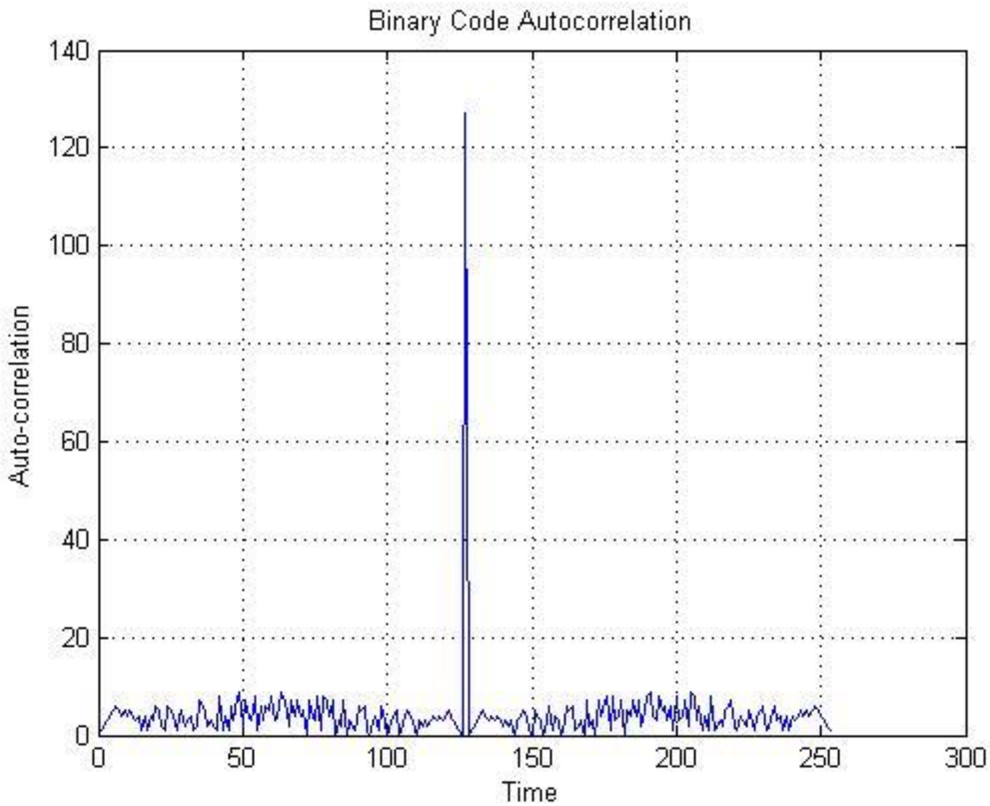

Figure 5.6 shows the auto correlation of maximum length sequence of 127

Main lobe: 127

Side lobe: 9

Discrimination Factor: 14.11

Side lobe attenuation: -22.911dB

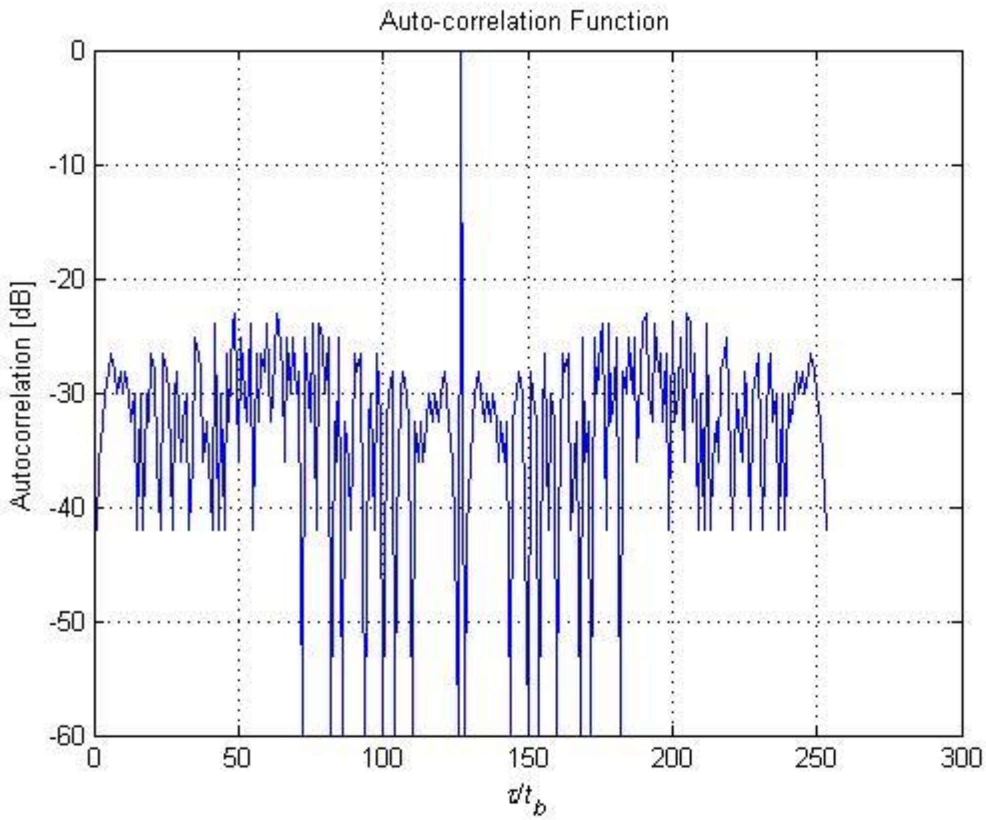

Figure 5.7 shows the auto correlation of maximum length sequence of 127 in dB

5.1.3 BIPHASE CODED SEQUENCES USING PSO ALGORITHM

For signal Length: 60

Peak Lobe: 60

Side Lobe: 4

Discrimination Factor: 15

Side Lobe Attenuation: -23.522dB

Signal Sequence: 1 1 1 1 -1 1 -1 -1 1 -1 1 1 1 1 1 -1 -1 -1 1 -1 -1 1 -1 -1 -1 -1 1 1 -1 -1 1 -1 1 -1 1 -1 -1 -1 1 -1 -1 1 1 -1 1 1 1 1 1 -1 -1 1 1 1 -1 -1 1 -1 1 -1

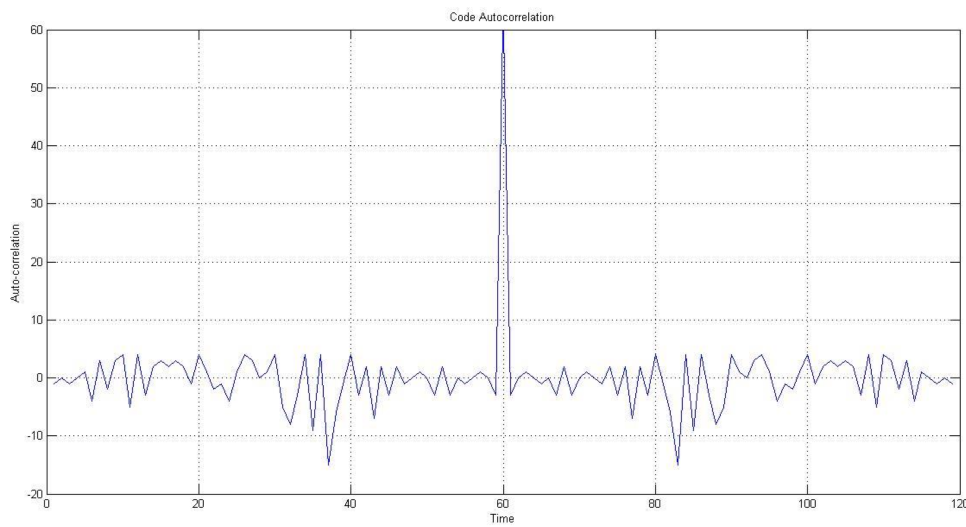

Figure 5.8 shows the auto correlation of input sequence of length 60

For signal Length: 61

Peak Lobe: 61

Side Lobe: 4

Discrimination Factor: 15.25

Side Lobe Attenuation: -23.665dB

Signal Sequence: 1 1 1 -1 1 -1 1 1 1 1 -1 -1 -1 -1 1 -1 -1 1 -1 1 1 -1 -1 -1 1 -1 1 1 -1 -1 1 1 -1 -1 -1 -1 -1 -1 1 -1 1 -1 1 -1 -1 -1 1 -1 -1 -1 -1 1 1 -1 1 1 1 1 -1 1 1

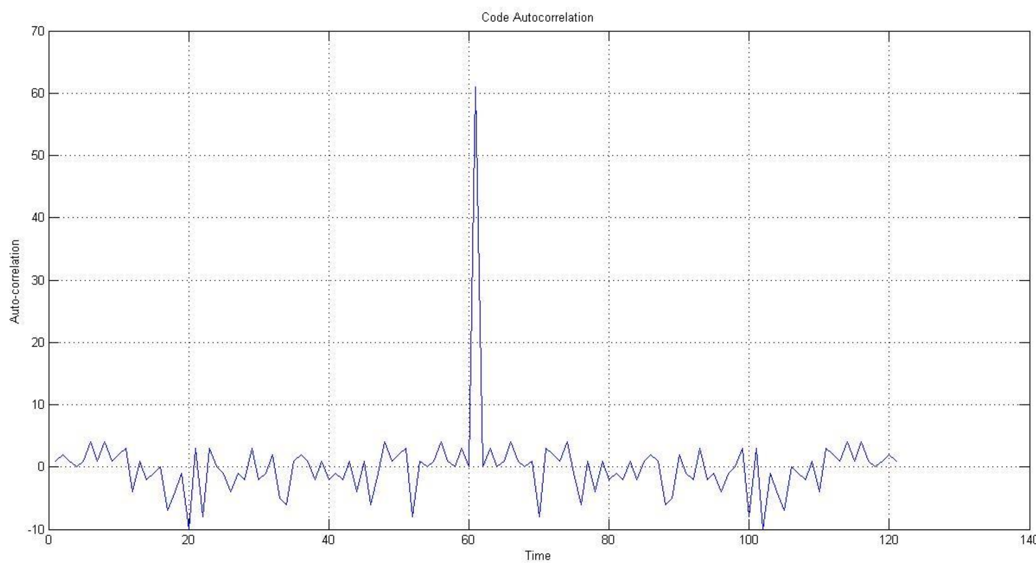

Figure 5.9 shows the auto correlation of input sequence of length 61

For signal Length: 62

Peak Lobe: 62

Side Lobe: 4

Discrimination Factor: 15.5

Side Lobe Attenuation: -23.807

Signal Sequence: -1 1 -1 1 1 1 1 1 1 -1 -1 -1 -1 1 -1 1 1 1 1 1 -1 -1 1 1 -1 1 -1 1 -1 -1 1 -1 1 1 -1 -1 -1 1 1 -1 -1 1 -1 -1 -1 -1 1 -1 1 -1 1 1 -1 1 1 1 -1 1 1 1 -1 1

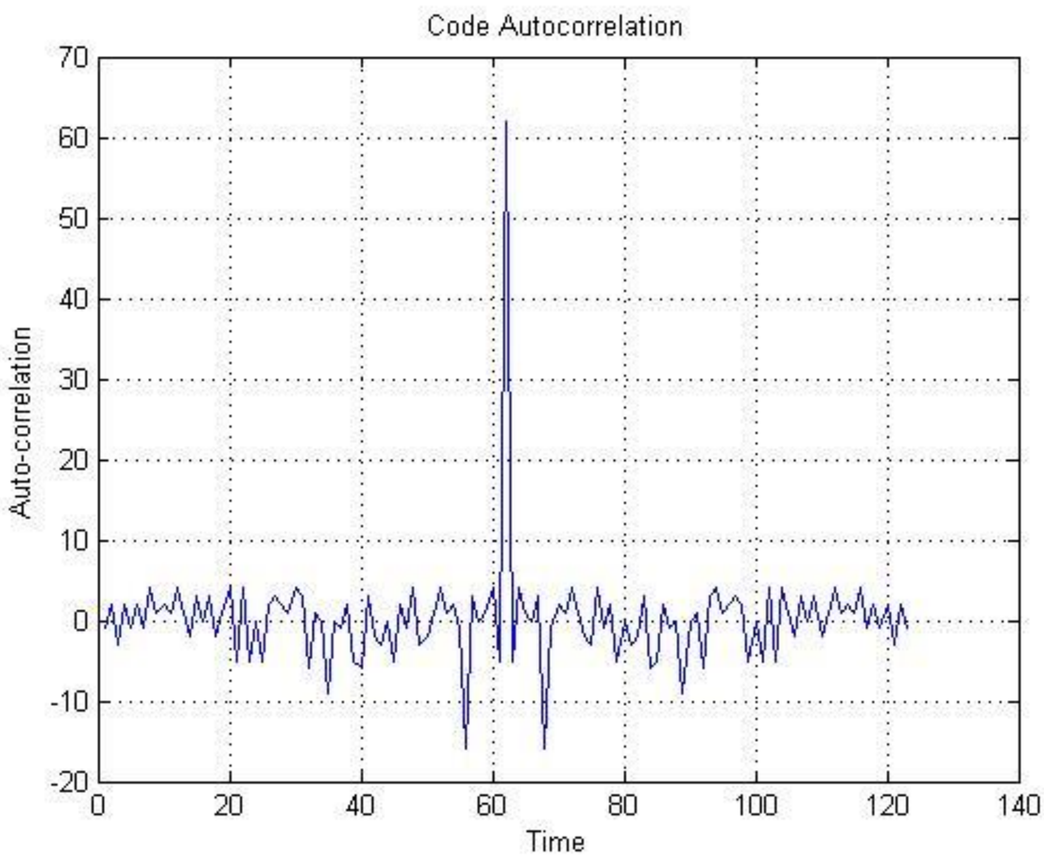

Figure 5.10 shows the auto correlation of input sequence of length 62

For signal Length: 63

Peak Lobe: 63

Side Lobe: 4

Discrimination Factor: 15.75

Side Lobe Attenuation: -23.946

Signal Sequence: -1 -1 1 1 1 1 1 -1 1 1 1 1 -1 -1 1 1 -1 1 1 -1 -1 -1 1 -1 -1 1 1 -1 -1 -1 -1 1 1 -1 1 1 -1 1 -1 1 1 1 -1 1 -1 1 -1 -1 -1 -1 1 1 -1 -1 1 -1 1 -1 1 -1 1 -1 -1 -1

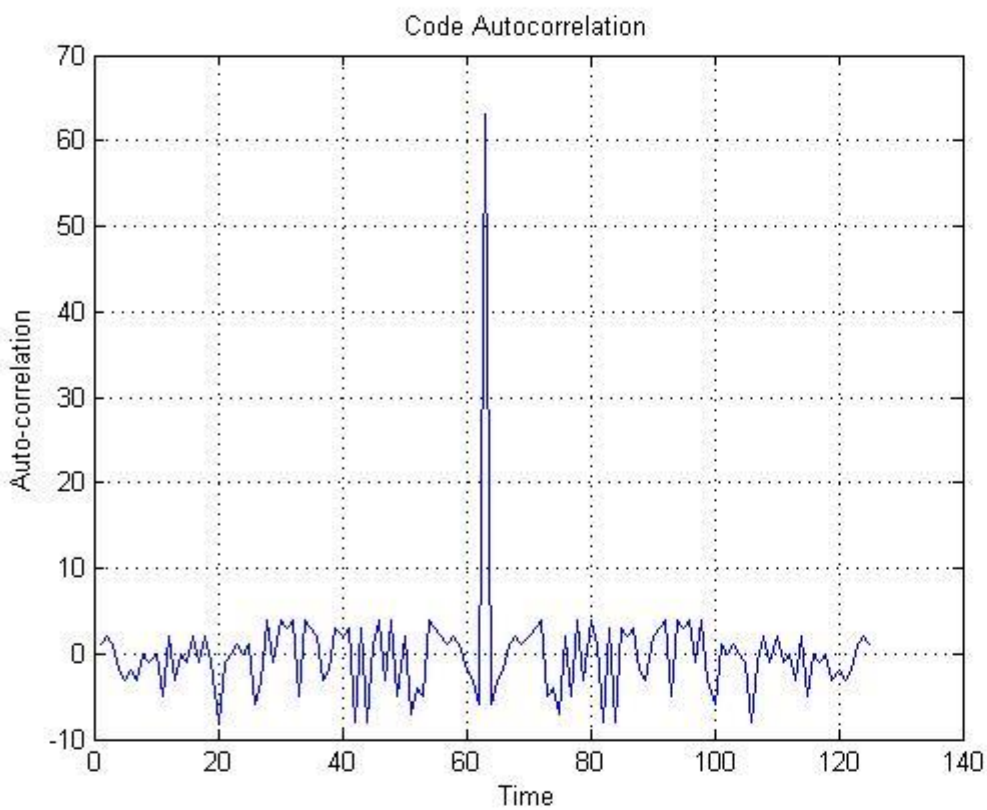

Figure 5.11 shows the auto correlation of input sequence of length 63

For signal Length: 64

Peak Lobe: 64

Side Lobe: 4

Discrimination Factor: 16

Side Lobe Attenuation: -24.082dB

Signal Sequence: -1 1 -1 -1 -1 -1 1 1 1 1 -1 -1 -1 1 -1 1 1 1 1 -1 -1 -1 1 1 1 -1 -1 -1 1 -1 -1 -1 1 -1 -1 1 -1 1 1 -1 -1 1 1 -1 -1 -1 -1 -1 1 -1 1 1 -1 1 1 1 1 -1 1 1 -1 1 1 -1

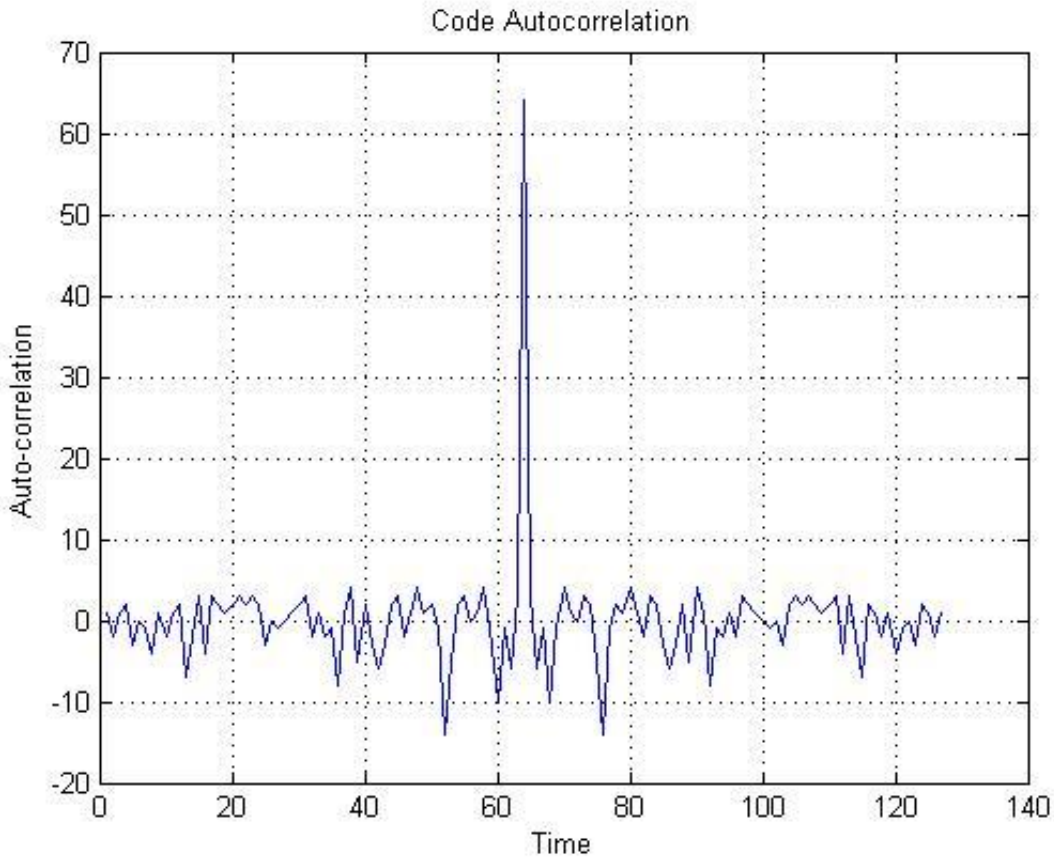

Figure 5.12 shows the auto correlation of input sequence of length 64

For signal Length: 65

Peak Lobe: 65

Side Lobe: 5

Discrimination Factor: 13

Side Lobe Attenuation: -22.279dB

Signal Sequence: -1 1 -1 -1 1 1 -1 1 1 1 1 -1 1 1 -1 -1 1 1 1 -1 1 1 1 1 -1 1 -1 1 1 1 -1 -1 -1 -1 -1 1 -1 -1 1 -1 -1 -1 -1 -1 1 1 -1 -1 -1 1 -1 1 -1 -1 1 1 1 1 1 1 -1 1 -1 -1 -1

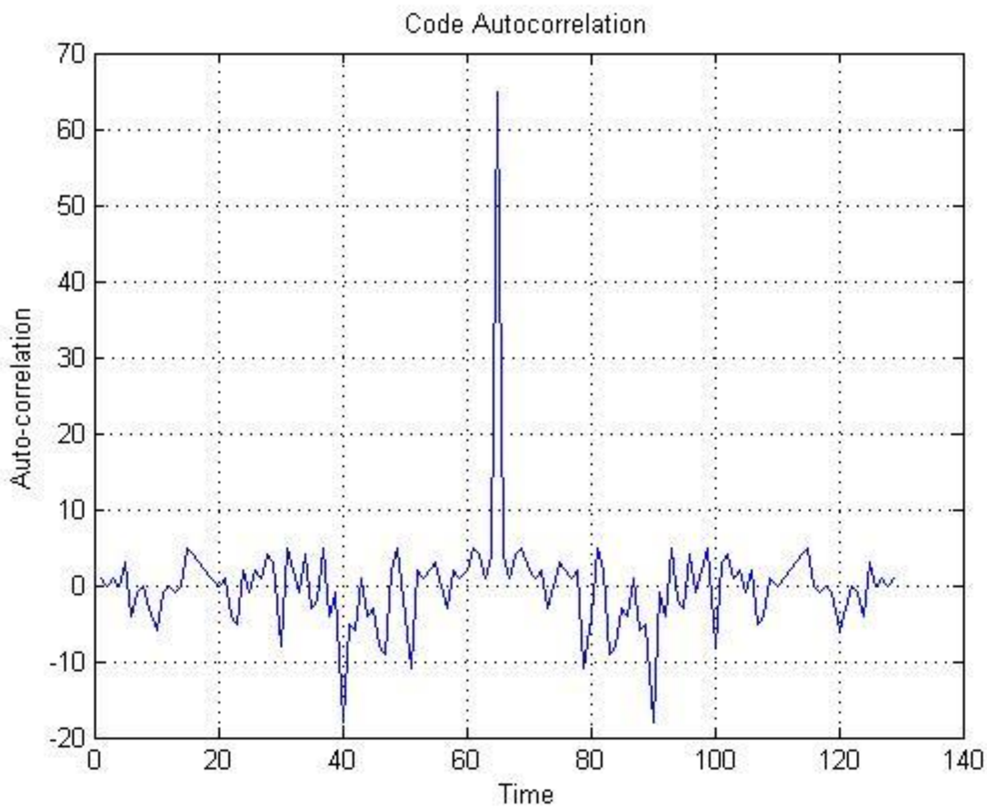

Figure 5.13 shows the auto correlation of input sequence of length 65

For signal Length: 66

Peak Lobe: 66

Side Lobe: 5

Discrimination Factor: 13

Side Lobe Attenuation: -22.411dB

Signal Sequence: 1 1 -1 -1 1 -1 -1 -1 1 -1 1 1 -1 1 -1 1 -1 1 1 1 1 1 -1 -1 1 1 -1 -1 -1 1 1 1 -1 1 1 1 1 1 -1 1 1 -1 1 1 -1 -1 -1 -1 1 -1 -1 1 -1 1 -1 1 -1 -1 -1 -1 -1 -1 -1 1 1 1

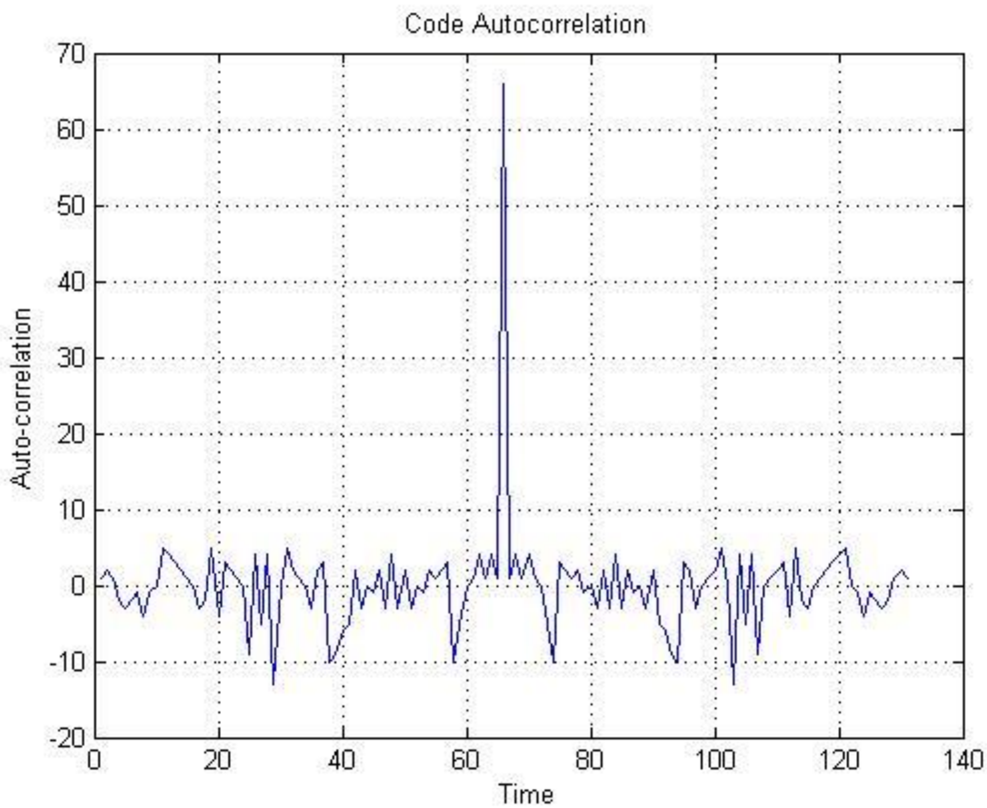

Figure 5.14 shows the auto correlation of input sequence of length 66

For signal Length: 67

Peak Lobe: 67

Side Lobe: 5

Discrimination Factor: 13.4

Side Lobe Attenuation: -22.542dB

Signal Sequence: -1 1 -1 -1 1 1 1 1 1 -1 -1 -1 -1 -1 1 1 1 1 1 1 1 1 -1 1 -1 1 1 -1 -1 -1 -1 1 -1 1 -1 -1 1 1 1 -1 1 1 -1 -1 -1 1 1 -1 -1 1 -1 1 -1 -1 1 -1 -1 -1 -1 -1 1 -1 1 1 -1 -1 1

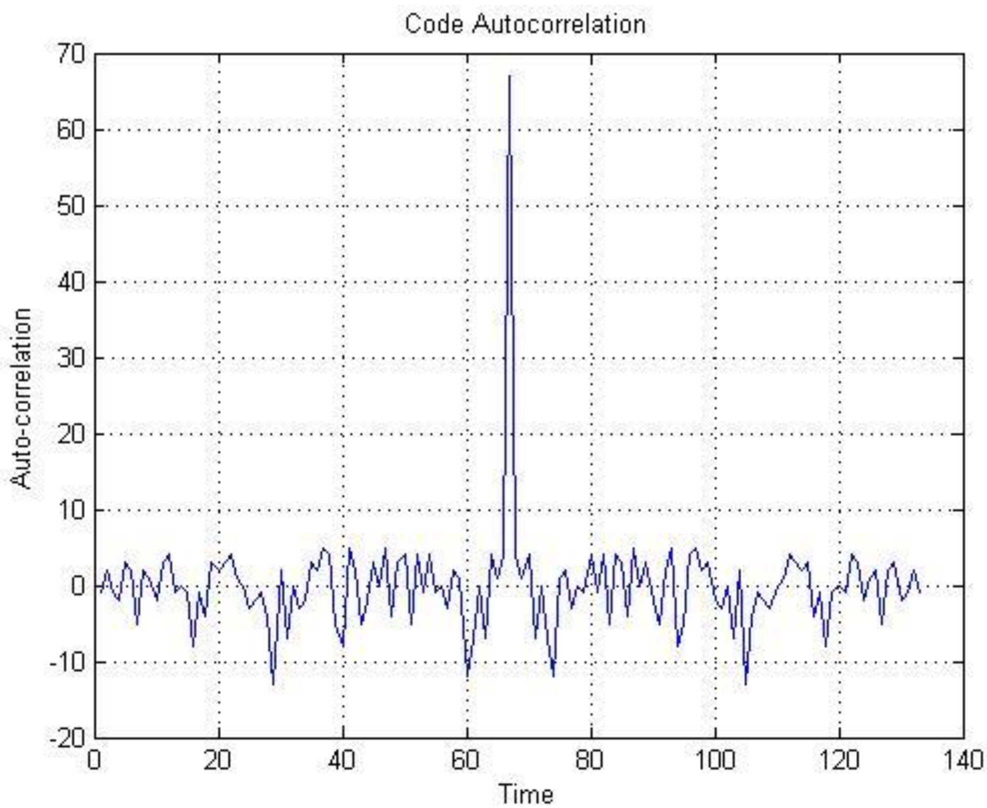

Figure 5.15 shows the auto correlation of input sequence of length 67

For signal Length: 68

Peak Lobe: 68

Side Lobe: 5

Discrimination Factor: 13.6

Side Lobe Attenuation: -22.671dB

Signal Sequence: 1 -1 1 1 -1 -1 1 1 -1 -1 1 1 1 1 -1 -1 1 -1 -1 -1 -1 -1 1 1 -1 -1 1 -1 1 1 -1 1 -1 -1 1 -1 1 1 -1 1 -1 1 -1 1 1 -1 -1 -1 1 -1 1 -1 1 -1 -1 -1 1 -1 1 1 1 1 1 1 1 -1 -1 1

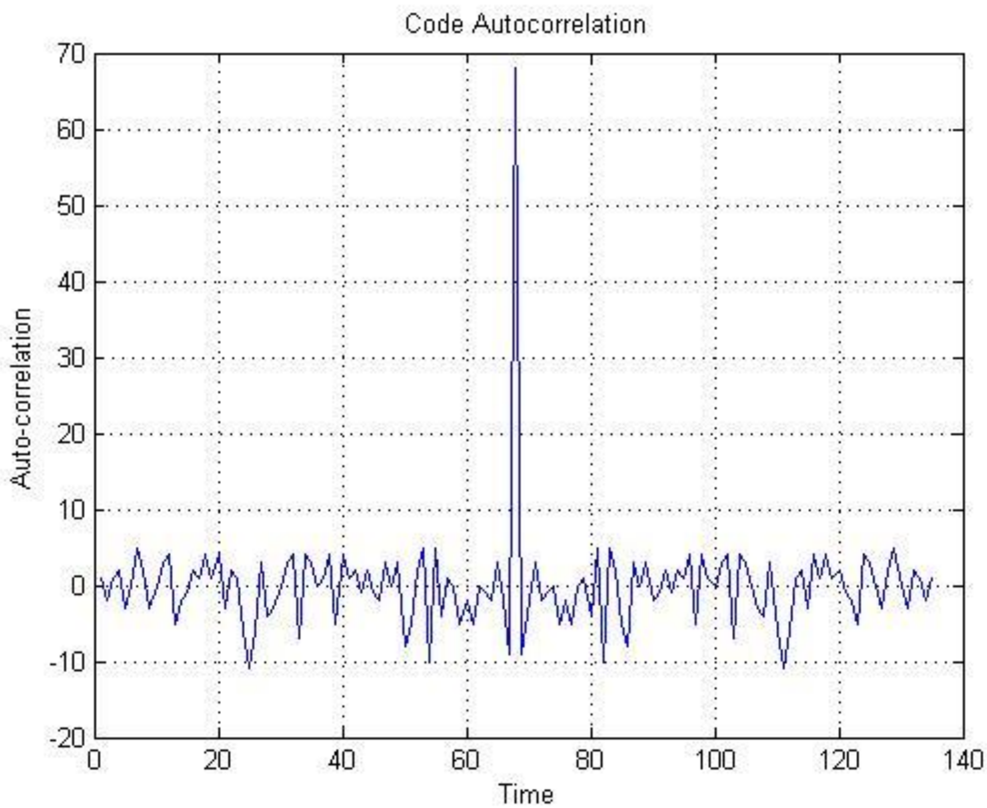

Figure 5.16 shows the auto correlation of input sequence of length 68

For signal Length: 69

Peak Lobe: 69

Side Lobe: 5

Discrimination Factor: 13.8

Side Lobe Attenuation: -22.798dB

Signal Sequence: 1 1 -1 -1 -1 1 1 1 1 1 -1 -1 -1 -1 -1 1 1 -1 -1 1 1 1 1 -1 1 -1 -1 1 -1 -1 1 -1 1 -1 1 -1 -1 1 -1 1 -1 -1 -1 1 1 -1 1 -1 1 1 1 -1 1 1 1 -1 1 1 1 -1 1 1 1 1 -1 -1 1 -1 -1

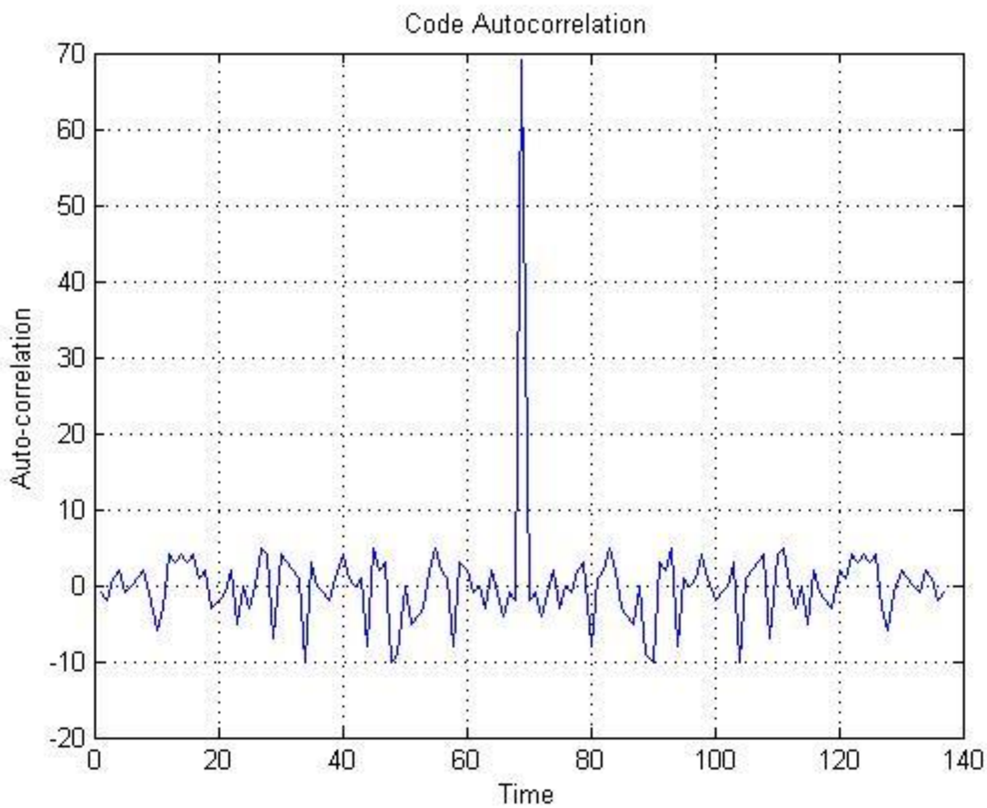

Figure 5.17 shows the auto correlation of input sequence of length 69

Signal Length	Peak Lobe	Side Lobe	Disc Factor	Side Lobe Attenuation	Signal Sequence
60	60	4	15	-23.522	1 1 1 -1 1 -1 -1 1 -1 1 1 1 1 1 -1 -1 -1 1 -1 -1 1 -1 -1 -1 -1 1 1 -1 -1 1 -1 1 -1 1 -1 -1 -1 1 -1 -1 1 1 -1 1 1 1 1 1 -1 -1 1 1 1 -1 -1 1 -1 1 -1
61	61	4	15.25	-23.665	1 1 1 -1 1 -1 1 1 1 1 -1 -1 -1 -1 1 -1 -1 1 -1 1 1 -1 -1 -1 1 -1 1 1 -1 -1 1 1 -1 -1 -1 -1 -1 -1 1 -1 1 -1 1 -1 -1 -1 1 -1 -1 -1 -1 1 1 -1 1 1 1 1 -1 1 1
62	62	4	15.5	-23.807	-1 1 -1 1 1 1 1 1 1 -1 -1 -1 -1 1 -1 1 1 1 1 1 -1 -1 1 1 -1 1 -1 1 -1 -1 1 -1 1 1 -1 -1 -1 1 1 -1 -1 1 -1 -1 -1 -1 1 -1 1 -1 1 1 -1 1 1 1 -1 1 1 1 -1 1
63	63	4	15.75	-23.946	-1 -1 1 1 1 1 1 -1 1 1 1 1 -1 -1 1 1 -1 1 1 -1 -1 -1 1 -1 -1 1 1 -1 -1 -1 -1 1 1 -1 1 1 -1 1 -1 1 1 -1 1 -1 1 1 -1 -1 -1 -1 1 1 -1 -1 1 -1 1 -1 1 -1 1 -1 -1 -1
64	64	4	16	-24.082	-1 1 -1 -1 -1 -1 1 1 1 1 -1 -1 -1 1 -1 1 1 1 1 -1 -1 -1 1 1 1 -1 -1 -1 1 -1 -1 -1 1 -1 -1 1 -1 1 1 -1 -1 1 1 -1 -1 -1 -1 -1 1 -1 1 1 -1 1 1 1 1 -1 1 1 -1 1 1 -1
65	65	5	13	-22.279	-1 1 -1 -1 1 1 -1 1 1 1 1 -1 1 1 -1 -1 1 1 1 -1 1 1 1 1 -1 1 -1 1 1 1 -1 -1 -1 -1 -1 1 -1 -1 1 -1 -1 -1 -1 -1 1 1 -1 -1 -1 1 -1 1 -1 -1 1 1 1 1 1 1 -1 1 -1 -1 -1
66	66	5	13.2	-22.411	1 1 -1 -1 1 -1 -1 -1 1 -1 1 1 -1 1 -1 1 -1 1 1 1 1 1 -1 -1 1 1 -1 -1 -1 1 1 1 -1 1 1 1 1 1 -1 1 1 -1 1 1 -1 -1 -1 -1 1 -1 -1 1 -1 1 -1 1 -1 -1 -1 -1 -1 -1 -1 1 1 1
67	67	5	13.4	-22.542	-1 1 -1 -1 1 1 1 1 1 -1 -1 -1 -1 -1 1 1 1 1 1 1 1 1 -1 1 -1 1 1 -1 -1 -1 -1 1 -1 1 -1 -1 1 1 1 -1 1 1 -1 -1 -1 1 1 -1 -1 1 -1 1 -1 -1 1 -1 -1 -1 -1 -1 1 -1 1 1 -1 -1 1

68	68	5	13.6	-22.671	1 -1 1 1 -1 -1 1 1 -1 -1 1 1 1 1 -1 -1 1 -1 -1 -1 -1 -1 1 1 -1 -1 1 -1 1 1 -1 1 -1 -1 1 -1 1 1 -1 1 -1 1 -1 1 1 -1 -1 -1 1 -1 1 -1 1 -1 -1 -1 1 -1 1 1 1 1 1 1 1 -1 -1 1
69	69	5	13.8	-22.798	1 1 -1 -1 -1 1 1 1 1 1 -1 -1 -1 -1 -1 1 1 -1 -1 1 1 1 1 -1 1 -1 -1 1 -1 -1 1 -1 1 -1 1 -1 -1 1 -1 1 -1 -1 1 -1 1 1 -1 1 -1 1 1 1 -1 1 1 1 -1 1 1 1 -1 1 1 1 1 -1 -1 1 -1 -1

Table 6.1: Generated Results

5.2 Conclusion and Future Scope

As the length of the code is increasing the amount of work done to extract best order of frequency is becoming huge. So we have gone for an optimized search instead of an exhaustive search in which time can be saved. The particle swarm optimization algorithm is one through which best order can be obtained which is having good auto-correlation property. The main intension of this project is to get good codes which are having good correlation properties. So, we have gone for good auto-correlation property. This can be extended to obtain a good compromise between auto-correlation and cross-correlation. This includes calculation of lobe energies. Certain optimization techniques like GA, Simulated Annealing can also be used in this approach.

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