# OPTIMAL POWER ALLOCATION FOR MIMO RADARS WITH HETEROGENEOUS PROPAGATION LOSSES

*Xiufeng Song, Peter Willett, and Shengli Zhou*

Dept. of Electrical and Computer Engr., Univ. of Connecticut, Storrs, CT, 06269

**ABSTRACT**

A multiple-input multiple-output (MIMO) radar can improve system performance with waveform and spatial diversities. Mathematically, the multiple independent waveforms increase the dimension of signal space, so optimal transmission power allocation deserves investigation. The majority of the literature prefers to omit the effect of propagation attenuation, and considers the receiving gain vectors to be independently and identically distributed (i.i.d.) in power allocation. In this paper, we integrate the propagation losses into MIMO radar signal model, and investigate the power allocation problems under three popular criteria: maximizing the mutual information, minimizing the minimum mean square errors, and maximizing the echo energy. As their objective functions are either convex or concave, the optimal strategies are theoretically guaranteed.

***Index Terms*—** MIMO radar, power allocation, mutual information, minimum mean square error, propagation attenuation.

## 1. INTRODUCTION

A multiple-input multiple-output (MIMO) radar system employs multiple distributed or co-located antennas in transmission and receiving, and it may outperform a monostatic configuration on target detection, information extraction, and target estimation [1–7]. If all the transmitters were to emit mutually independent waveforms, the dimension of signal space would be identical to the number of transmission antennas. Therefore, adaptively allocating the transmission power within the entire noise space is a smart choice.

MIMO radar power allocation is an active research subarea. In [2], the authors suggested two criteria in a white Gaussian noise environment: maximizing the mutual information (MI) between the received signal and the target scatterer matrix, and minimizing the minimum mean square error (MMSE) of the estimate of the target scatterer matrix. Later, the MI based power allocation was extended to MIMO radar space-time codes design [3], while the interaction between a jammer and a MIMO radar system is investigated from a game theoretic perspective [4]. In [6], the author suggested to maximize the total energy of the sampled echoes in power allocation.

In [1–6], the path gain for a bistatic geometry is globally modeled as a random scalar, and the path gain vectors—the collection of all path gain scalars for a certain receiver—are assumed to be independently and identically distributed (i.i.d.). However, as transmitter-target-receiver geometries may significantly differ from propagation distances and antenna gains [8], their power attenuation levels are not identical. As a result, the i.i.d. assumption is not appropriate. In this paper, a path gain scalar is modeled as a product of two components: the propagation loss factor and the target reflection coefficient. The former is a function of bistatic distance and antenna beampattern, and it depends on geometry. The target reflection coefficients are i.i.d. random variables if the antennas are sufficiently separated [1]. After including the propagation loss diversity, we revisit the MIMO radar power allocation problems under various criteria including MI maximization, MMSE minimization, and the energy maximization, and this is the main contribution of this paper. MIMO radar power allocation with propagation loss was also studied in [7], where its objective is to minimize the target localization Cramér-Rao bounds.

The rest of this paper is as follows. Section 2 gives the MIMO radar signal model with propagation losses, while the optimal power allocation strategies under different criteria are investigated in Section 3. There are numerical examples in Section 4, and conclusions are drawn in the end.

This work was supported by the U.S. Office of Naval Research under Grants N00014-09-10613 and N00014-10-10412.

## 2. SIGNAL MODEL

### 2.1. Classical Model

Let the MIMO radar system be composed of $n_t$ transmitters and $n_r$ receivers, all properly synchronized. Suppose that the transmitted waveform of the $j$th transmitter is $\boldsymbol{s}_j$, of which the size is $K \times 1$, and then the sampled echoes for receiver $i$ is modeled as [2–5]

$$\boldsymbol{y}_i = \boldsymbol{S}\boldsymbol{h}_i + \boldsymbol{w}_i, \tag{1}$$

where $\boldsymbol{S} = [\boldsymbol{s}_1, \boldsymbol{s}_2, \cdots, \boldsymbol{s}_{n_t}]$ is the $K \times n_t$ transmitted waveform matrix with $K \geq n_t$, $\boldsymbol{w}_i$ represents the $K \times 1$ receiver noise vector, and $\boldsymbol{h}_i = [h_{i,1}, h_{i,2}, \cdots, h_{i,n_t}]^T$ stands for the random path gain vector for receiver $i$. Defining $\boldsymbol{H} = [\boldsymbol{h}_1, \boldsymbol{h}_2, \cdots, \boldsymbol{h}_{n_r}]$, the received signal matrix $\boldsymbol{Y} = [\boldsymbol{y}_1, \boldsymbol{y}_2, \cdots, \boldsymbol{y}_{n_r}]$ can be compactly written as

$$\boldsymbol{Y} = \boldsymbol{S}\boldsymbol{H} + \boldsymbol{W}, \tag{2}$$

where $\boldsymbol{W} = [\boldsymbol{w}_1, \boldsymbol{w}_2, \cdots, \boldsymbol{w}_{n_r}]$ represents the $K \times n_r$ noise matrix. This classical model has three fundamental assumptions: ***1)*** the receivers are homogeneous, and then $\boldsymbol{w}_i$'s are i.i.d. complex Gaussian vectors; ***2)*** $\boldsymbol{h}_i$'s are i.i.d. complex Gaussian random vectors, and ***3)*** $\boldsymbol{W}$ and $\boldsymbol{H}$ are mutually independent. The first and the last assumptions are technically fair; however, the second one is arguable, as it ignores the spatial distinction of different bistatic paths. This paper will relax the second assumption, and revisit the MIMO radar power allocation problems.

### 2.2. Including Propagation Loss Diversities

Based on the *bistatic radar equation* [8, p.68], a path gain scalar $h_{i,j}$ contains two parts: the target reflection coefficient $g_{i,j}$ and the propagation loss factor $p_{i,j}$. Suppose that the transmitters and receivers are sufficiently separated; the reflection gains $g_{i,j}$'s for different bistatic constellations are independent [1]. Furthermore, if the target is comprised of a large number of small i.i.d. random scatterers, the $\boldsymbol{g}_i$'s would be i.i.d. complex Gaussian vectors with probability density function $\boldsymbol{g}_i \sim \mathcal{CN}(\mathbf{0}, \sigma_g^2 \boldsymbol{I}_{n_t})$ due to *the central limit theorem* [1], where $\boldsymbol{g}_i \triangleq [g_{i,1}, g_{i,2}, \cdots, g_{i,n_t}]^T$ denotes the target reflection gain vector for the $i$th receiver. The propagation loss factor $p_{i,j}$ is a function of target proximity and antenna properties [8, p.68]

$$p_{i,j} = \frac{c}{d_t^j d_r^i \sqrt{A_t^j A_r^i}}, \tag{3}$$

where $c$ is a constant, $d_t^j$ and $d_r^i$ respectively denote the distances between the target and transmitter $j$ and that between the target and the $i$th receiver, while $A_t^j$ and $A_r^i$ respectively denote the transmission and receiving antenna gains. Obviously, the $p_{i,j}$'s would most likely differ in a realistic MIMO configuration; therefore, the ideal condition that $\boldsymbol{p}_i = \boldsymbol{p}_k$ for $i \neq k$ may not be guaranteed, where $\boldsymbol{p}_i = [p_{i,1}, p_{i,2}, \cdots, p_{i,n_t}]^T$. As a result, $\boldsymbol{h}_i$'s are no longer identically distributed. Note that if the transmission antennas are omnidirectional the $p_{i,j}$'s would be unavailable, as one does not know where echoes are from. However, if the transmitters have a certain beamforming capability and they cooperatively and sequentially search voxels of interest (or track a moving target) assuming beam synchronization, the $p_{i,j}$'s are easily approximable.

Thus considering propagation losses, an improved MIMO radar signal model might be

$$\boldsymbol{Y} = \boldsymbol{S}(\boldsymbol{G} \odot \boldsymbol{P}) + \boldsymbol{W}, \tag{4}$$

where $\boldsymbol{G} = [\boldsymbol{g}_1, \boldsymbol{g}_2, \cdots, \boldsymbol{g}_{n_r}]$ is the target scatterer matrix, $\boldsymbol{P} = [\boldsymbol{p}_1, \boldsymbol{p}_2, \cdots, \boldsymbol{p}_{n_r}]$ denotes the propagation loss matrix, and $\odot$ indicates Hadamard product. In (4), each column of $\boldsymbol{Y}$ is expressed as $\boldsymbol{y}_i = \boldsymbol{S}(\boldsymbol{g}_i \odot \boldsymbol{p}_i) + \boldsymbol{w}_i$, where $\boldsymbol{y}_i$'s are independent Gaussian random vectors, but with different pdfs.

## 3. OPTIMAL MIMO RADAR POWER ALLOCATION

We are interested in the MIMO radar power allocation with heterogeneous propagation losses. As [1] and [5], we assume that the receiver noise is white, say $\boldsymbol{w}_i \sim \mathcal{CN}(\mathbf{0}, \sigma_w^2 \boldsymbol{I}_K)$, and that the waveforms are orthogonal, say $\boldsymbol{s}_j^T \boldsymbol{s}_k = 0$ for $j \neq k$, but with different power. As a consequence, the conditional pdf of $\boldsymbol{Y}$ for a given $\boldsymbol{S}$ is

$$f(\boldsymbol{Y}|\boldsymbol{S}) = \prod_{i=1}^{n_r} f(\boldsymbol{y}_i|\boldsymbol{S}), \tag{5}$$

where $f(\boldsymbol{y}_i|\boldsymbol{S}) \sim \mathcal{CN}\big(\mathbf{0}, \sigma_w^2 \boldsymbol{I}_K + \sigma_g^2 \boldsymbol{S}\boldsymbol{\Lambda}_i \boldsymbol{S}^H\big)$, and $\boldsymbol{\Lambda}_i = \mathrm{diag}\big([p_{i,1}^2, p_{i,2}^2, \cdots, p_{i,n_t}^2]\big)$. Let $E_j = \boldsymbol{s}_j^T \boldsymbol{s}_j$. The optimal power allocation strategy $\boldsymbol{E} = [E_1, E_2, \cdots, E_{n_t}]^T$ will be investigated under different criteria in the following. Since the objective functions of those criteria have distinct properties, the optimal power allocation solutions may not be the same, see Section 4.

### 3.1. Mutual Information Criterion

The mutual information (MI) criterion was suggested for MIMO radar power allocation in [2–4]. Under this criterion, the optimal strategy maximizes the MI between the received signal matrix $\boldsymbol{Y}$ and the radar scatterer matrix $\boldsymbol{G}$, which is defined as $I(\boldsymbol{Y};\boldsymbol{G}|\boldsymbol{S}) = h(\boldsymbol{Y}|\boldsymbol{S}) - h(\boldsymbol{Y}|\boldsymbol{G},\boldsymbol{S}) = h(\boldsymbol{Y}|\boldsymbol{S}) - h(\boldsymbol{W})$, where $h(\cdot)$ indicates differential entropy [2]. Since

$$\begin{aligned} h(\boldsymbol{Y}|\boldsymbol{S}) &= -\int f(\boldsymbol{Y}|\boldsymbol{S}) \log f(\boldsymbol{Y}|\boldsymbol{S}) d\boldsymbol{Y} \\ &= \sum_{i=1}^{n_r} \log \big[ \det(\sigma_w^2 \boldsymbol{I}_K + \sigma_g^2 \boldsymbol{S}\boldsymbol{\Lambda}_i \boldsymbol{S}^H) \big] + c_1, \end{aligned} \tag{6}$$

where $c_1 = n_r K \log \pi + n_r K$ is a constant, and since

$$h(\boldsymbol{W}) = -\int f(\boldsymbol{W}) \log f(\boldsymbol{W}) d\boldsymbol{W} = n_r K \log \sigma_w^2 + c_1, \tag{7}$$

we have

$$\mathcal{I} = \sum_{i=1}^{n_r} \log \big[ \det(\sigma_w^2 \boldsymbol{I}_K + \sigma_g^2 \boldsymbol{S}\boldsymbol{\Lambda}_i \boldsymbol{S}^H) \big] - n_r K \log \sigma_w^2, \tag{8}$$

where $\mathcal{I} \triangleq I(\boldsymbol{Y};\boldsymbol{G}|\boldsymbol{S})$ for notational simplicity. Let $\boldsymbol{U}$ denote the $K \times K$ orthnormal basis matrix including all $(\boldsymbol{s}_j/\sqrt{E_j})$'s, and then we have $\det(\sigma_w^2 \boldsymbol{I}_K + \sigma_g^2 \boldsymbol{S}\boldsymbol{\Lambda}_i \boldsymbol{S}^H) = \det(\sigma_w^2 \boldsymbol{I}_K + \sigma_g^2 \boldsymbol{U}^H \boldsymbol{S}\boldsymbol{\Lambda}_i \boldsymbol{S}^H \boldsymbol{U})$. Therefore, $\mathcal{I}$ could be simplified as

$$\mathcal{I} = \sum_{i=1}^{n_r} \log \big[ \det(\sigma_w^2 \boldsymbol{I}_K + \boldsymbol{\Gamma}_i) \big] - n_r K \log \sigma_w^2, \tag{9}$$

where $\boldsymbol{\Gamma}_i \triangleq \sigma_g^2 \mathrm{diag}([E_1 p_{i,1}^2, E_2 p_{i,2}^2, \cdots, E_{n_t} p_{i,n_t}^2, \mathbf{0}_{1\times(K-n_t)}])$. As the second item of (9) is irrelevant to $\boldsymbol{E}$, the optimal power allocation strategy can be obtained via

$$\max_{\boldsymbol{E}} \sum_{i=1}^{n_r} \log \big[ \det(\sigma_w^2 \boldsymbol{I}_K + \boldsymbol{\Gamma}_i) \big], \text{ s.t. } \sum_{j=1}^{n_t} E_j \leq \bar{E}, \tag{10}$$

where $\bar{E}$ bounds the total power. Substituting $\boldsymbol{\Gamma}_i$ into (10), the optimization is reformulated as

$$\max_{\boldsymbol{E}} f_1(\boldsymbol{E}) \triangleq \sum_{i=1}^{n_r} \sum_{j=1}^{n_t} \log(\sigma_w^2 + E_j \sigma_g^2 p_{i,j}^2), \text{ s.t. } \sum_{j=1}^{n_t} E_j \leq \bar{E}. \tag{11}$$

The objective function $f_1(\boldsymbol{E})$ has $n_t \times n_r$ items, and each parameter $E_j$ involves $n_r$ elements. As

$$\frac{\partial^2 f_1(\boldsymbol{E})}{\partial E_j^2} = -\sum_{i=1}^{n_r} \frac{(\sigma_g^2 p_{i,j}^2)^2}{(\sigma_w^2 + E_j \sigma_g^2 p_{i,j}^2)^2} < 0, \tag{12}$$

the Hessian matrix of $f_1(\boldsymbol{E})$ is negative definite. Therefore, $f_1(\boldsymbol{E})$ is concave, and the optimal solution of (11) can be numerically reached via gradient based approaches.

Theoretically, the maximum point of a concave function could be obtained by Lagrange multipliers. Define

$$L(\boldsymbol{E}, \lambda) = f_1(\boldsymbol{E}) + \lambda(\bar{E} - \sum_{j=1}^{n_t} E_j), \tag{13}$$

where $\lambda$ denotes the Lagrange multiplier. We have

$$\lambda = \sum_{i=1}^{n_r} \frac{\sigma_g^2 p_{i,j}^2}{\sigma_w^2 + E_j \sigma_g^2 p_{i,j}^2} \tag{14}$$

by letting $\frac{\partial L(\boldsymbol{E},\lambda)}{\partial E_j} = 0$ and $\frac{\partial L(\boldsymbol{E},\lambda)}{\partial \lambda} = 0$, and recalling the constraint and $\bar{E} = \sum_{j=1}^{n_t} E_j$. As opposed to the propagation loss free model based power allocation [2–4], $E_j$ is a nonlinear function of the $n_r$ path gains for a given $\lambda$. There is no closed-form expression of $E_j$, and the concise water-filling results of [2–4] do not hold here.

### 3.2. Minimum Mean Square Error Criterion

The minimum mean square error (MMSE) criterion was suggested for MIMO radar power allocation in [2]. Under this criterion, the optimal strategy minimizes the MMSE

$$\mathcal{E} = \mathbb{E}\{||\boldsymbol{G} - \hat{\boldsymbol{G}}||_F^2\} = \sum_{i=1}^{n_r} \mathbb{E}\{||\boldsymbol{g}_i - \hat{\boldsymbol{g}}_i||_F^2\}, \tag{15}$$

where $||\cdot||_F$ indicates the Frobenius norm, while $\hat{\boldsymbol{G}}$ and $\hat{\boldsymbol{g}}_i$ respectively denote the optimal estimates of $\boldsymbol{G}$ and $\boldsymbol{g}_i$. Since $\boldsymbol{y}_i$ and $\boldsymbol{g}_i$ are jointly Gaussian, the MMSE estimator is linear $\hat{\boldsymbol{g}}_i = \boldsymbol{B}_i\boldsymbol{y}_i$, where $\boldsymbol{B}_i$ can be obtained via

$$\begin{aligned}\boldsymbol{B}_i &= \arg\min_{\boldsymbol{B}} \mathbb{E}\{||\boldsymbol{g}_i - \boldsymbol{B}(\boldsymbol{S}(\boldsymbol{g}_i \odot \boldsymbol{p}_i) + \boldsymbol{w}_i)||_F^2\} \\ &= \sigma_g^2 \mathrm{diag}(\boldsymbol{p}_i)\boldsymbol{S}^H(\sigma_w^2 \boldsymbol{I}_K + \sigma_g^2 \boldsymbol{S}\boldsymbol{\Lambda}_i\boldsymbol{S}^H)^{-1}.\end{aligned} \tag{16}$$

Substituting $\boldsymbol{B}_i$ into (15), we have

$$\begin{aligned}\mathcal{E} &= n_t n_r \sigma_g^2 - \sigma_g^4 \sum_{i=1}^{n_t} \mathrm{Tr}\big(\boldsymbol{S}\boldsymbol{\Lambda}_i\boldsymbol{S}^H(\sigma_w^2\boldsymbol{I}_K + \sigma_g^2\boldsymbol{S}\boldsymbol{\Lambda}_i\boldsymbol{S}^H)^{-1}\big) \\ &= n_t n_r \sigma_g^2 - \sigma_g^2 \sum_{i=1}^{n_t} \mathrm{Tr}\big(\boldsymbol{\Gamma}_i(\sigma_w^2\boldsymbol{I}_K + \boldsymbol{\Gamma}_i)^{-1}\big).\end{aligned} \tag{17}$$

Let $f_2(\boldsymbol{E}) \triangleq \mathcal{E}$. Recalling $\boldsymbol{\Gamma}_i$, $f_2(\boldsymbol{E})$ is recast as

$$f_2(\boldsymbol{E}) = \sum_{i=1}^{n_r}\sum_{j=1}^{n_t} \frac{\sigma_g^2\sigma_w^2}{\sigma_w^2 + E_j\sigma_g^2 p_{i,j}^2}. \tag{18}$$

Consequently, the optimal strategy can be obtained via

$$\min_{\boldsymbol{E}} \; f_2(\boldsymbol{E}), \text{ s.t. } \sum_{j=1}^{n_t} E_j \le \bar{E}. \tag{19}$$

Again, since $\frac{\partial^2 f_2(\boldsymbol{E})}{\partial E_j^2} = \sum_{i=1}^{n_r} \frac{2\sigma_w^2\sigma_g^6 p_{i,j}^4}{(\sigma_w^2 + E_j\sigma_g^2 p_{i,j}^2)^3} > 0$, the Hessian matrix of $f_2(\boldsymbol{E})$ is positive definite. Therefore, $f_2(\boldsymbol{E})$ is convex, and the optimal solution of (11) can be numerically acquired. Similar to the MI criterion, the optimal solution here is no longer water-filling.

### 3.3. Echo Power Maximization Criterion

In [6], the author suggested to maximize the expectation of the energy of the received signal

$$\max_{\boldsymbol{E}} \; \mathcal{P} \triangleq \mathbb{E}\big\{\mathrm{Tr}(\boldsymbol{Y}\boldsymbol{Y}^H)\big\} \tag{20}$$

in power allocation. As $\mathbb{E}\big\{\mathrm{Tr}(\boldsymbol{y}_i\boldsymbol{y}_i^H)\big\} = K\sigma_w^2 + \mathrm{Tr}(\boldsymbol{\Gamma}_i)$, the optimal strategy can be obtained via

$$\max_{\boldsymbol{E}} \; f_3(\boldsymbol{E}) \triangleq \sum_{i=1}^{n_r}\sum_{j=1}^{n_t} E_j\sigma_g^2 p_{i,j}^2, \text{ s.t. } \sum_{j=1}^{n_t} E_j \le \bar{E}. \tag{21}$$

Obviously, $f_3(\boldsymbol{E})$ is a linearly weighted combination of $E_j$'s. Let $\xi_j = \frac{\partial f_3(\boldsymbol{E})}{\partial E_j} = \sum_{i=1}^{n_r} \sigma_g^2 p_{i,j}^2$. The optimal strategy puts all power to the transmitter with largest $\xi$ value, say $\xi_{\max}$. If all $\xi_j$'s are distinct, the MIMO system will degenerate to a multistatic one under the optimal transmission scenario. It is interesting to see that the binary on-off action for a transmitter does not depend on $\bar{E}$ under this circumstance. If more than one transmitter shares $\xi_{\max}$, $\bar{E}$ could be arbitrarily divided among them.

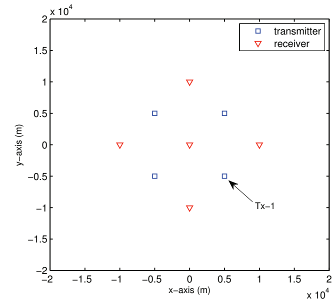



**Fig. 1**. The MIMO radar configuration in two dimensions.

## 4. NUMERICAL RESULTS

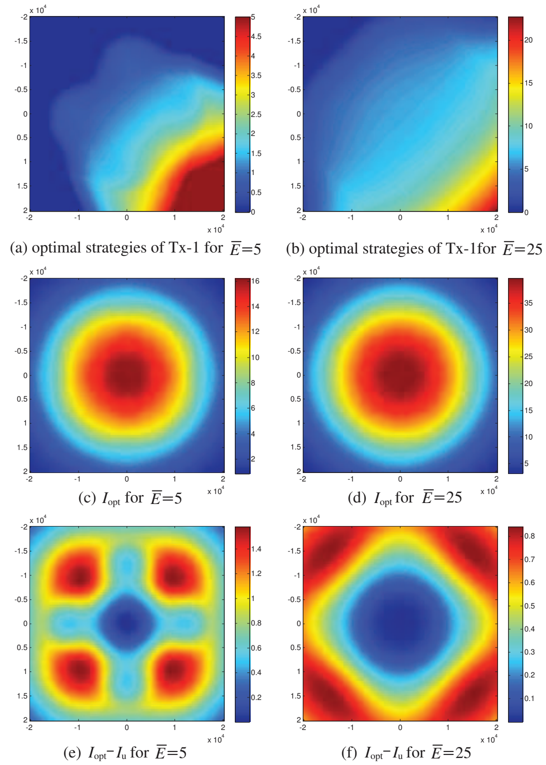
This section numerically shows the optimal power allocation strategies and performance gains under those three criteria, and compares them with those for the uniform strategy. Let $n_t = 4$ and $n_r = 5$, and they are distributed in a $40 \times 40$ km$^2$ surveillance area as shown in Fig. 1. Let all antennas be isotropic, and then the propagation loss could be simplified as $p_{i,j} = c/d_t^j d_r^i$. Furthermore, we set $\sigma_w = 1$ and $\sigma_g = 1$ for simplicity. In simulation, we uniformly divide the surveillance area into $100 \times 100$ square cells, and then use the center of each cell as a reference point to calculate the propagation gains and the optimal power allocation strategies. As the MIMO configuration is symmetric about $x-$axis, $y-$axis, and the coordinate origin, we only plot the optimal strategies of transmitter Tx-1. Those for the others can be obtained via a proper rotation of that for Tx-1.

The optimal strategies for Tx-1 with different power bounds under MI criterion are shown in Figs. 2 (a) and (b), where the value at a point, say $(x, y)$, stands for the optimal power level of Tx-1 if the target is located at $(x, y)$. Obviously, they are geometry dependent instead of uniform. Figs. 2 (c) and (d) show the optimal MI values $I_{\mathrm{opt}}$, where the value at $(x, y)$ indicates the MI level under the optimal strategy. Figs. 2 (e) and (f) depict the MI improvement over the uniform allocation strategy $I_u$. Clearly, with the optimal strategy the system performance could be improved.

The optimal strategies and performance gains under the MMSE criterion are collected in Fig. 3, and the observations are similar to those of the previous criterion. As for the energy based criterion, a transmitter is either full-loaded or zero-loaded. The binary on-off actions for Tx-1 are shown in Fig. 4 (a), and they do not depend on the total power. The normalized performance enhancements are illustrated in Fig. 4 (b). We can see that the geometrically adaptive allocation is better than the uniform one in most areas.

## 5. CONCLUSIONS

Adaptive power allocation among different transmitters is an active research topic for MIMO radar. In this paper, we integrate the propagation losses into the MIMO radar signal model, and recap the power



(a) optimal strategies of Tx-1 for $\overline{E}$=5 (b) optimal strategies of Tx-1for $\overline{E}$=25

(c) $I_{\rm opt}$ for $\overline{E}$=5 (d) $I_{\rm opt}$ for $\overline{E}$=25

(e) $I_{\rm opt}-I_{\rm u}$ for $\overline{E}$=5 (f) $I_{\rm opt}-I_{\rm u}$ for $\overline{E}$=25

**Fig. 2**. The power allocation strategies for Tx-1 and MIMO radar performance gains for different $\bar{E}$'s with MI criterion. The value at a point, say $(x, y)$, stands for the optimal power level of Tx-1 if the target is located at $(x, y)$ in figures (a) and (b), while it stands for the MI or MI enhancements under the optimal strategies if the target is presented at $(x, y)$ in the rest ones.

allocation problems under different criteria including MI, MMSE, and energy. Their optimal strategies are geometry dependent instead of uniform under the i.i.d. target reflection coefficient and the i.i.d. receiver noise conditions. The power allocation with heterogeneous propagation losses can also be investigated under other criteria including Neyman-Pearson and Kullback-Leiber divergence, or extended to space time coding models.

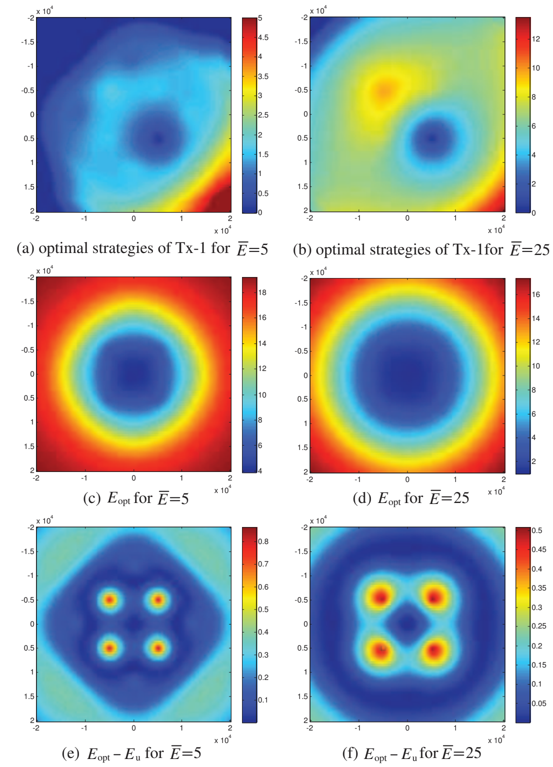
## 6. REFERENCES


[1] E. Fishler, A. Haimovich, R. S. Blum, L. J. Cimini, D. Chizhik, and R. A. Valenzuela, “Spatial diversity in radars–models and detection performance,” *IEEE Trans. Signal Process.*, vol. 54, no. 3, pp. 823–838, Mar. 2006.

[2] Y. Yang and R. S. Blum, “MIMO radar waveform design based on mutual information and minimum mean-square error estimation,” *IEEE Trans. Aerosp. Electron. Syst.*, vol. 43, no. 1, pp. 330–343, Jan. 2007.

[3] A. De Maio and M. Lops, “Design principles of MIMO radar detectors,” *IEEE Trans. Aerosp. Electron. Syst.*, vol. 43, no. 3, pp. 886–898, Jul. 2007.

[4] X. Song, S. Zhou, P. Willett, and P. B. Luh, “The MIMO radar and jammer games,” *IEEE Trans. Signal Process.*, vol. 60, no. 2, pp. 687–699, Feb. 2012.

(a) optimal strategies of Tx-1 for $\overline{E}$=5 (b) optimal strategies of Tx-1for $\overline{E}$=25

(c) $E_{\rm opt}$ for $\overline{E}$=5 (d) $E_{\rm opt}$ for $\overline{E}$=25

(e) $E_{\rm opt}-E_{\rm u}$ for $\overline{E}$=5 (f) $E_{\rm opt}-E_{\rm u}$ for $\overline{E}$=25

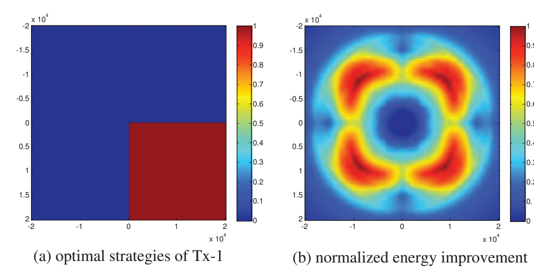
**Fig. 3**. The power allocation strategies for Tx-1 and MIMO radar performance gains for different $\bar{E}$'s with MMSE criterion. The meaning of each pixel is the same as the previous one.


[5] X. Song, P. Willett, and S. Zhou, “Detection performance for statistical MIMO radar with identical and orthogonal waveforms,” in *Proc. of IEEE Radar Conf.*, Kansas City, MO, May 2011.

[6] B. Friedlander, “Waveform design for MIMO radars,” *IEEE Trans. Aerosp. Electron. Syst.*, vol. 43, no. 3, pp. 1227–1238, Jul. 2007.

[7] H. Godrich, A. P. Petropulu, and H. V. Poor, “Power allocation strategies for target localization in distributed multiple-radar architectures,” *IEEE Trans. Signal Process.*, vol. 59, no. 7, pp. 3226–3240, Jul. 2011.

[8] N. J. Willis, *Bistatic Radar*. Raleigh, NC: SciTech Publishing Inc., 2005.

(a) optimal strategies of Tx-1 (b) normalized energy improvement

**Fig. 4**. Energy criterion based power allocation with unit energy: (a) the binary on-off strategies for Tx-1 (if the target falls into the low-right part, Tx-1 will be full loaded; otherwise, it is shut down.), and (b) normalized power improvements.