International Journal of Engineering Research and Development
***e**-ISSN: 2278-067X, **p**-ISSN: 2278-800X, www.ijerd.com*
Volume 3, Issue 9 (September 2012), PP. 30-37

Moving Target Estimation in Non-Homogeneous Clutter for MIMO Radar

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Abstract—In this paper, we consider velocity estimation and detection for non-stationary target using MIMO radar in non-homogeneous clutter. In the case of non-homogeneous clutter due to the azimuth-selective backscattering the clutter power will vary from one test cell to another and also from one transmit-receive pair to another. In this work, the non-homogeneous clutter is modeled using a subspace approach, whereby the subspace is spanned by a few Fourier bases and the non-homogeneity of the clutter is captured by coefficients that vary with different transmit-receive pairs and/or different resolution cells. We develop a maximum likelihood estimator (MLE) for velocity estimation and general likelihood ratio test (GLRT) for detection of target in non-homogeneous clutter. We also studied the Cramer Rao bound to show the asymptotic efficiency property of the maximum likelihood estimator. Numerical results show that the proposed estimator outperforms the covariance matrix estimator and reduces the Signal to noise ratio (SNR) threshold as number of antennas increases. Numerical results for GLRT detector shows improved detection performance as SNR increases.

I. INTRODUCTION

MIMO radar has received significant interest in recent years. There are two types of MIMO radar configuration one with colocated antenna and the other one is the widely separated antenna[1-3]. MIMO radar with widely separated antennas transmits multiple orthogonal waveforms which are separated at each receive antenna by matched filter processing [4]. Widely separated MIMO radar allows one to exploit the so-called spatial or geometric diversity to enhance target detection. In particular, radar targets often exhibit significant azimuth selective backscattering with tens of dB of fluctuation in their radar cross section (RCS). The spatial diversity of distributed MIMO radar was first discussed in [5] and later extended in [4] for moving target detection. The effect of clutter was included in [4], [6] for moving target detection and velocity estimation. The result of [4], [6] shows that the widely separated MIMO radar provides significant performance gain over the traditional phased array radar.

Our study is motivated by the fact that radar analysis and system design are usually performed under the assumptions that radar clutter is stationary and homogeneous that is the probability density of clutter power are assumed to be constant in time for a single resolution cell and constant in space from resolution cell to resolution cell. In practical there are many situations which do not satisfy these conditions like clouds, grass, tree and many other clutters which are non stationary. So non-homogeneous clutter is modeled to characterize the non-stationary and non-homogeneity of radar clutters[7,8]. Using this non-homogeneous clutter model, we derive the maximum likelihood estimator of target velocity. The main reason for using MLE is that under certain regularity conditions, it is asymptotically efficient. Asymptotically efficient means that the estimator achieves the Cramer- Rao Bound (CRB) when the amount of data is large or the signal-to-noise ratio is high[11]

II. SIGNAL MODEL

Considering the distributed MIMO radar with M transmitting antennas and N receiving antennas which are stationary and their locations are assumed known. The M transmit antennas send orthogonal waveforms $S_m(i)$,i=1,….,J, where J=number of samples. By orthogonal the waveforms are mutually orthogonal and they maintain orthogonality with respect to Doppler shifts and delays

$$\sum_i S_m(i) S^*_{m'}(i) = \begin{cases} 1 \text{ if } m = m' \\ 0 \text{ if } m \neq m' \end{cases} \quad (1)$$

As waveforms are orthogonal the signals sent from different transmitting antennas can be separated at any receiving antenna by matched filtering.

Assume the target does not leave the given cell under test for some K consecutive pulses of transmission from each transmitting antenna. By considering two hypothesis test problem H_1 target is present in the test cell and H_0 target is not present in test cell the received signal is given by

$$H_0 : X_{m,n} = C_{m,n} + W_{m,n} \qquad m=1,\ldots,M \text{ and } n=1,\ldots,N \quad (2)$$

$$H_1 : X_{m,n} = \alpha_{m,n} a(f_{m,n}) + C_{m,n} + W_{m,n} \quad (3)$$

where $C_{m,n}$ is clutter , $W_{m,n}$ is noise , $\alpha_{m,n}$ is amplitude of target and $a(f_{m,n})$ is steering vector due to Doppler frequency $f_{m,n}$.

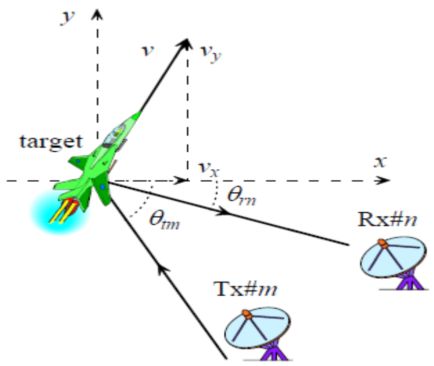

Fig 1: Geometry of MIMO Radar

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As shown in figure 3.1 target is moving with velocity V with horizontal and vertical component of velocity v_x and v_y respectively. From figure 3.1 the normalized Doppler frequency for different transmit receive pairs $f_{m,n}$ is given by[1,4,7]

$$f_{m.n} = \frac{v_x T}{\lambda}(\cos\theta_{tm} + \cos\theta_{tn}) + \frac{v_y T}{\lambda}(\sin\theta_{tm} + \sin\theta_{tn}) \quad (4)$$

Where λ is wavelength of carrier signal, T is pulse repetition interval,θ_{tm} and θ_{tm} are the angles of transmit and receiving antennas respectively, respectively, when viewed from an origin located at the target .As target is moving with some radial velocity V there exists a horizontal and vertical velocity component. Horizontal and vertical velocity v_x and v_y respectively are given by

$$v_x = V\cos(\theta) \quad (5)$$

$$v_y = V\sin(\theta) \quad (6)$$

Where V is the radial velocity of target and θ is the direction of the target moving. The signal steering vector, which is formed over the reception of K pulses is given by

$$a(f_{m,n}) = [1\ e^{-i2\pi f_{m,n}} \ \ldots\ e^{-i2\pi f_{m,n}(k-1)}]^T \triangleq a_{m,n}(v) \quad (7)$$

Where $i=\sqrt{-1}$ and $a_{m,n}(v)$ is steering vector for different transmit receive pairs.

From equations (3.2) and (3.3) noise $W_{m,n}$ is spatially and temporally white noise with zero mean and covariance matrix given by

$$E[W_{m,n}W^H_{n'm'}] = \sigma^2 I\delta(n-n')\delta(m-m') \quad (8)$$

Where σ² denotes the unknown variance of the noise, and δ(•) the discrete impulse function.

From equation clutter components $C_{m,n}$ contain reflections from stationary objects like ground, buildings and slow moving objects like grass wind within the considered test cell. By assuming that the clutter from any transmit-receive pair falls within a subspace which is expanded by the columns of a matrix $H \in C^{K\times L}$ given by

$$H=[h(f_1),h(f_2),\ldots,h(f_L)] \quad (9)$$

Where $h(f) = [1,e^{-j2\pi f},\ldots,e^{-j2\pi f(k-1)}]^T$ and $\{f_l\}_{l=1}^{L}$ are selected Doppler frequencies of clutter in low frequency region. Any given transmit receive pair can be expressed as a linear combination of the columns of matrix H given by

$$H=C_{m,n}\beta_{m,n} \quad (10)$$

where $\beta_{m,n}$ denotes the L × 1 complex amplitude vector associated with the clutter vectors viewed from the aspect of the (m,n)th transmit-receive antenna pair. As clutter is non-homogeneous $\beta_{m,n}$clutter amplitude is different for one transmit receive pair to other and vary from one test cell to other

$$\beta_{m,n} \neq \beta_{m',n'} \quad (11)$$

The clutter model of (3.15) is motivated by the widely known observation that the clutter in many practical scenarios has a low-rank structure, that is, $C_{m,n} \in S$, where *S* denotes a subspace of $C^{K\times 1}$ with a rank lower than *K* [9].

III. MAXIMUM LIKELIHOOD ESTIMATOR OF TARGET VELOCITY

The Maximum Likelihood (ML) method is a standard technique that is often used in parameter estimation problems. The main reason for its widespread use is that it, under certain regularity conditions, is asymptotically efficient. To apply the ML method thelikelihood function of the observed data is needed. The estimates are then obtained as the parameter values that maximize this function. An interpretation of this method is that the estimates are the parameter values that make the observed data most probable. Since we have assumed spatio-temporally white Gaussian noise, the likelihood function for the model in (3.1) is given by

$$P(X;v,\alpha,\beta,\sigma^2) = \frac{1}{(\pi\sigma^2)^{KMN}} \exp\left(-\frac{1}{\sigma^2}\sum_{m,n}\left\|x_{m,n} - \alpha_{m,n}a_{m,n}(v) - H\beta_{m,n}\right\|^2\right) \quad (12)$$

Where ‖ . ‖ denotes the vector 2-norm. Taking derivative of log-likelihood function given by$\ln P(X;v,\alpha,\beta,\sigma^2)$ with respect to σ² and setting it to zero ML estimate of σ² denoted by $\widehat{\sigma^2}$ given by

$$\widehat{\sigma^2} = \frac{1}{KMN}\sum_{m,n}\left\|x_{m,n} - \alpha_{m,n}a_{m,n}(v) - H\beta_{m,n}\right\|^2 \quad (13)$$

Substituting the equation in equation, ML estimate of remaining parameter can be determined by minimizing the function given by

$$\sum_{m,n}\left\|x_{m,n} - \alpha_{m,n}a_{m,n}(v) - H\beta_{m,n}\right\|^2 \quad (14)$$

For simplicity let $y_{m,n} = x_{m,n} - \alpha_{m,n} a_{m,n}(v)$ .Substituting $y_{m,n}$in equation ML estimate of remaining parameter can be determined by minimizing the function given by

$$\sum_{m,n} \left\| y_{m,n} - H\beta_{m,n} \right\|^2 \quad (15)$$

By expanding equation and taking derivative with respect to $\beta_{m,n}$ and setting it to zero,the ML estimate of $\beta_{m,n}$ denoted by$\widehat{\beta_{m,n}}$ given by

$$\widehat{\beta_{m,n}} = (H^H H)^{-1} H^H y_{m,n} \quad (16)$$

Substituting equation back into equation and expanding reduces to

$$\sum_{m,n} y_{m,n}^T P_H^{\perp} y_{m,n} = \sum_{m,n} [x_{m,n} - \alpha_{m,n} a_{m,n}(v)]^H P_H^{\perp} [x_{m,n} - \alpha_{m,n} a_{m,n}(v)] \quad (17)$$

Where $P_H^{\perp}$ is projection matrix given by

$$P_H^{\perp} = I - H(H^H H)^{-1} H^H \quad (18)$$

By substituting the equation with equation and taking derivative with respect to $\alpha_{m,n}$ and setting it to zero the ML estimate of $\alpha_{m,n}$ denoted by$\widehat{\alpha_{m,n}}$ given by

$$\widehat{\alpha_{m,n}} = \frac{a_{m,n}^H(v) P_H^{\perp} x_{m,n}}{a_{m,n}^H(v) P_H^{\perp} a_{m,n}(v)} \quad (19)$$

Finally by substituting equation into equation, ML estimate of the velocity v is given by

$$\widehat{V} = \arg\max_v \sum_{m,n} \frac{|a_{m,n}^H(v) P_H^{\perp} x_{m,n}|^2}{a_{m,n}^H(v) P_H^{\perp} a_{m,n}(v)} \quad (20)$$

A. Comparison with Covariance Matrix Estimator

The ML estimator of target velocity is notably different from thecovariance-matrix-based estimator in [4], [6]:

$$\widehat{V} = \arg\max_v \sum_{m,n} \frac{|a_{m,n}^H(v) c_{m,n}^{-1} x_{m,n}|^2}{a_{m,n}^H(v) c_{m,n}^{-1} a_{m,n}(v)} \quad (21)$$

By comparing (20) and (21) covariance matrix based estimation of velocity is more complex than maximum likelihood estimation. In maximum likelihood estimation it is sufficient to calculate $P_H^{\perp}$ once and for transmit receive pair, but in covariance matrix based estimation there is a need to calculate covariance matrix for every transmit receive pair and have to inverse it.

IV. CRAMER RAO BOUND

The ML estimator of target velocity was obtained in (20). In the following, the achievable accuracy of the ML estimator of $V_x$and $V_y$in the presence of non-homogeneous clutter is studied by means of the CRB.

In this paper as in the case of distributed MIMO radar the unknown parametersϵ are given by

$$\epsilon = [V_x, V_y, \eta_{11}, \eta_{12} \ldots\ldots\ldots\ldots\ldots . \eta_{MN}, \sigma^2]^T \quad (22)$$

Where $\eta_{mn} = [\alpha_{mn}^r, \alpha_{mn}^i, (\beta_{mn}^r)^T, (\beta_{mn}^i)^T]^T \varepsilon\, C^{(2L+2)\times 1}$subscript r and i indicates the real and imaginary parts of target amplitude $\alpha_{mn}$and clutter amplitude β_{mn} of the mnth transmit receive pairs respectively. It is tedious to compute the CRBs of the estimates of $v_x$and $v_y$directly. So first by determining the Fisher information matrix (FIM) of the estimates of the Doppler frequencies and then, using the transformation rule, to get the FIM of the estimated $v_x$and $v_y$it becomes easy to calculate CRB estimate of $v_x$and v_y. To estimate the FIM the equation is expanded to $[(2L+3)MN+1]\times 1$ vector θ given by

$$\theta = [\, f_{11}, f_{12}, \ldots\ldots\ldots f_{MN}, \eta_{11}, \eta_{12} \ldots\ldots\ldots\ldots\ldots . \eta_{MN}, \sigma^2]^T \quad (23)$$

and by linking these two vectors from equation vector θ is given by

$$\theta = G\epsilon \quad (24)$$

$$G = \begin{bmatrix} A_{MN\times 2} & 0_{(2L+2)} \\ 0_{(2L+2)} & I_{(2L+2)} \end{bmatrix} (25)$$

$$A_{MNX2} = [c_{11}, c_{12}, \ldots\ldots c_{MN}; s_{11}, s_{12}, \ldots\ldots\ldots s_{MN}]^T \quad (26)$$

$$c_{mn} = \frac{T}{\lambda}(\cos\theta_{tm} + \cos\theta_{rn}) (27)$$

$$s_{mn} = \frac{T}{\lambda}(\sin\theta_{tm} + \sin\theta_{rn}) (28)$$

The FIM estimation of θ is given by

$$[I(\theta)]_{ij} = -E\left[\frac{\partial^2 \ln p(x;\theta)}{\partial\theta_i\, \partial\theta_j}\right] \quad (29)$$

The FIM between the doppler frequencies f_{mn} and f_{lk} are given by

$$[I(\theta)]_{ij} = -E\left[\frac{\partial^2 \ln p(x;\theta)}{\partial f_{mn}\, \partial f_{lk}}\right]$$

$$= (2\pi)^2 |\alpha_{mn}|^2 \frac{(2K-1)K(K-1)}{3\sigma^2} \delta(m-l)\delta(n-k) (30)$$

Where $1 \leq \{i,j\} \leq MN$ and $\delta(.)$ is the kronecker delta function.

The FIM between the Doppler frequencies f_{mn} and (lk)th target and clutter parameters η_{lk} are given by

$$[I(\theta)]_{ij} = -E\left[\frac{\partial^2 \ln p(x;\theta)}{\partial f_{mn}\, \partial \alpha_{lk}^r}\right] = 2\pi\sigma^{-2} i\{\alpha_{mn}\} K(K-1)\delta(m-l)\delta(n-k) \quad (31)$$

$$[I(\theta)]_{ij} = -E\left[\frac{\partial^2 \ln p(x;\theta)}{\partial f_{mn}\, \partial \alpha_{lk}^i}\right] = -2\pi\sigma^{-2} r\{\alpha_{mn}\} K(K-1)\delta(m-l)\delta(n-k) (32)$$

$$[I(\theta)]_{ij} = -E\left[\frac{\partial^2 \ln p(x;\theta)}{\partial f_{mn}\, \partial \beta_{lkL}^r}\right] = 2\sigma^{-2} r\{\alpha_{mn} h^H(f_L) \frac{\partial a(f_{mn})}{\partial f_{mn}}\} K(K-1)\delta(m-l)\delta(n-k) \quad (33)$$

$$[I(\theta)]_{ij} = -E\left[\frac{\partial^2 \ln p(x;\theta)}{\partial f_{mn}\, \partial \beta_{lkL}^i}\right] = -2\pi\sigma^{-2} i\{\alpha_{mn}\} K(K-1)\delta(m-l)\delta(n-k) \quad (34)$$

Where $1 \leq i \leq MN$ and $MN+1 \leq j \leq (2L+3)MN$

The FIM between the η_{mn} and η_{lk} are given by

$$[I(\theta)]_{ij} = -E[\frac{\partial^2 \ln p(x;\theta)}{\partial \alpha^r_{mn}\, \partial \alpha^r_{lk}}] = -E[\frac{\partial^2 \ln p(x;\theta)}{\partial \alpha^i_{mn}\, \partial \alpha^i_{lk}}] = 2\sigma^{-2}\delta(m-l)\delta(n-k) \quad (35)$$

$$[I(\theta)]_{ij} = -E[\frac{\partial^2 \ln p(x;\theta)}{\partial \alpha^r_{mn}\, \partial \alpha^i_{lk}}] = 0 \quad (36)$$

$$[I(\theta)]_{ij} = -E[\frac{\partial^2 \ln p(x;\theta)}{\partial \alpha^r_{mn}\, \partial \beta^i_{lkL}}] = 2\sigma^{-2}r\{a^H(f_{mn})h(f_L)\}\delta(m-l)\delta(n-k) \quad (37)$$

$$[I(\theta)]_{ij} = -E[\frac{\partial^2 \ln p(x;\theta)}{\partial \alpha^i_{mn}\, \partial \beta^r_{lkL}}] = -\{-E[\frac{\partial^2 \ln p(x;\theta)}{\partial \alpha^r_{mn}\, \partial \beta^i_{lk}}]\}$$
$$= 2\sigma^{-2}i\{a^H(f_{mn})h(f_L)\}\delta(m-l)\delta(n-k) \quad (38)$$

$$[I(\theta)]_{ij} = -E[\frac{\partial^2 \ln p(x;\theta)}{\partial \beta^r_{mnL}\, \partial \beta^r_{lkj}}] = -E[\frac{\partial^2 \ln p(x;\theta)}{\partial \alpha^i_{mn}\, \partial \beta^i_{lk}}] = 2\sigma^{-2}r\{h^H(f_L)h(f_j)\}\delta(m-l)\delta(n-k) \quad (39)$$

$$[I(\theta)]_{ij} = -E[\frac{\partial^2 \ln p(x;\theta)}{\partial \beta^i_{mnL}\, \partial \beta^r_{lkj}}] = 2\sigma^{-2}i\{h^H(f_L)h(f_j)\}\delta(m-l)\delta(n-k) \quad (40)$$

Where $MN+1 \leq \{i,j\} \leq (2L+3)MN$

The FIM between the noise variance and other parameters is given by

$$[I(\theta)]_{i,(2L+3)MN+1} = 0 \quad (41)$$

Where $1 \leq i \leq (2L+3)MN$

The FIM between the noise variance by itself is given by

$$[I(\theta)]_{(2L+3)MN+1,(2L+3)MN+1} = \sigma^{-4}K \quad (42)$$

The FIM estimate of € is given by

$$I(€) = G^T I(\theta) G \quad (43)$$

From equation CRB estimate of (€) is calculated by inversing the I(€). CRB estimate of horizontal and vertical component of velocity is given by

$$Var(v_x) \geq [I^{-1}(€)]_{11} = [(G^T I(\theta) G)^{-1}]_{11} \quad (44)$$

$$Var(v_y) \geq [I^{-1}(€)]_{22} = [(G^T I(\theta) G)^{-1}]_{22} \quad (45)$$

V. GLRT DETECTOR

GLRT detector is based on the two hypothesis test one with the presence of the target and one with the absence of the target. By considering two hypothesis H_0 and H_1 as shown in equation GLRT is given by

$$GLRT = \frac{\max_{v,\alpha,\beta,\sigma^2} p_1(X;v,\alpha,\beta,\sigma^2)}{\max_{\beta,\sigma^2} p_0(X;\beta,\sigma^2)} \quad (46)$$

Where $p_1(X;v,\alpha,\beta,\sigma^2)$ and $p_0(X;\beta,\sigma^2)$ are the likelihood functions of H_0 and H_1 respectively. The ML estimate of unknown parameters under H_1 in the presence of target is shown in equation. The ML estimate of unknown parameters under H_0 in the absence of target is obtained by eliminating the equation and is given by

$$\widehat{\sigma^2} = \frac{1}{KMN}\sum_{m,n} x^H_{m,n} P^{\perp}_{H} x_{m,n} \quad (47)$$

$$\widehat{\beta_{m,n}} = (H^H H)^{-1} H^H x_{m,n} \quad (48)$$

GLRT detector is given by

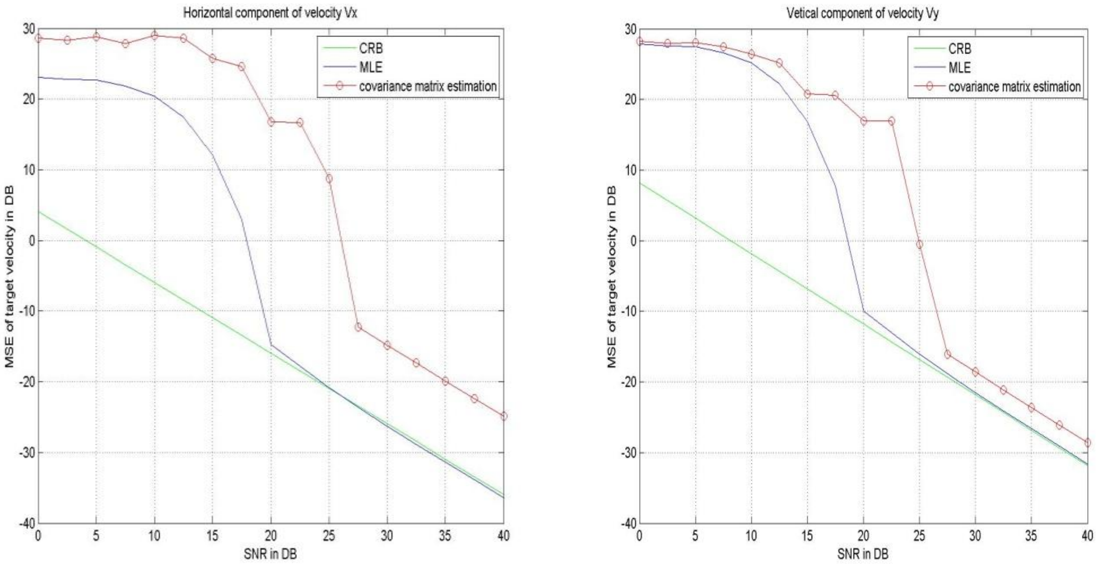
$$GLRT = \frac{\max_v \sum_{m,n} \frac{|a^H_{m,n}(v) P^{\perp}_{H} x_{m,n}|^2}{a^H_{m,n}(v) P^{\perp}_{H} a_{m,n}(v)}}{\sum_{m,n} x^H_{m,n} P^{\perp}_{H} x_{m,n}} \underset{H_0}{\overset{H_1}{\lessgtr}} \gamma \quad (49)$$

where γ is a threshold selected to meet a given probability of false alarm.

VI. SIMULATION RESULTS

A. Estimation

Computer simulations are carried out to assess the performance of maximum likelihood estimator and compared with covariance matrix estimator and Cramer Rao bound. The mean square error of target velocity for various SNR is simulated in non-homogeneous clutter.



(a) (b)

Fig 2: (a) MSE vs SNR for V_x ; (b) MSE vs SNR for V_y

Fig.2 shows that the simulated mean-squared error (MSE) curves of the maximum likelihood estimator and the covariance matrix estimator for horizontaland vertical target velocity. The performance of the MLE is obtained by a two-step approach: an initial coarse grid search followed by a refined search. The results show that, on one hand, the MSE curves of the MLE for horizontal and vertical velocityreach their respective CRB at high SNR, On the other hand, the ML estimator outperforms the covariance matrix estimator at almost all SNR and has a lower SNR threshold than the covariance matrix estimator. Rms velocity of clutter is chosen as 1.5m/s

***Table 1* System Parameter**

Number of transmitters	2
Number of receivers	2
Carrier frequency	1GHz
Transmitters angle	0 and 65 degree
Receiver angle	-30 and 40 degree
Pulse repetition frequency	500Hz
Target velocity	108km/hr
Target direction	30 degree
Number of pulses	16

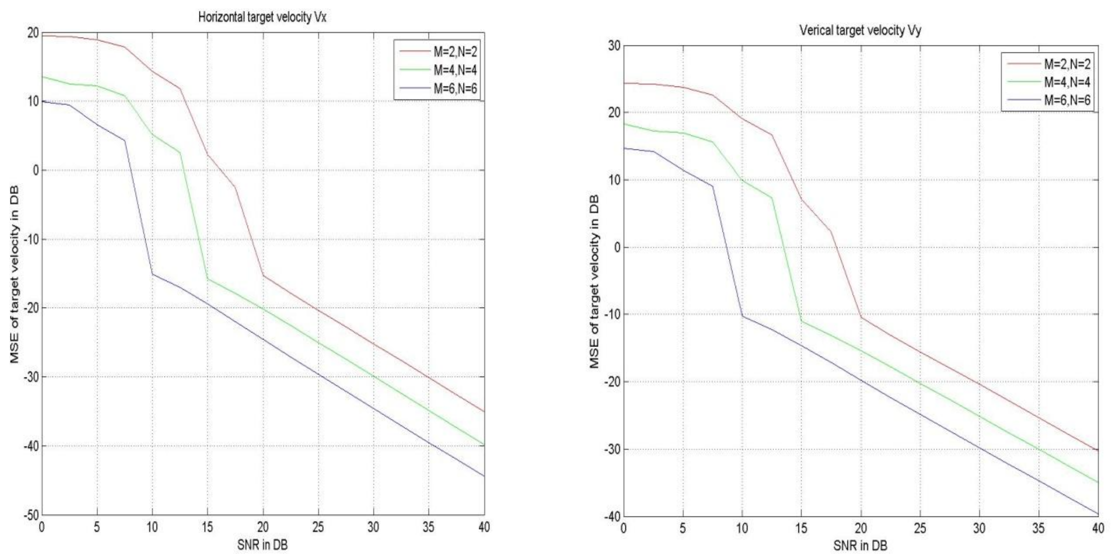
Simulations carried out in fig.2 are done for 200 Monte Carlo runs. In each Monte Carlo run the target amplitude and clutter amplitude are randomly generated as a zero mean Gaussian distributed random variable. For the simulation signal to noise ratio is taken as

$$\mathrm{SNR}= \sum_{m,n} \frac{\alpha_{m,n}^2}{\sigma^2} \qquad (49)$$

Where SNR is varied from 0 to 40db.Mean square error of target velocity is given by

$$\mathrm{MSE}=\frac{1}{T}\sum_{t=1}^{T} \|(\hat{v}_t - v\|^2 \qquad (50)$$

v is the true velocity of the target, T is the number of Monte Carlo runs and $\hat{v}_t$is the estimated velocity for different runs.



(a) (b)

Fig 3: (a) MSE vs SNR for V_x ; (b) MSE vs SNR for V_y

Table 2 **Number of Transmitters and Receivers**

Cases	Transmitters	receivers	Transmitting angles in degree	Receiving angles in degree
1	M=2	N=2	0 and 65	-30 and 40
2	M=4	M=4	0,15,25,65	-30,40,-67,-47
3	M=6	N=6	0,15,25,65,45,78	-30,40,-67,-47,-87,20

Fig.3 shows the MSE vs SNR of Maximum likelihood estimation for different transmit receive pairs. SNR threshold is the point at which there is a large change in slope of the MSE vs SNR graph. From the fig.3 we can see that as we increase the number of transmit receive pair MSE and SNR threshold slightly reduces. System parameters are same as in table 1 except for number of antennas.

Table 3 **SNR Threshold for different Transmit Receive pairs**

Cases	SNR threshold
1(M=2,N=2)	20db
2(M=4,N=4)	15db
3(M=6,N=6)	10db

B. Detection

Simulations for fig.4 are carried out at different SNR to detect the target in the presence of Non-homogeneous clutter by using the General likelihood ratio test detector. In this simulation probability of false alarm is varied from 10^{-2} to 10^{0}. Threshold is set to meet a given probability of false alarm. The amplitude of target is generated as a zero mean Gaussian random variable. Simulations are carried out for 4 cases SNR=10db, SNR=15db, SNR=20db and SNR=25db.System parameters are same as in table 1

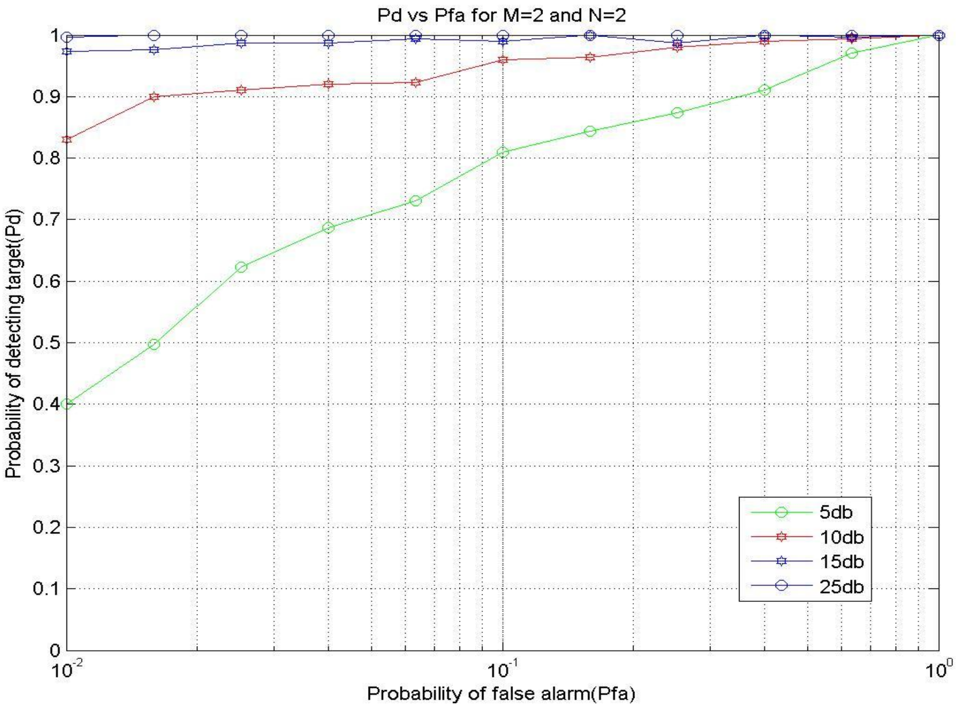


Fig .4p_d versus Pfa of GLRT detector

Fig.4 shows the simulation of probability of detection (p_d) versus Pfa of GLRT for different SNR. Simulation shows that as SNR increases the probability of detection is more that is target is detected easily at high SNR. At low SNR simulation results shows that as Pfa decrease that is false detection of target decreases it is difficult to detect the target. Increase of detection of target at low Pfa at low SNR is due to the fake detection of target even if the target is absent due to the noise and clutters. At high SNR the probability of detection is constant at all Pfa.

VII. CONCLUSION

In this paper the velocity estimation and detection of a moving target usingdistributed MIMO radar in non-homogeneous clutter environments is considered. The clutter was modeled to have a low-rank subspace structure with spatially non-homogeneous clutter power. The CRB of the velocity estimates is obtained via the reverse transformation of parameters. Numerical results show that the MSE of the ML estimator of the velocity matches the CRB at high SNR. Comparison with the covariance matrix estimator also shows that the proposed ML estimator has better performance in clutter with non-homogeneous power. Numerical results shows that as we increase the number of antennas MLE shows better performance and SNR threshold also reduces.

Detection of moving target in distributed MIMO radar by using GLRT in non-homogeneous environment is considered. Numerical results shows that as SNR increases the probability of detection will be more and also probability of detection will be same for any Pfa at high SNR

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