IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received December 28, 2017, accepted February 12, 2018, date of publication February 27, 2018, date of current version April 4, 2018.

Digital Object Identifier 10.1109/ACCESS.2018.2809550

Iterative Search Algorithm to Maximize System Capacity in Time-Varying MIMO DAS

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ABSTRACT In this paper, an iterative search algorithm to maximize system capacity in a time-varying MIMO distributed antenna system (DAS) is proposed. A common DAS model is employed, in which the transmit antennas are distributively located and the receiver can move arbitrarily in the region. Due to the small-scale fading effect and the receiver movement, the transmitters and receiver cannot obtain accurate channel state information (CSI) or optimize the system capacity. Therefore, we present a time-varying MIMO DAS model and corresponding channel evolution model to predict the time-varying channel. With the channel evolution model, the proposed iterative search algorithm can calculate the precoding matrix, and an iterative search process is employed to determine the optimal precoding matrix from a precoding matrix set. Meanwhile, error analysis show the error on the instantaneous mutual information with the proposed algorithm has a close relationship with the element number of the precoding matrix set and small-scale fading evolution coefficient. We also propose a non-uniform power allocation strategy which can improve the system capacity. Simulation results are presented to verity the analysis above and demonstrate the performance of system capacity with the proposed iterative search algorithm.

INDEX TERMS MIMO system, time-varying system, iterative methods, communication system performance.

I. INTRODUCTION

In the past decades, the capacity of co-located MIMO systems has been extensively explored with different communication environments and different encoding algorithms [1], [2]. Recently, the distributed antenna systems (DAS) has been proposed to realize combined gains of MIMO spatial multiplexing technology and macro-diversity technology. Unlike the conventional centralized antenna systems (CAS), in the DAS, multiple transmit antennas, which are connected to the central processing unit (CPU) by fiber or exclusive wireless link, are distributively located to reduce the physical transmission distance between the transmitters and the receivers [3]–[6]. In [7], the ergodic capacity of CAS and DAS with antennas uniformly distributed in the cell is analyzed and the results show that the DAS can improve the system coverage, enhance the performance of cell-edge users, and reduce the transmit power. On the other hand, placing a large number of antennas in different locations can reduce the correlations of antennas [8], [9], thus improving the spectral efficiency (SE) of the system.

From literatures, the DAS has attracted considerable attentions from various aspects. In [10], the determinant in the expression of capacity is expanded as the linear sum of determinants of quadratic forms, thereby analytic upper and lower bounds are obtained and are applicable for the DAS with double-sided correlated Rayleigh/Lognormal fading. In [11], for a single-cell single-user DAS with arbitrary antenna topology, the authors analyzed the outage performance as well as the diversity and multiplexing gains. In [12], for multi-cell networks with multiple remote antennas and one multi-antenna user in each cell, the input covariance matrices for the users are jointly optimized to maximize the achievable ergodic sum rate. In [13], several power allocation strategies with different optimization models are investigated for achieving maximum energy efficiency (EE) in downlink DAS and the results show that EE-oriented optimization achieves a higher system EE compared with the SE-oriented optimization scheme. For the uplink DAS with single-antenna nodes, a simplified Wyner model is considered where cooperative decoding using codebook information and oblivious bases stations are studied in [14].

However, the analysis and algorithm in the aforementioned literatures are mainly based on the case that the transmitters and receivers both have accurate channel state information.

While the CSI cannot be obtained accurately, the analysis for the upper and lower bounds of the system capacity and the algorithms for achieving maximum SE and EE in aforementioned works do not apply. The time-varying system model is proposed to deal with the incomplete CSI. In the time-varying system model. an appropriate channel evolution model is proposed to simulate the time-varying channel and some ergodic algorithms are employed to rectify the error of the channel evolution model. A detailed capacity analysis is performed for a temporally correlated channel modeled as a first-order Gauss-Markov process in [15]. In [16] and [17], channel tracking strategy based on codebook is proposed. Furthermore, a time-invariant codebook for channel tracking in a time-varying channel have been adopted in [18]. More modified schemes have been proposed in [19]–[21].

In this paper, a novel time-varying MIMO DAS is proposed. With the discreteness of the transmit antennas and receive antennas, the time-varying MIMO DAS channel model cannot be described as a first-order Gauss-Markov process. Considering the small-scale fading and the locations of transmitter and receiver, a more complicated channel evolution model is given. With the proposed channel evolution model, we propose an iterative search algorithm with a off-line codebook to maximize the system capacity. In the proposed iterative search algorithm, only the initial CSI, correlation coefficient of the small-scale fading and location information of the transmitters and receivers are required. To calculate the optimal precoding matrix, the concepts of matrix space and matrix distance are introduced. The iterative search algorithm can be explained as searching the optimal precoding matrix on a sphere where the points have a distance less than a threshold with the optimal precoding matrix in last iteration in the matrix space. The error analysis and simulation results show that the difference between the system capacity with the proposed algorithm and the ideal system capacity is quite small. Also the power allocation problem in the time-varying MIMO DAS is discussed in this paper.

The remaining of the paper is organized as follows. The time-varying MIMO DAS model and the channel evolution model are presented in Section II. The optimal problem of maximizing the system capacity and the iterative search algorithm are described in Section III. The parameter configuration in the proposed algorithm and error analysis are provided in Section IV. Simulation results are presented in Section V. Conclusions are drawn in Section VI.

Notation: Boldface lowercase letters denote vectors, while boldface uppercase letters denote matrices. We use $(\cdot)^T$, $(\cdot)^*$ to denote the transpose and conjugate transpose of a matrix or a vector. For a matrix $\mathbf{A}$, $tr(\mathbf{A})$ is its trace and $det(\mathbf{A})$ stands for its determinant. The symbol $\mathbf{I_M}$ denotes the $M \times M$ identity matrix. The symbol $E\{\cdot\}$ denotes the statistical expectation operation. The symbol $\|\cdot\|_F$ denotes Frobenius norm of a matrix or a vector. The symbol $Re\{\cdot\}$ denotes to extract real component of every element in a matrix.

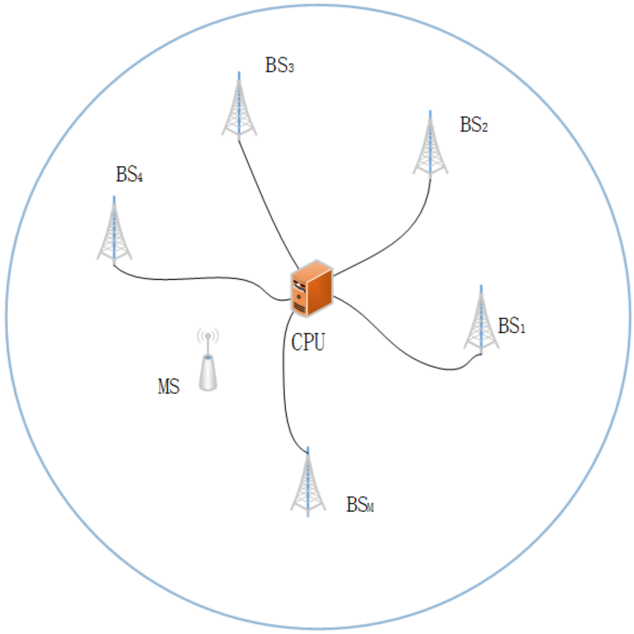

FIGURE 1. The time-varying MIMO DAS with *M* BSs and one MS.

II. SYSTEM MODEL

A time-varying MIMO DAS shown in Fig.1 is considered in this paper. There are M base stations (BS) and one mobile station (MS) in the cell and the BSs are laid out distributively, while the MS can move arbitrarily in the cell. Each BS is equipped with m_t antennas and the MS has m_r antennas. Every BS is connected to the CPU through the high-speed fiber-optic cable and every BS is assumed to have the accurate information of other BSs all the time. With this system model above, the downlink receive signal at the MS side can be expressed as follow,

$$\mathbf{y_t} = \sqrt{\rho}\mathbf{H_t}\mathbf{F_t}\mathbf{s_t} + \mathbf{n_t} \tag{1}$$

where the subscript t stands for the channel index which shows the channel evolution. $\mathbf{y_t} \in \mathbb{C}^{m_r*1}$ is the receive signal and $\mathbf{s_t} \in \mathbb{C}^{M*1}$ is original data with the unit energy $E\{\mathbf{s_t}\mathbf{s_t}^*\} = \mathbf{I_M}$. $\mathbf{n_t} \in \mathbb{C}^{m_r*1}$ stands for the noise and each element in $\mathbf{n_t}$ has a distribution as $\mathcal{CN}(0, 1)$. $\mathbf{F_t} \in \mathbb{C}^{M_t*M}$ is the precoding matrix, where $M_t = M * m_t$ is the total number of transmit antennas. The initial precoding matrix $\mathbf{F_0}$ can be obtained by the singular value decomposition (SVD) of the initial channel matrix $\mathbf{H_0}$ to maximize the sum rate and the precoding matrices at other channel index should be calculated by the iterative search algorithm which will be described in Section III. The channel matrix at channel index t is $\mathbf{H_t} \in \mathbb{C}^{m_r*M_t}$. With the DAS conception, the element of channel matrix $\{h_{t,q,p}\}$ can be modeled as follow,

$$h_{t,q,p} = g_{t,q,p}\sqrt{\beta_{t,q,p}} \tag{2}$$

where $g_{t,q,p} \sim \mathcal{CN}(0, 1)$ represents the small-scale fading from q-th receiver antenna to p-th transmit antenna and

$\beta_{t,q,p} \sim r_{t,q,p}{}^{-v}$ is the path loss. $r_{t,q,p}$ is the distance between q-th receiver antenna and p-th transmit antenna and $v \in [2, 6]$ is the path loss coefficient. With the expression of $\{h_{t,q,p}\}$, the channel matrix $\mathbf{H_t}$ can be expressed as follow,

$$\mathbf{H_t} = \mathbf{G_t} \circ \overline{\mathbf{D}}_{\mathbf{t}}^{\mathbf{1/2}} \tag{3}$$

where $\mathbf{G_t} \in \mathbb{C}^{m_r * M_t}$ is the small-scale fading matrix which is made up of $g_{t,q,p}$ and the element in the path-loss matrix $\overline{\mathbf{D}}_{\mathbf{t}} \in \mathbb{C}^{m_r * M_t}$ is $\overline{d}_{t,q,p} = \gamma^2 r_{t,q,p}^{-v}$. γ is the path loss coefficient which satisfies $\gamma r_{t,q,p}{}^{-v/2}$ equals the path loss value $\sqrt{\beta_{t,q,p}}$. As there is only one MS in the system, the distance between one certain transmit antenna and any receive antenna is equal. Then we can have that $\overline{d}_{t,q_i,p} = \overline{d}_{t,q_j,p}, \forall i, j$, and the equation (3) can be rewritten as,

$$\mathbf{H_t} = \mathbf{G_t}\mathbf{D}_{\mathbf{t}}^{\mathbf{1/2}} \tag{4}$$

where $\mathbf{D_t} \in \mathbb{C}^{M_t * M_t}$ is a diagonal matrix which can be expressed by $\mathbf{D_t} = diag([d_{t,1}, d_{t,2}, \ldots, d_{t,M_t}])$ and the element $d_{t,i} = \overline{d}_{t,1,i}$

Considering the time-varying characteristics of time-varying MIMO DAS, the evolution model of matrices $\mathbf{G_t}$ and $\mathbf{D_t}$ can be expressed as follow,

$$\begin{aligned} \mathbf{G_t} &= \epsilon \mathbf{G_{t-1}} + \sqrt{1-\epsilon^2}\mathbf{W} \\ \mathbf{D_t} &= \mathbf{D_{t-1}}\xi_{\mathbf{t-1}} \end{aligned} \tag{5}$$

where $\epsilon \in [0, 1]$ is the small-scale fading evolution coefficient which is given by Jakes' model and $\mathbf{W} \sim \mathcal{CN}(0, \sigma \mathbf{I})$ is the innovation matrix. Each element in the diagonal matrix ξ_{t-1} is the rate of the distances between BSs and MS at channel index t and $t-1$. With equation (4) and (5), the channel evolution model of the time-varying MIMO DAS can be obtained as,

$$\begin{aligned} \mathbf{H_t} &= (\epsilon \mathbf{G_{t-1}} + \sqrt{1-\epsilon^2}\mathbf{W})(\mathbf{D_{t-1}}\xi_{\mathbf{t-1}})^{1/2} \\ &= \epsilon \mathbf{G_{t-1}}\mathbf{D_{t-1}}{}^{1/2}\xi_{\mathbf{t-1}}{}^{1/2} + \sqrt{1-\epsilon^2}\mathbf{W}\mathbf{D_{t-1}}{}^{1/2}\xi_{\mathbf{t-1}}{}^{1/2} \\ &= \epsilon \mathbf{H_{t-1}}\xi_{\mathbf{t-1}}{}^{1/2} + \sqrt{1-\epsilon^2}\mathbf{W}\mathbf{D}_{\mathbf{t}}^{\mathbf{1/2}}. \end{aligned} \tag{6}$$

In this paper, the initial channel matrix $\mathbf{H_0}$, the path-loss matrix $\mathbf{D_t}$ and the small-scale fading evolution coefficient ϵ are assumed to be known by the transmitters and receiver. But due to the randomness, the small-scale fading matrix $\mathbf{G_t}$ and the innovation matrix $\mathbf{W}$ cannot be determined. With the time-varying MIMO DAS channel evolution model, it can be known that the precoding matrix $\mathbf{F_t}$ should be varied to maintain the system capacity at every channnel index. Therefore, in the next section, an iterative search algorithm to calculate the precoding matrix $\mathbf{F_t}$ is introduced.

III. ITERATIVE SEARCH ALGORITHM

A. INSTANTANEOUS MUTUAL INFORMATION

In the time-varying MIMO DAS, the downlink instantaneous mutual information between the transmit signal and the receive signal at channel index t is given by,

$$I(\mathbf{F_t}, \mathbf{H_t}) = log_2(det(\mathbf{I_M} + \frac{\rho}{M}\mathbf{F_t}\mathbf{H_t}\mathbf{H_t^*}\mathbf{F_t^*})) \tag{7}$$

where ρ is the SNR at the transmitter and M is the data stream number, which is assumed to equal the BS number in this paper. To maximize the instantaneous mutual information, the precoding matrices $\mathbf{F_t}$ should be optimized at every channel index and the optimal precoding matrix is the right singular matrix of the channel matrix $\mathbf{H_t}$. The initial precoding matrix can be obtained by the SVD of the initial channel matrix $\mathbf{H_0}$ as,

$$\begin{aligned} \mathbf{H_0} &= \mathbf{U_0}\Sigma_0\mathbf{V_0^*} \\ \mathbf{F_0} &= \overline{\mathbf{V}}_{\mathbf{0}} \end{aligned} \tag{8}$$

where $\overline{\mathbf{V}}_{\mathbf{0}}$ is the first M columns of the right singular matrix $\mathbf{V_0}$. For other channel indexes, as the channel matrix cannot be obtained accurately due to the innovation matrix $\mathbf{W}$, the precoding matrix cannot be calculated by SVD directly. Then the precoding matrices for other channel indexes should be obtained based on the initial precoding matrix $\mathbf{F_0}$ and the channel evolution model in equation (6). To calculate the precoding matrices, the distance between two matrices with the same scale are considered. For two arbitrary matrices with the same scale, $\mathbf{A} \in \mathbb{C}^{P*Q}$ and $\mathbf{B} \in \mathbb{C}^{P*Q}$, the distance is defined as follow,

$$d(\mathbf{A}, \mathbf{B}) = \|\mathbf{A} - \mathbf{B}\|_F \tag{9}$$

Proposition 1: With the distance definition in equation (9), we have that with one constant channel matrix and two different precoding matrices, the difference between the instantaneous mutual information, $I(\mathbf{F_1}, \mathbf{H})$ and $I(\mathbf{F_2}, \mathbf{H})$, have a positive correlation with the distance between the precoding matrices, $d(\mathbf{F_1}, \mathbf{F_2})$.

Proof: Without loss of generality, it is assumed that $I(\mathbf{F_1}, \mathbf{H})$ is larger than $I(\mathbf{F_2}, \mathbf{H})$. The difference between the instantaneous mutual information can be expressed as follow,

$$\begin{aligned} &I(\mathbf{F_1}, \mathbf{H}) - I(\mathbf{F_2}, \mathbf{H}) \\ &\overset{(a)}{=} tr(log_2(\mathbf{I_M} + \frac{\rho}{M}\mathbf{F_1}\,\mathbf{H}\mathbf{H}^*\mathbf{F_1^*}) - log_2(\mathbf{I_M} + \frac{\rho}{M}\mathbf{F_2}\,\mathbf{H}\mathbf{H}^*\mathbf{F_2^*})) \\ &\overset{(b)}{\leq} \frac{1}{ln2} tr((\mathbf{I_M} + \frac{\rho}{M}\mathbf{F_1}\,\mathbf{H}\mathbf{H}^*\mathbf{F_1^*}) - (\mathbf{I_M} + \frac{\rho}{M}\mathbf{F_2}\,\mathbf{H}\mathbf{H}^*\mathbf{F_2^*})) \\ &\overset{(c)}{=} \frac{\rho}{Mln2} tr(\mathbf{F_1}\,\mathbf{H}\mathbf{H}^*\mathbf{F_1^*} - \mathbf{F_2}\,\mathbf{H}\mathbf{H}^*\mathbf{F_2^*}) \\ &\overset{(d)}{=} \frac{\rho}{Mln2}(\|\mathbf{H}\mathbf{F_1}\|_F^2 - \|\mathbf{H}\mathbf{F_2}\|_F^2) \end{aligned} \tag{10}$$

where in step (a), the fact that $log_2(det(\mathbf{A})) = tr(log_2(\mathbf{A}))$ while the matrix $\mathbf{A}$ is a diagonal matrix or quasi-diagonal matrix is employed. The fact that $log_2(a) - log_2(b) \leq \frac{1}{ln2}(a-b)$ if the inequation $a \geq b \geq 1$ is satisfied is considered in step (b). And in step (d), the equation $tr(\mathbf{A}\mathbf{A}^*) = tr(\mathbf{A}^*\mathbf{A}) = \|\mathbf{A}\|_F^2$ is quoted.

Ignoring the effort of the coefficient $\frac{\rho}{M ln2}$, the factor $(\|\mathbf{HF_1}\|_F^2 - \|\mathbf{HF_2}\|_F^2)$ in equation (10) can be simplified as follow,

$$\begin{aligned}&\|\mathbf{HF_1}\|_F^2 - \|\mathbf{HF_2}\|_F^2\\ &\quad = (\|\mathbf{HF_1}\|_F + \|\mathbf{HF_2}\|_F)(\|\mathbf{HF_1}\|_F - \|\mathbf{HF_2}\|_F)\\ &\quad \le \|\mathbf{H}\|_F^2(\|\mathbf{F_1}\|_F + \|\mathbf{F_2}\|_F)(\|\mathbf{F_1} - \mathbf{F_2}\|_F)\\ &\quad = 2\sqrt{M}\|\mathbf{H}\|_F^2 d(\mathbf{F_1}, \mathbf{F_2}) \end{aligned} \tag{11}$$

where the inequations $\|\mathbf{AB}\|_F \le \|\mathbf{A}\|_F\|\mathbf{B}\|_F$ and $\|\mathbf{A}\|_F - \|\mathbf{B}\|_F \le \|\mathbf{A} - \mathbf{B}\|_F$ are employed. As the matrices $\mathbf{F_1}$ and $\mathbf{F_2}$ are the first M rows of unitary matrices, we have that $\|\mathbf{F_1}\|_F = \|\mathbf{F_2}\|_F = \sqrt{M}$.

Then it can be known that the difference between the instantaneous mutual information, $I(\mathbf{F_1}, \mathbf{H}) - I(\mathbf{F_2}, \mathbf{H})$, has a positive correlation with the distance between the precoding matrices, $d(\mathbf{F_1}, \mathbf{F_2})$.

With Proposition 1, an iterative search algorithm to maximize the system capacity in a time-varying MIMO DAS is proposed and the details of the algorithm will be introduced in next subsection.

B. ITERATIVE SEARCH ALGORITHM

Based on Proposition 1, to maximize the instantaneous mutual information, the distance between the calculated precoding matrix and the right singular matrix of the channel matrix should be minimized. At the channel index t, the optimization problem of maximizing the system capacity can be converted to minimizing the distance between the calculated precoding matrix $\mathbf{F_t}$ and the first M columns of right singular matrix, $\overline{\mathbf{V}}_\mathbf{t}$, which can be expressed as follow,

$$\min d(\mathbf{F_t}, \overline{\mathbf{V}}_\mathbf{t}) \tag{12}$$

To calculate the precoding matrix $\mathbf{F_t}$, a candidate set of the precoding matrix $\{\widetilde{\mathbf{F}}_\mathbf{t}\}$ and a modified set $\{\widetilde{\mathbf{V}}_\mathbf{0}\}$ are required. The modified set $\{\widetilde{\mathbf{V}}_\mathbf{0}\}$ is generated by the right singular matrix of the initial channel matrix, $\mathbf{V_0}$, in which the column vectors are orthogonal with each other. Each matrix $\widetilde{\mathbf{V}}_i$ in the modified set $\{\widetilde{\mathbf{V}}_\mathbf{0}\}$ can be generated with M column vectors of the matrix $\mathbf{V_0}$, which can be expressed as follow,

$$\begin{aligned}\mathbf{V_0} &= [\mathbf{v}_{0,1}, \mathbf{v}_{0,2}, \ldots, \mathbf{v}_{0,M_t}]\\ \widetilde{\mathbf{V}}_i &= [\mathbf{v}_{0,i_1}, \mathbf{v}_{0,i_2}, \ldots, \mathbf{v}_{0,i_M}]\end{aligned} \tag{13}$$

where $i_1 \neq i_2 \neq \cdots \neq i_M$, and the maximum matrix number in the modified set is equal to the combination number of $(i_1, i_2, \ldots, i_M)$. But considering the system computation complexity, the matrix number in the modified set should not be too much. Meanwhile, as the initial precoding matrix is known accurately, the modified set can be generated off-line, which can reduce the computation complexity effectively.

The candidate set of the precoding matrix at channel index t, $\{\widetilde{\mathbf{F}}_\mathbf{t}\}$, is generated with the modified set and the precoding matrix at last channel index, $\mathbf{F_{t-1}}$. And each matrix in the candidate set is projected into the unitary space $\mathbb{C}^{M_t * M_t}$ by SVD and the first M vectors is chosen to form the new precoding matrix, which is shown by,

$$\begin{aligned}\widetilde{\mathbf{F}}_\mathbf{t,i} &= \mathbf{F_{t-1}} + \alpha\widetilde{\mathbf{V}}_\mathbf{i}\\ \widetilde{\mathbf{F}}_\mathbf{t,i} &= \mathbf{U_{t,i}}\Sigma_\mathbf{t,i}\mathbf{V}^*_\mathbf{t,i}\\ \mathbf{F_{t,i}} &= \overline{\mathbf{U}}_\mathbf{t,i}\end{aligned} \tag{14}$$

where α is the modify radius, which will be discussed in section IV-A and $\overline{\mathbf{U}}_\mathbf{t,i}$ stands for the first M columns of the unitary matrix $\mathbf{U_{t,i}}$.

With the candidate set $\{\widetilde{\mathbf{F}}_\mathbf{t}\}$, the best precoding matrix can be chosen by maximizing the instantaneous mutual information, which can be shown as follow,

$$\begin{aligned}\mathbf{F_{t,i}}^\star &= \max_{\mathbf{F_{t,i}} \in \{\widetilde{\mathbf{F}}_\mathbf{t}\}} I(\mathbf{H_t}, \mathbf{F_{t,i}})\\ \mathbf{F_t} &= \mathbf{F_{t,i}}^\star\end{aligned} \tag{15}$$

With the obtained optimal precoding matrix $\mathbf{F_t}$ and equation (14), the candidate set for channel index $t+1$ can be generated. The precoding matrix $\mathbf{F_{t+1}}$ can be calculated by repeating the algorithm above.

IV. SYSTEM PARAMETER ANALYSIS

A. THE MODIFIED RADIUS

From equation (14), it can be known the modified radius reflects the distance between the precoding matrices of two adjacent channel index. Without loss of generality, the distance between the precoding matrices at channel index $t-1$ and t, $d(\mathbf{F_{t-1}}, \mathbf{F_t})$, is discussed in this subsection. It is assumed that the precoding matrix at channel index $t-1$, $\mathbf{F_{t-1}}$, is known by the BSs and MS while the precoding matrix $\mathbf{F_t}$ cannot be obtained accurately and should be calculated by the iterative search algorithm in Section III-B. As the precoding matrices is generated by the right singular matrices, the distance between two right singular matrices, $\mathbf{V_{t-1}}$ and $\mathbf{V_t}$ is considered as follow.

$$\begin{aligned}d(\mathbf{V_t}, \mathbf{V_{t-1}}) &= \|\mathbf{V_t} - \mathbf{V_{t-1}}\|_F\\ &= \sqrt{tr((\mathbf{V_t} - \mathbf{V_{t-1}})^*(\mathbf{V_t} - \mathbf{V_{t-1}}))}\\ &= \sqrt{tr(2\mathbf{I_{M_t}} - \mathbf{V_t^*V_{t-1}} - \mathbf{V_{t-1}^*V_t})}\\ &= \sqrt{2M_t - 2Re\{tr(\mathbf{V_t^*V_{t-1}})\}}\end{aligned} \tag{16}$$

From equation (16), the distance between $\mathbf{V_t}$ and $\mathbf{V_{t-1}}$ have a negative correlation with $tr(\mathbf{V_t^*V_{t-1}})$. To calculate the value of $tr(\mathbf{V_t^*V_{t-1}})$, the matrix $\mathbf{H_tV_{t-1}}$ is considered as follow,

$$\mathbf{H_tV_{t-1}} = \mathbf{U_t}\Sigma_\mathbf{t}\mathbf{V_t^*V_{t-1}} \tag{17}$$

$$= (\epsilon\mathbf{H_{t-1}}\xi_{t-1}{}^{1/2} + \sqrt{1-\epsilon^2}\mathbf{W}\mathbf{D_t^{1/2}})\mathbf{V_{t-1}} \tag{18}$$

where in equation (17), the SVD of the matrix $\mathbf{H_t}$ is employed and as the matrix $\mathbf{V_t^*V_{t-1}}$ is also a unitary matrix, the equation (17) can be regarded as the SVD of the matrix $\mathbf{H_tV_{t-1}}$ and $\mathbf{V_t^*V_{t-1}}$ is the right singular matrix. In equation (18), the channel evolution model in equation (6) is considered but as the random matrix $\mathbf{W}$ is unknown, the accurate value of $\mathbf{H_t V_{t-1}}$ cannot be obtained. To eliminate the influence of random matrices, the Hermitian matrix $(\mathbf{H_t V_{t-1}})^*(\mathbf{H_t V_{t-1}})$ is considered and it can be decomposed with SVD of $\mathbf{H_t}$ as follow,

$$\begin{aligned}(\mathbf{H_t V_{t-1}})^*(\mathbf{H_t V_{t-1}}) &= (\mathbf{U_t \Sigma_t V_t^* V_{t-1}})^*(\mathbf{U_t \Sigma_t V_t^* V_{t-1}}) \\ &= (\mathbf{V_t^* V_{t-1}})^* \mathbf{\Sigma_t^* \Sigma_t} (\mathbf{V_t^* V_{t-1}}) \end{aligned} \quad (19)$$

As the matrix $\mathbf{V_t^* V_{t-1}}$ is a unitary matrix and the matrix $\mathbf{\Sigma_t^* \Sigma_t}$ is a diagonal matrix, equation (19) can be regarded as the SVD of the Hermitian matrix $(\mathbf{H_t V_{t-1}})^*(\mathbf{H_t V_{t-1}})$. Meanwhile, with the channel evolution model in equation (6), another decomposition of the Hermitian matrix $(\mathbf{H_t V_{t-1}})^*(\mathbf{H_t V_{t-1}})$ can be gotten as follow,

$$\begin{aligned}&(\mathbf{H_t V_{t-1}})^*(\mathbf{H_t V_{t-1}}) \\ &= \epsilon^2(\mathbf{H_{t-1}}\xi_{\mathbf{t-1}}{}^{1/2}\mathbf{V_{t-1}})^*(\mathbf{H_{t-1}}\xi_{\mathbf{t-1}}{}^{1/2}\mathbf{V_{t-1}}) \\ &\quad + (1-\epsilon^2)(\mathbf{W D_t^{1/2} V_{t-1}})^*(\mathbf{W D_t^{1/2} V_{t-1}}) \\ &\quad + \epsilon\sqrt{(1-\epsilon^2)}\mathbf{V_{t-1}^*}(\xi_{\mathbf{t-1}}{}^{1/2}\mathbf{H_{t-1}^* W D_t^{1/2}} \\ &\quad + (\mathbf{D_t^{1/2}})^* \mathbf{W^* H_{t-1}}\xi_{\mathbf{t-1}}{}^{1/2})\mathbf{V_{t-1}} \end{aligned} \quad (20)$$

To eliminate the influence of the random matrix $\mathbf{W}$, the expectation of equation (20) is considered. With $\mathbf{W} \sim \mathcal{CN}(0, \sigma \mathbf{I})$, it can be known that $E\{\mathbf{H_{t-1}^* W}\} = E\{\mathbf{W^* H_{t-1}}\} = \mathbf{0}$ and $E\{\mathbf{W^* W}\} = m_r \sigma^2 \mathbf{I}$. We can have that,

$$\begin{aligned}&E\{(\mathbf{H_t V_{t-1}})^*(\mathbf{H_t V_{t-1}})\} \\ &= \epsilon^2 \mathbf{V_{t-1}^*}\xi_{\mathbf{t-1}}{}^{1/2*}\mathbf{V_{t-1}\Sigma_{t-1}^*\Sigma_{t-1}V_{t-1}^*}\xi_{\mathbf{t-1}}{}^{1/2}\mathbf{V_{t-1}} \\ &\quad + (1-\epsilon^2)m_r\sigma^2\mathbf{V_{t-1}^* D_t^{1/2*} D_t^{1/2} V_{t-1}} \end{aligned} \quad (21)$$

In equation (21), the expectation of the matrix $(\mathbf{H_t V_{t-1}})^*(\mathbf{H_t V_{t-1}})$ can be gotten with the matrices $\mathbf{\Sigma_{t-1}}, \mathbf{V_{t-1}}$,which can be obtained in last iteration, and $\xi_{\mathbf{t-1}}$, $\mathbf{D_t}$, which is supposed to be known at BSs and MS. Meanwhile, in equation (19), the matrices, $\mathbf{\Sigma_t^* \Sigma_t}$ and $\mathbf{V_{t-1}^* V_t}$, can be gotten by the SVD of the matrix $(\mathbf{H_t V_{t-1}})^*(\mathbf{H_t V_{t-1}})$. By the way, as the matrix $(\mathbf{H_t V_{t-1}})^*(\mathbf{H_t V_{t-1}})$ is replaced by its expectation in equation (21), there exists an obvious error so that the matrix $\mathbf{V_t}$ cannot calculated directly. Then the matching search algorithm in equation (15) is employed. With the accurate channel state information of the channel $\mathbf{H_{t-1}}$, the matrix $\mathbf{V_{t-1}^* V_t}$ can be calculated as follow.

$$\begin{aligned}&\mathbf{V_{t-1}^* V_t} \\ &= proj\{\epsilon^2 \mathbf{V_{t-1}^*}\xi_{\mathbf{t-1}}{}^{1/2*}\mathbf{V_{t-1}\Sigma_{t-1}^*\Sigma_{t-1}V_{t-1}^*}\xi_{\mathbf{t-1}}{}^{1/2}\mathbf{V_{t-1}} \\ &\quad + (1-\epsilon^2)m_r\sigma^2\mathbf{V_{t-1}^* D_t^{1/2*} D_t^{1/2} V_{t-1}}\} \\ &= \mathcal{A} \end{aligned} \quad (22)$$

With equation (14) and (16), the modified radius can be confirmed as follow,

$$\alpha = \frac{M}{M_t}\sqrt{2M_t - 2Re\{A\}} \quad (23)$$

where the coefficient $\frac{M}{M_t}$ is given based on the relationship between the precoding matrix and right singular matrix.

B. THE ERROR ANALYSIS

In the iterative search algorithm described in section III-B, the precoding matrix $\mathbf{F_t}$ is determined by maximizing the system capacity from the candidate set, $\{\widetilde{\mathbf{F}}_\mathbf{t}\}$. As the number of the precoding matrices in the candidate set is finite, it is quite possible that the obtained precoding matrix is unequal to the right singular matrix of the channel matrix and there is an error in the iterative search algorithm. In this subsection, the error between the obtained precoding matrix $\mathbf{F_t}$ and the optimal precoding matrix $\mathbf{F_t^\star}$ will be analyzed in detail.

To analyze the error in the iterative search algorithm, the concept of matrix space is employed. Considering the definition of matrix distance in equation (9), it can be known that every unitary matrix with same dimension has the same distance away from the zero matrix, which can be expressed as follow,

$$d(\mathbf{A}, \mathbf{0}) = \sqrt{M}, \quad A \in \mathcal{S}^{M\times M} \quad (24)$$

where $\mathcal{S}^{M\times M}$ stands for the matrix space with the dimension $M \times M$ and $\mathbf{A}$ is a unitary matrix in matrix space $\mathcal{S}^{M\times M}$. Then each unitary matrix can be considered as a point on a high dimension ball with the center $\mathbf{0}$ and the radius $\sqrt{M}$ in the matrix space $\mathcal{S}^{M\times M}$. The iterative search algorithm in equation (14) can be regarded as a sphere is made with the center $\mathbf{F_{t-1}}$ and the radius $\alpha\sqrt{M}$ in the matrix space and the generated matrices on the new sphere are projected to unitary matrices. And in equation (15), the new precoding matrix $\mathbf{F_t}$ is chosen from the projected unitary matrices. The error between the obtained precoding matrix and the optimal precoding matrix is the distance between the chosen projection point and the point corresponding to the optimal precoding matrix. To calculate the distance, the spherical surface where the projection points cover should be confirmed. With the center of sphere $\mathbf{F_{t-1}}$ and the radius $\alpha\sqrt{M}$, it can be known that the maximum central angle θ between the point corresponding to $\mathbf{F_{t-1}}$ and the projection points on the spherical surface can be expressed as follow,

$$\theta = \arcsin\frac{\alpha\sqrt{M}}{2r} = \arcsin\frac{\alpha}{2} \quad (25)$$

where r is the radius of the high dimension ball, which is equal to $\sqrt{M}$. With the maximum central angle, the spherical surface area S can be calculated in equation (26), as shown at the top of the next page, and $n = M * M_t$ is the number of the dimension of the matrix space and $\beta(x; P, Q)$ is the incomplete beta function which is defined as follow,

$$\beta(x; P, Q) = \int_0^x z^{P-1}(1-z)^{Q-1}dz, \quad x \in [0, 1] \quad (27)$$

Meanwhile, the element number in the candidate set $\{\widetilde{\mathbf{F}}_\mathbf{t}\}$ is assumed as M_0 and there are M_0 corresponding points on the spherical area S. The M_0 points are supposed to obey a uniform distribution on the area S and the area each point corresponds to is $\frac{S}{M_0}$ .The area is assumed as a square and the projection point locates at the center of the square. The maximal distance between the points corresponding to the

$$\begin{aligned} S &= \int_0^{2\pi}\int_0^{\theta}\cdots\int_0^{\theta} r^{n-1}\sin^{n-2}\phi_1\sin^{n-3}\phi_2\cdots\sin\phi_{n-2}d\phi_1 d\phi_2\ldots d\phi_{n-2}d\theta_0 \\ &= 2\pi r^{n-1}\int_0^{\theta}\sin^{n-2}\phi_1 d\phi_1\int_0^{\theta}\sin^{n-3}\phi_2 d\phi_2\cdots\int_0^{\theta}\sin\phi_{n-2}\phi_{n-2} \\ &= 2\pi r^{n-1}\left(\frac{1}{2}\beta\left(\sin^2\theta;\frac{n-1}{2},\frac{1}{2}\right)\right)\left(\frac{1}{2}\beta\left(\sin^2\theta;\frac{n-2}{2},\frac{1}{2}\right)\right)\cdots\left(\frac{1}{2}\beta(\sin^2\theta;\frac{2}{2},\frac{1}{2})\right) \\ &= \frac{2\pi r^{n-1}}{2^{n-2}}\prod_{i=2}^{n-1}\beta(\sin^2\theta;\frac{i}{2},\frac{1}{2}) \end{aligned} \tag{26}$$

chosen precoding matrix and the optimal precoding matrix is given by,

$$d_{max} = \frac{\sqrt{2}}{2}\sqrt{\frac{S}{M_0}} \tag{28}$$

With the derivation in equation (10) and (11), it can be known that the upper bound of the difference between instantaneous mutual information, $I(\mathbf{H_i}, \mathbf{F_i^\star})$ and $I(\mathbf{H_i}, \mathbf{F_i})$, is given by,

$$\begin{aligned} \Delta I &= I(\mathbf{H_i}, \mathbf{F_i^\star}) - I(\mathbf{H_i}, \mathbf{F_i}) \\ &\le \frac{\rho}{Mln2}(\|\mathbf{H_i}\mathbf{F_i^\star}\|_F^2 - \|\mathbf{H_i}\mathbf{F_i}\|_F^2) \\ &\le \frac{\rho}{Mln2}\|\mathbf{H_i}\|_F^2\|\mathbf{F_i^\star} - \mathbf{F_i}\|_F(\|\mathbf{F_i^\star}\|_F + \|\mathbf{F_i}\|_F) \\ &= \frac{2\rho\sqrt{M}}{Mln2}\|\mathbf{H_i}\|_F^2 d(\mathbf{F_i^\star} - \mathbf{F_i}) \end{aligned} \tag{29}$$

With the definition of the channel matrix in equation (4), it can be known the channel matrix is made of the small-scale fading matrix $\mathbf{G}$ and the path loss matrix $\mathbf{D}$. As the elements in matrix $\mathbf{G}$ has a distribution as $\mathcal{CN}(0, 1)$, we can have that,

$$E\{\|\mathbf{G_i}\|_F^2\} = m_r M_t \tag{30}$$

With equation (28), (29) and (30), the upper bound of the difference between instantaneous mutual information can be obtained as follow,

$$\begin{aligned} \Delta I &\le \frac{2\sqrt{M}m_r M_t\rho}{Mln2}\|\mathbf{D_t^{\frac{1}{2}}}\|_F^2 d_{max} \\ &= \frac{\sqrt{2M}m_r M_t\rho}{Mln2}\sqrt{\frac{S}{M_0}}\|\mathbf{D_t^{\frac{1}{2}}}\|_F^2 \end{aligned} \tag{31}$$

From equation (31), it can be known that the error is proportional with the antenna number. When the antenna number becomes large, the value of the error will increase exponentially and the value of M_0 should be increased to maintain the accuracy. Meanwhile, it can be known that the error in the iterative search algorithm has a position correlation with the factor $\sqrt{\frac{S}{M_0}}$. As the small-scale fading evolution coefficient ϵ is related to the spherical surface area S and M_0 is the element number in the candidate set $\{\widetilde{\mathbf{F}}_\mathbf{t}\}$, the small-scale fading evolution coefficient and the element number in the candidate set $\{\widetilde{\mathbf{F}}_\mathbf{t}\}$ have an effect on the error, which will be proved from the simulation results in Section V.

C. POWER ALLOCATION STRATEGY

In the time-varying MIMO DAS, as the distances between each BS and MS are not equal, the transmission power at each BS should be varied based on the channel between the BSs and MS to maximize the system capacity. Therefore, the power allocation should be considered in the time-varying MIMO DAS, and the receive signal in equation (1) should be rewritten with the power allocation as follow,

$$\mathbf{y_t} = \mathbf{H_t}\mathbf{P_t}\mathbf{F_t}\mathbf{s_t} + \mathbf{n_t} \tag{32}$$

where $\mathbf{P_t} = diag([\sqrt{\rho_{1,t}}, \sqrt{\rho_{2,t}}, \ldots, \sqrt{\rho_{M_t,t}}])$ means the transmission power of every transmit antenna. With the receive signal model in equation (32), the instantaneous mutual information in equation (7) is rewritten as follow,

$$I(\mathbf{H_t}, \mathbf{F_t}) = log_2[det(\mathbf{I_M} + \frac{1}{Mm_r\sigma^2}\mathbf{F_t}\mathbf{P_t}\mathbf{H_t}\mathbf{H_t^*}\mathbf{P_t^*}\mathbf{F_t^*})] \tag{33}$$

To maximize the instantaneous mutual information in equation (33) is equivalent to maximize the function as follow,

$$f(\mathbf{P_t}, \mathbf{F_t}) = det(\mathbf{I_M} + \frac{1}{Mm_r\sigma^2}\mathbf{F_t}\mathbf{P_t}\mathbf{H_t}\mathbf{H_t^*}\mathbf{P_t^*}\mathbf{F_t^*}) \tag{34}$$

Here, to simply the calculation, we define the equivalent channel $\widehat{\mathbf{H}}_\mathbf{t}$ as follow,

$$\widehat{\mathbf{H}}_\mathbf{t} = \mathbf{H_t}\mathbf{P_t} = \mathbf{G_t}\mathbf{D_t^{1/2}}\mathbf{P_t} = \widehat{\mathbf{U}}_\mathbf{t}\widehat{\Sigma}_\mathbf{t}\widehat{\mathbf{V}}_\mathbf{t}^* \tag{35}$$

With the definition of the equivalent channel in equation (35) and the optimal precoding matrix $\mathbf{F_t}$, which is the first M columns of $\widehat{\mathbf{V}}_\mathbf{t}$, the objective function $f(\mathbf{P_t}, \mathbf{F_t})$ can be converted as follow,

$$\begin{aligned} f(\widehat{\mathbf{H}}_\mathbf{t}, \mathbf{F_t}) &= det(\mathbf{I_M} + \frac{1}{Mm_r\sigma^2}\mathbf{F_t}\widehat{\mathbf{H}}_\mathbf{t}\widehat{\mathbf{H}}_\mathbf{t}^*\mathbf{F_t^*}) \\ &= det(\mathbf{I_M} + \frac{1}{Mm_r\sigma^2}\widehat{\Sigma}_\mathbf{t}\widehat{\Sigma}_\mathbf{t}^*) \\ &= \prod_{i=1}^{M}(1 + \frac{1}{Mm_r\sigma^2}\mathcal{D}_i^2) \end{aligned} \tag{36}$$

With the derivation in equation (36), it can be known that to maximize the instantaneous mutual information $f(\widehat{\mathbf{H}}_\mathbf{t}, \mathbf{F_t})$, the singular values of the equivalent channel, $\{\mathcal{D}_i\}$, should be discussed. With the definition of the equivalent channel in equation (35), the equivalent channel $\widehat{\mathbf{H}}_\mathbf{t}$ is determined by the small-scale fading channel $\mathbf{G_t}$, the path loss channel $\mathbf{D_t}$ and the power allocation channel $\mathbf{P_t}$. As the elements in the small-scale fading channel follow a normal distribution $\mathcal{CN}(0, 1)$, to remove the effect of randomness, the elements in matrix $\mathbf{G_t}$ are assumed as 1.

Proposition 2: With the assumptions above, the singular values, $\{\mathcal{D}_i\}$, can be expressed as follow,

$$\mathcal{D}_i = \begin{cases} \sqrt{m_r \sum_{k=1}^{M_t} \gamma^2 r_k{}^{-v} \rho_k}, & i = 1, \\ 0, & i \neq 1. \end{cases} \tag{37}$$

Proof: See Appendix.

With Proposition 2, the objective function in equation (36) can be simplified as follow,

$$\begin{aligned} f(\widehat{\mathbf{H}}_\mathbf{t}, \mathbf{F_t}) &= \prod_{i=1}^{M}(1 + \frac{1}{Mm_r\sigma^2}\mathcal{D}_i^2) \\ &= 1 + \frac{1}{M\sigma^2}\sum_{k=1}^{M_t}\gamma^2 r_k{}^{-v}\rho_k \end{aligned} \tag{38}$$

As the result in equation (38) is a linear function, maximizing the objective function is equal to maximize the power ρ_{i0} which corresponds the maximal distance factor $\gamma^2 r_{i0}^{-v}$. With the total power restriction $\sum_{i=1}^{M_t} \rho_i = \rho$ and the minimum power restriction $\rho_j \geq \rho_0, \ \forall j$, the optimal power allocation can be obtained as follow,

$$\begin{aligned} \rho_{i0} &= \rho - (M_t - 1)\rho_0 \\ \rho_i &= \rho_0, \ i \neq i0 \end{aligned} \tag{39}$$

From the result in equation (39), the proposed power allocation strategy is only determined by the distances between the BSs and MS, and it means that the proposed power allocation strategy can be directly obtained by the path loss matrix $\mathbf{D_t}$, which is assumed to be known by the BSs and MS in the system.

V. SIMULATION RESULTS

In this section, we perform Monte Carol simulation to investigate the system capacity performance of the proposed iterative search algorithm in the time-varying MIMO DAS. As aforementioned in Section II, the small-scale fading coefficient follows Jake's model $\epsilon = J_0(2\pi f_D T)$. When we generate ϵ, the $60GHz$ mmWave channel model is employed. The velocity of the MS is set form $1km/h$ to $25km/h$ and $f_c = 60GHz$. Then the small-scale fading coefficient varies from $0.9997(1km/h)$ to $0.8185(25km/h)$.

In Fig.2-3, the performance of instantaneous mutual information in a time-varying MIMO DAS with 4 BSs and one MS is given. Each BS and MS is equipped with 4 antennas and the radius of the cell is 500m, while the BSs are deployed in a circle with the radius 150m in the centre of the cell. In Fig.2, we perform the instantaneous mutual information with the transmit SNR 15 and the small-scale fading evolution coefficient 0.9 while the MS can move arbitrarily in the cell. From Fig.2, it can be known that with the precoding

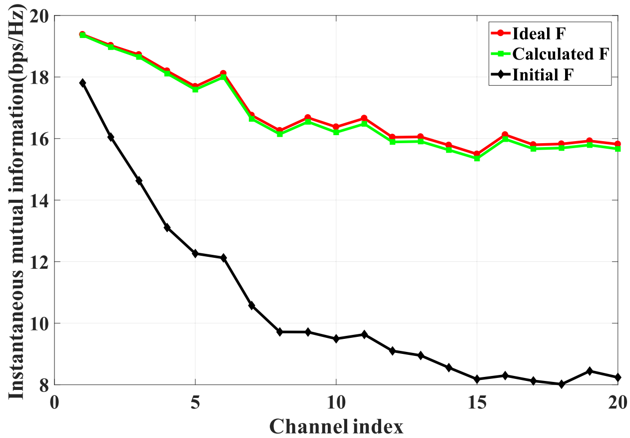

FIGURE 2. **The performance of instantaneous mutual information with different precoding matrices (SNR = 15, eps = 0.9).**

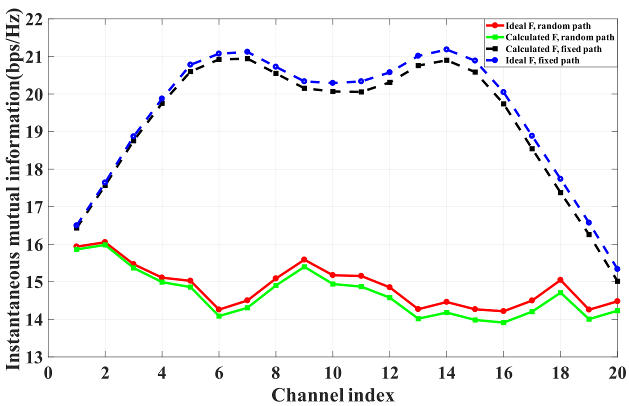

FIGURE 3. **The performance of instantaneous mutual information with fixed path and random path (SNR = 15, eps = 0.9).**

matrix obtained by the proposed algorithm, the instantaneous mutual information is quite close to the performance with the ideal precoding matrix and the error is less than 0.3bps/Hz. However, the instantaneous mutual information with the initial precoding matrix decreases with the channel index and after 20 channel indexes, the value of instantaneous mutual information becomes the value with an arbitrary unitary matrix. In Fig.3, the instantaneous mutual information where the MS moves along a random path and a fixed path are compared. As the elements in the path loss matrix $\mathbf{D}$ have an inverse ratio with the distance between the BS and the MS, the instantaneous mutual information can have a rapid increase when the MS moves to the BS. Therefore, in Fig.3, the instantaneous mutual information with the fixed path has two peaks while the instantaneous mutual information with random paths appears to be gentle. From Fig.3, it can be known that the mobile path of the MS have little influence on the error between the instantaneous mutual information with the ideal precoding matrix and that with the calculated precoding matrix, as the two groups of the instantaneous mutual information have similar difference.

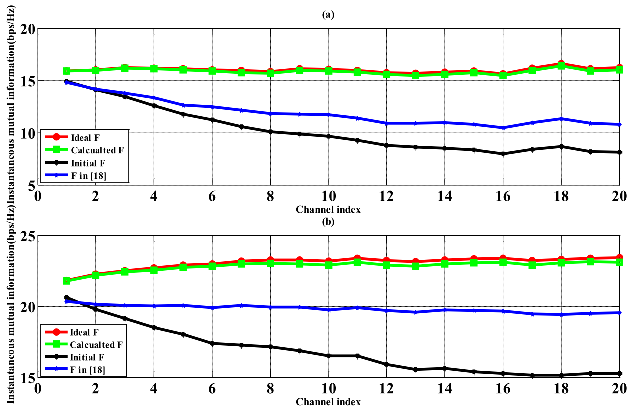

FIGURE 4. The performance of the proposed algorithm and the algorithm in [18] (SNR = 15, eps = 0.9).

In Fig.4, the performance of instantaneous mutual information with the iterative search algorithm proposed in this paper and the algorithm in [18] are compared. From Fig.4(a), it can be known the proposed iterative search algorithm has an obvious advance. Meanwhile, in Fig.4(a), the instantaneous mutual information obtained by the algorithm in [18] has a decline with the channel index as the algorithm in [18] does not take the change of matrix **D** in account and cannot deal with the movement of the MS. In Fig.4(b), to make the comparison fair, the location of the MS is invariable and the performance of instantaneous mutual information with the algorithm in [18] becomes stable. However, there is a gap between the instantaneous mutual information with the proposed iterative search algorithm and the algorithm in [18].

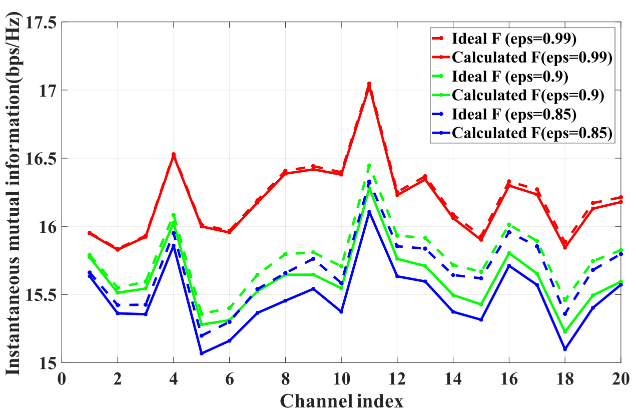

FIGURE 5. The performance of instantaneous mutual information with different epsilon (SNR = 15, $M = 4$).

To discuss the effect of the small-scale fading evolution coefficient, Fig.5 is given. In Fig.5, three groups of simulations with different epsilon are performed with same mobile path of MS and same innovation matrices. From Fig.5, it can be known that the error between the instantaneous mutual information with the ideal precoding matrix and the calculated precoding matrix will both decrease when the epsilon becomes larger. Meanwhile, the system can obtain better instantaneous mutual information with a large epsilon as the influence of the innovation matrix becomes small. However, as the MS movement has a significant effect on the channel matrix evolution, the epsilon only has a weak correlation with the evolution of channel matrix so that the variation trend of three groups of simulations are almost coincident.

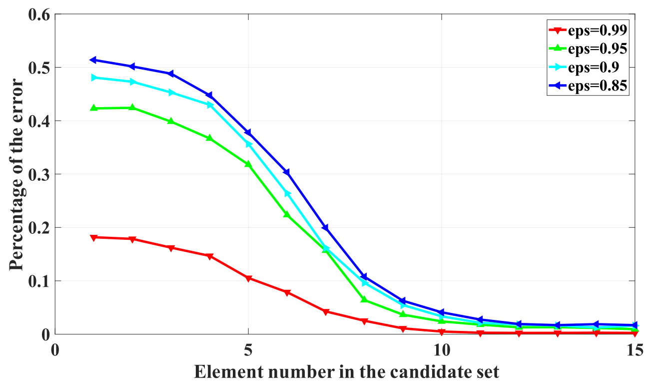

FIGURE 6. The percentage of the error with different element number in the candidate set (SNR = 15, $M = 4$).

In Fig.6, the element number in the candidate set, M_0, in the proposed algorithm is discussed. From Fig.6, it can be known that the error on the instantaneous mutual information has an obvious relation with the small-scale fading evolution coefficient, which verifies the result in Fig.5 again. However, when the iterative search algorithm adopts a small value of M_0, there exists a significant difference between the percentage of the error with different epsilon, but as M_0 becomes large, the results with different epsilon become close. When $M_0 = 2^{15}$, there is only a 2% difference between the percentages of the error. For most of the small-scale fading evolution coefficient, when $M_0 = 2^{10}$, there will be a error less than 5% on the system capacity.

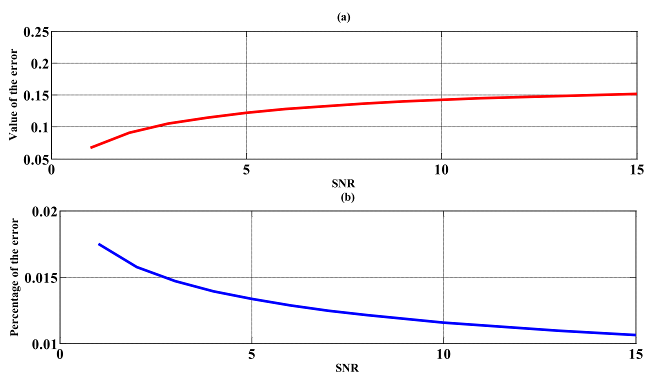

FIGURE 7. The percentage of the error with different SNR (eps = 0.9, $M = 4$).

In Fig.7, the performance of the error on instantaneous mutual information with the proposed iterative mutual information is analyzed. From Fig.7(a), it can be known the absolute value of the error has a positive correlation with the SNR, which verifies the error analysis result in equation (31).

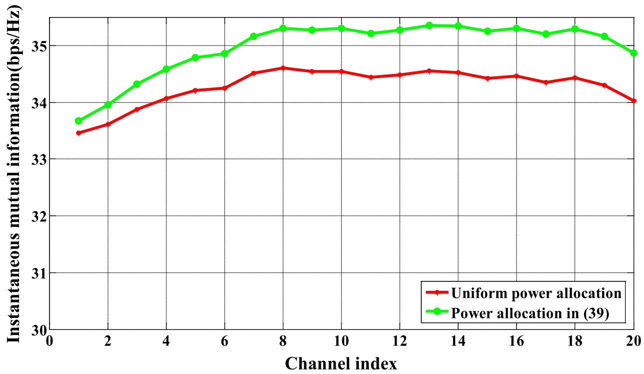

FIGURE 8. The performance of instantaneous mutual information with different power allocation(eps = 0.9, M = 4).

However, as the value of instantaneous mutual information becomes larger with a higher SNR, which can be known from equation (7), the percentage of the error has a decrease with the SNR in Fig.7(b). In Fig.8, we give the comparison between the uniform power allocation strategy and the power allocation strategy proposed in Section IV-C with the same total transmit power. From Fig.8, it can be known that with the proposed power allocation strategy, the instantaneous mutual information has 1bps/Hz increase to that with uniform power allocation strategy.

VI. CONCLUSIONS

In this paper, an iterative search algorithm to maximize the system capacity in the time-varying MIMO DAS is considered. With the proposed iterative search algorithm, the instantaneous mutual information with the calculated precoding matrix is very close to the value with the ideal precoding matrix, and the error can be less than 5%. With the discussion of the small-scale fading evolution coefficient, it can be known that epsilon has a close relationship with the error of proposed algorithm, but it has a weak effect on the stability of system capacity which is mainly impacted by the relative location between the MS and BSs. In addition, we give a power allocation strategy in the time-varying MIMO DAS, which has an advance to the uniform power allocation strategy on the instantaneous mutual information. In future, more researches in the time-varying MIMO DAS, such as the optimal base station number and base station deployment problem, will be focused.

APPENDIX

With the definition of the equivalent channel in equation (35), the rank of the equivalent channel $\widehat{\mathbf{H}}_\mathbf{t}$ can be calculated as follow,

$$\begin{aligned} Rank(\widehat{\mathbf{H}}_\mathbf{t}) &= Rank(\mathbf{G_t D_t^{1/2} P_t}) \\ &\leq \min\{Rank(\mathbf{G_t}), Rank(\mathbf{D_t^{1/2}}), Rank(\mathbf{P_t})\} \end{aligned} \quad (40)$$

As the elements in the random matrix $\mathbf{G_t}$ are assumed as 1, the rank of the matrix $\mathbf{G_t}$ is 1. Therefore, it can be known that the rank of the equivalent channel $\widehat{\mathbf{H}}_\mathbf{t}$ is 1 and the same with the rank of the matrix $\widehat{\mathbf{H}}_\mathbf{t}^*\widehat{\mathbf{H}}_\mathbf{t}$.

With the definition of the singular value, it can be known that the singular values of the matrix $\widehat{\mathbf{H}}_\mathbf{t}$ are the square roots of the eigenvalues of the matrix $\widehat{\mathbf{H}}_\mathbf{t}^*\widehat{\mathbf{H}}_\mathbf{t}$. As the rank of the matrix $\widehat{\mathbf{H}}_\mathbf{t}^*\widehat{\mathbf{H}}_\mathbf{t}$ is 1, only one eigenvalue of the matrix $\widehat{\mathbf{H}}_\mathbf{t}^*\widehat{\mathbf{H}}_\mathbf{t}$ is not equal to 0, denoted by λ_1. With the concept of trace, we can have that,

$$\lambda_1 = tr(\widehat{\mathbf{H}}_\mathbf{t}^*\widehat{\mathbf{H}}_\mathbf{t}) = \sum_{j=1}^{m_r}\sum_{k=1}^{M_t}\gamma^2 r_k^{-v}\rho_k = m_r\sum_{k=1}^{M_t}\gamma^2 r_k^{-v}\rho_k \quad (41)$$

Then the singular value of the equivalent channel matrix, $\mathcal{D}_1$, corresponding λ_1 is $\sqrt{m_r\sum_{k=1}^{M_t}\gamma^2 r_k^{-v}\rho_k}$, so it can be known that the singular values of the equivalent channel matrix, $\{\mathcal{D}_i\}$, are,

$$\mathcal{D}_i = \begin{cases} \sqrt{m_r\sum_{k=1}^{M_t}\gamma^2 {r_k}^{-v}\rho_k}, & i = 1, \\ 0, & i \neq 1. \end{cases} \quad (42)$$

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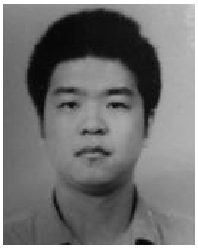

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