MIMO RADAR TARGET DETECTION USING LOW-COMPLEXITY RECEIVER

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ABSTRACT

This paper studies reduced complexity target detection using multiple-input-multiple-output (MIMO) radar with lower complexity. To reduce either hardware or software complexity, some parts of the test statistic are eliminated in the proposed method. For the general case where clutter-plus-noise and reflection coefficients are correlated, the test statistic requires the computation of a set of matched filters (MFs). These MFs correlate the clutter-plus-noise-free signal received at one receiver due to the signal transmitted from some transmit antenna with the signal received at another receiver. For a special case of uncorrelated clutter-plus-noise and reflection coefficients and orthogonal waveforms, the proposed method is equivalent to choosing a subset of transmitters to maximize detection probability. In this case we prove that selecting the transmitters at each receiver corresponding to the largest signal-to-clutter-plus-noise ratio (SCNRs) leads to the best detection performance. In the more general case our algorithm picks the best of these MFs to implement under the constraint that the total number of these MFs that one can implement at each receiver is limited.

Index Terms— MIMO radar, matched filter, transmitter selection, detection.

1. INTRODUCTION

In recent years, the performance of multiple-input-multiple-output (MIMO) radar systems have been widely investigated [1, 2]. Passive radar has also attracted attention over the past few years due to the advantages of low cost, low probability of intercept, etc. In passive radar, existing illuminators of opportunity be employed to save the cost and energy on transmission.

Passive MIMO radar [3] is a passive radar system employing multiple existing illuminators and multiple receivers. Active and passive MIMO radar implementations require large complexity when a large number of transmitters are present, so that the lower complexity approaches studied here, like transmitter selection approaches, are of considerable interest. Our problem is somewhat similar to antenna selection. In recent studies on antenna selection for MIMO systems, the selection strategies for minimizing the average error probability have been investigated in [4,5] when a maximum likelihood or zero forcing receiver is used. In [6–8], antenna selection is suggested for target localization in distributed MIMO radar by minimizing the trace of Cramér-Rao bound (CRB). In [9], the antenna selection for minimizing the volume of an η-confidence ellipsoid of estimation error is presented.

For a MIMO radar system, the hardware or software complexity depends heavily on the number of matched filters (MFs) employed . For many practical scenarios, when the number of transmitters is large, the number of candidate MFs is typically large. It is necessary to control the complexity and cost and to achieve the best possible performance simultaneously. In this paper, we present a limited-complexity receiver design method for maximizing the target detection performance. The proposed method can be used in active MIMO radar systems. If the location of the transmitters, the transmitted signals, and the statistical properties of the channels are learned or accurately estimated and any direct path signals have been perfectly separated, we can also use the approach in passive MIMO radar. We derive the log-likelihood ratio (LLR) function for a general case accounting for possibly correlated target reflection coefficients and clutter-plus-noise, and showed that a limited-complexity receiver can be achieved by MF selection. In a special case where the signals transmitted by the transmitters are mutually orthogonal and the clutter-plus-noise and the reflection coefficients are spatially white, the MF selection is equivalent to choosing a subset of transmitters. We prove that selecting the transmitters at each receiver corresponding to the largest SCNRs leads to the best detection performance. Further, we show that selecting a few transmitters (or MFs) can lead to detection performance which is close to the detection performance when all transmitters (or MFs) are selected.

2. SIGNAL MODEL FOR TARGET DETECTION

Consider a MIMO radar system with M transmitters located at known positions $(x_{t,m}, y_{t,m})$, $m = 1, 2, ..., M$ and N re-

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ceivers located at $(x_{r,n}, y_{r,n})$, $n = 1, 2, ..., N$. The signal from the m-th transmitter is assumed known and can be written as $\sqrt{E_m} s_m(t)$, $m = 1, 2, ..., M$, where $\int_{\mathcal{T}_m} |s_m(t)|^2 dt = 1$, E_m is the transmitted energy, and $\mathcal{T}_m$ is the observation duration. Consider the detection of a possible static target located at a given position (x, y). The received signal at the n-th single antenna receiver can be written as

$$r_n(t) = \sum_{m=1}^{M} \frac{\beta_{mn}\sqrt{E_m}}{R_{t,m}R_{r,n}} s_m(t-\tau_{mn}) + w_n(t), \tag{1}$$

where $w_n(t)$ is zero-mean complex Gaussian clutter-plus-noise, assumed to be temporally white such that $\mathbb{E}\{w_i(t)w_j^*(u)\} = N_{ij}\delta(t-u)$, where N_{ij} is the (i, j)-th element of a positive definite Hermitian matrix $\boldsymbol{N}$. The zero-mean and variance σ_{mn}^2 reflection coefficient β_{mn} is complex Gaussian distributed and independent of the clutter-plus-noise components. The term $R_{t,m}$ is the distance between the m-th transmitter and the target, $R_{r,n}$ is the distance between the n-th receiver and the target, and τ_{mn} is the time delay between the m-th transmitter and the n-th receiver. They satisfy

$$\begin{aligned} R_{t,m} &= \sqrt{(x_{t,m}-x)^2 + (y_{t,m}-y)^2}, \\ R_{r,n} &= \sqrt{(x_{r,n}-x)^2 + (y_{r,n}-y)^2}, \end{aligned} \tag{2}$$

and

$$\tau_{mn} = \frac{R_{t,m} + R_{r,n}}{c}, \tag{3}$$

where c is the speed of light. Define

$$\boldsymbol{\xi} = [\boldsymbol{\xi}_1^T, ..., \boldsymbol{\xi}_N^T]^T, \tag{4}$$

where $\boldsymbol{\xi}_n = [\xi_{1n}, ...\xi_{Mn}]^T$ and $\xi_{mn} = \beta_{mn}\sqrt{E_m}/(R_{t,m}R_{r,n})$. Define the covariance matrix of $\boldsymbol{\xi}$ as $\mathbb{E}\{\boldsymbol{\xi}\boldsymbol{\xi}^H\} = \boldsymbol{\Lambda}$. From (1), the target detection problem can be formulated as

$$\mathcal{H}_0 : r_n(t) = w_n(t) \tag{5}$$

$$\mathcal{H}_1 : r_n(t) = \sum_{m=1}^{M} \xi_{mn} s_m(t-\tau_{mn}) + w_n(t). \tag{6}$$

Define $\boldsymbol{r} = [r_1(t), ..., r_N(t)]^T$. The log-likelihood ratio (LLR) is given by

$$\begin{aligned} \mathcal{L} &= \ln\left(\frac{p(\boldsymbol{r}|\mathcal{H}_1)}{p(\boldsymbol{r}|\mathcal{H}_0)}\right) \\ &= C + \boldsymbol{x}^H((\boldsymbol{N}\otimes\boldsymbol{\Xi})^{-1} - (\boldsymbol{N}\otimes\boldsymbol{\Xi} + \boldsymbol{\Psi}\boldsymbol{\Lambda}\boldsymbol{\Psi}^H)^{-1})\boldsymbol{x}, \end{aligned} \tag{7}$$

where $\otimes$ denotes Kronecker product, $p(\boldsymbol{r}|\mathcal{H}_i)$ is the probability density function (pdf) of $\boldsymbol{r}$ under hypothesis $\mathcal{H}_i$, i=0,1, the constant $C = \ln(\det(\boldsymbol{N}\otimes\boldsymbol{\Xi})) - \ln(\det(\boldsymbol{N}\otimes\boldsymbol{\Xi} + \boldsymbol{\Psi}\boldsymbol{\Lambda}\boldsymbol{\Psi}^H))$, $\boldsymbol{\Xi}$ is an $MN\times MN$ matrix with the $((n_1-1)M+m_1, (n_2-1)M+m_2)$-th element ($n_1, n_2 = 1, ..., N$ and $m_1, m_2 = 1, ..., M$) given by

$$\Xi_{(n_1-1)M+m_1,(n_2-1)M+m_2} = \int_{\mathcal{T}_{m_1}} s_{m_1}^*(t-\tau_{m_1n_1}) s_{m_2}(t-\tau_{m_2n_2}) dt, \tag{8}$$

and $\boldsymbol{\Psi} = \text{Diag}\{\boldsymbol{\Psi}_1, ..., \boldsymbol{\Psi}_N\}$, where $\boldsymbol{\Psi}_n$ is an $MN \times M$ matrix whose i-th column is the $((n-1)M + i)$-th column of $\boldsymbol{\Xi}$. In (7),

$$\boldsymbol{x} = [\boldsymbol{x}_1^T, ..., \boldsymbol{x}_N^T]^T \tag{9}$$

is an $MN^2 \times 1$ complex Gaussian vector, where $\boldsymbol{x}_n = [x_{11n}, ..., x_{MNn}]^T$ is an $MN\times 1$ vector with the $((n'-1)M+m)$-th element ($m = 1, ..., M$ and $n' = 1, ..., N$) given by

$$x_{mn'n} = \int_{\mathcal{T}_m} s_m^*(t-\tau_{mn'}) r_n(t) dt. \tag{10}$$

3. LIMITED-COMPLEXITY RECEIVER DESIGN

From (7), we see that the test statistic and hence the detection performance is dependent on the received signals only via the MF output vector $\boldsymbol{x}$. The size of $\boldsymbol{x}$ determines the complexity of the associated hardware or software. We propose to select a subset of the vector $\boldsymbol{x}$ for subsequent processing to reduce complexity. Before proceeding, define a selection vector

$$\boldsymbol{a} \triangleq [\boldsymbol{a}_1^T, \boldsymbol{a}_2^T, ..., \boldsymbol{a}_N^T]^T, \tag{11}$$

where $\boldsymbol{a}_n = [\boldsymbol{a}_{11n}, ..., \boldsymbol{a}_{MNn}]^T$, in which $a_{mn'n} \in \{1, 0\}$ indicating whether or not the signal associated with the (m, n')-th transmitter to receiver path is processed at the n-th receiver. Define a selection matrix

$$\boldsymbol{J}(\boldsymbol{a}) \triangleq \text{Diag}\{\boldsymbol{J}_1(\boldsymbol{a}_1), ..., \boldsymbol{J}_N(\boldsymbol{a}_N)\} \tag{12}$$

where Diag$\{\cdot\}$ denotes a block diagonal matrix and

$$\boldsymbol{J}_n(\boldsymbol{a}_n) \triangleq \text{diag}_r\{\boldsymbol{a}_n\}, \tag{13}$$

in which diag$_r\{\cdot\}$ represents a diagonal matrix with the argument on its diagonal, but with the all-zero rows removed [10, 11]. The size of $\boldsymbol{J}_n(\boldsymbol{a}_n)$ is $u_n \times MN$, where

$$u_n = \|\boldsymbol{a}_n\|_0 \tag{14}$$

is the number of paths to be processed at receiver n and $\|\cdot\|_0$ denotes the ℓ_0-norm operator. For a given selection, the MFs corresponding to the zero elements in $\boldsymbol{a}$ are no longer needed and the associated hardware or software can be saved. Accordingly, the output vector is reduced from $\boldsymbol{x}$ to $\boldsymbol{J}(\boldsymbol{a})\boldsymbol{x}$. Then the test statistic in (7) becomes

$$\begin{aligned} T_s = (\boldsymbol{J}(\boldsymbol{a})\boldsymbol{x})^H \Bigg(&\left(\boldsymbol{J}(\boldsymbol{a})\boldsymbol{\Sigma}_0\boldsymbol{J}^T(\boldsymbol{a})\right)^{-1} \\ &- \left(\boldsymbol{J}(\boldsymbol{a})\boldsymbol{\Sigma}_1\boldsymbol{J}^T(\boldsymbol{a})\right)^{-1}\Bigg)\boldsymbol{J}(\boldsymbol{a})\boldsymbol{x}, \end{aligned} \tag{15}$$

where

$$\boldsymbol{\Sigma}_0 = \mathbb{E}\{\boldsymbol{x}\boldsymbol{x}^H|\mathcal{H}_0\} = \boldsymbol{N}\otimes\boldsymbol{\Xi} \tag{16}$$

$$\boldsymbol{\Sigma}_1 = \mathbb{E}\{\boldsymbol{x}\boldsymbol{x}^H|\mathcal{H}_1\} = \boldsymbol{N}\otimes\boldsymbol{\Xi} + \boldsymbol{\Psi}\boldsymbol{\Lambda}\boldsymbol{\Psi}^H, \tag{17}$$

in which $\mathbb{E}\{\cdot\}$ denotes expectation. For the special case, where signals associated with all paths are processed, (15) is equivalent to the test statistic in (7). From (15), we see that $\sum_{n=1}^{N} u_n$ MFs, $(1+\sum_{n=1}^{N} u_n)\sum_{n=1}^{N} u_n$ multipliers, and $(1+\sum_{n=1}^{N} u_n)(-1+\sum_{n=1}^{N} u_n)$ adders are required. To limit the cost, suppose receiver n can at most process signals associated with $A_n(A_n \leqslant MN)$ paths , namely $u_n \leqslant A_n$.

The test statistic T_s is compared to a threshold γ, such that a decision for H_1 is made if $T_s > \gamma$ and H_0 is chosen otherwise. If the Neyman-Pearson criterion is employed, the optimal selection can be obtained by solving the following optimization problem

$$\mathbf{P}_1 \begin{cases} \max\limits_{\boldsymbol{a}\in\{0,1\}^{MN^2}} & Pr(T_s > \gamma(P_{FA}; \boldsymbol{a}), \mathcal{H}_1) \quad (18a) \\ s.t. & 1 \le u_n \le A_n, n = 1, 2, ..., N \quad (18b) \end{cases}$$

The solution of $\mathbf{P}_1$ provides guidance to system designers on how to maximize detection performance with limited budget for a general case where the target reflection coefficients and the clutter-plus-noise components can be correlated.

4. MIMO RADAR TRANSMITTER SELECTION

Assume target reflection coefficients and clutter-plus-noise are spatially white such that the matrix $\boldsymbol{\Lambda}$ can be written as $\boldsymbol{\Lambda} = \mathrm{Diag}\{\boldsymbol{\Lambda}_1, ..., \boldsymbol{\Lambda}_N\}$, where $\boldsymbol{\Lambda}_n = \mathrm{diag}\ \{\sigma_{1n}^2 E_1/(R_{t,1}R_{r,n})^2, ..., \sigma_{Mn}^2 E_M/(R_{t,M}R_{r,n})^2\}$ and

$$\boldsymbol{N} = \mathrm{diag}\{N_{11}, N_{22}..., N_{NN}\}, \tag{19}$$

where N_{nn} is the power spectral density of $w_n(t)$. Without loss of generality, we assume $N_{11} = N_{22} =, ..., = N_{NN} = N_0$. Assume the transmitted signals are mutually orthogonal and maintain orthogonality for any delay τ of interest. Under these assumptions, the test statistic in (7) becomes

$$T_s = \sum_{n=1}^{N}\sum_{m=1}^{M} \frac{E_m\sigma_{mn}^2}{N_0(E_m\sigma_{mn}^2 + N_0(R_{t,m}R_{r,n})^2)}|x_{mn}|^2, \tag{20}$$

where

$$x_{mn} = \int_{\mathcal{T}_m} s_m^*(t-\tau_{mn})r_n(t)dt. \tag{21}$$

In this case, we see from (20) and (21) that we only need MN MFs, so the MF output vector become an $MN \times 1$ vector $\boldsymbol{x} = [x_{11}, x_{21}, ..., x_{MN}]^T$. Thus, we redefine an $MN \times 1$ selection vector $\boldsymbol{a} = [\boldsymbol{a}_1^T, ..., \boldsymbol{a}_N^T]^T$, where $\boldsymbol{a}_n = [a_{1n}, ..., a_{Mn}]^T$. After selection, the test statistic in (20) becomes

$$T_s = \sum_{n=1}^{N}\sum_{m=1}^{M} \frac{a_{mn}E_m\sigma_{mn}^2}{N_0(E_m\sigma_{mn}^2 + N_0(R_{t,m}R_{r,n})^2)}|x_{mn}|^2, \tag{22}$$

From (21), we can see that each MF output x_{mn} corresponds to a transmitter-and-receiver pair. Thus, at each receiver, the selection of MFs implies the selection of the associated transmitters. Define the SCNR of the (m,n)-th path as $\eta_{mn} = E_m\sigma_{mn}^2/N_0(R_{t,m}R_{r,n})^2$. Then (22) can be rewritten as a function of the SCNRs as

$$T_s = \sum_{n=1}^{N}\sum_{m=1}^{M} \zeta_{mn}, \tag{23}$$

where $\zeta_{mn} = \frac{\rho_{mn}}{N_0(\rho_{mn}+1)}|x_{mn}|^2$ and $\rho_{mn} = \eta_{mn}a_{mn}$. Let $\boldsymbol{\eta} = [\eta_{11}, ..., \eta_{MN}]^T$, $\boldsymbol{\rho}_n = [\rho_{1n}, ..., \rho_{Mn}]^T$ and $\boldsymbol{\rho} = [\boldsymbol{\rho}_1^T, ..., \boldsymbol{\rho}_n^T]^T$.

Lemma 1. *Denote by $\rho_{(1)}, \rho_{(2)} ..., \rho_{(K)}$ the decreasing sequence of nonnegative $\rho_{11}, \rho_{21}, ..., \rho_{MN}$ and define $\boldsymbol{\rho}_{(K)}=[\rho_{(1)}, \rho_{(2)} ..., \rho_{(K)}]^T$, where $K = MN$. Let $\boldsymbol{a}^1$ and $\boldsymbol{a}^2$ be two feasible solutions for $\mathbf{P}_1$, and correspondingly $\boldsymbol{\rho}^1 = \boldsymbol{a}^1 \odot \boldsymbol{\eta}$ and $\boldsymbol{\rho}^2 = \boldsymbol{a}^2 \odot \boldsymbol{\eta}$, where $\odot$ denotes Hadamard product. If $\boldsymbol{\rho}_{(K)}^1 \geq \boldsymbol{\rho}_{(K)}^2$, where '$\geq$' means $\rho_{(k)}^1 \geqslant \rho_{(k)}^2$, $k = 1, ..., K$, and $\rho_{(k)}^1$ and $\rho_{(k)}^2$ are the k-th element of $\boldsymbol{\rho}_{(K)}^1$ and $\boldsymbol{\rho}_{(K)}^2$, respectively, then*

$$P_D(\boldsymbol{\rho}^1) \geqslant P_D(\boldsymbol{\rho}^2) \tag{24}$$

where $P_D(\boldsymbol{\rho}) = Pr(T_s > \gamma|\mathcal{H}_1)$ and γ is determined by the required level of false alarm probability and the vector $\boldsymbol{\rho}$.

Proof. See [12]. □

From Lemma (1), the following conclusion is obviously,

Theorem 1. *If the corresponding SCNRs of the selected transmitters at receiver n are the largest[1] A_n values in $\{\eta_{1n}, ..., \eta_{Mn}\}$, we can obtain the optimal solution of $\mathbf{P}_1$.*

5. SIMULATION RESULTS

In this section, numerical simulations are presented to illustrate our conclusions. We set $N_0 = 1$, $E_m = 10^{13}$ and $\sigma_{mn} = 1$, for all m and n. The target is located at (x, y)=(0, 0) m. Suppose the transmitted waveforms are $s_m(t) = \frac{1}{\sqrt{T}}\exp(j2\pi f_m t), 0 < t < T$, where $T = 1ms$. Define $\boldsymbol{f} = [f_1, f_2, ..., f_M]$ as the frequency vector . All these results are obtained based on 10^4 Monte Carlo simulations.

Table 1: Detection probability of different selections

Selection Combination	SCNR (dB)	P_D
$\{<1,1>, <1,2>\}$	{10,10}	0.8798
$\{<1,1>, <2,2>\}$	{10,3.98}	0.7286
$\{<1,1>, <3,2>\}$	{10,0.46}	0.6868
$\{<2,1>, <1,2>\}$	{3.98,10}	0.7422
$\{<2,1>, <2,2>\}$	{3.98,3.98}	0.4354
$\{<2,1>, <3,2>\}$	{3.98,0.46}	0.3196
$\{<3,1>, <1,2>\}$	{0.46,10}	0.6785
$\{<3,1>, <2,2>\}$	{0.46,3.98}	0.3117
$\{<3,1>, <3,2>\}$	{0.46,0.46}	0.1880

[1] For some case where $\eta_{m_1 n} = \eta_{m_2 n}$ and $m_1 < m_2$, we select the m_1-th transmiter preferentially.

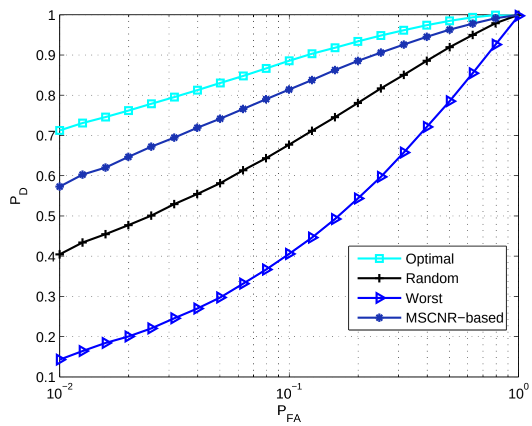

Fig. 1: The average ROC curves of the optimal selection, random selection, worst selection and MSCNR-based selection

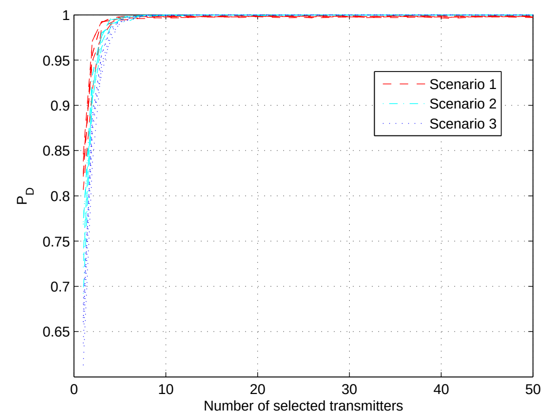

Fig. 2: Detection probabilities of the MSCNR-based selection vs. the number of transmitters.

First, consider uncorrelated noise, reflection coefficient and orthogonal waveforms. Assume there are $M = 3$ transmitters and $N = 2$ receivers. The three transmitters are located at $(x_{t,1}, y_{t,1})$=(0,1) *km*, $(x_{t,2}, y_{t,2})$= (0, 2) *km*, and $(x_{t,3}, y_{t,3})$ =(0, 3) *km*. The two receivers are located at $(x_{r,1}, y_{r,2})$=(-1, 0) *km* and $(x_{r,2}, y_{r,2})$=(1, 0) *km*. Suppose the number of transmitters that can be selected is $A_1 = A_2 = 1$. Table 1 shows the performance of all selection schemes. Denote by $< m, n >$ the m-th transmitter being selected at the n-th receiver. The frequency vector for this example is $\boldsymbol{f} = [\frac{10}{T}, \frac{20}{T}, \frac{30}{T}]$, which ensures that the waveforms are approximately orthogonal. The false alarm probability is 10^{-2}. Table 1 shows that higher detection probability can be achieved when the subset of the selected transmitters have larger SCNRs. For example, the corresponding SCNRs of the selection $\{< 2, 1 >, < 1, 2) >\}$ are $\{3.98, 10\}$ dB, which is larger than the the corresponding SCNRs of the selection $\{< 3, 1 >, < 3, 2 >\}$, which are $\{0.46, 0.46\}$ dB. The resulting detection probabilities of them are 0.7422 and 0.1880 respectively. Clearly, the former selection with higher SCNRs has bigger detection probability. We can see that optimal selection is $\{< 1, 1 >, < 1, 2 >\}$, and the corresponding SCNRs are the largest, which verifies Theorem 1.

Next, assume the clutter-plus-noise and the reflection coefficients are spatially correlated. The correlation of clutter-plus-noise are set as N_{ij}=0.1, $i, j = 1, 2, i \neq j$ and the correlation of reflection coefficients are set as $\mathbb{E}\{\beta_{m_1n_1}\beta^*_{m_2n_2}\}$=0.1, $m_1, m_2 = 1, ...M$, n_1, n_2=1, ..., N, $m_1 \neq m_2$ or $n_1 \neq n_2$. $M = 8$ transmitters are randomly and uniformly located in a ring with inner radius 2 *km* and outer radius 5 *km*. There are $N = 2$ receivers located at $(x_{r,1}, y_{r,1})$=(-1, 0) *km* and $(x_{r,2}, y_{r,2})$=(1, 0) *km*. The frequency vector for this case is $\boldsymbol{f} = [\frac{1}{2T}, \frac{2}{2T}, ..., \frac{4}{T}]$. Suppose the number of transmitters that can be selected is $A_1 = A_2 = 2$. Fig. 1 plots the ROC for the optimal selection, random selection, worst selection and the maximum SCNR-based (MSCNR-based) selection, each averaged over different transmitter replacements. We test 100 random placement of the transmitters in this figure. We can see that the ROC of MSCNR-based selection is close to the optimal selection in this case.

At last, we consider a larger number of transmitters. In this case, reflection coefficients are uncorrelated and the transmitted waveforms are non-orthogonal. Consider five different transmitter placements. In each transmitter placement, $M = 50$ transmitters are randomly located in a ring with inner radius 3 *km* and outer radius 8 *km*. The single receiver is located at $(x_{r,1}, y_{r,1})$=(0.5, 0) *km*. We consider three scenarios. The frequency vector $\boldsymbol{f}$ for each case is $[\frac{3}{50T}, \frac{6}{50T}, ..., \frac{3}{T}]$ (scenario 1), $[\frac{6}{50T}, \frac{12}{50T}, ..., \frac{6}{T}]$ (scenario 2) and $[\frac{9}{50T}, \frac{18}{50T}, ..., \frac{9}{T}]$ (scenario 3). Fig 2 shows the detection probabilities of the MSCNR-based selection vs. the number of selected transmitters (or MFs) under $P_{FA} = 10^{-2}$ for each placement and each transmitted frequency. This figure shows that in all tested cases, the detection performance for properly selecting 9 transmitters (or MFs) is very close to the performance for selecting all 50 MFs.

6. CONCLUSIONS

We studied the limited-complexity receiver design for MIMO radar, considering that usually only a limited number of MFs can be implemented at each receiver due to cost considerations. We investigated the target detection performance and formulated an optimization problem to maximize the detection performance for a fixed false alarm level. For the case of uncorrelated clutter-plus-noise and uncorrelated reflection coefficients and orthogonal waveforms, we prove selecting the transmitters at each receiver corresponding to the largest SCNRs leads to the best detection performance. Further, we show that selecting a few transmitters (or MFs) can lead to detection performance which is almost equal to the detection performance when all transmitters (or MFs) are selected for a numerical example.

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