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Dector Signal Design for MIMO Radar

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Abstract

This paper mainly aims to design optimal set of sequences having low auto-correlation side-lobe peaks and low cross-correlation peaks with high Doppler tolerance for MIMO RADAR and assess the probability of detection and noise tolerance for the generated optimal codes with a standard detector. The generalized likelihood ratio test detector (GLRT) is designed for known and unknown covariance matrix of Gaussian distributed noise and clutter. The performance is evaluated using real time simulator.

Keywords: *Generalized Likelihood Ratio Test, Receiver Operator Characteristics (ROC), Particle Swarm Optimization (PSO), Probability of False Alarm (PFA), Signal to noise Ratio (SNR), Autocorrelation side-lobe peaks (ASPs), Cross-correlation side-lobe peaks (CPs).*

1. Introduction

When a single transmitting and receiving antenna is used, signals are degraded due to multipath propagation, which in turn lowers the link capability and reliability of the system. And in 1990, Multiple Input Multiple Output (MIMO) system was introduced to provide spatial diversity and spatial multiplexing and antenna beam formation, by which link performance and efficacy and total coverage range can be improved. MIMO improving spatial resolution, providing a considerably enhanced immunity to interference, provide antenna diversity, spatial multiplexing [17,18]. The basic idea behind antenna diversity is to transmit the same information over many independent fading paths and then combine these paths in such a way to reduce the fading of the resultant signal, thereby improving the error rate performance. In other words, the signal with its multiple copies is transmitted to achieve the benefit from multiple independent fading paths which assure that all the links will not go in deep fade simultaneously. Thus, the possibility of obtaining reliable data from receiver increases significantly. Diversity offers a number of replicas of a transmitted signal over time, frequency or space [19, 20]. Time Diversity is same data is repeatedly transmitted to the same channel at different times [21,28]. Frequency Diversity is the same data is repeatedly transmitted to the same channel at different frequency bands. Spatial Diversity is a number of antennas are separated by approximately $\lambda/2$ distance to implement independent fading channels [22,26].

On the other hand, to increase the range resolution of radar system, the length of sequence required will have to be more. And in turn to procure more security to the sequence, incorporating multiple phases in the sequence is one of the adaptable solutions. As a whole the sequence generation becomes more complex in order to meet all these criteria. To address these problems there is obviously only one way that can be used for salvation is optimization of sequences. Conducted a trail to find a meaningful solution to address all the complexities arising in MIMO RADAR object tracking, by optimizing the poly phase codes with higher probability of detection.

1.1 Estimators

The Estimation is a statistical signal processing that deal with the decision making and the extraction of relevant information from noisy data. The estimation of an unknown parameter from a collection of data, additive noise, signal distortion, and multiple interfering signals, make the detection and estimation, a challenging task [1,4]. Based on the assumptions made about the unknown parameter, the estimation methods can be classified into two types, one is classical parameter estimation and the other, a Bayesian estimation. In classical parameter estimation methods, no probabilistic assumption about the unknown parameter is made rather it is treated as the deterministic unknown [2,3]. Maximum Likelihood Estimation (MLE) follows a definite method, it to be applicable for complex estimation

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problems. It is asymptotically optimal for vast data records. This method can be a substitute when Probability density function (PDF) is already available. PDF consist of θ, the unknown factor, and is said to be the likelihood factor θ is predicted using MLE by reducing the likelihood factor for the obtained information. It becomes minimal variance unbiased estimator when the sample size is increased. Its normal distribution and sample variance are approximate and is applied in the generation of parametric confidence bounds and hypothesis tests [6,7].

1.2 Detectors

The detection problem in its simplest form assumes that both signal and noise characteristics are completely known. If the characteristics of signal and noise are unknown, it leads to detection of signal more challenging and complex. A detector problem may be classified under two broad classes parametric detection and non-parametric detection. In non-parametric detection, the PDF of the data is unknown and the parametric detection approaches to hypothesis testing are presented [1,5]. A simple detection problem arises when the signal due to the presence of noise. Such problem is termed as binary hypothesis testing problem. Transmission of the two possible signals depends on the requirements. In detection theory, a hypothesis is a statement about the source of the observed data. In the simplest case, we have the null or void hypothesis (H_0) that there is no variation from the usual and alternate hypothesis (H_1) that there is a change. The hypotheses H_0 assume target is absent, H_1 target is present, and the objective is to decide which one of these hypotheses is true based on the observed data. If both the hypotheses contain unknown parameters, finding the Bayesian solution becomes very tedious and often the involved integrals do not yield closed form solution. To overcome these limitations, GLRT is one of the commonly adapted approaches for composite hypothesis testing [8,25]. Due to these limitations, it is advisable to adapt a variant hypothesis testing process termed as GLRT, that forms the most commonly used methods for the composite hypothesis testing [15,16]. In this testing, first, undetermined aspects are identified through data acquired from the hypotheses and are interchanged by the MLE in likelihood ratio. Though there is no optimal approach with GLRT, in general a GLRT decides H_1 if

$$L_G(X) = \frac{p\left[x;\hat{\theta}_1, H_1\right]}{p\left[x;\hat{\theta}_0, H_0\right]} > \gamma \tag{1}$$

where $\hat{\theta}_1 \rightarrow$ MLE of θ_1 assuming H_1 is correct (i.e., maximizes $p(x;\ \hat{\theta}_1)$, and $\hat{\theta}_0 \rightarrow$ MLE of θ_0 assuming H_0 is correct (i.e., maximizes $p(\mathbf{x};\ \hat{\theta}_0)$). Information about the unknown parameters is also provided by this approach, as the initial procedure in estimating L_G(x) is to discover the MLEs [9, 10].

2. Literature Survey

Chin Yuan Chong et al., [17,27] derived the generalized likelihood ratio test linear quadratic (GLRT-LQ) to multiple inputs multiple outputs (MIMO) to identify the constant false alarm rate (CFAR) recognition and determination. A novel detector is theoretically formed and verified using Monte Carlo simulation. The detection performance is compared with optimal Gaussian detector under non-Gaussian and Gaussian clutter. It is clear that the new detector functions better with non-Gaussian clutter. Guolong et al., [9, 25] discovered a detector that works on the basis of generalized likelihood ratio test for compound-Gaussian case. It is created with an assumption for its known covariance matrix and a fully adaptive detector with an inserted secondary data. Thus, the derived GC-GLRT [11,13] provides a better performance related to spikier clutter with an acceptable adaptive loss. It is also noted that, rising the amount of transmitting antenna does not actually increase the performance unless an increase in transmitting energy exists thus set as a disadvantage to be concerned in future work.

Roja and Uttara Kumari., [21,23] An orthogonal polyphase MIMO along with an undefined covariance matrix in contrast to compound-Gaussian case and GLRT with defined covariance matrix is adopted, which possess superior performance regarding spikier clutter. A fully adaptive secondary data based GLRT detector is used in the receiver. PSO algorithm is also applied to obtain superior correlation properties. Siva et al., [22,24] The Subspace Compressive GLRT (SSC-GLRT) detector has been introduced to optimize the target identification operation of MIMO radar with clutter and is compared

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with traditional GLRT detector. C-GLRT involves vast number of samples and undergoes a substantial loss of target detecting operation. SSC-GLRT improves the performance when tested on GLRT in the presence of clutter [12,31]. This also further suggests that adding Dynamic clutter suppression on SSC-GLRT further improves the performance.

3.Proposed work

3.1 Particle swarm optimization

Remarkable improvement in Optimization technique has experienced in the last few decades, and nowadays, advancement in fundamentals continues to happen at a furious pace. Understanding optimization problems has been progressively improved and especially the rich behavioral theories and expressive power of artificial intelligence programming makes it appropriate for a wide range of optimization problems that arises in engineering and applied science. We have also learned how to approximate combinatorial hard optimization problems by simpler convex problems, which are tractable and provide solutions guaranteed to be close to the original optimal solution. In the literature, in case of Deng Hai et al., [36] where simulated annealing algorithm is used for optimization, the rate of convergence is very low in finding the optimal solution. Hammad A. Khan et al., [37] proposal of Cross entropy (CE) technique suffers in Doppler tolerance as the length of the sequence increases. synthesized sequences are of complex nature in the Threshold accepting (TA) technique proposed by S.P.Singh et al., [34] genetic algorithm proposed by Bin et al., [39] suffers from slow convergence rate along with requirement of adjustments in many parameters. Though particle swarm optimization algorithm, which has fast convergence rate was used by Xiangneng et al., [38] it suffers in handling high dimensional problems. These drawbacks in the literature motivated us to derive solutions in the existing domain and instigated us to come up with modified PSO algorithm to overcome them.

PSO calculation is somewhat altered to advance the polyphase codes with the end goal that the combination rate and populace size can be decreased. Certain high level forms of PSO includes varieties in fundametal factors like learning factors, speed, interia wight and size and it is discovered that PSO is touchy for these elements. Speed plays a fundamental capacity in (PSO), where it is exposed to dynamic change dependent on verifiable conduct of the particles and their associates. Unexpectedly, MPSO involves new speed vector concerning the greatest distance between any two areas in the arrangement region. equation (7) relates the speed update, where the individual best position impacts the new situation of the particle. The ith particles position and speed for the d dimensional hunt space is Xi and Vi separately. The particles keep up memory of their past best position Pi.

In every emphasis, pbest is the particles p vector with best wellness in the nearby area. The particles new position is resolved utilizing the velocity.In this calculation for a fixed limit esteem T, on the off chance that the consistently dispersed arbitrary number U(0, 1) is lower than T, equation (2) produces the speed vector, else equation (7) creates the speed vector.

$$v_{id}^{t+1} = w\beta d\left(p_{gd}^{t} - p_{id}^{t}\right) \tag{2}$$

Where ‘w’ is an Inertia weight, ‘d’ is the Maximum Distance between any two points and ‘β’ Fraction of Objective Function Value.The distance between the global and personal best particles is given by,

$$d = \frac{d_{max} - d_{gi}}{d_{max}} \tag{3}$$

Where ‘d_{max}’ represents the maximum distance between two points in the solution space and d_{gi} represents the distance between the global best particle and the i^{th} particle.The maximum distance d_{max} between two points in the solution space (x, y) is computed as

$$d_{max} = \sqrt{\sum_{i=1}^{D} (y_i - x_i)^2} \tag{4}$$

The distance between the global best particles x_p and i^{th} particle x_q can be calculated as

$$d_{pq} = \sqrt{\sum_{i=1}^{D} \left(x_{pi} - x_{qi}\right)^2} \tag{5}$$

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Where 'D' represents the dimension of swarm. Fraction of objective function values of global best and current particles are given as,

$$\beta = \frac{f(p_g)}{f(x_i)} \tag{6}$$

where $f(p_g)$ and $f(x_i)$ are the fitness value of the global best particle and i^{th} particle x_i. By dynamically adjusting the velocity, the inertia weight has to control exploration and exploitation of the search space.

$$v_{id}^{t+1} = wv_{id}^{t} + c_1 r_1 (p_{id}^{t} - x_{id}^{t}) + c_2 r_2 (p_{id}^{t} - x_{id}^{t}) \tag{7}$$

Where v_{id}^t, x_{id}^t, $p_{id}^t$and p_{gd}^t is the velocity, position vector, personal best position, and global best position of particle i in dimension d at time t. C_1 and C_2 are Learning factors.

$$x_{id}^{t+1} = x_{id}^{t} + v_{id}^{t+1} \tag{8}$$

3.2 Detector Design

To find the probability of detection for the generated sequence, the flow of process is shown as below using GLRT module.

A. Detector Design for Noise

A MIMO radar model with multiple transmitter (t_x) receiver (r_x) antennas is considered. Antennas are isolated for providing uncorrelated reflection coefficients between the transmitters and receivers. Target detection problem with MIMO radar is defined based on equation

$$H_0 : \begin{matrix} r_i = n_i \\ r_{ij} = n_{ij} \end{matrix} \tag{9}$$

$$H_1 : \begin{matrix} r_i = Aa_i + n_i \\ r_{ij} = n_{ij} \end{matrix} \tag{10}$$

Where r_i and r_{ij} are the signals that are received from the primary and secondary database, A is the transmit code matrix, α_i is the complex values that accounts to target back scatter and channel propagation impacts within the transmitting and receiving antennas. The clutter vectors denoted as n_i are anticipated as compound Gaussian random vectors.

$$n_i = \sqrt{\sigma_i g_i} \tag{11}$$

The textures σ_i are defined as the non-negative random variables and the speckle elements g_i are correlated to N-dimension complex Vectors. σ_i is the undefined deterministic parameter. This is an independent vector, and the null average complex vectors have covariance matrix.

$$M_1 = E[n_i n_i^+] = \sigma_1 M_0 \tag{12}$$

Where $M_0 = E[g_1 g_1^+]$ is the covariance structure. Derivation of generalized likelihood ratio test of MIMO radar systems with an undefined covariance matrix versus compound Gaussian clutter is carried out. Initially, with an assumption that clutter covariance is a known factor; a GLRT is identified by augmenting the likelihood criteria of the prime component over the other unknown factors.

Case (i) Assume M_0 is known

Using prime component and assuming M_0 is known, GLRT detector is evaluated by substituting the undefined factors by its maximal likelihood parameters in the likelihood ratio. Then decision is

$$\frac{\max \sigma_i,\ldots,\alpha_r,\sigma_1,\ldots,\sigma_r\, f(r_1,\ldots,r_r \mid H_1,\alpha_1,\ldots,\alpha_r,\sigma_1,\ldots,\sigma_r)}{\max \sigma_i,\ldots,\alpha_r,\, f(r_1,\ldots,r_r \mid H_0,\sigma_1,\ldots,\sigma_r)} \mathop{\gtrless}_{H_0}^{H_1} T \tag{13}$$

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Where, $f(r_1,...,r_r \mid H_1,\alpha_1,...,\alpha_r,\sigma_1,...,\sigma_r)$ and $f(r_1,...,r_r \mid H_0) = f(r_1,...,r_r \mid H_0,\sigma_1,...,\sigma_r)$ are the PDFs of the data under hypothesis test H_0 and H_1 respectively. The joint conditional PDFs of the data under H_0

$$f(r_1,...,r_r \mid H_0) = \frac{1}{\pi^{Nr}\prod_{i=1}^{r}\det(M_i)}\exp\left\{-\sum_{i=1}^{r} r_i^{+} M_i^{-1} r_i\right\} \tag{14}$$

The joint conditional PDFs of the data under H_1

$$f(r_1,...,r_r \mid H_1) = \frac{\exp\left\{-\sum_{j=1}^{r}(r_i - A\alpha_i)^{+} M_i^{-1}(r_i - A\alpha_i)\right\}}{\pi^{Nr}\prod_{i=1}^{r}\det(M_j)} \tag{15}$$

Take the logarithmic on both sides of equation (7) then.

$$f(r_1,..., r_r \mid H_0) = -Nr\ln\pi - N\sum_{i=1}^{r}\ln\sigma_i - r\ln\det(M_0) - \sum_{i=1}^{r}\ln\sigma_i - r\ln\det(M_0) - \sum_{i=1}^{r}\frac{r_i^{+}M_0^{-1}r_i}{\sigma_i} \tag{16}$$

To find the minima value of the equation (9) differentiates with respective to α_i and equate to zero. Then estimates is

$$\sigma_i = \frac{r_i^{+} M_0^{-1} r_i}{N} \tag{17}$$

For the simplification take the logarithmic of equation (8), then

$$f(r_1,...,r_r \mid H_1) = -Nr\ln\pi - N\sum_{i=1}^{r}\ln\sigma_i - r\ln\det(M_0) - \sum_{i=1}^{r}\frac{(r_i - A\alpha_i)^{+} M_0^{-1}(r_i - A\alpha_j)}{\sigma_i} \tag{18}$$

Find the maximum value of the equation (11) differentiate with respective to α_i and equate to zero. Then estimator is

$$\hat{\alpha}_i = (A^{+} M_0^{-1} A) A^{+} M_0^{-1} r \tag{19}$$

Maximize the above equation (11) to differentiate with respective σ_i and to zero. The maximum likelihood estimator is

$$\hat{\sigma}_{i1} = \frac{r_i^{+}(M_0^{-1} - M_0^{-1} A (A^{+} M_0^{-1} A) A^{+} M_0^{-1}) r_i}{N} \tag{20}$$

Substituting equation (7), (8), (10) and (13) into equation (6), after simplification the GLRT detector is

$$\prod_{i=1}^{r}\frac{r_i^{+} M_0^{-1} r_i}{r_i^{+}(M_0^{-1} - M_0^{-1} A (A^{+} M_0 A)^{-1} A^{+} M_0^{-1}) r_i} \underset{H_0}{\overset{H_1}{\gtrless}} T \tag{21}$$

T is the modified threshold value which is the modification of the original threshold.

Case (ii) Assume M_o is unknown

The covariance matrix Mo in the left-hand side of equation (14) is replaced by an appropriate estimate according to the secondary component for which the correlation characteristics are common, such that the obtained detectors become entirely adaptive. On the basis of the secondary component received by the receivers, adopting covariance matrix is done as.

$$\widehat{M}_{0i} = \frac{N}{K}\sum_{k=1}^{k}\frac{n_i k n_i^{+} k}{n_i^{+} k n_{i,k}} \tag{22}$$

Substituting equation (15) in equation (14), then the detectors is

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$$\prod_{i=1}^{r} \frac{r_i^+ \widehat{M}_0^{-1} r_i}{r_i^+ (\widehat{M}_0^{-1} - \widehat{M}_0^{-1} A (A^+ \widehat{M}_0^{-1} A)^{-1} A^+ \widehat{M}_0^{-1}) r_i} \underset{H_0}{\overset{H_1}{\gtrless}} T_2 \tag{23}$$

The detection threshold T2 is an appropriate alteration of the original value in the equation (14)

B. Detector Design for Clutter

The target detection with MIMO radar model can be expressed in terms of binary hypotheses as given below:

$$\begin{aligned} H_0 &: r_i = n_i \\ H_1 &: r_i = C\alpha_i + n \end{aligned} \tag{24}$$

Where n_i is the identically dispersed and statistically independent null-average complex Gaussian vector. The covariance matrix of n_i is given as

$$M_i = E\left[n_i n_i^+\right] = M_0 \tag{25}$$

Based on GLRT, likelihood ratio test is the optimum outcome to the hypotheses test problem given in the equation (17), which ignores the parameter α_1. This problem is overcome by substituting the undefined aspects with their maximal likelihood (ML) estimations in each hypothesis. GLRT is the following decision.

$$\frac{\max \alpha_i,\ldots,\alpha_r\, f(r_1,\ldots,r_r \mid H_1, M, \alpha_1,\ldots,\alpha_r)}{f(r_1,\ldots,r_r \mid H_0, M)} \underset{H_0}{\overset{H_1}{\gtrless}} T_2 \tag{26}$$

Where $f(r_1,\ldots,r_r \mid H_1, M, \alpha_1,\ldots,\alpha_r)$ denotes the PDF of the data under $H_1$and $f(r_1,\ldots,r_r \mid H_0, M)$ represent the PDF of the data under H_0. The conditional joint PDF of the data under H_0

$$f(r_1,\ldots,r_r \mid H_0, M) = \frac{1}{\pi^{Nr} \det^r(M)} \exp\left[-\sum_{i=1}^{r} r_i^+ M^{-1} r_i\right] \tag{27}$$

The conditional joint PDFs of the data under the probability at zero (H_1) is given as

$$f(r_1,\ldots,r_r \mid H_1, M, \alpha_1,\ldots,\alpha_r) = \frac{1}{\pi^{Nr} \det^r(M)} \exp\left[-\sum_{i=1}^{r} (r_i - C\alpha_i)^+ M^{-1} (r_i - C\alpha_i)\right] \tag{28}$$

Substituting equation (20) and (21) in (19). Then the GLRT is given by the equation

$$\sum_{i=1}^{r} r_i^+ M^{-1} r_i - \sum_{i=1}^{r} \min_{\alpha_i} (r_i - C\alpha_i)^+ M^{-1} (r_i - C\alpha_i) \underset{H_0}{\overset{H_1}{\gtrless}} T_2 \tag{29}$$

Where, T_2 is appropriate variation of the original threshold. This work aims to focus the performance evaluation of probability of false alarm (PFA) and probability of detection (PD). The matrix of the transmit code (C) is orthogonal in nature, and the signal-to-clutter ratio (SCR) is given as

$$SCR = \frac{\sigma^2}{NS} tr[C^+ R_0^{-1} C] \tag{30}$$

The probability of false alarm PFA can be evaluated as

$$pfa = e^{-r} \sum_{k=0}^{N-1} \frac{r^k}{k!} \tag{31}$$

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Where T is the detection threshold value.

4. Results

In order to optimize the polyphase sequences, experiments are carried for different length of sequences (N), different set sizes (L) and for different phases (M), using modified particle swarm optimization technique and the results are compared with existing literature values.

Table 1. ASPs and CPs values of the designed polyphase sequence set with (M=4, L=3, N= 128 and λ = 0.9).

PSO Technique	Sequence1	Sequence2	Sequence3
Sequence1	-27.53	-26.02	-25.67
Sequence2	-26.02	-27.53	-26.37
Sequence3	-25.67	-26.37	-26.93

Existing Method	Sequence1	Sequence2	Sequence3
Sequence1	-22.10	-18.49	-18.60
Sequence2	-18.49	-20.30	-18.55
Sequence3	-18.60	-18.55	-20.44

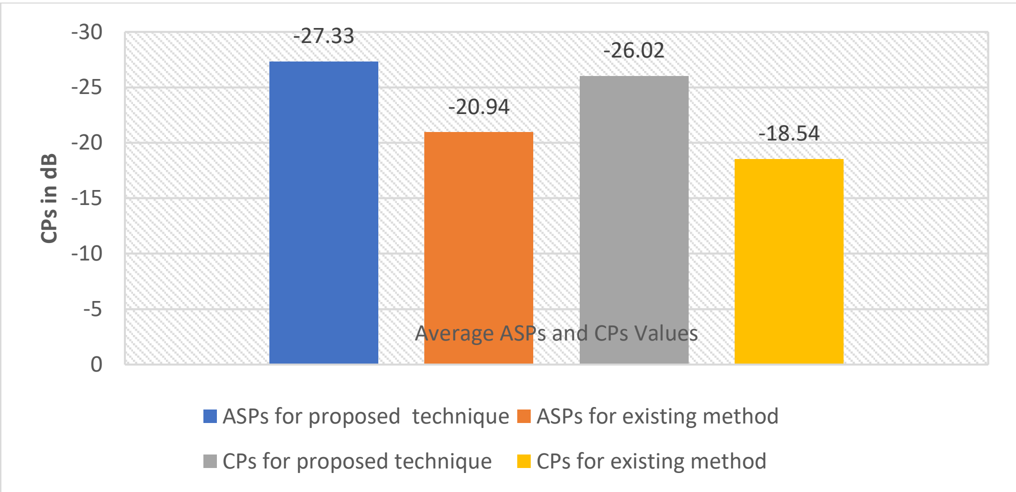

Fig. 1. Comparison of average ASPs and CPs values of existing method with PSO technique.

The diagonal values illustrate the normalized ASP whereas the other terms indicate the normalized CP values respectively. The average values of ASPs and CPs in existing method proposed by Wenwu Chen et. al. [35] are given as the -20.94dB and -18.54dB. Whereas the proposed method decrements the values by 6.39dB and -7.46dB and the obtained results are said to be -27.33dB and -26.02dB respectively, thus achieving an improved result. Keeping the value of phase, set size and λ =0.9 as constant and varying the sequence length (N= 40 to 500) and inertia weight (w = 0.4 to 0.9), ASP values of PSO is compared with existing methods proposed by Balaji et al. [33] and SP Singh et al. [34] respectively and is listed in table 1 and also depicted in Figure 1.

4.1. Performance of GLRT

The range of transmitting antennas that affect the performance of detection is investigated in Figure 2 The detection probability versus Signal to clutter ratio are plotted for various number of transmitting

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antennas. The solid curves in the Figure 2 shows the receiver operator characteristics for GLRT and dashed curves shows the characteristics of GC-GLRT.

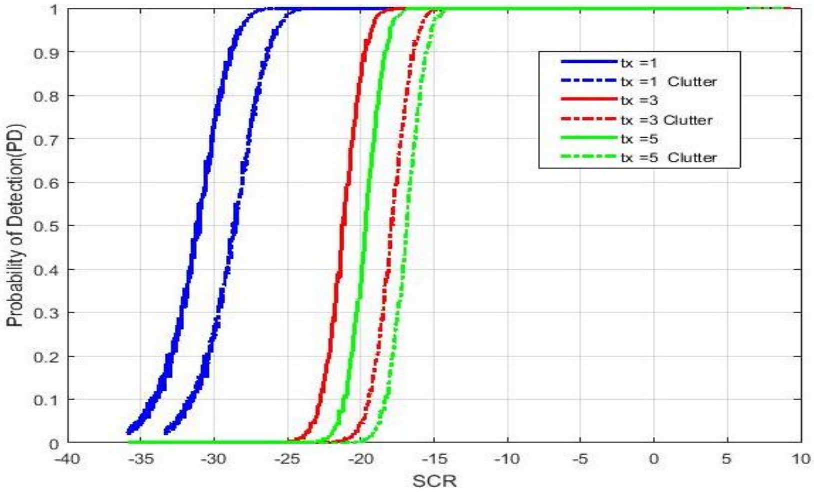

Fig. 2. PD Vs SCR for P_{fa} =10^{-3}, rx=5, and transmitters (tx) is variable.

From the characteristics curve, it is observed that the detection performance for tx = 1 is better compared to that of tx=3 and tx =5, thus illustrating an incremental result in detection performance with decrement in number of transmitting antenna. The gap between GLRT and GC-GLRT for tx=1, tx=3 and tx=5 at pd= 0.5 are about 2.07dB, 1.53dB and 0.57dB respectively which demonstrates that the detection performance is less when clutter is present in the signal. The relation between detection performance and the quantity of receiving antennas is analyzed in the Figure 2. Similarly, the effect of several range of receiving antennas that affect the performance of detection is inspected via Figure 3 in which the solid curve and dashed curve shows the receiver operator characteristics for GLRT and GC-GLRT respectively. The plot shows the relationship between the Probability of Detection Vs Signal to clutter ratio.

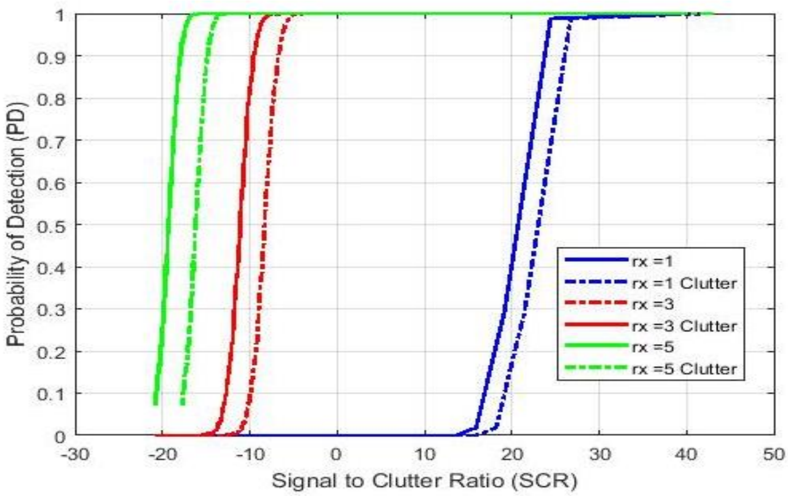

Fig. 3. PD Vs SCR for P_{fa} =10^{-3}, tx=5 and receiver (r_x) as variable.

Similarly, the effect of several range of receiving antennas that affect the performance of detection is inspected via Figure 3 in which the solid curve and dashed curve shows the receiver operator characteristics for GLRT and GC-GLRT, respectively. The plot shows the relationship between the Probability of Detection Vs Signal to clutter ratio.

Better results are obtained for the detection performance when the number of receiving antenna (rx)is 5 when compared to that of rx = 3 and rx = 1. This indicates that the performance of detection upsurges with the increase in the range of receiving antennas. The gap between GLRT and GC-GLRT for rx=5,

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rx=3 and rx=1 at pd= 0.5 is found to be 3.01dB, 2.81dB and 3.1dB respectively and demonstrates that detection performance is less when clutter is present in the signal when compared to the noise in the signal. Generated optimal code is tested in RAdar Seeker Test Evaluation Facility (RASTEF) LAB for simulation purpose. A seeker which is a rectangular anechoic chamber having Frequency range from 3 GHz to 110 GHz and distance Range of 30 meters, is used to track range, velocity and the target angle. With Convoluted Target Echo absorbers, the ECM simulator can be run to measure radar parameters for a distance range of 100 km to 322 km.

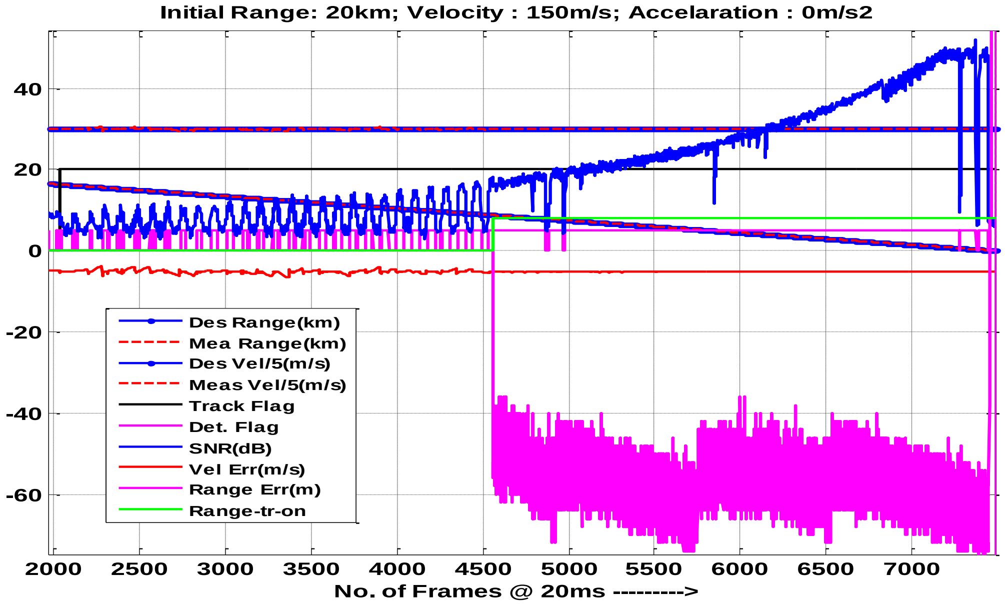

Fig. 4. Designated and measured range and velocity of polyphase sequence.

Generated optimal code is fed to the simulator that comprises real time software to generate and transmit the wave. The transmitted wave is received by the Radar seeker to produce the data. The designated range is 20km. Up to 10 km, targets range is not tracked but its velocity is tracked. The velocity tracked starts at 18 km onwards and remain constant with 150 m/s. Here the velocity of the polyphase sequence is measured. The designated velocity is considered to be 30km. Initially it starts at 30 km but Traf–Flag becomes on at 18 km. Target tracking starts at 10 km from which predicts an error between measured velocity and designated velocity.

5. Conclusion

The results of the proposed algorithm are validated and compared to other algorithms using standard radar database. The particle swarm optimization algorithm produced a decrement of 13.73 % in the average ASPs and 11.81 % decrement in CPs. In this research, a novel and potential optimal polyphase code set is designed using particle swarm optimization and its modified version and its performance is assessed using GLRT detector in noise and clutter environments, on the standard data base. The contributions of research are listed as below.

- From the Receiver Operator Characteristics (ROC) of GLRT, it is shown that the probability of performance detection rises with decrement in amount of transmitters or increment in the number of receivers, for probability of false alarm (PFA) rate of 10^{-3}. The probability of detection for the generated optimal code sets is good up to the minimal SNR of -34.57 dB for a system comprising of 3 transmitters and 5 receivers.
- From the Receiver Operator Characteristics (ROC) of GLRT, it is shown that the probability of performance detection rises with the decrement in amount of receivers or increment in the number of transmitters, for probability of false alarm (PFA) rate of 10^{-3}. The probability of detection for the generated optimal code sets is good up to the minimal SNR of -30.12dB for a system comprising of 3 receivers and 5 transmitters.

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- The experimental results indicate the escalation of the research towards finding optimal polyphase code design, with high probability detection performance at probability of false alarm rate of 10^{-3}.

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