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High-Performance GLR Detector for Moving Target Detection in OFDM Radar-Based Vehicular Networks

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Abstract
Nowadays, orthogonal frequency division multiplexing (OFDM) radars have been used in many applications such as target detection and recognition in vehicular networks and surveillance systems, according to their frequency diversity property. The model of the received signal in an OFDM radar based on target's parameters has a non-linear form with respect to unknown velocity and scattering coefficients, so there is no possibility of achieving a closed form solution for Maximum Likelihood Estimation of the unknown parameters and so the Neyman–Pearson detector. Therefore, in all published works, the generalized likelihood ratio (GLR) detector is obtained for the target with known velocity, or in case of simultaneous unknown velocity and scattering coefficients, only a wide two-dimensional grid search over all possible values of the unknown parameters is considered to maximize the Likelihood ratio. In this paper, a new method is proposed for simultaneous estimations of target velocity and scattering coefficients using a coordinate descent approach, which reduces the above nonlinear problem to two linear problems, and makes the implementation of GLR detector efficient. The simulation results confirm the efficiency of the proposed method.

Keywords OFDM radar · Generalized likelihood ratio · Maximum likelihood estimation · Coordinate descent algorithm

1 Introduction

High resolution is one of the specifications of modern radars in today's world [1–3]. Common radars, due to low resolution, can only find a target and determine its position, but they cannot provide an image of the target, or indicate exact features of the target. Therefore, to increase both range and Doppler resolutions, OFDM radars are introduced [4–14].

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One of the most important applications of OFDM radars is target recognition [15, 16]. Information of the target reflection coefficients in different frequencies is a key feature that can be used in target recognition. Numerous studies have been conducted on OFDM radars [7–22], however, detection in an OFDM radar is rather a new subject, and there is few studies in this area [23–32]. The OFDM signal model versus target parameters including the unknown velocity and scattering coefficients has a nonlinear form, so there is no possibility of achieving a closed form solution for Maximum Likelihood Estimation of the unknown parameters and so the Neyman–Pearson (NP) detector. Therefore, the GLR detector is usually obtained for the target with known velocity [4–9], or in case of simultaneous unknown velocity and scattering coefficients, only a wide two-dimensional grid search over all possible values of the unknown parameters is considered to maximize the Likelihood ratio. GLR in different engineering applications such as detection of fluctuating targets, aircraft vibration, and fault in industrial turbines can be found in [33–37]. The wide two dimensional grid search has a high computational load [23–28]. In this paper, we present an efficient method, which remarkably reduces the computational load compared to two dimensional grid search method.

As to recent works on radar-based networks towards wireless sensing [38–40], we wish to review some state-of-the-art articles, as follows. In [41], a wireless sensor platform is considered to establish a sensor network synchronized in accordance with the microsecond level. Critical performance metrics of the sensor network are quantified, including power consumption and wireless transmission range. The sensor network's static/dynamic measurement accuracy has also been verified in a series of pedestrian bridge experiments. In addition, the ability of the sensor network to detect the vehicle speed is evaluated. In [42], a system architecture for cognitive radar-communication (CRC) transceiver is proposed, and a cognitive waveform design approach, which is suitable for simultaneously performing both data communication and target detection, is then presented. The aims in this work is towards estimating target scattering coefficient (TSC) from the radar scene and facilitating high data rate communications. A similar approach can also be found in [43]. Two fuzzy clustering schemes in radar sensor networks (RSN) data processing is presented for target detection in [44]. The author(s) designed cluster-head (CH) selection mechanism for both intra-cluster single-hop and multi-hop data transmission on the basis of constant false alarm rate (CFAR) under fading environment. In [45], several high-resolution range profile (HRRP) recognition approaches in RSNs are investigated. Firstly in this work, the HRRP target recognition in a radar network is studied, then use of two distance criterions in order to HRRP target recognition are analyzed in RSNs. More future trends can be followed in [40].

In the proposed method, using a coordinate descent approach, which reduces the above nonlinear problem to two linear problems these unknown parameters are estimated via maximum likelihood estimation method. So, in this method, the ML estimation of both unknown parameters have a closed form solution, which can be used in the structure of GLR detector, and therefore, GLR test statistic is achieved without any grid search. To illustrate the efficiency of the proposed method compared to the two dimensional grid search method, we compared them in two scenarios. In the first scenario, we let both methods have approximately the same performance and compare their computation times. In the second scenario, we let both methods have equal computation times and compare their performance. The results in both Scenarios show that the proposed method is more efficient than the two dimensional grid search method.

We represent formulation and characteristics of the problem for targets detection in OFDM radar in the second section. In this regard, a review on the parametric OFDM measurement/assessment model to detect a mobile point (moving target) is done in the presence of clutter through a specified range cell on which the detection process is formulated as a hypothesis test (HT) to determine presence of a target in the targeted range cell. Considering unknown parameters in our model, the GLR test is applied [14]. In the third section, we propose a new method based on conventional GLR detector for target with non-existing speed and scattering features (shown under the coefficients of scattering). We also calculate and compare the computational order of both methods. The simulation results are given in the fourth section to illustrate priority of the proposed method to the common grid search method, we compare them in two different scenarios.

2 Problem Formulation

2.1 OFDM Signaling Model

We assume the target which is moving with a relative constant speed of υ in terms of the radar platform and is a far field case in the presence of clutter. It is also assumed that the radar has the complete information about test environment. As follows, firstly we design a parametric measurement modelling. Then, we do discussion on some statistical suppositions regarding the effect of clutter/noise.

For experiments, OFDM signaling scenario with L actively used subcarriers, a bandwidth of B (Hz), and pulse duration of T (seconds) are considered. Let a vector as below.

$$W = [w_0, w_1, \dots, w_{L-1}]^T \tag{1}$$

where $w_\imath$ for all values of $\imath = 0, 1, \dots, L-1$ presents complicated weights communicated on L subcarriers, and satisfies the following condition.

$$\sum_{\imath=1}^{L} w_\imath = 1 \tag{2}$$

We fuse information of the specific range cell (shown by the round trip time of τ) by substituting the below form.

$$t = \tau + nT_p \tag{3}$$

for all values of $n = 1, 2, \dots, N$ and, T_p is a notation for PRI (pulse repetition interval), and N is number of temporal measurements within a considered CPI (coherent processing interval). We also suppose OFDM radar contains N pulses, and L subcarriers. Received signal model is presented as follows [26].

$$X = WS^t\Phi^t(\upsilon) + WS^c\Phi^c + E \tag{4}$$

Where $X = [x(t_1)\, x(t_2)\, \dots\, x(t_N)]$ is an $L \times N$ complex matrix that represents received signal at N pulses and L sub-carriers.

$\Phi^t(\upsilon) = [\phi^t(t_1, \upsilon)\, \phi^t(t_2, \upsilon)\, \dots\, \phi^t(t_N, \upsilon)]$ is an $L \times N$ complex matrix that represents Doppler Information in different N pulses. $\Phi^c(t) = [\phi^c(t_1)\, \phi^c(t_2)\, \dots\, \phi^c(t_N)]$ is an $L \times N$ complex matrix consists of entries equal to 1. $E = [e(t_1)\, e(t_2)\, \dots\, e(t_N)]$ is an $L \times N$ complex matrix consists of noise. $x(t) = [x_1(t), x_2(t), \dots, x_L(t)]^T$ is an $L \times 1$ vector that represent outputs at the L sub-channels.

$W = diag(w_1, w_2, \ldots, w_L)$ is an $L \times L$ complex diagonal matrix that w_l represents complex weight transmitted over the l-th sub-channel.

$S^t = diag(s_1^t, s_2^t, \ldots, s_L^t)$ is an $L \times L$ complex diagonal matrix consists of the scattering coefficients of target at all sub-channels. Each s_l^t represents the scattering coefficient of target at the l-th sub-channel.

$S^c = diag(s_1^c, s_2^c, \ldots, s_L^c)$ is an $L \times L$ complex diagonal matrix consists of scattering coefficients of clutter at all of the L sub-channels. Each s_l^t represents scattering coefficient of clutter at the l-th sub-channel.

$\Phi^t(t, v) = [e^{jw_{1_D}t}, e^{jw_{2_D}t}, \ldots, e^{jw_{L_D}t}]^T$ is an $L \times 1$ complex vector that consists of Doppler information at time t, in which $w_{l_D} = 2\pi\beta f_l$ where $f_l = f_c + l\Delta f$ is the carrier frequency over l-th sub-channel, and Δf and c are subcarrier spacing and the speed of propagation respectively.

$\phi^c(t) = [1, 1, \ldots, 1]^T$ is an $L \times 1$ vector with all elements equal to 1.

$e(t) = [e_1(t), e_2(t), \ldots, e_L(t)]^T$ is an $L \times 1$ vector representing noise over L sub-channels. Now, consider that the scattering coefficients of target are deterministic (not random) but unknown, and all of the undesired reflections from the environment are assumed as clutter. Thus, we encounter with two undesired processes, clutter and noise.

2.2 Clutter and Noise Statistical Model

Here, we wish to discuss about the clutter statistical model. We suppose that clutter has under a Gaussian distribution with zero mean value and unknown covariance matrix of C_1 (matrix is positive definite). So the clutter model is considered as Eq. (5).

$$S^c\Phi^c \sim \mathbb{C}\mathcal{N}_{L,N}(0, C_1) \tag{5}$$

And assume an independency among all pulses considered as below.

$$WS^c\Phi^c \sim \mathbb{C}\mathcal{N}_{L,N}(0, I_N \otimes WC_1W^H) \tag{6}$$

We also suppose that the measurement noise in our model is based on a Gaussian distribution, with zero mean value, and unknown covariance matrix C_2 which is similarly positive definite.

$$E \sim \mathbb{C}\mathcal{N}_{L,N}\left(0, I_N \otimes \ C_2\right) \tag{7}$$

Consider that the noise and clutter are independent and have the same distribution we can write the distribution of overall interference (noise along with clutter) as below.

$$\theta = WS^c\Phi^c + E \sim \mathbb{C}\mathcal{N}_{LN,LN}(0, I_N \otimes CC) \tag{8}$$

where $CC = C_2 + WC_1W^H$ is the unknown covariance matrix of the total interference including noise and clutter.

2.3 Detection Problem

Detector in each radar system conventionally makes the decision about the presence or absence of a target in each individual resolution cell [14]. In this part of paper, we wish to represent a strong statistical HT (hypothesis test) with using our OFDM measurement model represented in a Sect. (2.1). To do decision making whether a sample target is existent or not existent in the targeted range cell in our test, a standard and well-known process is the design of a decision problem to choose between two possible hypotheses of the target-free hypothesis (maybe noted as null hypothesis in somewhere), or the target-present hypothesis (maybe noted as alternate hypothesis in somewhere). The problem can be illustrated in Eq. (9).

$$\begin{cases} H_0 : S^t = 0, & \text{CC is unknown} \\ H_1 : S^t \neq 0, & \upsilon, \text{ CC are unknown} \end{cases} \tag{9}$$

where υ is the velocity of target. Since Σ, Φ^{t} and S^{t} were unknown, the optimal Neyman Pearson (NP) detector cannot be used. In a similar way of [26] the sub-optimal Generalized Likelihood Ratio Test (GLRT) is derived as per the above-mentioned problem as follows.

$$\mathrm{GLRT} : \max_{,S^{t}} \frac{\left|XX^{H}\right|}{\left|\left(X - WS^{t}\Phi^{t}\right)\left(X - WS^{t}\Phi^{t}\right)^{H}\right|} \underset{<_{H_0}}{\overset{>^{H_1}}{}} \gamma \tag{10}$$

Problem FormulationFinding the test statistic of GLRT, needs a maximization over all possible unknown target velocities and scattering coefficients. Maximizing is one of the drawbacks of detector structure, because it needs a lot of time or computational capacity to find the maximum through a huge two dimensional grid search, and slows down the procedure of detection. This drawback comes from the fact that the observation model in (4) has a nonlinear form in terms of unknown parameters υ and S^{t}, so we cannot find a closed form solution for ML estimations of the unknown parameters.

3 Proposed Method

In this paper based on a coordinate descent approach, we present a new method which makes it possible to find a closed form solution of ML estimations of unknown target velocity and scattering coefficients without wide grid search, and so implement the GLR test efficiently. This is down in two steps; the first step is improving the OFDM signaling model, in a way that each unknown parameter of the signaling model appear in a linear form, considering the other parameter is known. The second step is determining maximum likelihood estimation of the unknown parameters using the linear model, through a coordinate descent algorithm. So, having the closed form estimation of the target velocity and scattering coefficients, we use them in GLR detector structure (10) without need to the grid search maximization.

3.1 Modifications on OFDM Signaling Model

Since there are two unknown parameters in the signal model (4), i.e. velocity or Doppler information of the target (Φ^{t}) and the scattering coefficient S^{t}, we reformulate this nonlinear model to two linear models based on each unknown parameter considering the other one is known.

In the first step, we assume that S^{t} is known, and Φ^{t} is unknown; and modify the observation model (4) to achieve a linear model based on the unknown parameter Φ^{t}. Reformulating (4) we can write:

$$\breve{X} = \tilde{W}\tilde{S}^{t}\breve{\Phi}^{t} + \tilde{W}\tilde{S}^{c}\breve{\Phi}^{c} + \breve{E} = \tilde{W}\tilde{S}^{t}\breve{\Phi}^{t} + \breve{\theta} \tag{11}$$

where $\breve{\mathrm{X}} = \mathrm{vec}(\mathrm{X})$ is an $\mathrm{LN} \times 1$ complex vector, which shows receiving signals, we get it by putting columns of the matrix X below each other.

$\breve{\Phi}^{t} = \mathrm{vec}\left(\Phi^{t}\right)$ is an $\mathrm{LN} \times 1$ complex vector that shows Doppler information of target, and we get it by putting columns of matrix Φ^{t} below each other. $\breve{\Phi}^{c} = \mathrm{vec}(\Phi^{c})$ is an $\mathrm{LN} \times 1$ vector with all arrays equal to 1. $\tilde{\mathrm{S}}^{t} = \mathrm{I}_{N} \otimes \mathrm{S}^{t}$ is an $\mathrm{LN} \times \mathrm{LN}$ complex diagonal matrix consisting of scattering coefficients of target, where $\otimes$ denotes the Kronecker multiplication. $\tilde{\mathrm{S}}^{c} = \mathrm{I}_{N} \otimes \mathrm{S}^{c}$ is an $\mathrm{LN} \times \mathrm{LN}$ complex diagonal matrix consisting of scattering coefficients.

$\tilde{\mathrm{W}} = \mathrm{I}_{N} \otimes \mathrm{W}$ is an $\mathrm{LN} \times \mathrm{LN}$ complex diagonal matrix that indicates transmitted weights. $\breve{\mathrm{E}} = \mathrm{vec}(\mathrm{E})$ is an $\mathrm{LN} \times 1$ complex vector, that indicates noise and interference, stacked in a vector form. $\breve{\theta} = \mathrm{vec}(\theta)$ is an $\mathrm{LN} \times 1$ complex vector, that indicates interference (noise + clutter), stacked in a vector form.

According to Eq. (11), we achieve the linear form based on the unknown parameter $\breve{\Phi}^{t}$. Therefore, it can be easily estimated in a closed form using maximum likelihood estimation method. Then, according to the property of maximum likelihood estimation, actually an estimation of target velocity can be made [14].

We can rewrite Eq. (11) in a matrix form as:

$$\tilde{\mathrm{X}} = \tilde{\mathrm{W}}\tilde{\mathrm{S}}^{t}\tilde{\Phi}^{t} + \tilde{\mathrm{W}}\tilde{\mathrm{S}}^{c}\tilde{\Phi}^{c} + \tilde{\mathrm{E}} = \tilde{\mathrm{W}}\tilde{\mathrm{S}}^{t}\tilde{\Phi}^{t} + \tilde{\theta} \tag{12}$$

where $\tilde{\mathrm{X}} = \mathrm{diag}\left(\breve{\mathrm{X}}\right)$, $\tilde{\Phi}^{t} = \mathrm{diag}\left(\breve{\Phi}^{t}\right)$, $\tilde{\Phi}^{c} = \mathrm{diag}\left(\breve{\Phi}^{c}\right)$, $\tilde{\mathrm{E}} = \mathrm{diag}\left(\breve{\mathrm{E}}\right)$, and $\tilde{\theta} = \mathrm{diag}\left(\breve{\theta}\right)$ are $\mathrm{LN} \times \mathrm{LN}$ diagonal complex matrices.

In Eq. (12), $\tilde{\mathrm{S}}^{t}$, $\tilde{\Phi}^{t}$ and $\tilde{\mathrm{W}}$ are three diagonal matrices, so it is possible to change the places of parameters $\tilde{\mathrm{S}}^{t}$ and $\tilde{\Phi}^{t}$, without any changes in equation. So, the equation can equivalently be written as Eq. (13).

$$\tilde{\mathrm{X}} = \tilde{\mathrm{W}}\tilde{\Phi}^{t}\tilde{\mathrm{S}}^{t} + \tilde{\theta} \tag{13}$$

Putting the diagonal elements of matrices $\tilde{\mathrm{X}}$, $\tilde{\mathrm{S}}^{t}$ and $\tilde{\theta}$ in vector form, we have Eq. (14).

$$\breve{\mathrm{X}} = \tilde{\mathrm{W}}\tilde{\Phi}^{t}\breve{\mathrm{S}}^{t} + \breve{\theta} \tag{14}$$

Where, $\tilde{\mathrm{S}}^{t} = \mathrm{diag}\left(\breve{\mathrm{S}}^{t}\right)$, and $\breve{\mathrm{S}}^{t}$ is an $\mathrm{LN} \times 1$ complex vector including the elements of main diameter $\tilde{\mathrm{S}}^{t}$.

If target velocity is assumed to be known, Eq. (14) is a liear observation model in terms of unknown target scattering coefficients.

3.2 Maximum Likelihood Estimation of Unknown Parameters

In the OFDM signaling model (4), unknown parameters are put together in the form of multiplication. So, ML estimation of the parameters in this condition is not easy and needs a huge grid search. In this section, based on the coordinate descent approach we find a much more efficient ML estimator for these parameters. First we assume that target scattering coefficients ($\tilde{\mathrm{S}}^{t}$) are known. Based on Eq. (11), ML estimation of $\breve{\Phi}^{t}$ can be found as shown in Sect. 3.2.1. Then we assume that target velocity or Doppler information ($\tilde{\Phi}^{t}$) is known. Now, based on Eq. (14) ML estimation of $\breve{\mathrm{S}}$ can be derived as shown in Sect. 3.2.2.

The above two steps should be repeated in a coordinated decent algorithm until it converges and we reach the ML estimation of both unknown parameters.

3.2.1 Maximum Likelihood Estimation of Target Unknown Doppler Information

Assuming $\tilde{S}^t$ is known, and applying maximum likelihood estimation to the linear Eq. (11), we reach to the closed form solution as Eq. (15).

$$\widehat{\breve{\Phi}}^{t} = \left[\left(\tilde{W}\tilde{S}^{t}\right)^{H}\left(\tilde{W}\tilde{S}^{t}\right)\right]^{-1}\left(\tilde{W}\tilde{S}^{t}\right)^{H}\breve{X} = \left(\tilde{W}\tilde{S}^{t}\right)^{-}\breve{X} \tag{15}$$

where $(.)^{-}$ indicates the generalized inverse operator.

3.2.2 Maximum Likelihood Estimation of Target Scattering Coefficients

Having the estimation value of $\tilde{\Phi}^t\left(\tilde{\Phi}^t = \mathrm{diag}\left(\widehat{\breve{\Phi}}^{t}\right)\right)$ from Eq. (15) and applying the maximum likelihood estimation to Eq. (14) we will have:

$$\widehat{\breve{S}}^{t} = \left[\left(\tilde{W}\tilde{\Phi}^{t}\right)^{H}\left(\tilde{W}\tilde{\Phi}^{t}\right)\right]^{-1}\left(\tilde{W}\tilde{\Phi}^{t}\right)^{H}\breve{X} = \left(\tilde{W}\tilde{\Phi}^{t}\right)^{-}\breve{X} \tag{16}$$

3.3 Efficient GLR Detector

Knowing estimations of both unknown parameters from previous steps, and rearranging them we have $\hat{S}^t$ and $\hat{\Phi}^t$ such that: $\widehat{\breve{S}}^{t} = \mathrm{vect}\left(\hat{S}^t\right)$, $\widehat{\breve{\Phi}}^{t} = \mathrm{vect}\left(\hat{\Phi}^t\right)$. Now we can replace them in GLR detector structure easily and achieve the GLR detector structure. So, the efficient GLR detector is as follows:

$$\mathrm{GLRT}: \frac{\left|XX^{H}\right|}{\left|\left(X - W\hat{S}^{t}\hat{\Phi}^{t}\right)\left(X - W\hat{S}^{t}\hat{\Phi}^{t}\right)^{H}\right|} \underset{H_0}{\overset{H_1}{\gtrless}} \gamma \tag{17}$$

3.4 Complexity Analysis

In previous parts of this section, an efficient GLR detector for target with unknown velocity and scattering coefficients in OFDM radar is proposed. The superiority of this method to the grid search method is a remarkable saving in the computation time. In this part, both methods are compared for their computational order.

3.4.1 Computational Order of GLR Detector Using Grid Search Method

We assume that the received signal by OFDM radar has L different frequencies and N pulses. So, for achieving GLR detector structure in grid search method, in each iteration, the necessary number of multiplication is:

$$L^2\left(17L \times N + 10L^2 + 3N^2 + 2N\right)$$

And the necessary number of summations is:

$$L^2\left(14L \times N + 4N^2 - 9 + 8L^2\right)$$

So in each step of estimation, the necessary computational order is:

$$L^2 \times N^2$$

Also, we assume a grid search on V velocities and S scattering coefficients. Therefore the overall necessary computational order will be as:

$$V \times S \times L^2 \times N^2$$

3.4.2 Computational Order of the Proposed Efficient GLR Detector

We consider the same assumptions for the number of frequencies and pulses as the previous section. We also consider the steps of the coordinate decent algorithm to be M. In each step of estimation, the necessary number of multiplication is:

$$L^2\left(24L \times N + 20L^2 + 10N^2 + 2N\right)$$

And the necessary number of summations is:

$$L^2\left(28L^2 + 11N^2 + 21L \times N - 14\right) - 7L \times N$$

So in each step of estimation, the necessary computational order is:

$$L^2 \times N^2$$

So the overall necessary computational order of the proposed algorithm is
Number of multiplication necessary:

$$M \times L^2 \times N^2$$

Considering that usually V × S is much greater than M, Therefore, the necessary computations in the grid search method are more than the proposed method. In grid search method the computations repeat over and over while there are a limited number of repetitions to estimate unknown parameters in the proposed method. So, the computation time in the proposed method is much lower. In the next section, we will investigate this issue through simulation results. Algorithm 1 illustrates the proposed method.

Algorithm 1. The proposed method for GLR detector with considering the known S^t

1. **Convert X, $\boldsymbol{\Phi}^t$, $\boldsymbol{\Phi}^c$ and E to LN × 1 vectors.**
2. **Convert $\mathbf{S}^t$, W and $\mathbf{S}^c$ to LN × LN diagonal matrices.**
3. **Use (11) to estimate ML of $\boldsymbol{\Phi}^t$.**
4. **Diagonalize $\breve{\mathbf{X}}$, $\breve{\boldsymbol{\Phi}}^t$, $\breve{\boldsymbol{\Phi}}^c$, $\breve{\mathbf{E}}$ and $\breve{\boldsymbol{\theta}}$.**
5. **Replace MLE of (15) in (14)**
6. **Estimate ML of $\breve{\mathbf{S}}^t$.**
7. **Replace (3) and (7) results in (17) to follow the GLRT closed form.**

Table 1 Different scenarios

Scenarios	Description
Scenario (1)	The velocity of the target is known (for achieving an upper bound in performance comparison of both conventional grid search and the proposed method (optimum case))
Scenario (2)	
Exact grid search	Target velocity is unknown and the GLR detector uses an exact grid search
Inexact grid search	Target velocity is unknown and the GLR detector uses an inexact grid search
Scenario (3)	Target velocity is unknown and the GLR detector uses a target velocity estimation based on the proposed method

Table 2 Simulation parameters

Parameters	Values
TCR	5 dB
CNR	10 dB
v	305 m/s
P_{fa}	0.1
N	500
f_c	10^9 Hz

4 Simulation Results

We have executed Monte-Carlo simulation based on 10,000 repeats to obtain performance characteristics of detection in each method for different scenarios, described in Table 1; on which distribution of Σ_c is chosen as *CN* (0,1). TCR and CNR are considered equal to 5 and 10 dB, respectively. Table 2 describes settings in brief.

We have also assumed that the target velocity components are (305,305) m/s, and therefore the target velocity changes from 0 to 430 m/s. In this study, some scenarios are considered and the effects of frequency diversity of OFDM signaling on their performance are evaluated. In Scenario1, the target velocity is assumed to be known. In Scenario2, target velocity is unknown and the GLR detector uses an exact grid search. In Scenario3, the target velocity is assumed unknown and the GLR detector is used through the target velocity estimation, using the proposed method.

Our goal in Scenario1 is achieving an upper bound for performance comparison of both grid search and the proposed method. In this case, with the assumption of known velocity, the nonlinear observation model reduces to a linear model and so the GLR detector can be obtained easily [26]. Figure 1 shows the performance of GLR detector for different number of subcarriers (L) in the first scenario. According to Fig. 1, the detector performance improves as the number of subcarrier (L) increases, which represents the frequency diversity in OFDM radar.

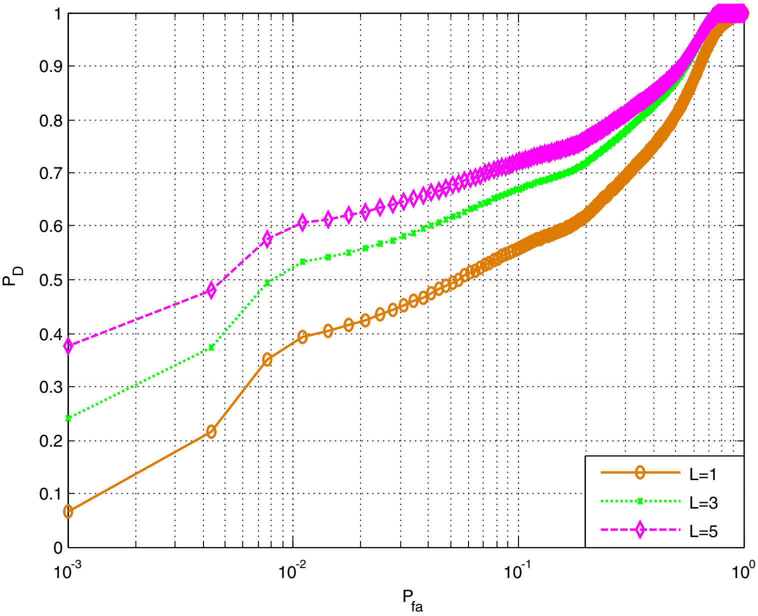

Fig. 1 The probability of detection for different values of probability of false alarm in different values of subcarriers (L) in Scenario1

4.1 Comparing the Results of Both Methods with the Known Velocity Upper Bound

4.1.1 The Grid Search Method and the Effect of Grid Size

Considering the nonlinear OFDM signaling model based on velocity and scattering coefficients of target, achieving GLR detector, requires a big grid search in all possible velocity values and scattering coefficients as can be seen in the structure of the GLRT in Eq. (10). To have a performance near to the known velocity upper bound we first consider 5×10^5 search points to make sure that real unknown parameters will be captured in grid search and the GLR detector achieves the optimal performance.

The simulation result in this scenario is shown in Fig. 2. According to Fig. 2, by increasing the number of subcarriers (L), the GLR detector performance improves.

We can see that the results of the second scenario are closely near to the known velocity upper bound (Scenario1) and have a negligible loss. In grid search, good results are obtained if the real unknown parameters fall in near vicinity of search points of the formed grid, which needs a huge grid size. Thus, this great performance is obtained at the expense of huge computation time. To reduce the computation time we should decrease the grid size. This may cause a considerable distance between the serach poits and real unknown parameters and so decrease the GLRT performance. To make the computation time of the grid search method comparable with the proposed method we should decrease the grid size to nearly 600 points. In this case (scenario 2-inexact grid search) GLR detector performance decreases considerably as is shown in Fig. 3.

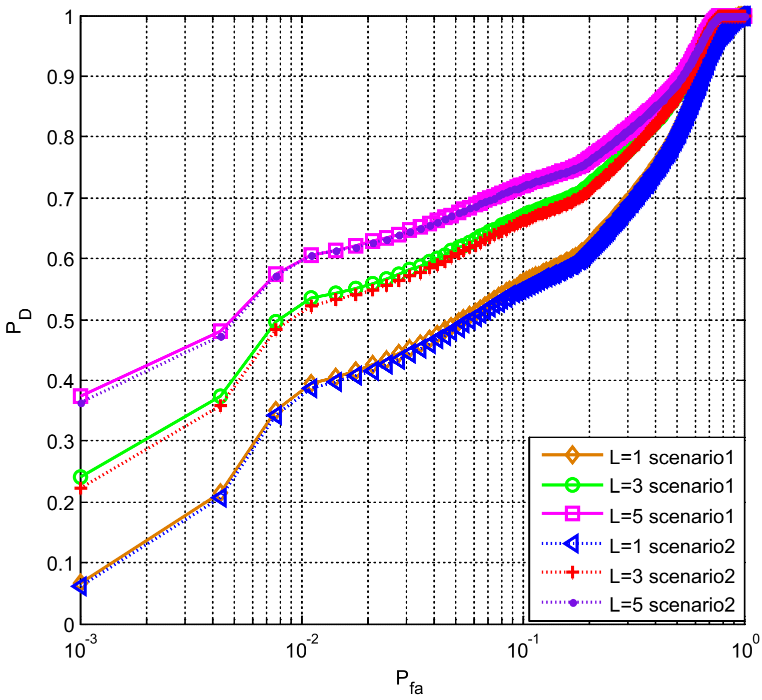

Fig. 2 the GLR detector performance in Scenario2 in exact grid search

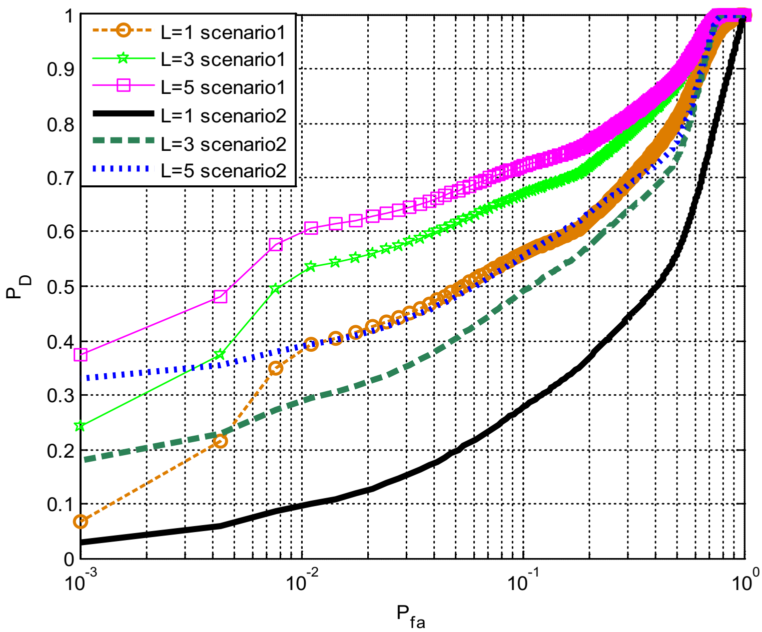

Fig. 3 The GLR detector performance in Scenario2 in inexact grid search

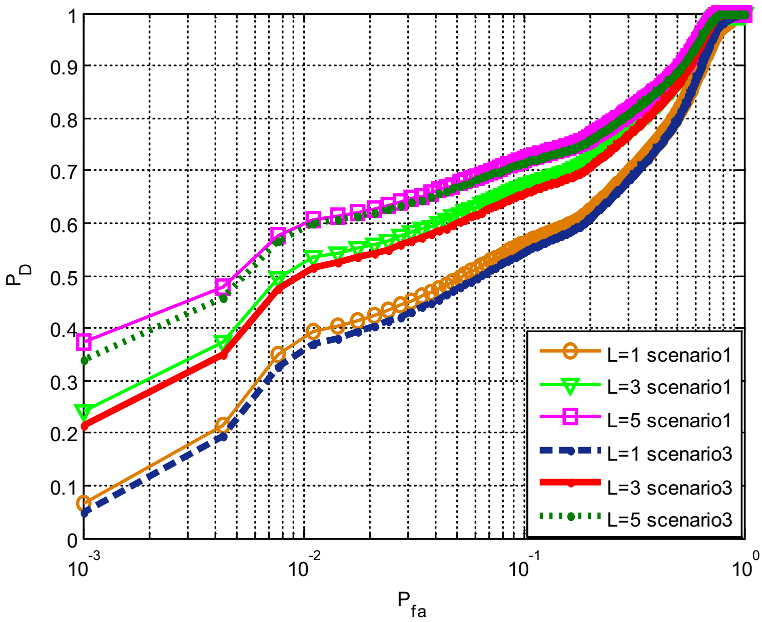

Fig. 4 The GLR detector performance in proposed method in Scenario3

4.1.2 The Proposed Method

In the proposed method, the GLR detector has two unknown parameters to be estimated, Φ^t and S^t. These two parameters are estimated by maximum likelihood method in a coordinate descent algorithm using Eqs. (15) and (16). For starting this algorithm we consider the initial condition for velocity to be zero in Eq. (16).

The value of $\tilde{S}^t$ is then estimated in the first step ($\tilde{S}^t_1$). This value is replaced in Eq. (15) to estimate $\tilde{\Phi}^t_1$. This loop is repeated until the estimated values converge to some specific values with a predefined convergence error. These values are considered as estimated values for velocity and scattering coefficients of target. Finally, they would be replaced in GLR detector structure of Eq. (17).

Figure 4 shows the GLR detector performance using the proposed method and its comparison with the first scenario. As it is shown in this figure, the proposed GLR detector performance has a close detection performance compared to the known velocity upper bound (scenario1). Also, it is shown that as the number of subcarriers (L) increases, the detection performance is closer to the upper bound of scenario 1.

4.2 Performance and Computation Time Comparison of the Grid Search and the Proposed Method

In previous Section, both grid search and the proposed method were compared with the upper bound of the first scenario, in which the velocity is known. Now, the detection performance and computation time of Scenario2 and Scenario3 are compared among each

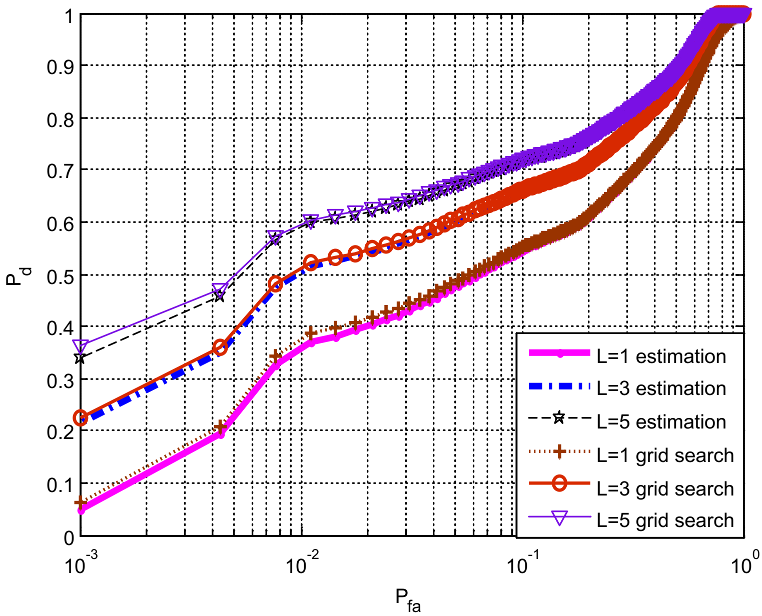

Fig. 5 The performance of detector in two cases, proposed method and inexact grid search method

other. Figure 5 shows the detection performance of the proposed method compared with fast inexact grid search method as defined above.

Figure 6 illustrates the detection performance of the exact grid search method compared with the proposed method. It can be observed from Fig. 5 And Fig. 6 that the proposed method has much better performance compared to inexact grid search method, while has a comparable performance with the exact grid search. Also, with increasing the frequency diversity in OFDM radar, this slight performance loss decreases.

The important advantage of the proposed method over the exact grid search is the computation efficiency. As mentioned earlier, the proposed method has a comparable performance, which tends to be identical with increasing number of subcarriers (L).

However, its computation time is much lower than the grid search method. In Table 3, the simulation's computation (or execution) times are shown for the proposed method, exact and inexact grid search methods, which has been executed on a pentium4 computer. According to Table 3, the computation time in the proposed method is very lower than the exact grid search method, while they have nearly the same performance.

4.3 Computing the Performance of Both Methods to Have the Same Computation Time

In this section, assuming that both methods have the same time for processing, their detection performances are compared. Since the computation time in the proposed method is lower than the exact grid search, so the size of grid search should decrease to reach the same processing time. Then, the performance of detection in both method can be compared. The results have been shown in Fig. 7. As it could be seen in this figure, the

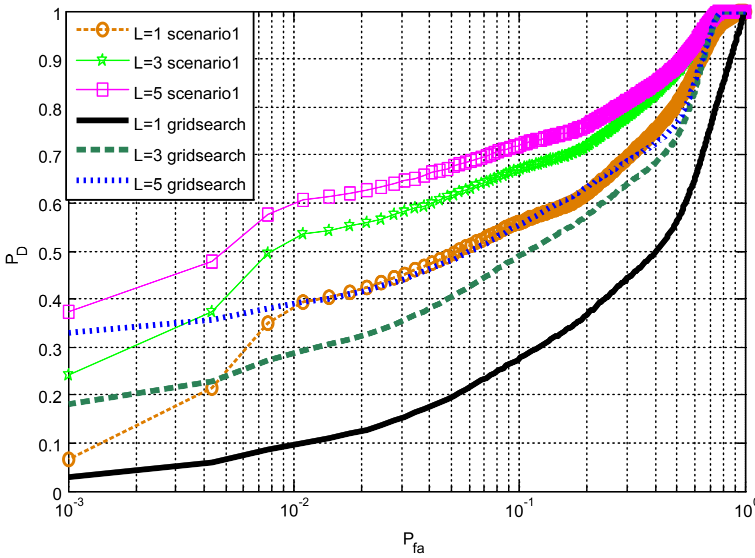

Fig. 6 The performance of detector in two cases, proposed method and exact grid search method

Table 3 Computation time in different methods (all times are in second (s))

Scenarios	Number of subcarriers		
	L = 1	L = 3	L = 5
The proposed method	26.96	33.87	41.83
Inexact grid search	27.76	34.43	43.71
Exact grid search method	25,331	27,101	30,589

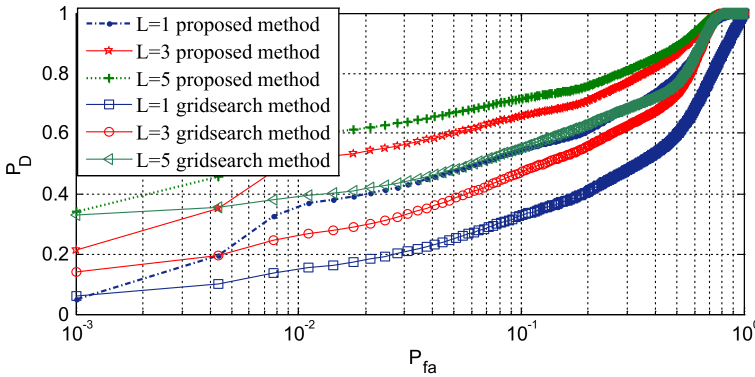

Fig. 7 The evaluation of GLR detector in both methods when the computation times are same in both them

proposed method has much better performance compared to the same processing time grid search method.

5 Conclusions

In this paper, an efficient GLR detector is proposed for detection of a moving target with unknown velocity and scattering coefficients in OFDM radar. The unknown target parameters appear in nonlinear form in the received OFDM signal model, so there is no possibility to achieve a closed form solution for their ML estimations simultaneously.

So, the desired GLR detector requires a big grid search to find an estimation of unknown target velocity and scattering coefficients.

In this paper, we present a new efficient GLR detector to reduce the computational complexity. In this method, we modify the nonlinear OFDM model and make two linear models based on two unknown parameters considering the other one is known. Using a coordinate descent algorithm, we find a closed form solution for estimation of unknown parameters via maximum likelihood estimation method. Performance of the proposed efficient GLR detector is compared with GLR detector that uses two dimensional grid search algorithm and simulation results show that the proposed method needs a much less computation time while detection performance is comparable. When we force both methods to have the same computation time, the proposed efficient detector has much better detection performance compared to the grid search method.

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