NONUNIFORM PULSE REPETITION INTERVAL OPTIMIZATION FOR PULSE DOPPLER RADARS

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ABSTRACT

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In this thesis, a method of optimization of nonuniform pulse repetition interval for pulse Doppler radars is investigated. PRI jittering technique is used for the selection of inter-pulse intervals. An environment with white Gaussian noise and clutter interference is defined and applying generalized likelihood ratio test, a sufficient statistic function for the detection of the target is derived. The effect of jitter set selection on range and Doppler ambiguity resolution and clutter rejection is investigated. Jitter sets for Doppler ambiguity resolution are investigated by the minimization of the sufficient statistic function value at other estimated target velocities. Jitter sets for range ambiguity resolution are investigated by minimization of the number of ambigous hits at other estimated ranges. The clutter rejection properties of jitter sets are evaluated by defining a constraint function on zero velocity clutter rejection. The problems stated are solved using MATLAB with genetic algorithms.

It is observed that there is a trade off between Doppler ambiguity resolution and clutter rejection properties of jitter sets. Low jitter values are needed for good clutter rejection. The performance of jitter sets are optimized according to range ambiguity resolution and clutter rejection properties by defining cost functions. It is observed that good range ambiguity resolution and clutter rejection can be achieved by an optimized PRI jittering technique. Finally, the effects of quantization of Doppler filter coefficients and target returns using improvement factor as the performance criterion are evaluated.

Keywords: range ambiguity, Doppler ambiguity, clutter rejection, PRI jittering, genetic algorithm, improvement factor

ÖZ

DARBE DOPPLER RADARLARDA EŞ ARALIKLI OLMAYAN DARBE YİNELEME ARALIKLARININ OPTİMİZASYONU

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Bu araştırmada, darbe Doppler radarlar için eş aralıklı olmayan darbe tekrarlama aralıklarına bir eniyileme yöntemi araştırılmıştır. Darbe tekrarlama aralığı seğirtme tekniği ara darbe aralıklarının seçilmesi amacıyla kullanılmıştır. Beyaz Gauss gürültüsü ve parazit yankı karışması içeren bir ortam tanımlanmış ve genelleştirilmiş olabilirlik oranı testi uygulanarak hedefin tesbiti için bir yeterli istatistik fonksiyonu türetilmiştir. Seğirme kümesi seçiminin menzil ve Doppler belirsizlikleri çözümüne ve parazit yankı söndürmeye etkisi araştırılmıştır. Hedefin Doppler hızının bilindiği varsayılarak, tahmin edilen diğer hedef hızlarındaki yeterli istatistik fonksiyonu değerinin en aza indirgenmesiyle Doppler belirsizliği çözümü için seğirme kümeleri araştırılmıştır. Hedef menzilinin bilindiği varsayılarak, tahmin edilen diğer menzillerdeki belirsiz rastlama sayısının en aza indirgenmesiyle menzil belirsizliği çözümü için seğirme kümeleri araştırılmıştır. Seğirme kümelerinin parazit yankı söndürme özelliği sıfır hızındaki parazit yankı söndürmesi üzerine bir kısıt fonksiyonu tanımlanmasıyla değerlendirilmiştir. Belirtilen problemler MATLAB'da genetik algoritmaları kullanılarak çözülmüştür.

Seğirme kümelerinin Doppler belirsizliği çözme ve parazit yankı söndürme özellikleri arasında bir ödünleşim olduğu gözlenmiştir. İyi parazit yankı söndürmesi için küçük seğirme değerleri gerekmektedir. Menzil belirsizliği çözümü ve parazit yankı söndürmesi için maliyet fonksiyonları tanımlanarak seğirme kümelerinin performansı optimize edilmiştir. Darbe tekrarlama aralığı seğirtmesi tekniği kullanılarak iyi menzil belirsizliği çözümü ve parazit yankı söndürmesi elde edilebileceği gözlenmiştir. Son olarak, Doppler süzgeç katsayılarının ve hedef yansımalarının kuvantalanmasının etkileri iyileşme faktörünün başarım ölçütü olarak kullanılmasıyla değerlendirilmiştir.

Anahtar Kelimeler: menzil belirsizliği, Doppler belirsizliği, parazit yankı söndürme, darbe tekrarlama aralığı seğirtmesi, genetik algoritma, iyileşme faktörü

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CHAPTER 1

INTRODUCTION

A doppler radar is one which utilizes the Doppler effect to determine the radial velocity component of relative radar-target velocity or to select targets having particular velocities, and a pulsed doppler radar does this with pulsed transmissions [18].

In coherent pulsed Doppler radars, ambiguity can occur in both range and radial velocity measurements when the pulse repetition frequency (PRF) is constant [6]. For a fixed carrier frequency, the ambiguity domain is constant. As the PRF increases, the maximum mesurable range without ambiguity decreases and the maximum measurable Doppler frequency without ambiguity increases.

There are several methods proposed to improve maximum resolvable range and/or Doppler. Some of those methods depend on variation of carrier frequency and some depend on PRF variation [3, 6]. Generally, the methods using PRF variation performs better. Two main PRF variation schemes are encountered [2]:

- Block-to-block stagger(Multiple PRF)
- Pulse-to-pulse stagger(Staggered PRF)

Multiple PRF system involves use of several fixed PRF's. Comparing the sequential measurements of ambigous range and Doppler in each PRF, ambiguities are eliminated.

Chinese Remainder Theorem (CRT) is a commonly used algorithm to resolve range and Doppler ambiguities in multiple PRF systems [2, 3]. It is an analytic procedure for calculating the unambiguous range from the measured ranges on different PRF’s. This technique will be mentioned in more detail in later sections. CRT has some disadvantages. If there are several targets at one look angle, CRT will yield ambigous results. Furthermore, a small measurement range error on a single PRF can cause a large error in the resolved range [4].

Clustering algorithm which uses a cost function to indicate the goodness of the resolution process is proposed and compared with CRT [4]. The average squared error for all range and/or Doppler of interest is calculated and used as the cost function. The best cluster is found when the cost function value is minimum. This algorithm has good anti-error capability with respect to CRT. An algorithm based on the choice of particular values for the PRF’s is proposed for the velocity ambiguity resolution, where a quasi-maximum likelihood function is tried to be maximized for ambiguity order estimation, where ambiguity order represents the integer part of the true target Doppler velocity or target range [6]. This algorithm can be used only for low PRF and limited by particular values of PRF’s [7].

Residue table look up algorithm which makes use of the differences of the residues on different PRF to resolve ambiguities is proposed [7]. First, one PRF is selected as reference and the differences of the residues on other PRF’s and the reference PRF is used to make a look up table. That look up table is used to find the true range and/or Doppler of the target. This method also takes the measurement errors into account and leaves some room for admitting the error.

Staggered PRF technique is another technique generally used in low PRF Moving Target Indication (MTI) radars to prevent blind speeds [8]. The time interval between pulses of a staggered pulse train is different and this pattern is repeated. Using this method the first blind speed is increased. There are some works on how to select the stagger pattern to have a good velocity response and also good clutter cancellation [8, 9, 10]. In those papers, Fourier analysis techniques are emphasized. The main disadvantage of pulse-to-pulse staggering approach is that the data are now nonuniformly sampled sequence making it more difficult to apply coherent Doppler filtering to the data and complicating analysis [3].

A technique for frequency analysis of unevenly sampled radar by using discrete forier transform (DFT) is described in [11]. Some limitations of DFT, when applied to unevenly spaced data points are described. A new technique which tries to find the set of corresponding Fourier coefficients that best fit the original data points in the least square sense when an inverse DFT is applied, is proposed. Applicability of spectral analysis from irregular samples, and the basic radar problems of Doppler ambiguity and clutter suppression are analyzed by a new method called NSSL (National Severe Storms Laboratory) magnitude convolution [12]. It is based on uniformly extended multirate samples, and thus on legitimate usage of DFT. This algorithm works above the Nyquist frequencies and offers a filter for the rejection of clutter. This method is used for radar Doppler processing of an interlaced sampling scheme and range is assumed unambigous.

PRF jittering is basically an Electronic Counter-Counter Measure (ECCM) technique which has long been used in radars to decorrelate second time around echoes and to control Doppler blind zones [3]. The PRF is varied either randomly or according to predefined set of frequencies in this technique.

The usage of nonuniform pulse repetition interval (PRI) to resolve range and Doppler ambiguities has potential advantages of consuming less radar timeline, dealing with multiple targets, resolving the blind speed and blind range problems with the removal of ambiguity. It is also used as an ECCM technique in radars. Despite all of those potential advantages, the nonuniform PRI in literature is worked usually on the Doppler ambiguity resolution and preventing blind speeds.

In this thesis, the problem considered is the selection of nonuniform pulse repetition intervals for pulsed Doppler radars to resolve range and Doppler ambiguties, taking into account the clutter cancellation. PRF jittering technique is used to select nonuniform PRI set. Instead of transmitting a sequence of regularly spaced pulses, some offset in pulse transmission instants is implemented. The maximum likelihood estimation technique is used to get a sufficient statistic for the detection of the target in Gaussian noise and clutter condition. In designing PRI jitter pattern, the jitter set is selected also to have sufficient zero Doppler clutter rejection. The optimization process for range and Doppler ambiguity resolution is implemented on the sufficient statistic function by using the genetic algorithm. The performance of the optimization process is then investigated through computer simulations, for which the variable parameters are evaluated carefully for the jitter set selection. The effect of quantization of the samples taken from target returns and quantization of the filter coefficients to the performance of improvement factor is evaluated. The organization of the thesis is as follows:

In Chapter 2, a review of fundamental range and Doppler ambiguity resolution methods are given.

In Chapter 3, the main problem of this thesis is stated and formulated. The detection methodology for the proposed radar waveform using the GLRT test is presented and the details of proposed constraints on clutter rejection is developed and described. The approach for range ambiguity resolution is described.

In Chapter 4, the optimization methods are described and a brief summary of the proposed form of the genetic algorithm is provided. The details of the jitter set optimization, using the constraints developed in Chapter 3, are given. The optimizations according to the cost functions for range and Doppler ambiguity resolution and clutter rejection are provided. The simulation results for the optimization process are also presented. A new approach for the optimization of the Doppler frequency response is developed and the results of the optimization is given. The results of range ambiguity resolution approach is provided. An optimization approach to select the jitter sets for range ambiguity resolution and clutter cancellation and the optimization results are given. Then, the simulations to observe the effect of quantization of Doppler filter coefficients and target return on the improvement factor performance are provided.

Chapter 5 includes some concluding remarks.

CHAPTER 2

REVIEW OF FUNDAMENTAL RANGE AND DOPPLER AMBIGUITY RESOLUTION METHODS

In this chapter, the fundamental methods found in the literature to resolve range and Doppler ambiguity are given. Firstly, the basic radar formulas to measure the range and radial velocity of the targets are given. Secondly, the range and Doppler ambiguity problem is stated. Then, the fundamental methods that are used to resolve range and Doppler ambiguity, which are multiple PRF and staggered PRF, are given in more detail. Finally, the PRF jittering technique is described.

2.1 Radar

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 natural environment [1]. It operates by radiating an electromagnetic wave into space and detecting the echo signal reflected from a target. The range to the target is determined by measuring the time taken by the pulse to travel to the target and the back. The range is given by

$$R = c\Delta t / 2, \tag{2.1}$$

where c = 3.10^8 m/sec denotes the speed of light and Δt denotes round trip transmit time of the wave transmitted and reflected back to the origin.

The velocity of the target can be determined from the Doppler effect, which is the change in the carrier frequency between the transmitted and received signals due to motion of the target. The Doppler frequency shift of the target is given by

$$f_d = \frac{2v_r f_0}{c} \tag{2.2}$$

where v_r is the radial velocity of the target, f_0 is the carrier frequency of radar.

2.2 Range and Doppler Ambiguity

The transmitted wave of the radar is usually periodic and constant. If an echo from a target is received after the second transmitted pulse, the measured propagation time wil not be the correct one since the reference transmitted pulse is not the right one. So, the real range of the target can not be distinguished if the echo from the target is received after a time period greater than the PRI. If the target is located beyond the maximum range, the measured range of the target will be ambigous due to folding over of the signal. If the PRI of the transmitted signal is low, the maximum unambigous range of the radar will be low. If the PRI of the transmitted signal is high, the maximum unambigous range will be high.

The maximum unambigous range of a radar using constant PRF is given by

$$R_u = \frac{c}{2f_p} \tag{2.3}$$

where f_p denotes PRF of the transmitted signal.

The maximum velocity of the target that can be obtained without any ambiguity is also dependent on PRF. If the Doppler frequency of the target is greater than the transmitted PRF, the real velocity of the target can not be measured because of the aliasing, which is called Doppler ambiguity. If the PRF is low, the maximum unambigous velocity is low, and if the PRF is high, the maximum unambigous velocity is high.

The maximum velocity of the target without any ambiguity is given by

$$V_u = \frac{c \, . f_p}{2 \, f_0} \tag{2.4}$$

where V_u denotes the maximum unambigous velocity of the target.

So, high PRF radars will be unambigous in Doppler but ambigous in range, and low PRF radars will be unambigous in range but ambigous in Doppler. Medium PRF radars are ambigous in both range and Doppler.

The Doppler frequency spectrum is unambigous up to PRF, so the measured Doppler frequency will be up to PRF. The target velocities will be folded over at each PRF. If the image of target Doppler frequencies falls into clutter region the target may not be detected. Those regions are called blind Doppler zones. During pulse transmission, the radar can not receive the echos from the target. Those ranges are called range blind zones. Unambigous range and Doppler zones for a constant PRF radar system is shown in Figure 2.1.

The maximum unambigous range and Doppler limitation of a radar with constant PRI can be seen by combination of (2.3) and (2.4)

$$R_u . V_u = \frac{c^2 . f_p}{4 . f_0} = \frac{c}{4 . \lambda_0} \tag{2.5}$$

where λ_0 denotes the wavelength of the radar.

From (2.5), the limitation in the unambigous range and Doppler frequency for a constant PRF system is seen clearly. The product of these parameters is constant and independent of PRF, it is only dependent on wavelength of radar.

The methods that are used generally for the resolution of range and Doppler ambiguity problem are multiple PRF method and staggered PRF method.

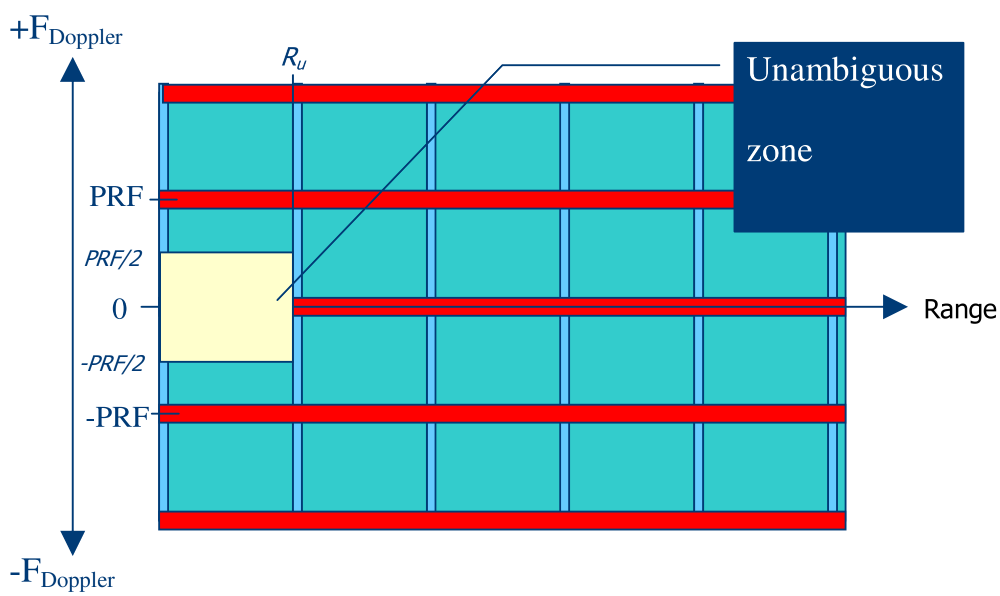

Figure 2.1 Unambigous range and Doppler zones for a constant PRF pulse Doppler radar system

2.2.1 Multiple PRF [4, 5, 6, 7]:

Multiple PRF method involves use of several fixed PRF's. Ambiguity resolution is achieved by searching for the coincidence between unfolded range and/or Doppler estimates for each PRF. This method is a widely used method in radars. The generally used algorithms to resolve range and/or Doppler ambiguity by the measured values from each PRF are CRT, clustering algorithm, and residue table look up algorithm which are described below.

2.2.1.1 Chinese Remainder Theorem (CRT):

The most common algorithm for resolving range and/or Doppler ambiguities is CRT. The CRT is an analytic procedure for calculating the unambiguous range or Doppler from the measured range and/or Doppler on different PRFs.

In this method, the period between PRFs is expressed in units of range and/or Doppler cells [3]. For the range ambiguity problem in three PRF system, this results in each PRI being divided into a number of range cells, designated by m_1, m_2, m_3. The three ambiguous range cell numbers which correspond to the target's measured range for each PRF, denoted by a_1, a_2, a_3, are then determined. The target's unambiguous range is given by

$$R_u = (C_1 a_1 + C_2 a_2 + C_3 a_3) MODULO(m_1 m_2 m_3) \tag{2.6}$$

where the C_i are given by

$$\begin{aligned} C_1 &= b_1 m_2 m_3 \\ C_2 &= b_2 m_1 m_3 \\ C_3 &= b_3 m_1 m_2 \end{aligned} \tag{2.7}$$

and the b_i 's are the smallest positive integers such that

$$\begin{aligned} b_1 m_2 m_3 MODULO(m_1) &= 1 \\ b_2 m_1 m_3 MODULO(m_2) &= 1 \\ b_3 m_1 m_2 MODULO(m_3) &= 1 \end{aligned} \tag{2.8}$$

The CRT has some defects for the multiple PRF system despite its wide usage. First, small errors on a single PRF can cause large errors in the resolved range and/or Doppler and the algorithm gives no possible indication of a possible error [4]. Secondly, this algorithm will produce ambigous results if there are several targets at one look angle [5]. Those ambigous results must be eliminated to be able to find the real target. Furthermore, if the target falls into range and Doppler blind zones on some PRF's, the target may not be detected.

2.2.1.2. Clustering Algorithm:

Clustering algorithm is proposed to improve the defects of CRT by Trunk and Brockett [4]. In this algorithm, firstly the estimates for the all possible ranges denoted by R_{ki} are generated by,

$$R_{ki} = R_i + KR_{ai} \tag{2.9}$$

where R_{ai} is the ambiguous range for the i-th PRF and integer K is selected according to the maximum range of interest $R_{\max}$. Then the average squared error denoted by $C(j)$ for m consecutive range is calculated by,

$$C(j) = \frac{1}{m}\sum_{i=j+1}^{j+m}\left|R_{oi} - \overline{R}\right|^2 \tag{2.10}$$

where $\overline{R}$ denotes median value of the m ordered ranges and R_{oi} denotes the generated all possible ranges by the m ambiguous measurements. An example of a range resolution clustering algorithm is given in Figure 2.2.

At the smallest value of $C(j)$ the best cluster occurs. The clustering algorithm provides an improvement in performance with respect to Chinese Remainder Theorem for the measurement errors.

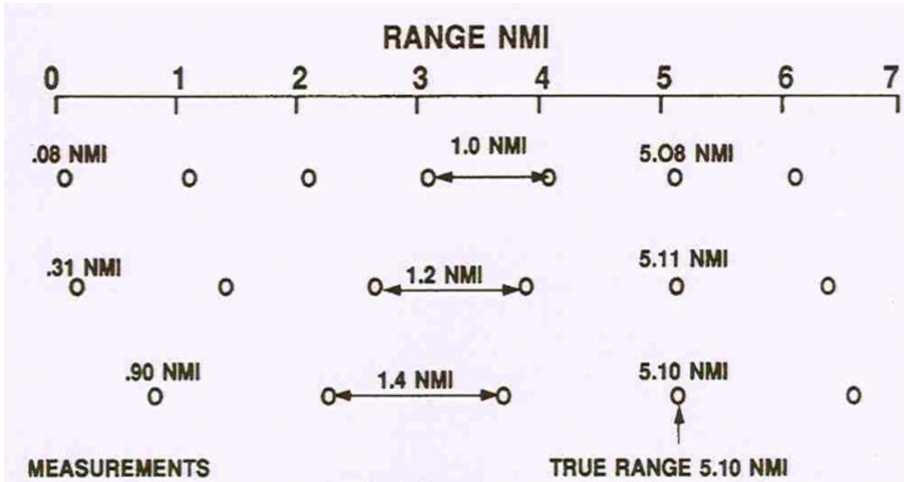

Figure 2.2 Example of range ambiguity resolution using clustering algorithm [4]

2.2.1.3 Residue Table Look Up Algorithm

Residue Look-Up Table Algorithm is proposed to improve the ability against measurement errors and for less computational throughout [7]. It takes presumptive redundancy error into account and its fast implementation relies on the established look-up table.

The differences of the residues on different PRF are used to resolve ambiguities. First, the residue of one of the PRF is selected as reference and the differences of the residues on other PRF's and the reference PRF for all possible ambiguity orders are taken into a look-up table. Then, the differences between the measured ambiguous range of other PRF's and the reference PRF are calculated and compared with the values in the look-up table. Also, if an error exists in the measured ambiguous range values, the method leaves some room for admitting the error.

2.2.2 Staggered PRF

Staggered PRF is a method which is used to avoid blind speed problem by changing the PRF of the MTI radar on a pulse-to-pulse basis [8, 9]. The transmission times of the staggered PRF radar vary in a cyclic manner. A typical staggered PRF waveform is given in Figure 2.3.

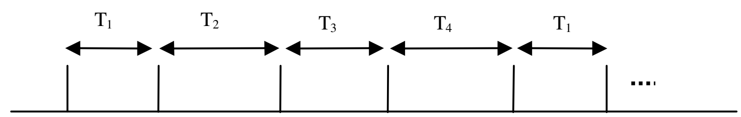

Figure 2.3: Staggered pulse train with four different pulse intervals

The filter samples the Doppler frequency at nonuniform times for staggered PRF case rather than the uniformly spaced times when the PRF is constant. The frequency response of this filter is

$$H(f) = w_0 + w_1 e^{j2\pi f T_1} + w_2 e^{j2\pi f (T_1 + T_2)} + \ldots + w_n e^{j2\pi f (T_1 + T_2 + \ldots T_n)} \qquad (2.14)$$

A comparison of the frequency response of constant PRF and staggered PRF waveform is shown in Figure 2.4.

There are some constraints when using staggered PRF, which are [1]

- The minimum PRI must be greater than the time interval determined by the maximum detection range.
- The first blind speed of the target after staggering must be greater than the maximum speed of the target.

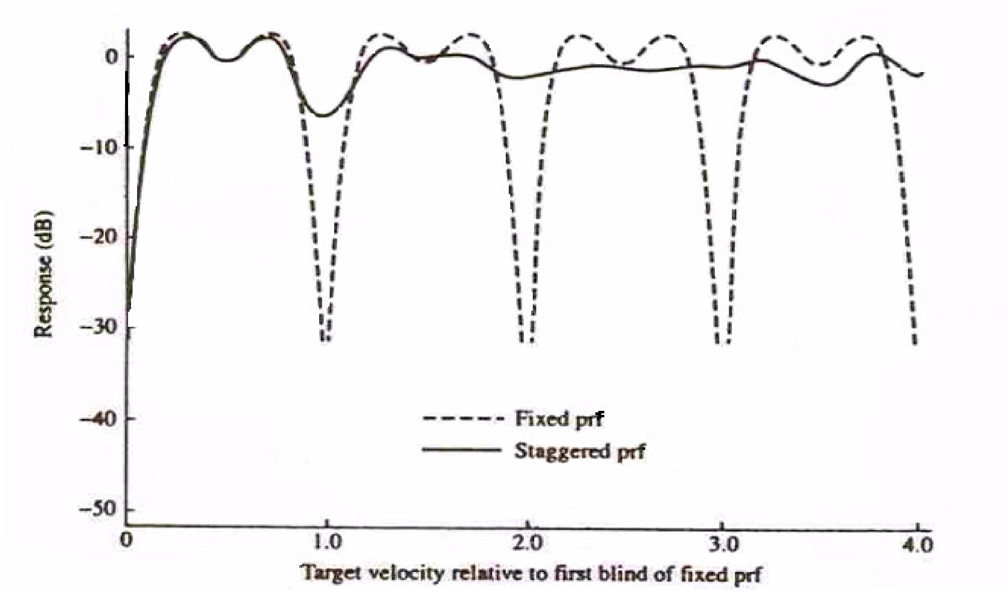

Figure 2.4 Frequency response of a weighted four period staggered waveform compared with the frequency response using a constant PRF waveform [8].

- The first notch in the frequency response is often the deepest, but it must be smaller than a given value.

The main problems concerned with the design of staggered PRF MTI systems are:

- Selection of the ratio of staggering to obtain maximum flat frequency response

- The effect of staggering on the improvement factor of the MTI system.

- The maximization of the improvement factor in the staggered PRF condition.

Improvement factor is an IEEE defined measure of performance parameter which includes the signal gain and the clutter attenuation parameters. It is defined as the signal-to-clutter ratio at the output of the clutter filter, divided by the signal-to-clutter ratio at the input of the clutter filter, averaged uniformly over all target radial velocities of interest. It is expressed as

$$I_f = \left. \frac{(signal / clutter)_{out}}{(signal / clutter)_{in}} \right|_{f_d} \tag{2.15}$$

There have been research on the optimization of the staggered PRF waveform according to the constraints given above [9, 10]. The frequency response of an optimized staggered PRF waveform when low PRF is used is shown in Figure 2.5. Since low PRF is used no clutter fold-over occurs. The clutter is assumed to have zero mean Doppler frequency and gaussian shape power spectral density with the spectral width, denoted by σ, taken as $0.02B_1$, where B_1 denotes first blind velocity of the constant PRF. The signal-to-clutter ratio (SCR) gain versus Doppler frequency is shown for a 5 pulse staggered waveform. The SCR gain is same for all target range bins since low PRF waveform is used and same Doppler processing is applied to the range bins. For this example, the first blind velocity is increased 10 times of the blind velocity of the constant PRF case.

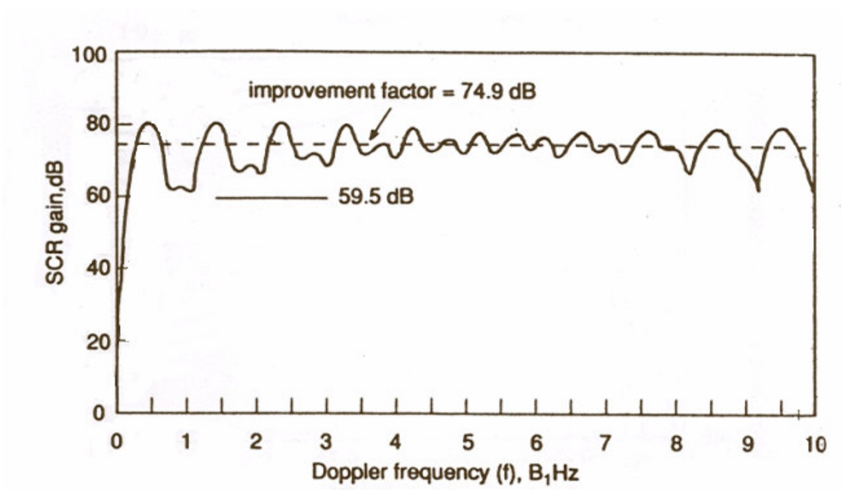

Figure 2.5 Example of a staggered PRF Doppler frequency response of a five pulse staggered waveform $\sigma = 0.02B_1$ [8]

2.3 PRF Jittering:

PRF jittering is an effective ECCM technique for radars [3]. It has been used in radars to control Doppler blind zones and decorrelate second-time-around echoes. This technique is also effective against repeater jammers that use a time delay slightly less than the PRI to generate false targets at closer ranges than the true target. The radar PRF is automatically varied, either randomly or according to a predefined set of frequencies, between two or more frequencies. A typical PRF jitter set is given in Figure 2.6. PRF jittering technique is used generally during low PRF operation [3].

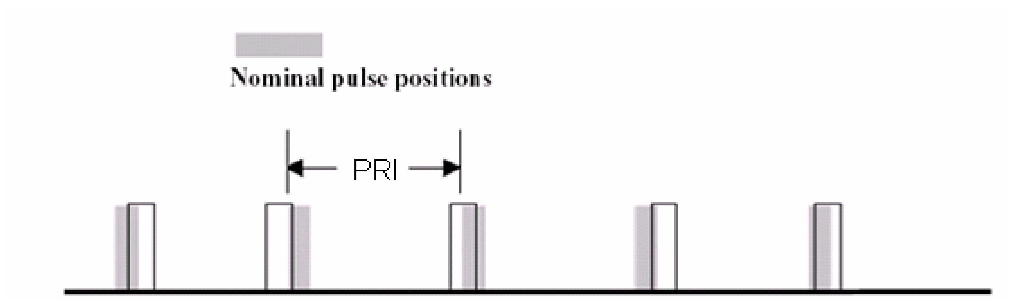

Figure 2.6 Example of a typical PRI jittering set

As shown in Figure 2.6, the pulses are transmitted with different inter-pulse periods. So, the measured time delays for the pulses will be different and there will be a potential to resolve range ambiguity and find the true range of the target. Also, since nonuniform inter-pulse periods are used, the Doppler ambiguity can be resolved by the usage of a Doppler signal processing technique.

CHAPTER 3

NONUNIFORM PRI SELECTION APPROACH

In this chapter, the approach for the nonuniform PRI selection method and the formulation of the detection problem is given. This approach is used to optimize the radar waveform for the resolution of the range and Doppler ambiguity and sufficient clutter rejection. The optimum nonuniform PRI set to be able to resolve range and Doppler ambiguity while having sufficient clutter rejection is investigated.

The nonuniform PRI selection approach is formulated by the use of PRF jittering technique. In the first part of the chapter, PRF jittering technique is described and the detection model is given [13]. In this study, generalized likelihood ratio test (GLRT) is used for the detection problem and ML estimation technique is used to get a sufficient statistic for the detection of the target.

In the second part, the optimization criterion for the PRF jitter set is described. Velocity interval selection method for the optimization problem is described. The approach for range ambiguity resolution is also given in this chapter.

3.1 Effects of PRF Jitter:

The limitations of the constant PRF radar systems for range and Doppler ambiguity resolution can be clearly seen from the formula given in Eq. (2.5). PRF jittering technique is used for the selection of nonuniform PRI and resolution of range and Doppler ambiguities. The transmission instants of the regular PRI system is changed by giving some offset [14]. Let

$$t_k = kT_0 + \delta T_k \quad k = 0,1,\ldots K-1 \tag{3.1}$$

where t_k denotes the transmission times of the pulses, δT_k denotes the deviation from the hypothetic regular train of PRI, T_0 denotes the PRI, and K denotes the number of pulses. In Figure 3.1, the model for the PRF jitter waveform is shown. The downward ticks on the time axis denote the reference train (kT_o), the upward colored ticks denote the transmisson times of the pulses with color code corresponding to the code that the waveform uses. T_{max} value denotes the maximum time delay that can occur from the targets at the instrumented range.

The delay of the echo from a target with respect to the k'th transmitted pulse can be given as

$$\tau_k = \frac{2r_0}{c} + \frac{2vT_0k}{c} + \frac{2v}{c}\delta T_k \qquad k = 0,1,\ldots,K-1 \tag{3.2}$$

where r_0 denotes the distance of the target from the radar at the moment, the 0'th pulse hits the target, and v is the radial velocity of the target.

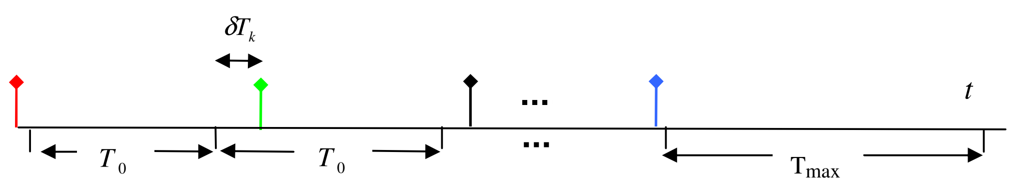

Figure 3.1: Representation of PRF jitter waveform

The phase change in the carrier of an echo due to delay is given by

$$\begin{aligned}\Omega_k &= 2\pi f_0 \tau_k \\ &= \frac{4\pi f_0 v T_0}{c}k + \frac{4\pi f_0 v \Delta T_k}{c}\end{aligned} \tag{3.3}$$

where

$$\Delta T_k = \delta T_k \tag{3.4}$$

Without losing generality, the first term in Eq. (3.2) is assumed to be some integer multiple of the carrier period, $1/f_0$, and hence dropped.

The return taken from the kth pulse can be given as:

$$y(k) = ae^{j\Omega_k} + \nu_k \tag{3.5}$$

where $a = A(k)$ denotes the magnitude of the return taken from the target. The same random variable is used for all *k*. Phase noise is neglected for the target. The ν_k is given as,

$$\nu_k = h(k) + \eta(k) \tag{3.6}$$

where *h(k)* and *η(k)* are clutter and noise responses taken from the kth pulse. For clutter responses, the same random variable is used for all k.

For medium and high PRF radars, folding over of the clutter occurs. In our case, the folding over of the clutter is assumed to be zero as in our low PRF case.

η(k) and *h(k)* are taken as zero mean Gaussian random variables. So, ν_k is an independent identically distributed (i.i.d.) zero mean Gaussian sequence. A sufficient statistic regarding to detection of the target can be obtained as [13, 15]

$$\Lambda = \sum_{k=0}^{K-1} \left\{ \left| y(k) \right|^2 - \left| y(k) - ae^{j\Omega_k} \right|^2 \right\} \tag{3.7}$$

where *a* is a parameter to be estimated. In other words, the problem falls in the class of detection with unknown parameters. A well known method in such problems is to use the generalized likelihood ratio test (GLRT). In this case, it corresponds to estimate *a* using the observations by the maximum likelihood (ML) estimation technique. After finding an estimate for *a*, Λ is computed and by comparing it with a threshold a decision is made.

To obtain the ML estimate of *a*, we minimize

$$\sum_{k=0}^{K-1} \left| y(k) - a e^{j\Omega_k} \right|^2 \tag{3.8}$$

which yields

$$\hat{a} = \frac{1}{K} \sum_{k=0}^{K-1} y(k) e^{-j\Omega_k} \tag{3.9}$$

This value of *a* is then substituted in Eq. (3.7) to get a sufficient statistic. After algebraic simplifications, we obtain

$$\Lambda = \frac{1}{K} \left| \sum_{k=0}^{K-1} y(k) e^{-j\Omega_k} \right|^2 \tag{3.10}$$

The sequence $\{\Omega_k\}$ actually depends on the radial velocity of the target and therefore Eq. (3.10) can be rewritten as:

$$\Lambda(v) = \frac{1}{K} \left| \sum_{k=0}^{K-1} y(k) e^{-j\Omega_k(v)} \right|^2 \tag{3.11}$$

$\Lambda(v)$ is the sufficient statistic value to decide whether there is a target or not at the selected target test velocity, v. If Λ(v) is greater than a certain treshold, the presence of a target is decided. So, the design and operation of the detector can be as follows:

- Determine a set of velocities: $\{v_m\}_{m=1}^{M}$

- Compute Λ(v) for each element in this set.

- Decide on presence of a target of velocity when Λ(v) exceeds a certain threshold.

In designing PRI jitter pattern, we determine δT_k to have sufficient zero Doppler clutter rejection, which corresponds to having almost zero response for the time invariant part of *y(k)*.

$$C(v) = \sum_{k=0}^{K-1} e^{j\Omega_k(v)} \approx 0 \quad v_L < v < v_H \tag{3.12}$$

where v_L and v_H represents the minimum and maximum velocity values for the target.

3.2 Effects of PRF Jitter on Doppler Ambiguity:

When the PRF is regular, the velocity response of function $\Lambda(v)$ for test target with zero velocity is shown in Figure 3.2 for 8 Khz PRF with 8 pulses.

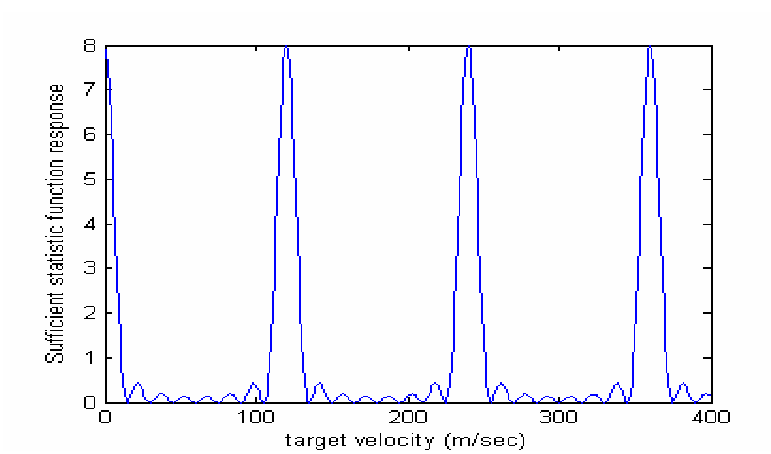

Figure 3.2: Sufficient statistic function for constant PRF versus target velocity for f_0=10 Ghz, f_p=8 kHz, K=8 pulses

As seen from Figure 3.2, because of Doppler ambiguity for constant PRF case, the $\Lambda(v)$ is periodic for every 8 khz which corresponds to 120 m/sec Doppler velocity. For the resolution of Doppler ambiguity, the peak value of the function should be only at the target Doppler velocity and almost zero response should be obtained at other test Doppler velocities up to the maximum test Doppler velocity of interest. For constant PRF, the test Doppler frequencies corresponds to frequencies f_p/K, which corresponds to null responses of sufficent statistic function $\Lambda(v)$. Since the sufficient statistic function gives zero response at the test Doppler velocities other than the selected test Doppler velocity, the detection can be performed for the selected test Doppler velocity up to unambiguous Doppler frequency.

When PRF jittering is applied, the response of the sufficient statistic function changes. To select the test target velocities and to resolve Doppler ambiguity a method called velocity interval selection method is developed.

3.2.1. Velocity Interval Selection Method

When we apply PRF jittering, the response of the sufficient statistic function with respect to the target Doppler velocities changes. For the detection of targets, the sufficient statistic function response after application of the jitter set, should give almost zero response at test velocities other than the selected test velocity. We want to cover all of the target velocities of interest with a good probability of detection, P_d. When the velocity interval between the test velocities is selected high, the targets with velocities between the test target velocities will have a large signal-to-noise ratio (SNR) loss, and have a lower P_d.

While selecting the velocity interval and the target test velocities, assuming that we have the required P_d for a target at the selected velocity, we want the minimum P_d which is denoted by P_{dmin} to be greater than a given P_d value for all target velocities of interest. In Figure 3.3, the selection procedure for velocity interval is shown for two neighbouring target test velocities.

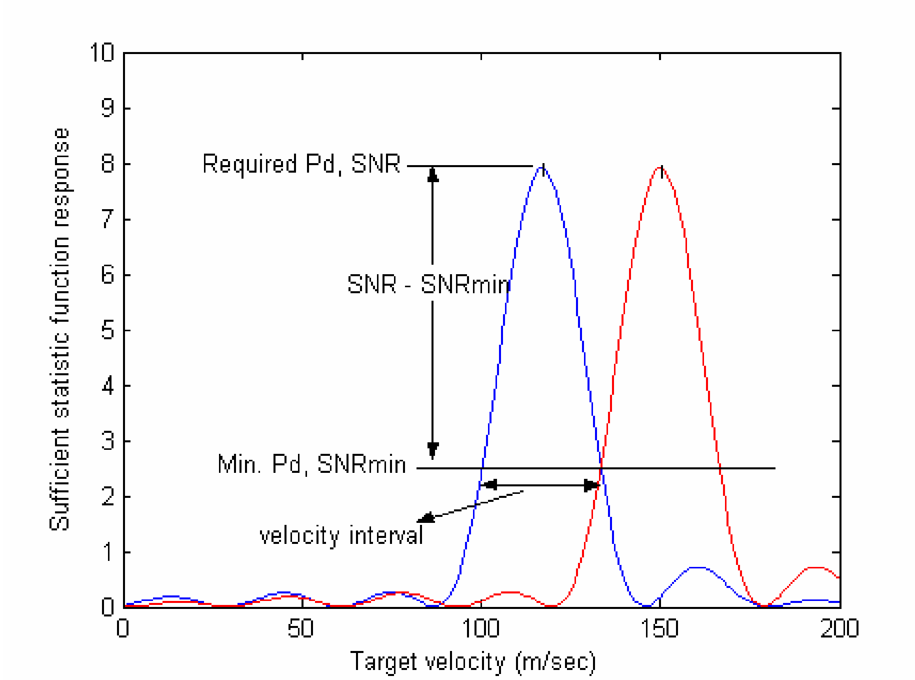

Figure 3.3 The selection of velocity interval for PRF jittering technique

The difference between the SNR's of P_{dmin} and required P_d values are calculated and the velocity interval is determined according to the width of the Doppler filter at the corresponding values of sufficient statistic function.

Thus, we want to examine the change of the detection performance with respect to the selection of target test Doppler velocity.

The detection problem considering the noise becomes:

$$\Lambda(v) = \left| \sum_{k=0}^{N-1} y(k) e^{-j\Omega_k(v)} + \sum_{k=0}^{N-1} n(k) e^{-j\Omega_k(v)} \right|^2 \tag{3.13}$$

where n(k) denotes white Gaussian noise, $y(k) = ae^{-j\Omega_k(v_m)}$ denotes return from target at velocity v_m. For Swerling-2 model, the real and imaginary parts of the return are taken as i.i.d zero-mean Gaussian random variables. If the radar carrier is assumed to be frequency-hopping, then all returns can be assumed to be mutually independent. Let

$$v(k) = n(k)e^{-j\Omega_k(v)} \tag{3.14}$$

since the $e^{-j\Omega_k(v)}$ component has a magnitude of 1, it will not affect the probability density function and *v(k)* will also have a gaussian distribution. So, Eq. (3.13) becomes

$$\Lambda(v) = \left| \sum_{k=0}^{N-1} y(k)e^{-j\Omega_k(v)} + \sum_{k=0}^{N-1} v(k) \right|^2 \tag{3.15}$$

Let σ_n denote the standard deviation of *v(k)*. The total power of *v(k)* including real and imaginary parts will be $2\sigma_n^2$. Let σ_s denote the standard deviation of *y(k)*. Then, $2\sigma_s^2$ will be the signal power taken from target samples.

Therefore, for noise only case the total returned power will be $2\sigma_n^2$. For target and noise case, the total power will be $2\sigma_s^2 + 2\sigma_n^2$.

For convenience we can define SNR as [15]

$$SNR = \frac{\sigma_s^2}{\sigma_n^2} \tag{3.16}$$

It is seen that

$$\frac{\sigma_s^2 + \sigma_n^2}{\sigma_n^2} = 1 + SNR \qquad (3.17)$$

Since *v(k)* has Gaussian distribution, $\left|\sum_{k=0}^{K-1} v(k)\right|^2$ has a chi square distribution with degree of freedom 2. The probability density function for the chi square distribution with degree of freedom N is given by,

$$p(y) = \frac{y^{\frac{(N-2)}{2}} e^{-\frac{y}{2\sigma^2}}}{\sigma^N 2^{N/2} \Gamma(N/2)} \quad y \geq 0 \qquad (3.18)$$

For our case N is equal to 2. So, the probability density function is

$$p(y) = \frac{e^{-\frac{y}{2\sigma^2}}}{2\sigma} \quad y \geq 0 \qquad (3.19)$$

We want to cover all target velocities of interest, but the velocities that we can look at are at discrete values. For target velocities different from the tested target velocities, there will be a loss in SNR and the P_d will be decreased. After determining the P_{dmin} value for all target velocities of interest, we can select the velocity interval for the target velocities. Calculating the difference in SNR for the minimum required P_d and the targeted P_d value, the treshold for the velocity filter response can be found as shown in Figure 3.3 and the velocity interval between test target velocities can be decided.

For noise only case, taking the false alarm probability which is denoted by P_f as 10^{-5}, we can find γ such that $P_f(x>\gamma) = 10^{-5}$. Using "chi2inv" function of the MATLAB γ can be found as 23.05.

For signal and noise case, the returned signal is defined as in Eq. (3.15). If the required P_d for signal and noise case is selected as $P_d > 0.85$, the threshold power required for $P_d > 0.85$ and $P_f=10^{-5}$ is equal to 0.3205. So, the required SNR can be calculated using Eq. (3.17) as

$$10\log_{10}((23.05/0.325 - 1) = 18.441 \text{ dB}$$

If the minimum required detection probability P_{dmin} is selected as $P_{dmin} > 0.3$, the treshold power can be found as 2.408. The required SNR can be calculated using Eq. (3.17) as 9.326 dB for this treshold. So, calculating the SNR difference between the required P_d and P_{dmin} and finding the threshold of the velocity filters and the corresponding target velocity bins at that threshold values, the velocity interval can be found.

The selected velocity interval values for different number of pulses and different PRF's are shown in Table 3.1 for $P_d > 0.85$, $P_f = 10^{-5}$ and $P_{dmin} > 0.3$. Using a MATLAB program velocity interval is calculated according to the described procedure

Table 3.1: The velocity intervals for different values of PRF and K for P_d=0.85, P_{dmin}=0.3 and P_f=10^{-5}

		PRF(kHz)							
		10	**12**	**14**	**16**	**18**	**20**	**22**	**24**
number of pulses (K)	**4**	57	69	81	91	103	115	127	137
	6	37	45	53	61	69	75	83	91
	8	29	33	39	45	51	57	63	67
	10	23	27	31	37	41	45	49	55
	12	19	23	27	31	33	37	41	45
	14	17	19	23	25	29	33	35	39
	16	15	17	19	23	25	29	31	33
	18	13	15	17	21	23	25	27	31
	20	11	13	15	19	21	23	25	27
	22	11	13	15	17	19	21	23	25
	24	9	11	13	15	17	19	21	23

3.3 Effects of PRF Jitter on Range Ambiguity Resolution

When constant PRF is used, range ambiguity occurs if a low PRF waveform is not used. Since the time delays taken from the targets are same and can not be distinguished, the real range of the target can not be determined. So, the measured target range is ambiguous. When PRF jittering technique is used, the returns from the targets will be taken with different time delay according to the pulses sent. The performance of resolving range ambiguity by using PRF jittering technique is the major concern of this section.

Since we know the pulse intervals sent to the target, we can calculate the expected returns from the target for each range. While designing PRF jitter sets, the aim is to reduce the number of hits of a target at range R with the returns that are expected at other range bins. In Figure 3.4, number of returns taken for each test range bin from a target at 30 km and with constant PRF=10 kHz which corresponds to 15 km maximum unambiguous range, is given. The waveform used is as shown in Figure 3.1, the number of pulses, K, is 8. For this example the maximum range of the target is taken as 75 km. As seen from Figure 3.4, at ranges that are multiples of the maximum unambigous range, there are a large number of ambigous hits, because of range ambiguity.

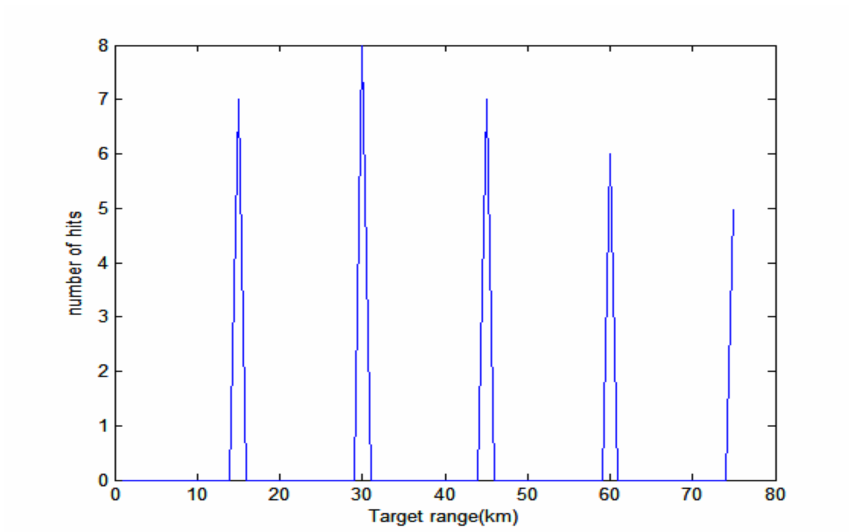

Figure 3.4 Number of hits taken from a target at R=30 km, for constant PRF=10 kHz, K=8 pulses.

For a jitter set δT = [-5 -15 5 15 8 10 -10 -8] μsec, number of returns taken for each test range bin from a target at 30 km, PRF=10 kHz is given in Figure 3.5. As seen in Figure 3.5, the number of ambigous hits at other range bins $R \neq R^*$, where R^* denotes the true target range, is reduced and there is a potential of removing range ambiguity using PRF jittering technique.

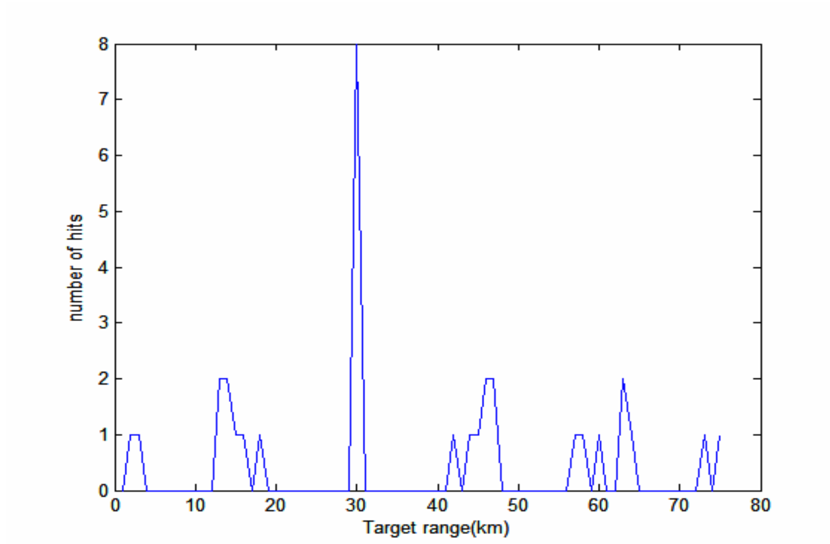

Figure 3.5 Number of hits taken from a target at R=30 km, for PRF=10 kHz, K=8 pulses, δT = [-5 -15 5 15 8 10 -10 -8] μsec.

All target range bins should be tested for range ambiguity. A cost function for the range ambiguity is defined as H(R, R^*) which denotes the number of hits taken from a target at range R = R* at range bin R. At range bins R ≠ R^* the number of hits should be low to be able to determine the real range of the target. The optimization procedure to find jitter sets that reduce range ambiguity is:

1- Take a PRF jitter set.

2- Put a target at range bin R = R^*

3- Compute maximum H(R, R^*), for R ≠ R^*.

4- Go to step 2 and do this until all target range bins are covered.

The maximum H(R, R^*) value found from this procedure gives us the worst case ambiguity for the selected jitter set. If we can reduce this value to almost zero, range ambiguity can be resolved.

CHAPTER 4

OPTIMIZATION RESULTS

In this chapter, the results of the optimization of the PRF jitter set for unambiguous estimation of the range and Doppler according to the constraints developed in Chapter 3 is given.

Firstly, the optimization methods used for the problem are given in this chapter. Then, the optimization using genetic algorithm is discussed, also the details of the genetic algorithm are provided. A discussion on the effects of the specified parameters on the performance of the optimization processes is given, along with the optimized cost and score functions. Then, the results of the optimizations for the Doppler ambiguity problem are given. A new approach to select test target velocities is described and the results of this approach are also given. The approach and the results of the optimization for the range ambiguity problem are provided next. Then, an optimization considering range ambiguity and clutter rejection functions is given. Finally, the effects of quantization on the performance of improvement factor is investigated and evaluated.

4.1 Optimization Methods

4.1.1 Genetic Algorithm [17, 18]

In nature, variety is defined as variation in the chromosomes of the entities in the population. The variation in both the structure and the behaviour of the entities in their environment is a result of this variety. Differences in the rate of survival and reproduction reflect this variation in structure and behaviour. Some entities are better able to perform tasks in their environment, survive and reproduce at a higher rate, whereas less fit entities survive and reproduce at a lower rate. Over a period of time and many generations, the population comes to contain more individuals whose chromosomes are translated into structures and behaviours that enable those individuals to better perform their tasks in their environment and to survive and reproduce. So, as time passes the structure of individuals in the population changes as a result of natural selection. When these visible and measurable differences in structure that arose from differences in fitness are observed, it is concluded that the population has evolved. In this process, structure arises from fitness.

When there exists a population of entities, the existence of some variability having some differential effect on the rate of survivability, is almost inevitable. So, for an entity, to have the ability to reproduce itself, is the most important condition for starting the evolutionary process.

Any problem in adaptation can be formulated in genetic terms. Once formulated in those terms, such a problem can be solved by 'genetic algorithm'. The genetic algorithm simulates Darwinian evolutionary processes and naturally occuring genetic operations on chromosomes.

Genetic algorithm is a highly parallel mathematical algorithm that transforms a set (population) of individual mathematical objects (typically fixed-length character strings patterned after chromosome strings), each with an associated *fitness* value, into a new population (i.e., the next *generation*) using operations patterned after the Darwinian principle of reproduction and survival of the fittest after naturally occuring genetic operations.

4.1.1.1 The Representation Problem for the Genetic Algorithms

Since genetic algorithms directly manipulate a coded representation of the problem and because the representation scheme can limit the window by which a system observes its world, representation is a key issue in genetic algorithm work [15]. The conventional genetic algorithm operating on fixed-length character strings is capable of solving a great many problems. Nevertheless, the use of fixed-length character strings leaves many issues unsettled. For many problems, the most natural representation for a solution is a hierarchical computer program rather than a fixed-length character string. The hierarchies in representing the tasks and subtasks (that is, programs and subroutines) that are needed to solve complex problems have a central importance in genetic coding. The hierachical computer program should have the potential of changing its size and shape since the size and shape of this program that will solve a given problem are generally not known in advance [16].

Virtually any programming language is capable of expressing and executing the general, hierarchical computer programs. MATLAB is used as the computer program, in the method provided in this thesis. It is preferred due to its ability to perform alternative computations conditioned on the outcome of intermediate calculations, to perform operations in a hierarchical way, to perform computations on variables of many different types and since the problem involved requires iteration, due to its recursion and dynamic variability.

4.1.1.2 Detailed Description of the Proposed Genetic Program

For the conventional genetic algorithm and genetic programming, the structures undergoing adaptation are a *population* of individual points from the search space, rather than a single point. Genetic methods differ from most other search techniques in that they simultaneously involve a parallel search involving hundreds or thousands of points in the search space.

In the proposed genetic program, the structure chosen to undergo adaptation is the jitter values, δT_k, which are the deviation from the hypothetic regular train of PRI of the waveform. The number of elements in the jitter set, *K*, is an input to the program. A population consists of individuals which represent the jitter set by *K* numbers, as in Eq. (3.1). The generation of each individual, denoted by δT, in the initial population is produced by randomly generating *K* numbers by uniform distribution. Although the numbers are generated randomly, there is a restriction on the maximum and minimum value of jitter values which are input to the program. Also, jitter values are selected according to a predetermined resolution value, which can be determined by the physical constraints for the implementable jitter values, and given as an input to the program.

As described before, fitness of an individual is the probability that it survives to the age of reproduction and reproduces. The most common approach to measuring fitness is to create an explicit fitness measure for each individual in the population. Each individual in the population is assigned a scalar fitness value by means of some well-defined explicit evaluative procedure. In this work, the fitness value assigned to the jitter set is denoted by $F(\delta T)$. This selection is due to the proposed optimization criterion provided in Chapter 3. The maximum value of the the sufficient statistic function $\Lambda(v, v^*)$, which is defined in Chapter 3, when $v \neq v^*$, where v^* represents assumed target velocities which are assumed to be same with the target test velocities, is tried to be minimized to resolve the Doppler ambiguity. Here, $\Lambda(v, v^*)$ when $v \neq v^*$ is calculated for each selected target test velocity and the negative sign of maximum of $\Lambda(v, v^*)$ is assigned as the fitness value. The jitter set, with the highest $F(\delta T)$ is the best jitter set among all the jitter set, satisfying also $C(\delta T) < c_0$, is said to be the best jitter set. Here, c_0 denotes the maximum allowable value to satisfy clutter rejection function, $C(\delta T)$, defined in Eq. 3.12 and should be close to zero.

To modify the structures undergoing adaptation in genetic programming, an operation known as 'crossover' is applied to the individuals, namely, jitter sets. This operation creates variation in the population by producing new offsprings that consist of parts taken from each parent. The crossover operation starts with two parental individuals and produces two offspring individuals. The parents are chosen from the part of the population which is composed of a predetermined number of individuals with the highest fitness values, satisfying $C(\delta T) < c_0$.

The number of pulses that will be used in the jitter set, the PRI value that the jittering is applied, the maximum and minimum values for the jitter set elements, the number of individuals to be created in the population and the number of generations to be created are input to the program. Also, the minimum resolution for the elements of the jitter set which may arise due to the physical constraints of the waveform generation is provided as an input. The P_f value, required P_d value and the determined P_{dmin} value are also input to the program to be able to select the velocity interval as described in detail in Chapter 3.

The jitter set values are represented as decimal numbers, in individuals, δT. The initial generation is created by assigning random numbers to the elements of the jitter set between the maximum and the minimum jitter values with an input jitter resolution. Then, the operation begins by reducing the population to the individuals satisfying $C(\delta T) > c_0$. Next, by independently selecting, using a uniform probability distribution, one random point in each parent in the population created in the previous step, to be the crossover point, offsprings are produced. Offsprings are produced by deleting the crossover fragment of the first parent from the first parent and then inserting the crossover fragment of the second parent at the crossover point of the first parent. Number of offsprings to be produced are restricted to complete the number of individuals to the predetermined population. This operation is done to increase the probability of every individual in the population to overcome the lower bound restriction. For all the individuals in this population, fitness values, i.e., $F(\delta T)$ are evaluated and individuals are put in order according to increasing fitness values. Among all the individuals, ordered with respect to their fitnesses in this population, 10% of them with the best fitness values are selected to form a part of a new generation, created to improve quality in the sense of better $F(\delta T)$. The remaining individuals of this new generation are formed by crossover operation implemented on the 10% of the population.

By this way, the probability of maximizing the fitness value of every individual in the population is increased. This provides better initial populations with possible highest fitness values and adequate lower bounds, for next generations, thus increasing the quality for every next generation.

In addition to the two primary genetic operations of reproduction and crossover in genetic programming, mutation property of the genetic programming is also used to be able to introduce random changes in structures in the population.

The number of the mutant individuals is input at the beginning of the program. The mutation operation removes whatever is currently at the selected point of an individual δT, and inserts a randomly generated decimal value representing the pulse number at that point. By this way, random changes are introduced and transferred to the next generations.

4.1.2. Optimization Using Optimization Toolbox in MATLAB

Other than using genetic algorithm, optimization is realized also with the optimization toolbox of MATLAB. In this approach, 'fminimax' function of the toolbox is used. The structure is

[d, fval, exitflag, output]=fminimax(Fun, d_0, a, b, Aeq, Beq, lb, ub, nonlcon, options)

The function 'fminimax' minimizes the maximum of a function of several variables. In our case, the function for which we want to minimize the maximum value is $\Lambda(v, v^*)$ when $v \neq v^*$. The target test velocities v^* between v_l and v_h are selected according to the velocity interval selection method. When $v = v^*$, the sufficient statistic function gives the maximum value. We want the cross correlation of this function for the other target test velocities to be minimum, nearly equal to zero. Also, the clutter rejection function, $C(\delta T)$ is taken as the constraint function defined in 'nonlcon' of the minimax function. A set of lower and upper bounds for the jitter set δT is defined, so that a solution is found in the range lb <= δT_k <= ub, where lb denotes lower bound and ub denotes upper bound for the jitter values.

During the search, the 'fminimax' function finds δT that minimize the maximum of the function $\Lambda(v, v^*)$ for v ≠ v* , starting from an initial jitter set δT_0. To enlarge the search space, the optimization is repeated many times with different initial sets, δT_0. This is done by creating a set of different initial points of search to be used for the function. Initial points are created randomly according to a predetermined resolution for the δT_k. Since the search space for the jitter set is very large, and since the fminimax function finds local minimum values for the function and there are many local minimums, this function needs many iterations and too much run time to be able to find good solutions. The genetic algorithm gives better results in less run time and has better control on parameters like jitter resolution which are the reasons of preference of the genetic algorithm with respect to the fminimax function of the MATLAB.

4.2 Optimization Results of the Velocity Interval Selection Method

In this section, the studies on jitter set optimization acording to the velocity interval selection method which is defined in Chapter 3, are presented. Various scenarios were considered with design related parameters such as the number of generations and initial population, number of pulses in the jitter set, the upper and lower bounds for the jitter set elements, the resolution of the jitter set elements, the selected PRI for the hypothetic regular train, the constraint value for the clutter rejection function, C(δT), P_{dmin} value which is effective on the selection of velocity, all varied to some extent. The optimization processes resulted in nonuniform pulse intervals.

Simulation results for only the genetic algorithm is given in this section, since it produces the best results in less run time. The MATLAB optimization toolbox does not provide good results and it is harder to control the design parameters like jitter resolution in the MATLAB optimization toolbox.

Since simultaneous illustration of the effects of all the design related parameters on the performance of the algorithm is a difficult task, the effect of the parameters are given by varying one parameter at a time.

4.2.1 Effect of Initial Population and Number of Generations

The values of maximum population and maximum number of generations to be produced is an input parameter in the genetic programming codes. During the simulations, it is observed that, as the number of pulses in the jitter set increase, the jitter resolution decrease, upper and lower bound values for the jitter set elements increase and the best jitter set is found at later generations. As an example, if we select the jitter set elements with upper and lower bounds, -10 μsec $< \delta T_k <$ 10 μsec, and select jitter resolution of 1 μsec, and use 8 pulses for the set, there are 8^{21} possible jitter sets and to be able to find the optimum solution, the initial population set must be selected at a very large value and also the number of generations must be large. In case of keeping the number of generations less than enough, the algorithm results in an intermediate valuey that is not optimum. In the optimization process it is seen that for small upper and lower bounds, small number of pulses and low jitter resolution, the genetic algorithm finds the global optimum solution at each run with normal run times (e.g 0.1-500 minutes) depending on the values of those parameters. As the initial population is increased the number of generations required to find the optimum solution for that initial population also increase.

4.2.2 Effect of Number of Pulses

The optimization process does not include the optimization of the number of pulses that will be used. The process begins with the assumption that the number of pulses to be used is given. The programs are capable of optimizing the nonuniform pulse intervals with any number of pulses. The number of pulses effects the velocity interval selection and the results of the optimization process is dependent on the number of pulses. The run time and the number of iterations required to reach the optimum jitter set increases with increasing number of pulses used.

The results for 4, 6, 8, 10, 12, 14, 16 pulses are given in Table 4.1. PRF = 15 kHz, jitter resolution=1 μsec and upper and lower bounds for the jitter values are taken as +25 μsec and -25 μsec, respectively. The velocity interval is selected according to velocity interval selection method with the parameters $P_d>0.85$, $P_{dmin}>0.3$ and $P_f=10^{-5}$. The minimum target velocity is taken as 50 m/sec and maximum target velocity of interest is taken as 400 m/sec for this optimization. The fitness values are normalized values with respect to the peak value of the sufficient statistic function, when the target velocity is equal to one of the test velocities. The constraint value is the normalized $C(\delta T)$ value with respect to maximum value of the $C(\delta T)$ function which corresponds to K for the optimization. The table and graph of number of pulses versus fitness and constraint values are given in Table 4.1 and Figure 4.1. As we increase the number of pulses, we are able to resolve the ambiguity, but since the velocity interval decreases when the number of pulses decrease, it also gets harder to find good jitter sets since there are many velocities to cover. So as we increase the number of pulses, better fitness values is found as shown in Figure 4.1, but the fitness values do not change too much.

Table 4.1- The results of optimization for different number of pulses for parameters

Number of Pulses	***Test velocities***	***Fitness value***	***Constraint value***	***jitter set(μsec)***
4	*v=80:80:400*	0,0655	0,3577	[23 -4 9 -19]
6	*v=50:50:400*	0,0713	0,2385	[-5 -2 16 -6 0 3]
8	*v=50:36:410*	0,0423	0,1789	[-5 16 -14 17 -10 -24 -10 5]
10	*v=50:28:414*	0,0454	0,1431	[-2 9 -17 24 -11 12 24 13 -15 3]
12	*v=50:22:402*	0,0380	0,1192	[-10 4 -13 16 -10 -23 -9 17 -8 18 -2 14]
14	*v=50:18:410*	0,0469	0,1022	[10 -23 19 17 -18 -5 10 -1 15 -15 22 -6 17 -14]
16	*v=50:16:402*	0,0394	0,0894	[-14 1 -22 10 -20 3 -19 -18 -13 8 20 6 -17 18 -8 7]

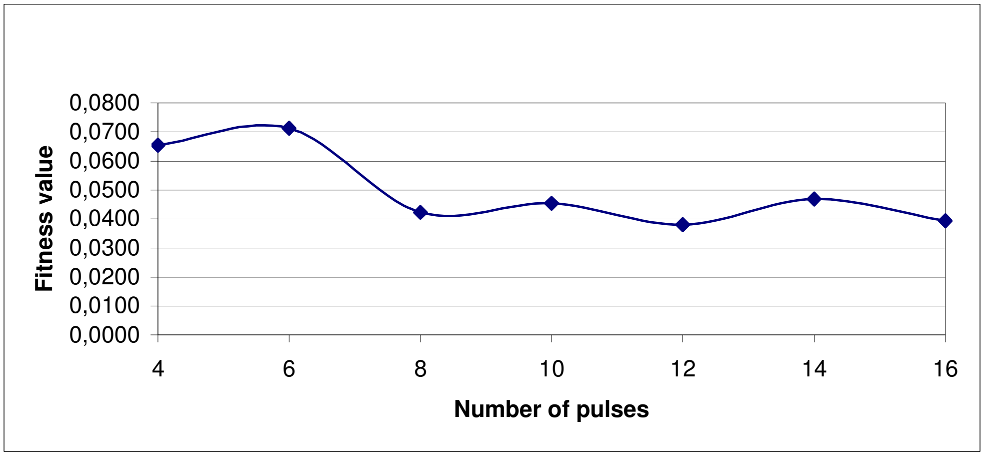

Figure 4.1 Number of pulses versus fitness value results of the optimization.

4.2.3 Effect of Upper and Lower Bounds on Jitter Values

The upper and lower bounds for the jitter set elements can be given to the genetic program. When the maximum and minimum jitter values are increased, better results for the optimization process are found, but as these bounds are increased with same jitter resolution, it is harder to find a global optimum solution, also the run time for the optimization increases, since the search space increases. After some maximum and minimum bound values for the jitter set, the results do not change too much. Different values of upper and lower bounds are tried as given in Table 4.2. PRF=15 kHz, jitter resolution=0.01 µsec and K=6 pulses are the parameters taken for this optimization. $P_d>0.85$, $P_{dmin}>0.3$ and $P_f=10^{-5}$ are the velocity interval selection parameters, the test velocities are found as 50:50:400 for these parameters. The minimum target velocity is taken as 50 m/sec and maximum target velocity of interest is taken as 400 m/sec for this optimization. The fitness values are normalized values with respect to the peak value of the sufficient statistic function which corresponds to K, when the target velocity is equal to one of the test velocities. The constraint value is the normalized $C(\delta T)$ value with respect to maximum value of the C(δT) function which corresponds to K for the optimization. The graph of number of pulses versus fitness values is given in Figure 4.2.

Table 4.2- The results of selection of upper and lower bounds of jitter values on optimization performance

Max. Jitter(±, μsec)	*Fitness Value*	*Constraint Value*	*jitter set(μsec)*
10	0,0824	0,2871	[-5,37 -4,18 9,90 -9,74 -2,08 3,17]
15	0,0692	0,2630	[-2,21 2,08 9,18 -12,29 4,07 6,42]
25	0,0689	0,2624	[-8,21 -4,64 1,15 -20,19 -2,58 0,55]
40	0,0693	0,2633	[-5,57 -1,77 4,42 -17,17 0,32 3,06]

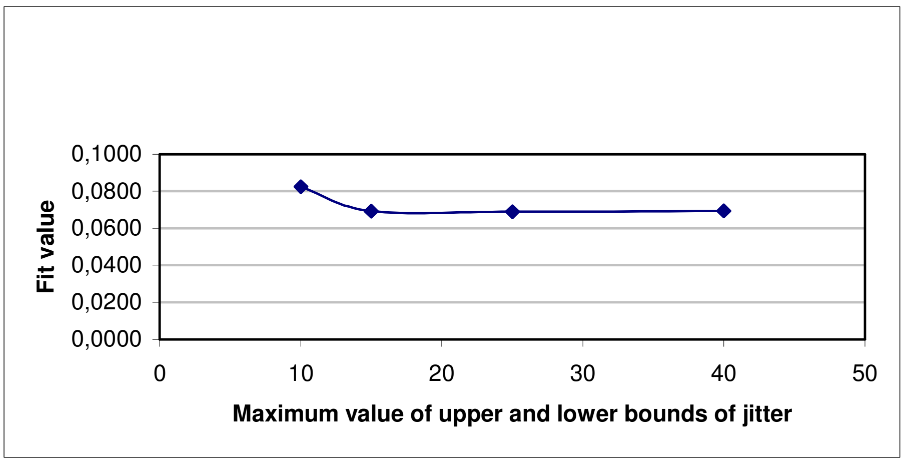

Figure 4.2- Effect of maximum value of upper and lower bounds of jitter values on optimization.

4.2.4 Effect of Jitter Set Resolution

The jitter set resolution can be given as input to the genetic program. When the jitter set resolution is increased, it is harder to find a global optimum solution, also the run time for the optimization increases. For better jitter resolution values, the values found from the optimization do not change very much. Different values of jitter resolution are tried in the optimization and the fitness values found after optimization are given in Table 4.3. PRF=15 kHz, upper and lower bounds for the jitter values are taken as +25 μsec and -25 μsec, respectively and K=4 pulses are the parameters taken for this optimization. P_d>0.85, P_{dmin}>0.3 and $P_f=10^{-5}$ are the velocity interval selection parameters, the test velocities are found as v=80:80:400 for these parameters. The minimum target velocity of interest is taken as 50 m/sec and maximum target velocity of interest is taken as 400 m/sec for this optimization. The fitness values are normalized values with respect to the peak value of the sufficient statistic function which corresponds to K, when the target velocity is equal to one of the test velocities. The constraint value is the normalized C(δT) value of the jitter set with respect to maximum value of the C(δT) function which corresponds to K for the optimization.

Table 4.3 The results of selection of jitter resolution on optimization performance

Jitter Resolution(μsec)	*Fitness Value*	*Constraint value*	*jitter set(μsec)*
1	0,0671	0,361	[-20 -8 5 17]
0.1	0,0626	0,356	[-20,0 -7,8 4,5 16,9]
0.01	0,0625	0,357	[-20,10 -7,82 4,47 16,74]
0.001	0,0625	0,358	[-19,512 -7,117 5,164 17,329]

4.2.5 Effect of PRI Selection

The hypothetic regular PRI value is given as an input to the program. PRI is an important parameter for the selection of velocity interval. If the PRF is low, the ambiguity order of the Doppler gets larger. In Figure 4.3 the velocity response for a constant PRF system when we apply sufficient statistic function to a target at zero velocity with PRF=8 khz with K=8 pulses is given. In Figure 4.4 the velocity response with PRF=16 kHz is given with K=8 pulses.

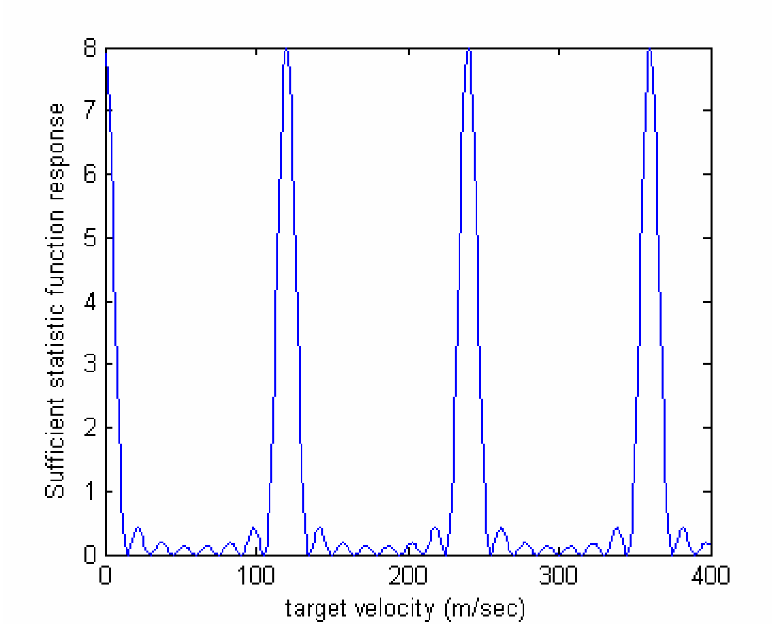

Figure 4.3 Sufficient Statistic function vs. target velocity response for constant PRF system, PRF=8 Khz.

The constant PRF system with PRF= 8Khz have an Doppler ambiguity order of 3 if the maximum target velocity is 400 m/sec. The constant PRF system with PRF=16 Khz has ambiguity order of 1. When we apply PRF jittering, we try to reduce the peaks of the sufficient statistic function for other target velocities to be able to resolve Doppler ambiguity. So, it is harder to decrease a constant PRF system with ambiguity order 3 than a system with ambiguity order of 1. The results of an optimization for different PRF values is given in Table 4.4.

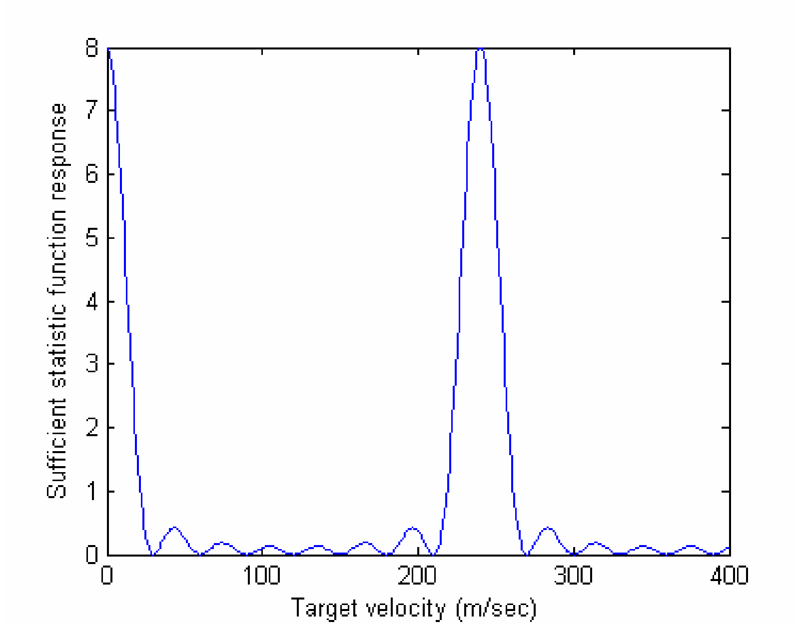

Figure 4.4 Sufficient Statistic function vs. target velocity response for constant PRF system, PRF=16 Khz.

Table 4.4- The results of selection of PRF on optimization performance

PRF(kHz)	test velocities	Fit value	Constraint value	jitter set(μsec)
10	*v=56:56:392*	0,2010	0,4439	[-14,87 -11,32 14,84 -0,50]
13	*v=72:72:444*	0,1250	0,3536	[-4,42 -18,64 -1,64 15,51]
15	*v=80:80:400*	0,0625	0,3574	[-20,10 -7,82 4,47 16,74]
17	*v=96:96:384*	3,74E-07	0,2543	[-15,18 8,22 -9,49 13,94]
19	*v=104:104:416*	1,11E-06	0,2506	[-22,31 4,03 -9,13 17,16]
20	*v=112:112:448*	0,0631	0,3628	[-14,18 14,77 4,32 -6,20]

Upper and lower bounds for the jitter values are taken as +25 μsec and -25 μsec, respectively. Jitter resolution = 0.01 μsec and K=4 pulses are the parameters taken for this optimization. P_d>0.85, Pdmin>0.3 and $P_f=10^{-5}$ are the velocity interval selection parameters. The minimum target velocity of interest is taken as 50 m/sec and maximum target velocity of interest is taken as 400 m/sec for this optimization. The fitness values are normalized values with respect to the peak value of the sufficient statistic function which corresponds to K, when the target velocity is equal to one of the test velocities. The constraint value is the normalized C(δT) value of the jitter set with respect to maximum value of the C(δT) function which corresponds to K for the optimization.

As seen in Table 4.4, when the velocity interval increases, the number of velocity bins is decreased and good jitter sets that reduce the Doppler ambiguity can be found.

The effect of PRF jittering on Doppler ambiguity resolution can be understood better if we look at the velocity response characteristic of the target after application of PRF jittering. In Figure 4.5, the velocity response of sufficient statistic function for constant PRF=15 kHz and K=16 is shown for target velocity Doppler filters of v=64 m/sec, v=80 m/sec and v=96 m/sec. When PRF jittering is applied with δT = [-14 2 -22 10 -20 3 -19 -18 -13 8 20 6 -17 18 -8 - 8 7], the velocity responses of those filters is given in Figure 4.6. As seen from Figure 4.5, the peaks are reduced when we apply PRF jittering.

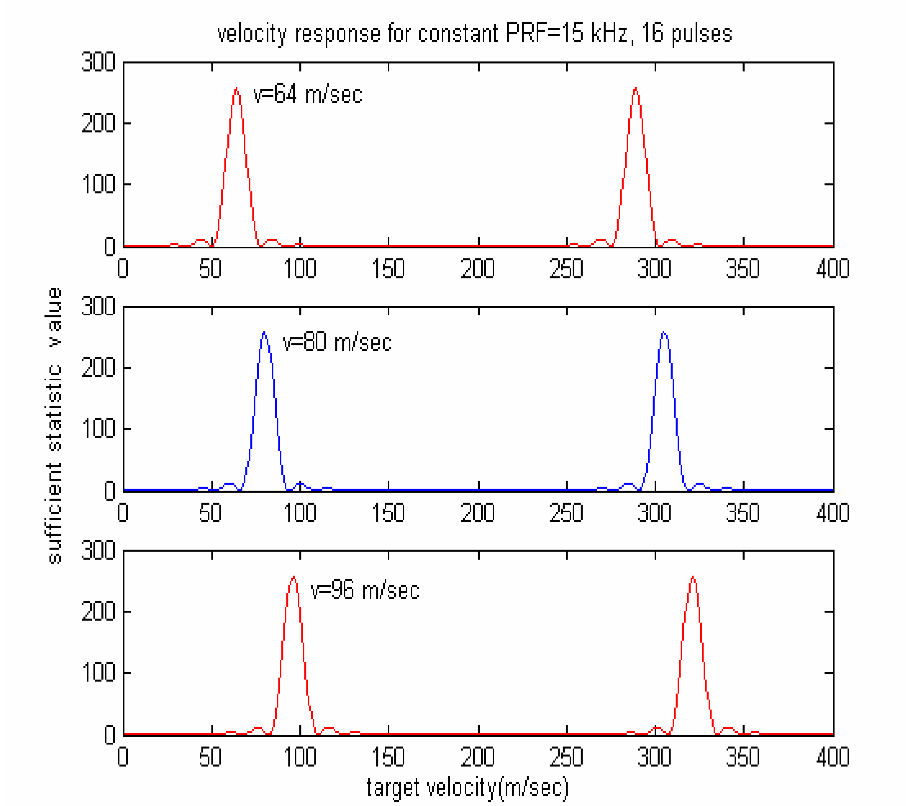

Figure 4.5 The velocity response of sufficient statistic function of v=64 m/sec, v=80 m/sec and v=96 m/sec Doppler filters, for constant PRF=15 kHz, K=8 pulses

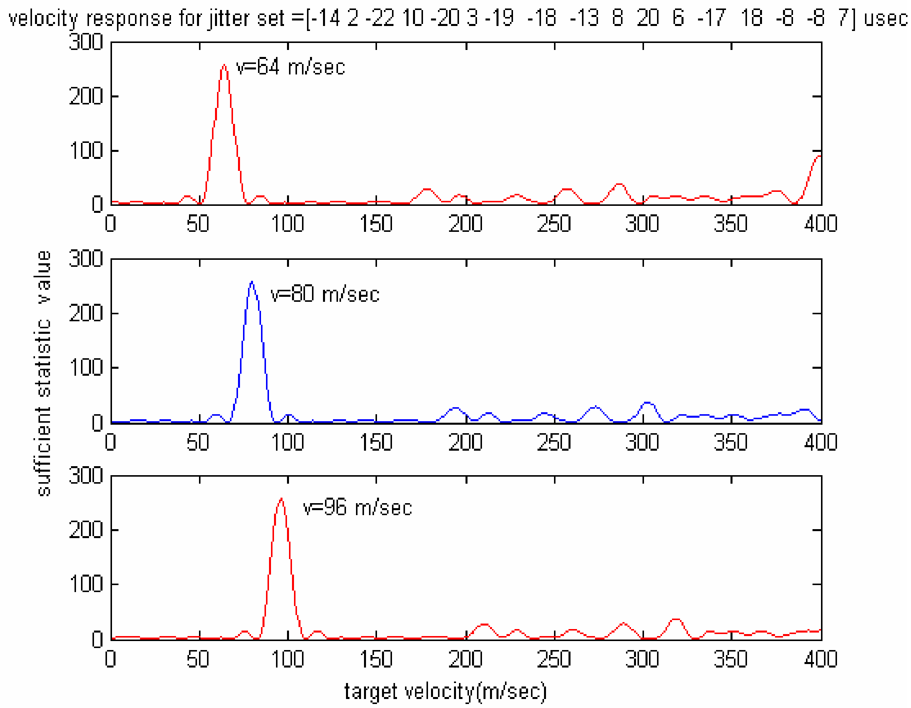

Figure 4.6 The velocity response of sufficient statistic function for v=64 m/sec, v=80 m/sec and v=96 m/sec filters for δT =[-14 2 -22 10 -20 3 -19 -18 -13 8 20 6 -17 18 -8 - 8 7] µsec, PRF=15 kHz, K=8 pulses

4.2.6 Effect of P_{dmin}

P_{dmin} is a parameter that is given as an input to the genetic program. It affects the velocity interval selection. When P_{dmin} is increased, the targets with velocities between the test velocities will have a better P_d, but it is harder to find better jitter sets when this value is increased since the velocity interval decreases.

4.2.7 Effect of Bound on Constraint Value

It is planned to generate populations with individuals which satisfy $C(\delta T) < c_0$, in the genetic program. The constraint function value, c_0, must be close to zero to be able to have good clutter rejection. When we take c_0 near to zero during selection of individuals in the genetic algorithm, it is seen that no individuals can satisfy the constraint. As can be seen from Table 4.1, Table 4.2 and Table 4.3, the constraint values for the jitter sets are on the order of 10^{-1}. So, firstly the constraint value does not taken into consideration and the results given in Table-4.1, Table 4.2 and Table 4.3 are the results of the optimization where constraint value is not taken into account.

When the jitter set is optimized according to the maximum of the C(δT) for the selected test target velocities, it is seen that the optimum jitter sets for the constraint function are almost equal to the constraint function values given in Table 4.1, Table 4.2 and Table 4.3. Best jitter sets according to the constraint function optimization are on the order of 10^{-1}.

4.2.7 Summary of Optimization Results for Velocity Interval Selection Method

The optimization results of the velocity interval selection method show that it is possible to resolve Doppler ambiguity by using PRF jittering technique. When the velocity interval is low, there are many test Doppler velocity filters and it is harder to find jitter sets with good Doppler ambiguity resolution performance. By increasing the PRF value, increasing the number of pulses and increasing the upper and lower bounds for jitter Doppler ambiguity resolution performance increeases. Increase of the jitter resolution does not effect the performance very much. One of the most important conclusions of this part is the constraint function, C(δT), does not give good enough results for the clutter cancellation property. The clutter cancellation is an important task for pulse Doppler radars, and we want the value of the constraint function to be nearly equal to zero, on the order of 10^{-2}, 10^{-3} or even smaller. Selection of velocity interval and designing velocity filters for the velocities equally seperated by that velocity interval value doesn't satisfy the clutter cancelletion requirements, so another method, which is given in next section is investigated for the optimization of the nonuniform pulse intervals.

4.3.1 A New Approach for the Target Test Doppler Velocity Selection

Since the clutter rejection property of the velocity interval selection method does not satisfy the requirements, a new method is defined in this section. Taking the Doppler ambiguity problem and the defects when we apply PRF jittering as cost functions, a good Doppler velocity response for the clutter rejection function is investigated and C(δT) function is tried to be optimized. When PRF jittering is applied, a typical velocity response is shown in Figure 4.7. To have good Doppler spectrum cost functions are defined according to constraints of Doppler ambiguity resolution, clutter rejection and good velocity coverage which are described below in more detail.

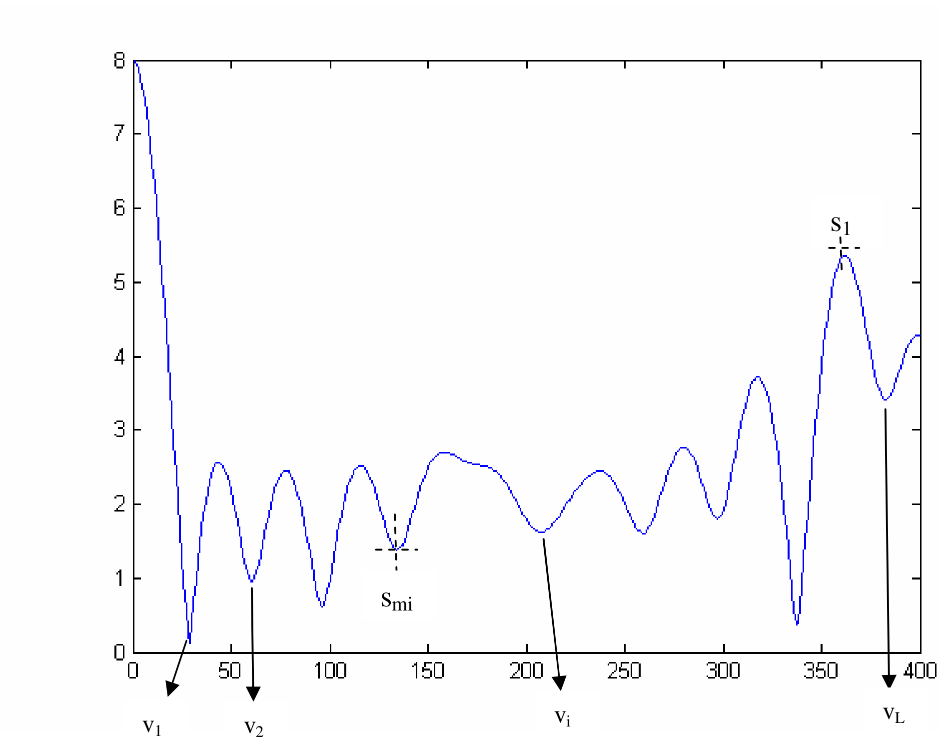

Figure 4.7 Selection of test Doppler velocities for PRF jittering set

Three cost parameters are taken into consideration. The maximum value of the velocity response other than the selected velocity should be low to be able to resolve Doppler ambiguity. This is shown in Figure 4.7 as s_1. The cost function for this parameter is taken as

$$\text{Cost peak} = \alpha . s_1^2 \qquad (4.1)$$

where s_1 denotes the maximum value of the velocity filter response with respect to the peak value of the zero velocity filter, and α denotes the weight parameter for this cost function.

The second cost function is defined for the nulls of the velocity response function. The velocities corresponding to the nulls of the function are selected as the test velocities in the algorithm. The values of the C(δT) function should be low at that velocities to be able to have good clutter cancellation. The cost function for null velocities is defined as:

$$\text{CN} = \beta . \sum_{i=1}^{L} s_{mi}^2 \qquad (4.2)$$

where s_{mi} denotes the values of the clutter rejection function at the velocities that produces nulls, L denotes the number of null velocities and β denotes the weight for the cost null.

The final cost parameter for the velocity response is for good velocity coverage of the target velocities of interest. If the nulls occur at very long velocity intervals, the target velocities between these nulls will have a low probability of detection, so the velocity intervals between the nulls of the function are calculated and if they are greater than a determined value they are taken as a cost for the velocity response of the function. So, velocity interval cost is defined as:

$$\text{CV} = \delta . \left| \sum_{i=1}^{L-1} v_{mi} - \overline{v} \right|^2 \qquad \text{for } v_{mi} > v_{int} \qquad (4.3)$$

where v_{mi} denotes the velocity interval between test velocities, v_{int} denotes the velocity interval calculated by the given P_{dmin} value as in velocity interval selection method, $\bar{v}$ denotes average velocity interval between null velocities and δ denotes the weight for the velocity interval cost function. All of these costs are taken into account by a total cost function:

$$J = \alpha.s_1^2 + \beta.\sum_{i=1}^{K-1} s_{mi}^2 + \delta.\left|\sum_{i=1}^{K-1} v_{\text{int}} - \bar{v}\right|^2 \qquad (4.4)$$

and this value of cost function is given as the fitness value of the genetic algorithm. The jitter set which has the minimum cost is the best set for the optimization. So, the optimization process is described as:

1- Generate jitter sets and calculate the zero velocity filter response for the function.

2- Find nulls and peaks of the function,

3- Find corresponding velocities for the nulls and peaks of the function, also calculate velocity intervals between the selected test velocities.

4- Calculate cost functions for the jitter sets and the total cost function, *J*.

5- Find the best jitter sets, generate new jitter sets from these jitter sets and go to first step to generate new jitter sets from these best jitter sets.

4.3.2 Results for the New Approach

To be able to determine the weights *α, β,* γ of the cost function *J*, firstly the cost functions are optimized one by one, by applying 1 as weight to one of them and 0 to the other cost functions weights.

For the optimizations given in this section, PRF=16 kHz, K=8 pulses, jitter resolution=1 μsec and lower bounds for the jitter values are taken as +25 μsec and -25 μsec, respectively. The velocity interval cost is calculated according to the parameters P_d>0.85, Pdmin>0.3 and $P_f=10^{-5}$. The minimum target velocity is taken as 50 m/sec and maximum target velocity of interest is taken as 400 m/sec for the optimizations. The graph of the best jitter set according to the optimization made by taking weights of the cost functions α=1, β=0, γ=0 is given in Figure 4.8. The best jitter set found from the optimization is δT =[11 -17 22 -4 5 10 -19 -12] μsec. The jitter set lowers the peak value of the constraint function at other target velocities as expected. Cost peak=0,1329 is the result of the optimization. For constant PRF case, cost peak results in a value of 1. If the other two cost parameters is considered as seen from Figure 4.8, when the best jitter set tries to lower the peak value of the function, the null values of the function increases. That means the null cost increases when we try to optimize jitter set according to the peak cost.

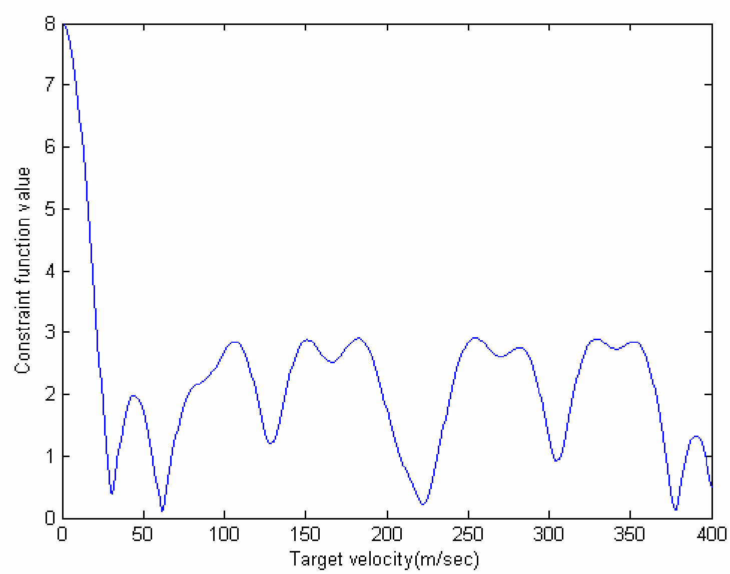

Figure 4.8 Constraint function response versus target velocity for δT =[11 -17 22 -4 5 10 -19 -12] μsec

The graph of the best jitter set according to the optimization made by taking weights of the cost functions α=0, β=1, γ=0 is given in Figure 4.9. The best jitter set for the optimization is found as δT =[0 -1 -1 1 0 0 1 -1] μsec and cost null=0.0025 for this jitter set. As seen from Figure 4.9, the response of the constraint function is very similar to the constant PRF case. The cost function for the constant PRF case is zero, so the optimization tries to take the jitter set values near to zero. The cost peak parameter is high, nearly equal to 1 as in constant PRF case. The Doppler ambiguity is not resolved by using this jitter set.

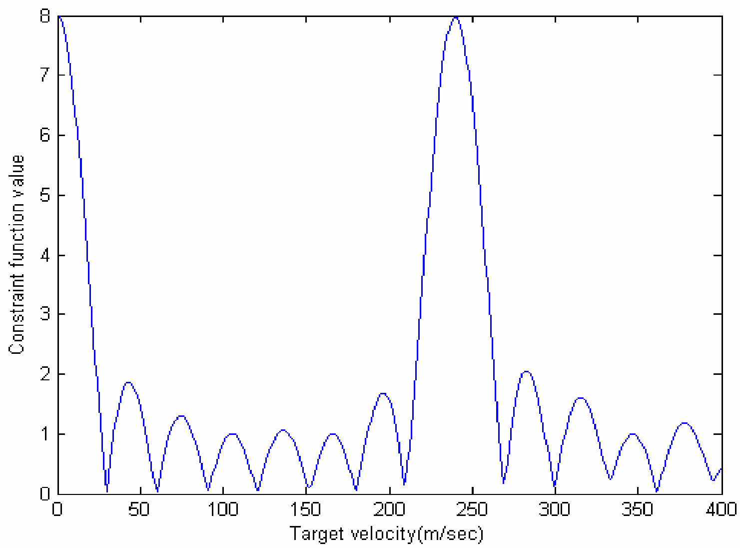

Figure 4.9 Constraint function response versus target velocity for δT =[0 -1 -1 1 0 0 1 -1] μsec

The graph of the best jitter set according to the optimization made by taking weights of the cost functions α=0, β=0, γ=1 is given in Figure 4.10. The best jitter for the optimization is found as δT =[-9 -9 7 10 9 6 -6 -9] μsec, with a velocity interval cost=0.1878. The velocity interval cost is found as 1, according to the velocity cost function, Eq. (4.3), for constant PRF case. As seen from Figure 4.10, the best jitter set produces nulls near the multiple of PRF to be able to reduce the velocity interval cost. The null cost increases since the jitter set increases the values of the constraint function at the test velocities.

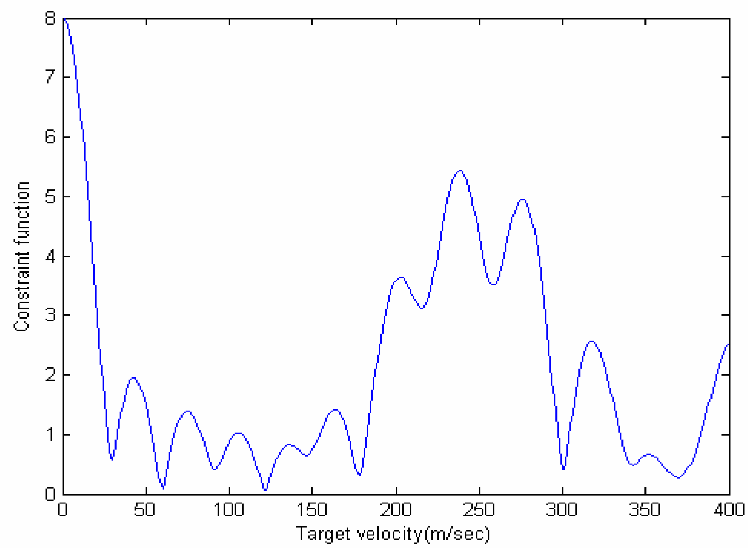

Figure 4.10 Constraint function response versus target velocity for δT =[-9 -9 7 10 9 6 -6 -9] μsec.

Optimizations with different PRF values, number of pulses and different *α, β, γ* weights have also been done. The results differ according to the selected weights. According to the weights applied, the results are between the results shown in Figure 4.8, Figure 4.9 and Figure 4.10. It is seen that the three cost parameters can not be optimized simultenously and there is a trade off between the cost parameters. As the null cost is decreased, the constraint function becomes similar to the constant PRF case, and the resolution of Doppler ambiguity can not be achieved. When the peak cost is decreased, the null cost increases and the clutter rejection property of the jitter set worsens. When the velocity interval cost is decreased, the null cost also increases and clutter rejection property worsens. According to the optimizations it is seen that, there is a trade off between the Doppler ambiguity resolution and clutter cancellation. So, the jitter set should be selected after deciding on the importance of these cost functions and suitable weights should be applied.

4.4 Optimization Results for the Range Ambiguity

In this section, the optimizations on jitter set optimization according to the range ambiguity resolution method which is defined in Chapter 3, are presented. The optimization procedure given in Chapter 3 is applied using genetic algorithm. In fact, the genetic algorithm is not as satisfactory as it is for Doppler ambiguity resolution problem for the range ambiguity problem. It seems to work similarly as the random search method, but for many jitter sets good results for range ambiguity can be found, so it seems to be sufficient for the range ambiguity problem to use the genetic algorithm.

The parameters that are important for the range ambiguity problem are number of pulses in the jitter set, the selected PRI for the hypothetic regular train, instrumented range, range bin resolution and the pulse width.

If there is range ambiguity, the $H(R, R^*)$ function for $R \neq R^*$, has a minimum value of 1 since there is an irreducable range ambiguity. The $H(R, R^*)$ function for $R \neq R^*$ can only be 0 for the low PRF case, since all the returns are taken before the next pulse for this case.

When the genetic algorithm is applied to find jitter sets, with the optimization process given in Chapter 3, many global optimum solutions that give $\max(H(R, R^*)) = 1$ for $R \neq R^*$ are found. In Figure 4.11, the results of $H(R,R^*)$ function for this jitter set and PRF is given. The corner line in Figure 4.12 represents the number of hits when $R=R^*$. For this simulation pulse width, denoted by T_w is taken as 0 µsec, PRF is taken as 10 kHz. δT = [-18 -15 -12 -10 2 4 7 10] µsec and range bin resolution denoted by Δr=150 m, instrumented range denoted by R_{max} = 75 km are the parameters taken. In Figure 4.12, the $H(R,R^*)$ function when $R \neq R^*$ is shown to see the number of ambigous hits more clearly.

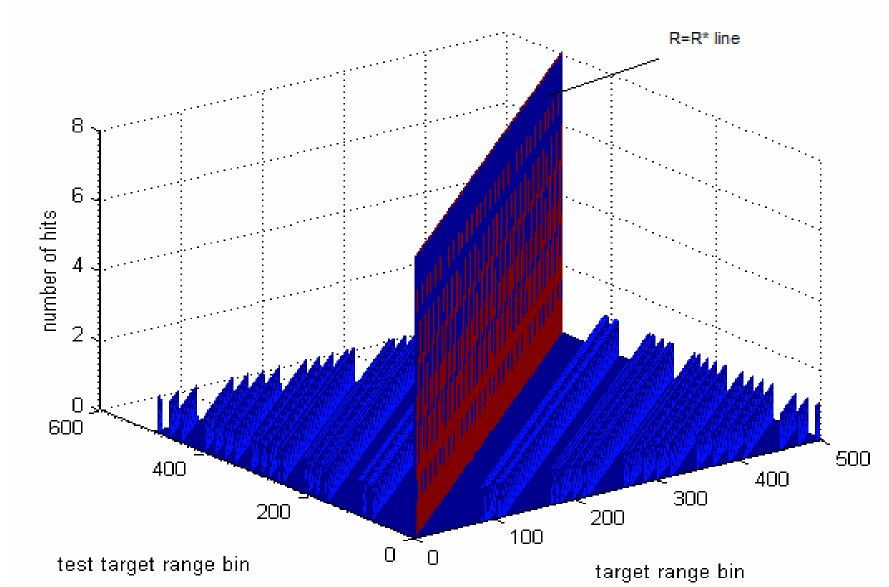

Figure 4.11 H(R, R*) function for δT =[-18 -15 -12 -10 2 4 7 10] µsec, T_w=0 µsec, PRF=10 kHz, Δr=150m and R_{max}=75 km

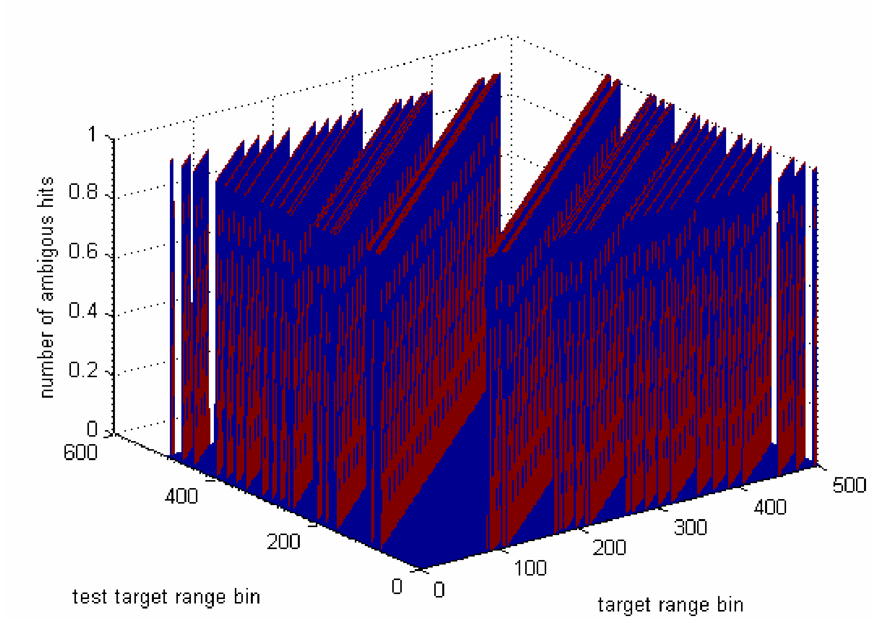

Figure 4.12 H(R, R*) function when R=R* for δT =[-18 -15 -12 -10 2 4 7 10] µsec, T_w=0 µsec, PRF=10 kHz, Δr=150m and Rmax=75 km

As seen from Figure 4.12, there is a symmetry for the response of the $H(R, R^*)$ function with respect to range and the maximum of H(R, R*) is the same for all ranges. Therefore, it is sufficient to take a range and calculate H(R, R*) function for that range to find the maximum number of ambigous hits. By this way, the dimension of the function can be reduced by one and the time required for the optimization is drastically reduced.

4.5 Optimization Approach for Range and Doppler Ambiguity

The optimization of jitter sets according to the range and Doppler ambiguity were given independently in the sections before. As given in Doppler ambiguity resolution results, the Doppler ambiguity and clutter rejection properties of the jitter sets produce a trade off. The optimization should be made according to the criterion defined for these parameters. In this section, the clutter rejection property of the jitter set and the range ambiguity resolution property are taken as cost parameters and the optimization of the jitter sets according to these cost parameters is done accordingly.

The cost function for the range ambiguity is taken as:

$$CR=\alpha_1 . \max(H(R, R^*))^2 \text{ when } R \neq R^* \tag{4.5}$$

where α_1 is the coefficient of the cost function. For the Doppler cost function, the test velocities are found as in Section 4.3. Since the clutter rejection property is optimized, clutter rejection functions for all target velocities are found and the maximum of them are taken as the cost function. The cost function for Doppler performance is defined by

$$CD = \beta_1 . \max_{v_m}\left(\frac{1}{K}\left|\sum_{l=1}^{L-1} e^{-j\Omega_k(v_m)}\right|^2\right) \tag{4.6}$$

where β_1 is the coefficient of the cost Doppler function Then, the total cost that will be optimized by the genetic algorithm is given by

$$CT = CR + CD \tag{4.7}$$

4.5.1 Optimization Results for Range Ambiguity and Clutter Rejection Function

In this section, the results of optimization according to the cost function defined in Eq. (4.5), Eq. (4.6) and Eq. (4.7) are given. The results can be optimized in different ways according to the constraints for the cost Doppler and cost range functions. In this section some examples of the optimization and resultant jitter sets are given.

The upper and lower bounds for the jitter sets are taken low, since in Section 4.3, it is found that this function gives good results when the jitter values are low. The upper and lower bounds of the jitter sets are taken as 5 µsec and -5 µsec, respectively. The jitter resolution is taken as 0.5 µsec and the range bin is taken as 75 m. The instrumented range is taken as 75 km and the maximum Doppler of the target is taken as 400 m/sec.

The best jitter set of the optimization by genetic algorithm for PRF=16 kHz, K= 8 pulses by taking α_1=1 and β_1=10000 is δT =[0.5 -1.5 0 3.5 -3 1 2 0.5] µsec. The $H(R,R^*)$ function for the range ambiguity for R=30 km is given in Figure 4.13. As shown in Figure 4.13, the maximum range ambiguity for this function is 1. The zero velocity response, $C(\delta T)$ of this jitter set is given in Figure 4.14. The cost Doppler function is found as 0,9585, so for β_1=1, the cost Doppler function is $9{,}585.10^{-5}$.

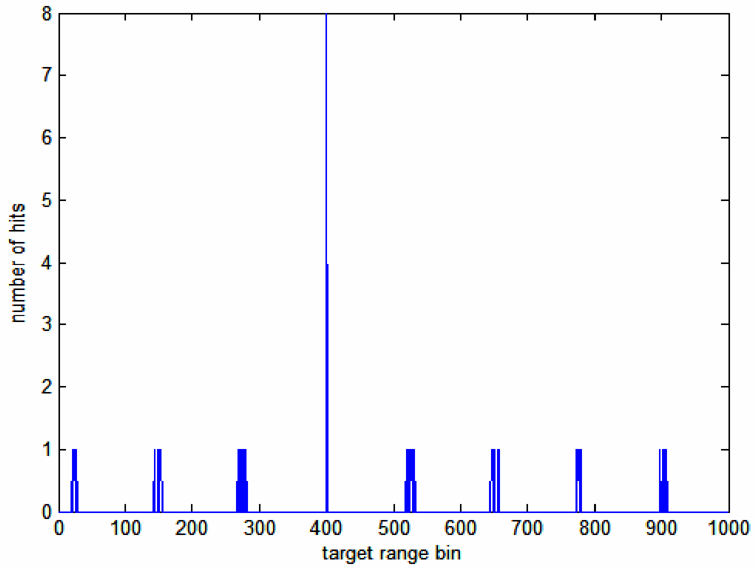

Figure 4.13 Number of hits versus range for a target at R=30 km, δT =[0.5 -1.5 0 3.5 -3 1 2 0.5] µsec.

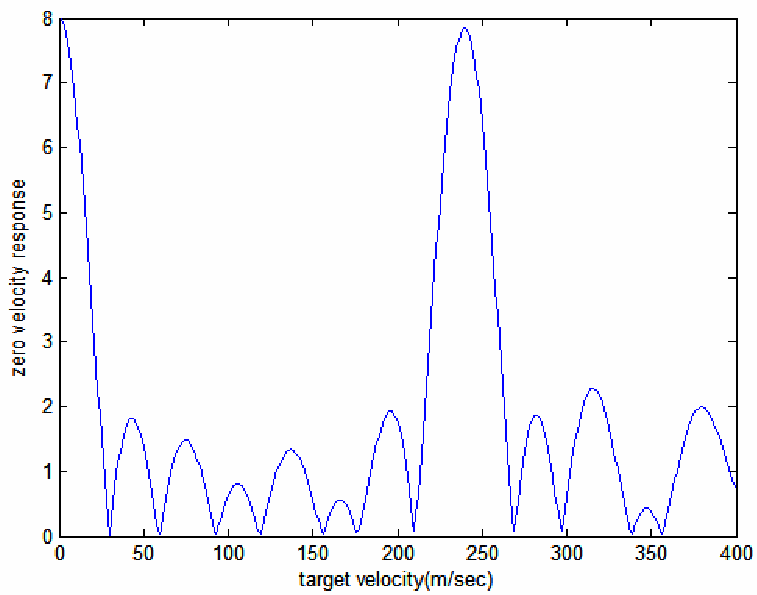

Figure 4.14 C(δT) versus target velocity for δT =[0.5 -1.5 0 3.5 -3 1 2 0.5] µsec.

After changing the coefficients of the cost function and taking α_1=1 and β_1=100000, the best jitter set of the optimization by genetic algorithm for PRF=16 kHz, K= 8 pulses is δT =[1 -1.5 -3 -2.5 1 1.5 0 -3] μsec. The H(R, R*) function for the range ambiguity for R=30 km is given in Figure 4.15. As shown in Figure 4.15, the maximum range ambiguity for this function is 2. The velocity response of this jitter set is given in Figure 4.16. The cost Doppler function is found as 7,1441, so for β_1=1, the cost Doppler function is 7,1441.10^{-5}.

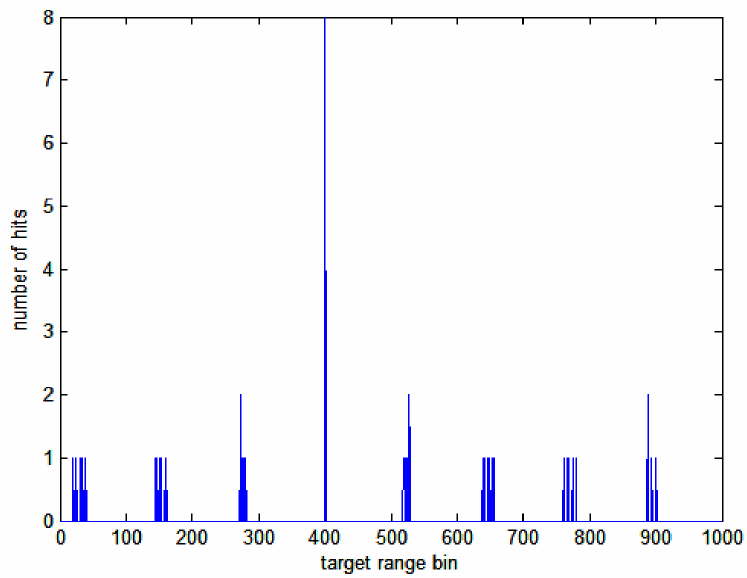

Figure 4.15 Number of hits versus range for a target at R=30 km, δT =[1 -1.5 -3 -2.5 1 1.5 0 -3] μsec.

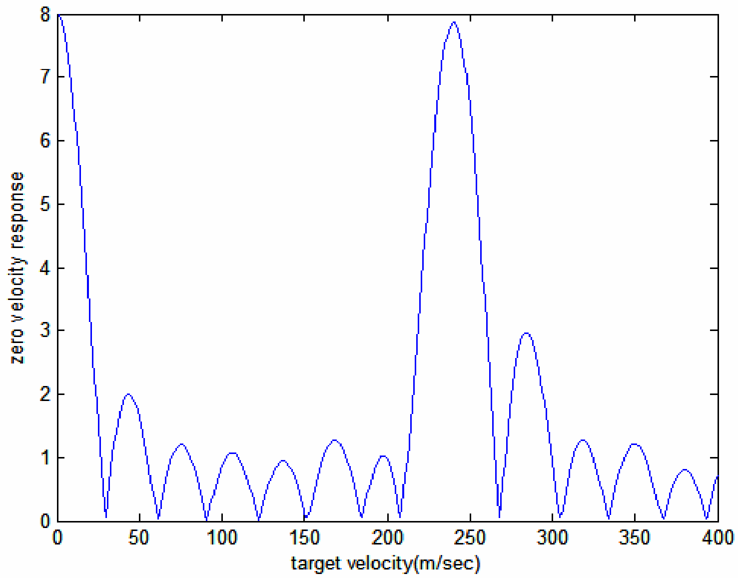

Figure 4.16 C(δT) versus target velocity for δT =[1 -1.5 -3 -2.5 1 1.5 0 -3] μsec.

When we change PRF=8 kHz, taking K=8 pulses, α_1=1 and β_1=10000, the best jitter set of the optimization by genetic algorithm is δT =[0.5 -0.5 0 -2.5 1.5 -1 0 -1.5] μsec. The H(R, R*) function for the range ambiguity for R=30 km is given in Figure 4.17. As shown in Figure 4.17, the maximum range ambiguity for this function is 2. The velocity response of this jitter set is given in Figure 4.18. The cost Doppler function is found as 2,1697, so for β_1=1, the cost Doppler function is 2,169.10^{-4}.

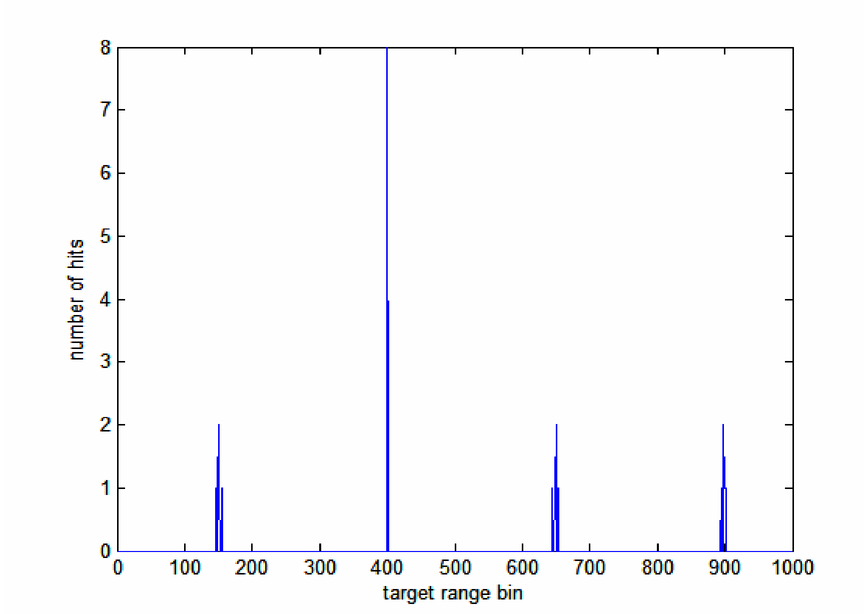

Figure 4.17 Number of hits versus range for a target at R=30 km, δT =[0.5 -0.5 0 -2.5 1.5 -1 0 -1.5] µsec.

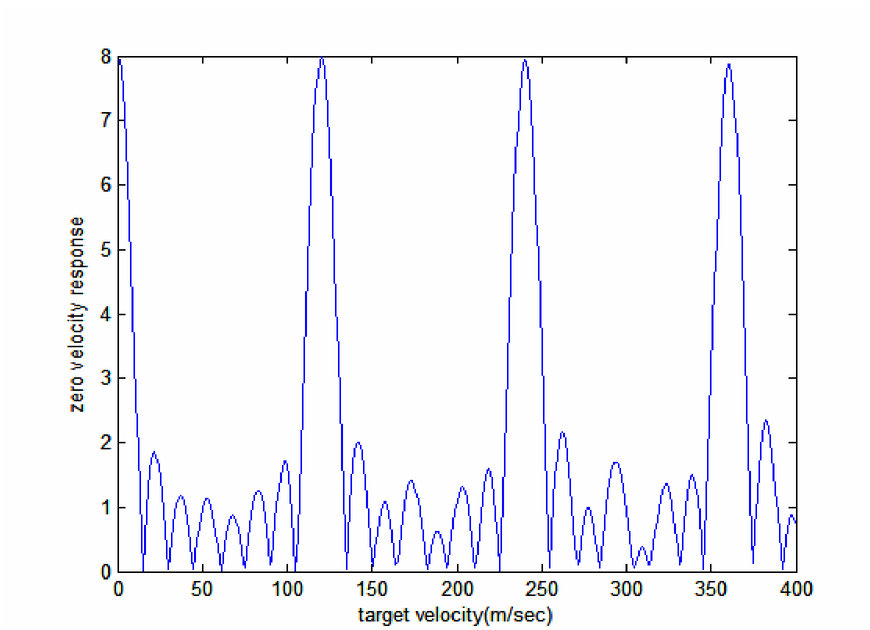

Figure 4.18 C(δT) versus target velocity for δT =[0.5 -0.5 0 -2.5 1.5 -1 0 -1.5] µsec.

When we change the PRF to 32 kHz, which corresponds to a high PRF case for maximum Doppler of interest equal to 400 m/sec, taking K=8 pulses, α_1=1 and β_1=10000, the best jitter set of the optimization by genetic algorithm is δT =[-3 -2 -4 -1.5 0 2.5 0.5 1.5] μsec. The H(R, R^*) function for the range ambiguity for R=30 km is given in Figure 4.19. As shown in Figure 4.19, the maximum range ambiguity for this function is 1. The velocity response of this jitter set is given in Figure 4.20. The cost Doppler function is found as 0,1064, so for β_1=1, the cost Doppler function is 1,064.10^{-5}.

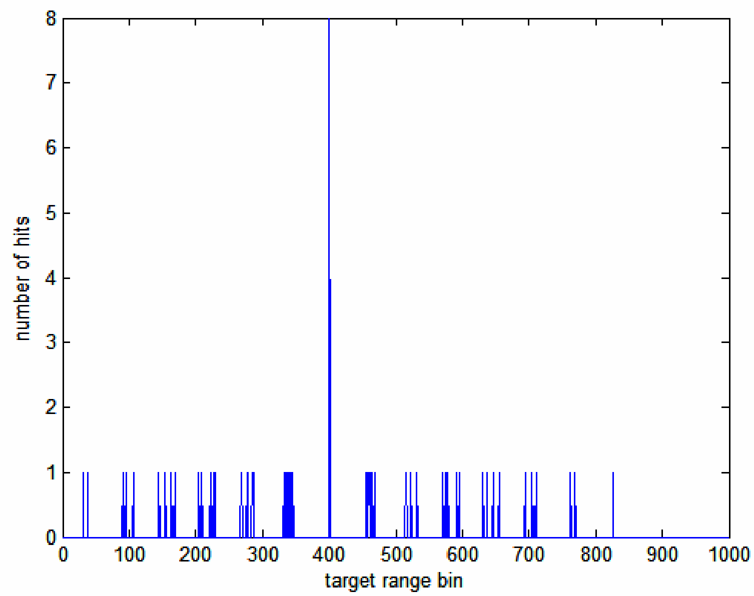

Figure 4.19 Number of hits versus range for a target at R=30 km, δT =[-3 -2 -4 -1.5 0 2.5 0.5 1.5] μsec.

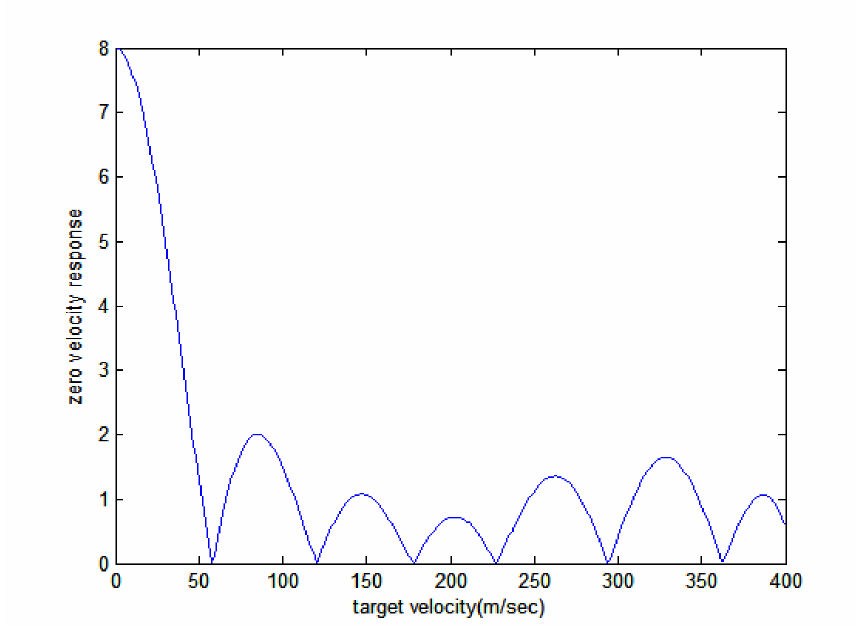

Figure 4.20 C(δT) versus target velocity for δT =[-3 -2 -4 -1.5 0 2.5 0.5 1.5] μsec.

When we take K=16 pulses, and PRF=16 kHz, α_1=1 and β_1=10000, the best jitter set of the optimization by genetic algorithm is δT =[1.5 -2 -2.5 0.5 -1 -3 -2.5 -1.5 0 1 2 0.5 -1.5 1.5 1 -2] μsec. The H(R, R^*) function for the range ambiguity for R=30 km is given in Figure 4.21. As shown in Figure 4.21, the maximum range ambiguity for this function is 2. The velocity response of this jitter set is given in Figure 4.22. The cost Doppler function is found as 0,9302 ,so for β_1=1, the cost Doppler function is 9,302.10^{-5}.

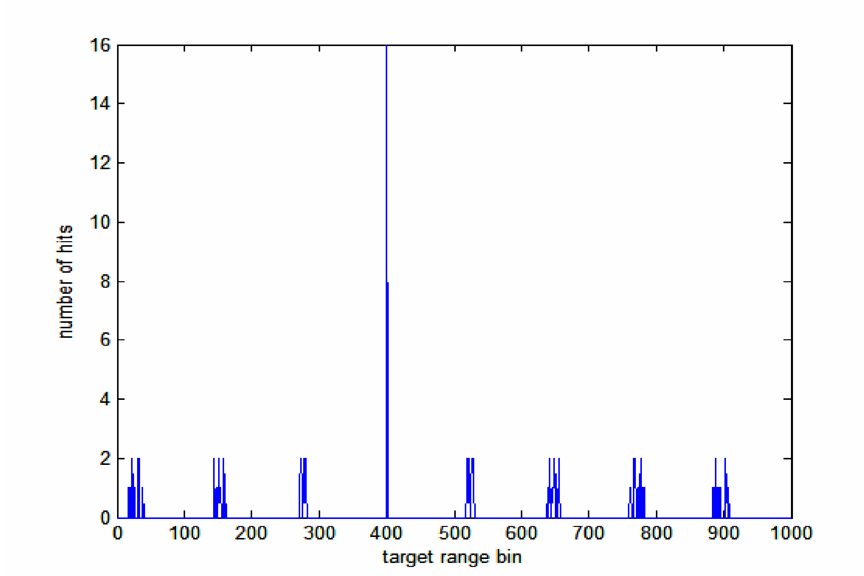

Figure 4.21 Number of hits versus range for a target at R=30 km, δT =[1.5 -2 -2.5 0.5 -1 -3 -2.5 -1.5 0 1 2 0.5 -1.5 1.5 1 -2] µsec.

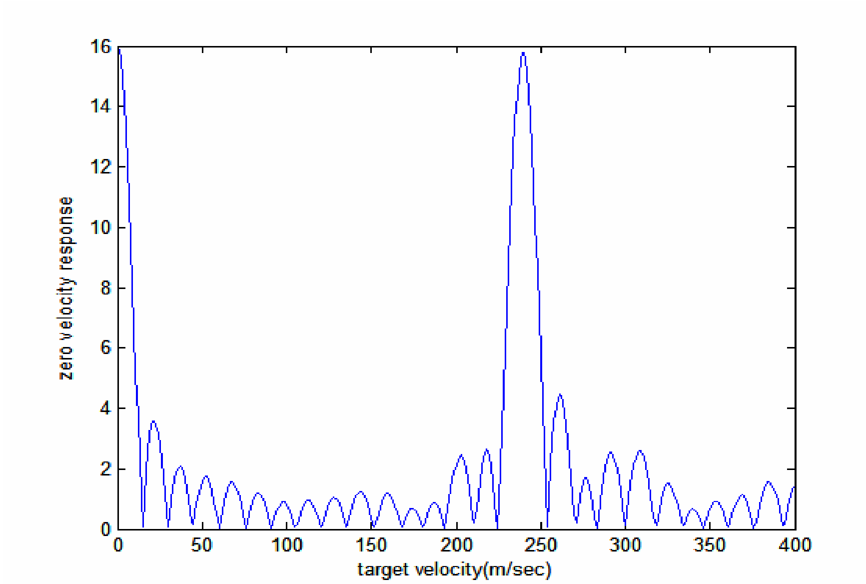

Figure 4.22 C(δT) versus target velocity for δT =[1.5 -2 -2.5 0.5 -1 -3 -2.5 -1.5 0 1 2 0.5 -1.5 1.5 1 -2] µsec.

4.6.1 Effect of Quantization on Improvement Factor

In the preceding sections the effect of PRF jittering on range Doppler ambiguity resolution and clutter cancellation is investigated. In this section, the effect of quantization of the target returns and Doppler filter coefficients on the performance of improvement factor, defined in Eq. 2.15, is investigated. The return signal of the target is given in Eq. 3.5. Since the cancellation of the zero Doppler frequency clutter is taken into consideration, this equation can be expressed as

$$y(k) = ae^{j\Omega_k} + h + n_k \tag{4.8}$$

where h is the constant clutter response taken from the range bin of the target, and n_k is the white gaussian noise samples. When the $y(k)$ values are quantized, there will be a difference between the target returns and the quantized target returns which are denoted by $y_q(k)$.

The sufficient statistic function is given in Eq. 3.11. The Doppler filter coefficients for the test velocities are given by

$$df(v) = e^{-j\Omega_k(v)} \tag{4.9}$$

When $df(v)$ are quantized, there will be a difference between the Doppler coefficients and the quantized Doppler coefficients, denoted by $df_q(v)$. The change of improvement factor, I_f, according to the clutter to signal ratio(CSR) at the input of the Doppler filters are simulated according to different number of bit representations for $y_q(k)$ and $df_q(v)$. The target returns and the clutter returns are created for the given CSR and SNR values. Then, these returns are quantized with respect to the number of bits given input to the program.

The output signal and clutter powers after application of the sufficient statistic function are calculated. The effect of noise power is also added to the improvement factor according to the SNR value to be able to see the effect of random changes to the performance. The improvement factor when using quantized values $df_q(v)$, $y_q(k)$ and exact values $df(v)$, $y(k)$ are calculated for different values of CSR. To reduce the numeric effects occuring due to the dominant clutter signal, CSR is varied randomly by uniform distribution ±%10 of the average CSR value for the simulations. For the simulations SNR=40 dB and the improvement factor for a target at v=180 m/sec is evaluated. The results given in the simulations are the average values for the improvement factor after 100 Monte Carlo simulations.

4.6.2 Simulation Results of Quantization Effects on Improvement Factor

The results of simulation for SNR=40 dB, average CSR=0 dB for constant PRF=16 kHz and K=8 pulses is given in Figure 4.23. The smooth line shows the average improvement factor after 100 Monte Carlo simulations of Gaussian noise and the dashed line shows the improvement factor resulting from quantization. As seen from Figure 4.23, when 12 bit quantization or more is used the difference between I_f of quantized and exact versions are almost zero.

When SNR=40 dB, average CSR=20 dB values are taken for the constant PRF case, the results are given in Figure 4.24. The smooth line shows the average improvement factor after 100 Monte Carlo simulations of Gaussian noise and the dashed line shows the improvement factor resulting from quantization. As seen from Figure 4.24, when 14 bit quantization or more is used the difference between I_f of quantized and exact versions are almost zero.

For SNR=40 dB, average CSR=40 dB and constant PRF case, the results are given in Figure 4.25. The smooth line shows the average improvement factor after 100 Monte Carlo simulations of Gaussian noise and the dashed line shows the improvement factor resulting from quantization.As seen from Figure 4.25, when 16 bit quantization or more is used the difference between I_f of quantized and exact versions are almost zero.

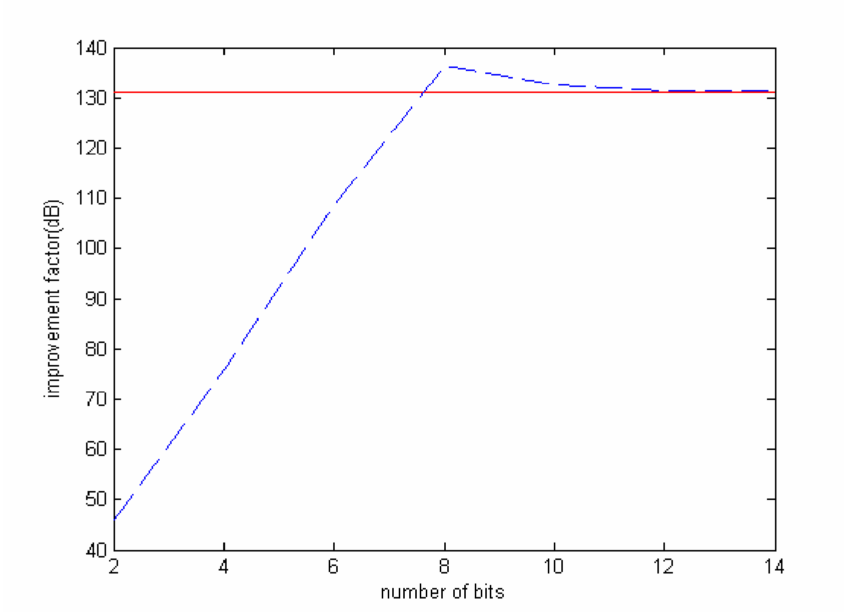

Figure 4.23 Number of bits versus I_f for SNR=40dB, average CSR=0dB, constant PRF =16 kHz, K=8 pulses, v_m=180 m/sec.

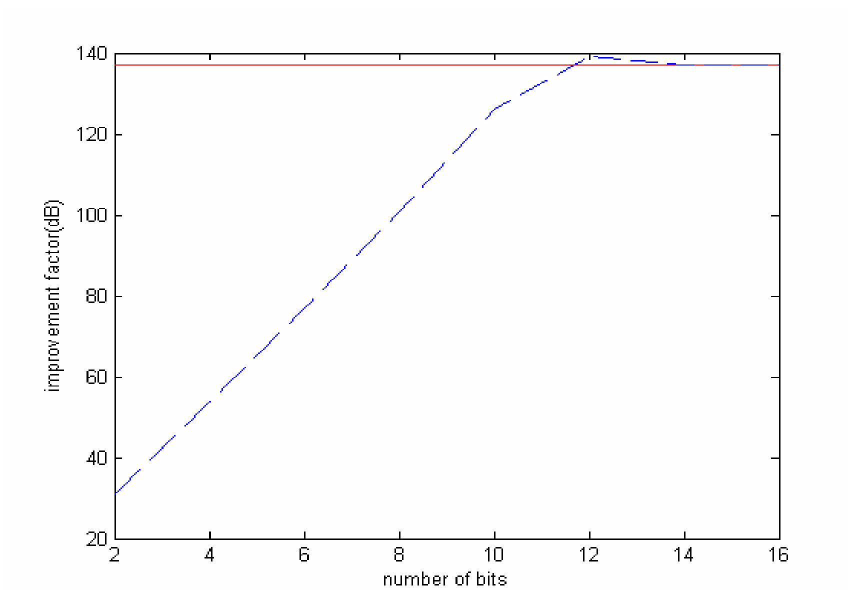

Figure 4.24 Number of bits versus I_f for SNR=40dB, average CSR=20dB, constant PRF=16 kHz, K=8 pulses, v_m=180 m/sec.

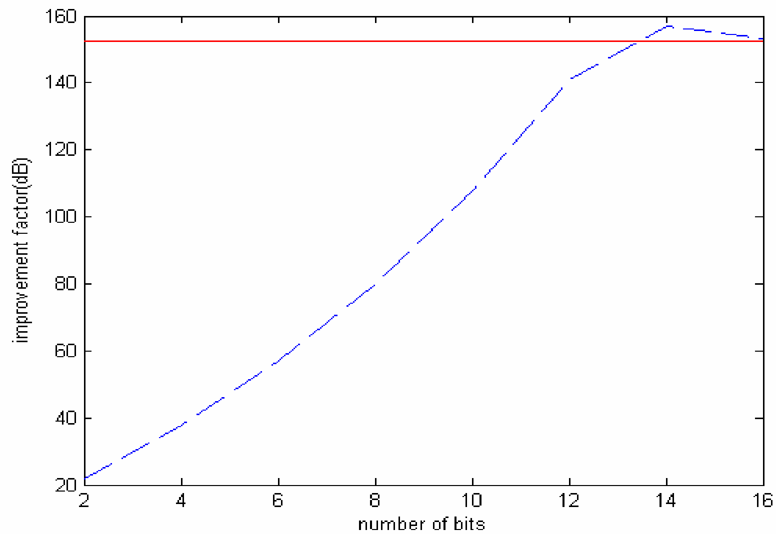

Figure 4.25 Number of bits versus I_f for SNR=40dB, average CSR=40dB, constant PRF=16 kHz, K=8 pulses, v_m=180 m/sec.

As shown in Figure 4.23, Figure 4.24 and Figure 4.25, the improvement factor is higher than the improvement factor with no quantization case for some different values of number of bits. For average CSR=0 dB, 8 bit quantization seems to be the best, for average CSR=20dB 12 bit quantization seems to be the best and for CSR=40 dB 14 bit quantization seems to be the best. Since those peak improvement factor values are at different number of bit values and all possible CSR values should be taken into account, those number of bits values do not have the best performance for other CSR cases and they should not be taken as the best values of number of bits for quantization, on the average.

The result of simulation for SNR=40 dB, average CSR=0 dB for $\delta T = [1 \quad -1.5 \quad -3 \quad -2.5 \quad 1 \quad 1.5 \quad 0 \quad -3\,]$ µsec is given in Figure 4.26. The smooth line shows the average improvement factor after 100 Monte Carlo simulations of Gaussian noise and the dashed line shows the improvement factor resulting from quantization. As seen from Figure 4.26, when 12 bit quantization or more is used the difference between I_f of quantized and exact versions are almost zero.

For SNR=40 dB, average CSR=20 dB and constant PRF case, the results are given in Figure 4.27. The smooth line shows the average improvement factor after 100 Monte Carlo simulations of Gaussian noise and the dashed line shows the improvement factor resulting from quantization. As seen from Figure 4.27, when 12 bit quantization or more is used the difference between I_f of quantized and exact versions are almost zero.

For SNR=40 dB, average CSR=40 dB and constant PRF case, the results are given in Figure 4.28. The smooth line shows the average improvement factor after 100 Monte Carlo simulations of Gaussian noise and the dashed line shows the improvement factor resulting from quantization. As seen from Figure 4.28, when 14 bit quantization or more is used the difference between I_f of quantized and exact versions are almost zero.

The simulations with different jitter sets are done and the results are similar, 12 or 14 bits of quantization is sufficient for when the CSR is below 40 dB.

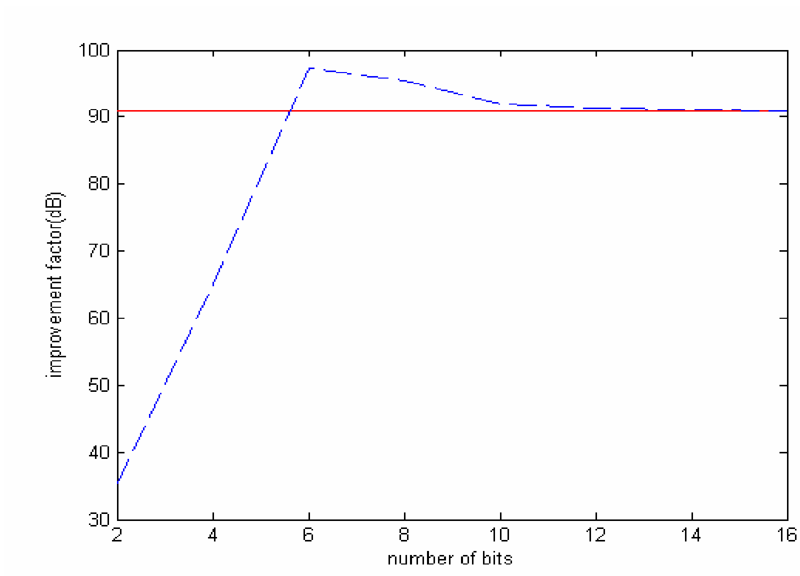

Figure 4.26 Number of bits versus I_f for SNR=40dB, average CSR=0dB, δT = [1 -1.5 -3 -2.5 1 1.5 0 -3] μsec, PRF=16 kHz, K=8 pulses, v_m=180 m/sec.

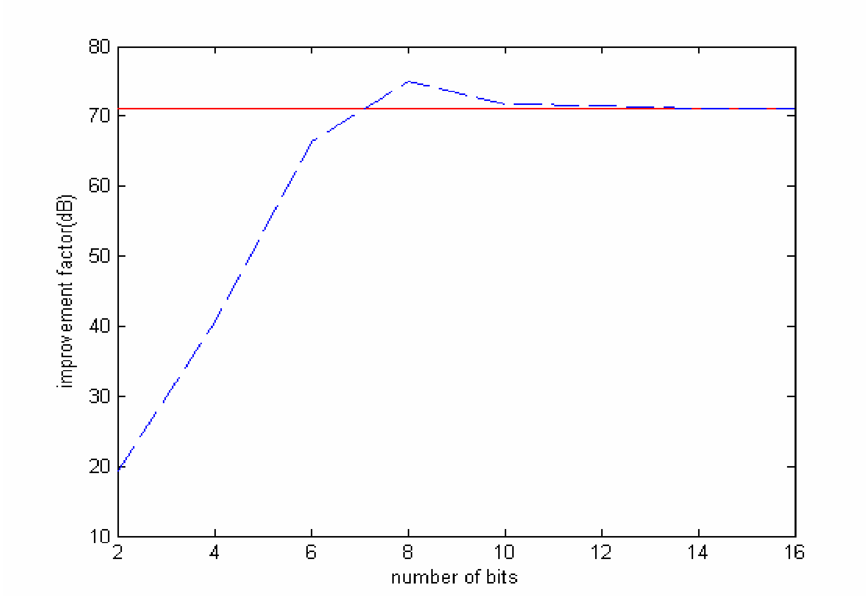

Figure 4.27 Number of bits versus I_f for SNR=40dB, average CSR=20dB, δT = [1 -1.5 -3 -2.5 1 1.5 0 -3] μsec, PRF=16 kHz, K=8 pulses, v_m=180 m/sec.

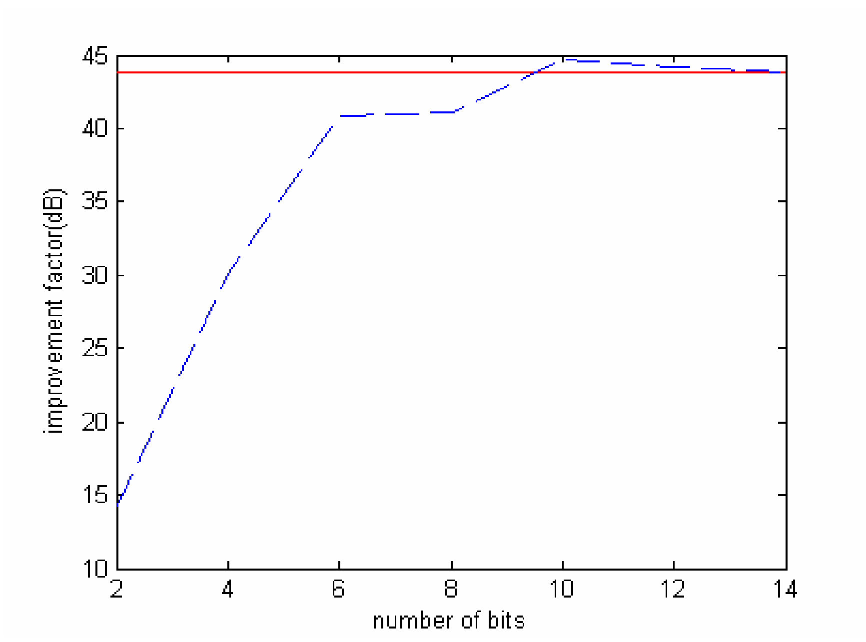

Figure 4.28 Number of bits versus I_f for SNR=40dB, average CSR=40dB, δT = [1 -1.5 -3 -2.5 1 1.5 0 -3] μsec, PRF=16 kHz, K=8 pulses, v_m=180 m/sec.

To investigate the effect of number of pulses, K=16 pulses case is simulated. For SNR=40 dB, average CSR=20 dB and PRF=16 kHz case, the results of the quantization effect for K=16 pulses with δT = [1.5 -2 -2.5 0.5 -1 -3 -2.5 -1.5 0 1 2 0.5 -1.5 1.5 1 -2] μsec is given in Figure 4.29. The smooth line shows the average improvement factor after 100 Monte Carlo simulations of Gaussian noise and the dashed line shows the improvement factor resulting from quantization. As seen from Figure 4.29, when 10 bit quantization or more is used the difference between I_f of quantized and exact versions are almost zero.

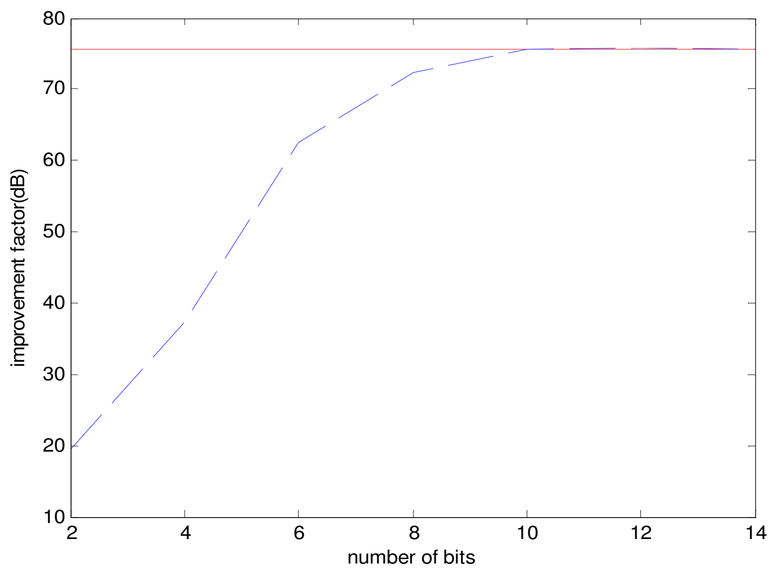

Figure 4.29 Number of bits versus I_f for SNR=40dB, average CSR=20dB, δT = [1.5 -2 -2.5 0.5 -1 -3 -2.5 -1.5 0 1 2 0.5 -1.5 1.5 1 -2] μsec, PRF=16 kHz, K=16 pulses, v_m=180 m/sec.

CHAPTER 5

CONCLUSIONS

In this thesis, an optimization approach for the selection of nonuniform pulse repetition interval is developed with particular emphasis on the issues of reducing the range and Doppler ambiguity and sufficient clutter rejection.

PRI jittering technique is used for the selection of nonuniform pulse repetition intervals. The jitter values of the set are selected randomly by uniform distribution. The formulation of the problem is stated by a detection model in which the noise and clutter are assumed to be white gaussian. Using generalized likelihood ratio test the ML estimate and a sufficient statistic for the detection problem is obtained. A method for selecting the velocity interval between the target test velocities considering the probability of detection for the velocity domain of targets is developed. An approach to investigate the range ambiguity resolution property of the PRI jittering technique is also developed.

The proposed optimization methods are based on the suggested optimization criterion on the cost functions. Optimization is realized by genetic coding or by MATLAB optimization toolbox. Since the second is a tool for local extrema search and needs proper initial conditions, the genetic coding was preferred for the optimization process of jitter sets.

The performance of the proposed optimization approach and algorithms developed for optimization are studied through computer simulations. The results of the optimization for proposed velocity interval selection method show that Doppler ambiguity can be resolved by this method. However, the clutter rejection capability is found to be unsatisfactory. Then, a method by defining cost functions to improve the Doppler frequency domain of the zero velocity filter is developed. The Doppler ambiguity resolution, clutter rejection and Doppler velocity domain coverage properties of the jitter sets are evaluated using this approach. The optimizations using this approach show that there is a trade off between Doppler ambiguity resolution and clutter rejection properties of the jitter sets. Low jitter values should be selected for the jitter set to prevent clutter spreading, but larger jitter values are needed for Doppler ambiguity resolution.

The range ambiguity resolution simulations show that it is possible to resolve range ambiguity by the PRF jittering technique. Then, optimizations of jitter sets considering the range ambiguity resolution and clutter rejection properties are done. The results show that jitter sets that resolve range ambiguity and that have good clutter rejection can be found. The clutter is assumed to be at zero Doppler velocity for the problem. The evaluation of the jitter sets according to different clutter conditions can be done, which can be the subject of another study.

The quantization effects of Doppler filter coefficients and target returns on the performance degradation is also evaluated in the thesis. The improvement factor degradation by different levels of quantization is simulated and it is seen that at low values of number of bits for quantization there is a considerable degradation in the performance, but at higher values of number of bits such as 16 bits for quantization, the degradation becomes negligible.

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