Efficient Channel Estimation Method for MIMO Antenna Selection Systems Exploiting Temporal Correlation of Channel

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***Abstract*—This paper addresses the issue of MIMO channel estimation with the aid of a rough estimate of temporal correlation statistics where MIMO antenna selection system is employed. Under the temporally correlated channel, proposed method controls allocation of length of training symbols for each antenna element so that the elements which are likely to be selected are estimated more precisely than the other elements. In order to utilize this estimation scheme effectively, this paper also proposes the antenna selection method which takes account of a difference of channel estimation accuracy among antenna elements. When the ML channel estimation was adopted, the proposed selection method is with almost the same computational cost as the conventional selection methods. The proposed method does not rely on spatial correlation statistics which is not always stable in real propagation scenarios. The numerical simulation using 3GPP-SCM revealed that the proposed method works effectively under shorter training symbols employed.**

I. Introduction

MIMO transmission attracts much attention since it achieves much higher transmission capability by carrying an information via spatial degree of freedom of radio propagation channel. Especially for the multi stream MIMO transmission, its performance is dramatically affected by whether the surrounding propagation environment is capable of conveying spatial degrees of freedom effectively or not. In order to improve such inherent channel capabilities, MIMO antenna selection system has been proposed which enables to control the channel conditions by actively changing the antenna subset to use so that the rank of the channel matrix can be improved[1]. In addition, the system can save hardware cost by reducing expensive RF chains while not losing its performance to a large extent. In the system, the antenna subset for transmission is optimally chosen to enhance the MIMO channel capacity. A number of antenna selection algorithms have been proposed in order to perform a near-optimal selection with a smaller computational complexity [4]. Many of them require a full channel state information, so the channel measurement must precede the antenna selection.

Generally in pilot symbol aided channel estimation with a constant noise power, the more energy is put into the transmission of training symbols, the lower the estimation error can be. The authors' interest is how to estimate the channel precisely within a limited set of resources.

The authors had investigated that the channel estimation of MIMO antenna selection systems is improved by using the Kalman filter under the assumptions that a temporal correlation is perfectly characterized as Gauss-Markov model, and a spatial correlation is available[2].

This paper proposes a novel channel estimation scheme for MIMO antenna selection systems which exploits *only* a temporal correlation statistics. In antenna selection system, a channel state information for all the antenna elements is required as a selection criteria. However, if the channel state information is estimated within the same precision for all the antenna elements, the measurements for elements which turned out to be not selected become in vain since they are only discarded. Therefore, we propose an estimation scheme which measures channel precisely only for the elements which are likely to be selected in the next step, and the rest of the elements are coarsely estimated by shorter training symbols. In order to utilize this scheme effectively, we also consider an antenna selection method which takes account of a difference of estimation precision of each antenna element. If the ML channel estimation was adopted, the proposed selection method requires almost the same computational cost as the conventional selection method. The proposed method has robustness in the points that it does not rely on certain mathematical model of temporal correlation, as well as spatial correlation which is sensitive to the movement of the receiver.

It should be noted that for the estimation of time-variant frequency selective fading channels, exploiting temporal correlation is quite common in literature. However, the proposed method is substantially different from them in the points that the proposed method deals with only a resource allocation of channel estimation dedicated for antenna selection systems, and has nothing in common with the Kalman-based methods. In fact, the currently estimated channel state itself is independent with the previously estimated one. This feature is advantageous in a way that it can prevent degradation of capacity even when sudden change of channel state would happen induced by shadowing, rotation of mobile station, etc.

A. Mathematical Notations

The subscripts $\top$, $\mathcal{H}$, $*$ indicate transpose, Hermitian transpose (transpose and complex conjugate), and complex conjugate respectively. $\boldsymbol{I}_N$ denotes the $N \times N$ identity matrix. Also the inverse, trace, determinant, and Frobenius norm of the matrix $\boldsymbol{X}$ are denoted by $\boldsymbol{X}^{-1}$, $\operatorname{tr}\boldsymbol{X}$, $\det\boldsymbol{X}$, and

$\|\boldsymbol{X}\|_{\mathrm{F}}$, respectively. A diagonal matrix having elements of $x_{1,1}, x_{2,2}, \cdots, x_{n,n}$ is denoted by $\mathrm{diag}[x_{1,1}, x_{2,2}, \cdots, x_{n,n}]$. Since we often discuss correlations between each matrix element, it is convenient to treat matrix as one column vector that consists of all its elements. For any $m \times n$ matrix $\boldsymbol{A} = [\boldsymbol{a}_1\, \boldsymbol{a}_2 \cdots \boldsymbol{a}_n]$, the vec operator generates a $mn \times 1$ vector defined as $\mathrm{vec}\,\boldsymbol{A} \triangleq \left[\boldsymbol{a}_1^\top\, \boldsymbol{a}_2^\top\, \cdots \boldsymbol{a}_n^\top\right]^\top$ where $\triangleq$ means definition. The Kronecker product $\otimes$ is required with the use of the vec operator.

II. System Model

A. MIMO Antenna Selection System

For simplicity, we consider antenna selection system only for the receiver side with N_{Tx} transmit antennas and N_{Rx} receive antennas, and N_{RF} RF chains satisfying $1 \leq N_{\mathrm{RF}} < N_{\mathrm{Rx}}$. For a narrowband frequency nonselective MIMO channel, if we connect the i-th RF chains to the c_i-th $(1 \leq c_i \leq N_{\mathrm{Rx}})$ antenna element, the received vector $\boldsymbol{y} \in \mathbb{C}^{N_{\mathrm{RF}}}$ can be expressed as

$$\boldsymbol{y} = \boldsymbol{A}_{\tau_k} \boldsymbol{H}_k \boldsymbol{x} + \boldsymbol{n} \tag{1}$$

where $\boldsymbol{n} \in \mathbb{C}^{N_{\mathrm{RF}}}$ is additive noise vector typically assumed to have a white complex Gaussian distribution with average power σ_n^2, and $\boldsymbol{x} \in \mathbb{C}^{N_{\mathrm{Tx}}}$ is the normalized transmit vector such that $\mathrm{E}_{\boldsymbol{x}} \boldsymbol{x}\boldsymbol{x}^{\mathcal{H}} = \boldsymbol{I}_{N_{\mathrm{Tx}}}$. $\boldsymbol{H}_k \in \mathbb{C}^{N_{\mathrm{Rx}} \times N_{\mathrm{Tx}}}$ is the complex channel gain matrix at time instant k. The channel is normalized such that $\mathrm{E}\|\boldsymbol{H}_k\|_{\mathrm{F}}^2 = P_r N_{\mathrm{Rx}}$ where P_r is average receive signal power for each receive antenna. Average signal to noise ratio (SNR) per receive antenna can be expressed as P_r/σ_n^2. $\boldsymbol{A}_{\tau_k}$ performs extraction and permutation of row vectors of $\boldsymbol{H}_k$. By using the antenna connection vector $\boldsymbol{\tau}_k \triangleq [c_1\, c_2 \cdots c_{N_{\mathrm{RF}}}]^\top$, $\boldsymbol{A}_{\tau_k}$ is expressed as

$$\begin{bmatrix} [\boldsymbol{H}_k]_{c_1,:} \\ [\boldsymbol{H}_k]_{c_2,:} \\ \vdots \\ [\boldsymbol{H}_k]_{c_{N_{\mathrm{RF}}},:} \end{bmatrix} = \boldsymbol{A}_{\tau_k} \boldsymbol{H}_k, \quad \boldsymbol{A}_{\tau_k} \triangleq \sum_{i=1}^{N_{\mathrm{RF}}} \mathbf{f}_i \mathbf{e}_{<\boldsymbol{\tau}_k, \mathbf{f}_i>}^\top$$

where $[\boldsymbol{H}_k]_{c_n,:}$ means the c_n-th row vector of $\boldsymbol{H}_k$, and $\mathbf{e}_i, \mathbf{f}_j$ are the so-called standard basis of $\mathbb{C}^{N_{\mathrm{Rx}}}, \mathbb{C}^{N_{\mathrm{RF}}}$, respectively. Antenna subset is selected so that the Shannon capacity of extracted channel matrix $\boldsymbol{A}_{\tau_k} \boldsymbol{H}_k$ becomes the largest of all the combinations. Since the true channel matrix is not available directly, we determine the connection $\boldsymbol{\tau}_k$ by referring the estimated channel matrix $\widehat{\boldsymbol{H}}_k$ instead. From the Foschini-Telatar equation for equal transmit power allocation, $\boldsymbol{\tau}_k$ is determined such that:

$$\boldsymbol{\tau}_k = \arg\max_{\tau} \log_2 \det \left(\boldsymbol{I}_{N_{\mathrm{RF}}} + \boldsymbol{A}_\tau \widehat{\boldsymbol{H}}_k \widehat{\boldsymbol{H}}_k^{\mathcal{H}} \boldsymbol{A}_\tau^{\mathcal{H}} \right) \tag{2}$$

III. Channel Estimation with a Selection Bias

In this section, we design a channel estimation scheme based on the idea of how to save the energy to measure the channels which are not to be selected. Concretely, the proposed method assigns longer training symbols to the antenna elements which are likely to be selected in the next step, and estimate them precisely compared to the other antenna elements.

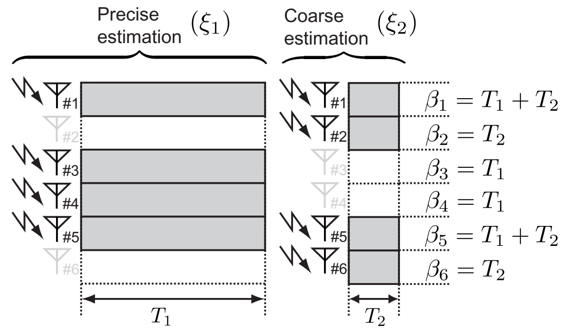

Fig. 1. Precision control considering temporal correlation. In this example, we assume $\boldsymbol{\xi}_1 = (1, 3, 4, 5)^\top$ and $\boldsymbol{\xi}_2 = (1, 2, 5, 6)^\top$.

A. Precise and Coarse Estimation

We introduce a two stage channel estimation which consists of precise estimation phase and coarse estimation phase. In antenna selection systems, since the number of antenna elements is larger than the number of RF chains, receptions of training symbols must be repeated several times with changing a connection of RF switches. The repeated trainings are required at least $N_m = \lceil N_{\mathrm{Rx}}/N_{\mathrm{RF}} \rceil$ times where $\lceil x \rceil$ means the smallest integer greater than or equal to x. At the precise estimation phase, the measurement is done by longer training symbols, and the channel is estimated precisely. The rest of measurement is utilized for the coarse estimation phase by using shorter training symbols.

In the precise estimation phase, a measured antenna subset should be chosen in such a way that they have a high probability to be selected in the next frame. In order to realize this, we introduced the assumption that "In temporally correlated channel, the antenna subset which is selected as best combination in the $(k-1)$-th fading block is likely to have high transmission capability also in the k-th fading block." The assumption is considered reasonable because in temporally correlated channel, the channel state information does not change significantly between the adjacent fading blocks.

This plot is illustrated in Fig.1. Let us assume that the subset $\boldsymbol{\tau}_{k-1} = (1, 3, 4, 5)^\top$ of receiver elements was chosen for transmission at the $(k-1)$-th fading block. Then, in k-th fading block, same subset $(\boldsymbol{\xi}_1 = \boldsymbol{\tau}_{k-1})$ is precisely measured by the training symbols with length of T_1. The rest of the elements, $\boldsymbol{\xi}_2 = (1, 2, 5, 6)^\top$ are coarsely measured with length of $T_2\,(T_1 > T_2)$.

In later discussion, we denote a total length of training symbols as $N_t \triangleq T_1 + T_2$. Also we introduce a parameter α which indicates ratio between T_1 and T_2 as follows:

$$T_1 = \alpha N_t, \quad T_2 = (1 - \alpha) N_t \quad (0.5 \leq \alpha < 1) \tag{3}$$

If $\alpha = 0.5$, the proposed method is equivalent to the conventional method.

IV. Antenna Selection Considering Estimate Error

The channel estimation scheme explained so far has a characteristic that the estimation error varies by antenna element. In order to efficiently exploit this feature, we cannot utilize directly the antenna selection criteria of (2) because the criteria assumes uniform estimation error at each element.

In later discussion, we consider the best antenna selection method when the channel estimation error is generally expressed as multivariate Gaussian distribution. Let us denote a true channel of time instant k be $\boldsymbol{H}_k$, and the corresponding estimate be $\widehat{\boldsymbol{H}}_k$. A behavior of the estimation error is fully characterized by the error covariance matrix defined as

$$\boldsymbol{P}_k \triangleq \mathrm{E}_{\boldsymbol{n}} \mathrm{E}_{\boldsymbol{H}_k} \operatorname{vec}\left(\boldsymbol{H}_k - \widehat{\boldsymbol{H}}_k\right)\left[\operatorname{vec}\left(\boldsymbol{H}_k - \widehat{\boldsymbol{H}}_k\right)\right]^{\mathcal{H}} \quad (4)$$

where E means expectation with respect to its subscript. Although obtaining $\boldsymbol{P}_k$ seems difficult, we will show later that it can be calculated easier like (12) by only using length of training sequences if the ML channel estimation was adopted.

A. Antenna Selection Method Maximizing Lower-Bound of Mutual Information

Though how to incorporate the estimation error into the antenna selection criterion can be considered in various ways, desired properties are its validity and feasibility of optimization. In this paper, we propose to maximize a lower bound of mutual information. This means that antenna subset is chosen such that the capacity degradation in the worst case scenario is minimized.

B. Lower-Bound of Mutual Information

According to [5], we derive the lower-bound[8] of degraded channel capacity caused by the estimate error of channel.

If the receiver employes a synchronized detection, i.e. $\widehat{\boldsymbol{H}}_k$ is used at the Rx side as if it were a true channel matrix, (1) can be separated into the two terms [3] as

$$\begin{aligned}\boldsymbol{y} &= \boldsymbol{A}_{\tau_k}\widehat{\boldsymbol{H}}_k\boldsymbol{x} + \boldsymbol{A}_{\tau_k}\left(\boldsymbol{H}_k - \widehat{\boldsymbol{H}}_k\right)\boldsymbol{x} + \boldsymbol{n}\\ &= \boldsymbol{A}_{\tau_k}\widehat{\boldsymbol{H}}_k\boldsymbol{x} + \hat{\boldsymbol{n}} \end{aligned} \quad (5)$$

where the first term contains information received at the Rx, and the second term $\hat{\boldsymbol{n}}$ is called the effective noise term which is regarded as an additive noise caused by the estimate error, because a synchronized detection virtually cannot exploit the information in this term. The covariance matrix of $\hat{\boldsymbol{n}}$ is expressed as

$$\begin{aligned}\boldsymbol{\Phi} &\triangleq \mathrm{E}_{\boldsymbol{x}}\mathrm{E}_{\boldsymbol{n}}\mathrm{E}_{\widehat{\boldsymbol{H}}_k}\hat{\boldsymbol{n}}\hat{\boldsymbol{n}}^{\mathcal{H}}\\ &= \mathrm{E}_{\widehat{\boldsymbol{H}}_k}\boldsymbol{A}_{\tau_k}\widehat{\boldsymbol{H}}_k\widehat{\boldsymbol{H}}_k^{\mathcal{H}}\boldsymbol{A}_{\tau_k}^{\mathcal{H}} + \sigma_n^2\boldsymbol{I}_{N_{\mathrm{RF}}}\\ &= \boldsymbol{A}_{\tau_k}\boldsymbol{R}_k\boldsymbol{A}_{\tau_k}^{\mathcal{H}} + \sigma_n^2\boldsymbol{I}_{N_{\mathrm{RF}}} \end{aligned} \quad (6)$$

where $\boldsymbol{R}_k$ is determined by $\boldsymbol{P}_k$ of (4) as described later. The mutual information of this channel has a lower-bound as

$$\begin{aligned}&\mathcal{I}(x, y|\widehat{\boldsymbol{H}}_k) \geq\\ &\log_2\det\left(\boldsymbol{I}_{N_{\mathrm{RF}}} + \boldsymbol{A}_{\tau_k}\widehat{\boldsymbol{H}}_k\widehat{\boldsymbol{H}}_k^{\mathcal{H}}\boldsymbol{A}_{\tau_k}^{\mathcal{H}}\boldsymbol{\Phi}^{-1}\right) \triangleq C_{\mathrm{LB}}\,. \end{aligned} \quad (7)$$

Instead of directly maximizing the instant channel capacity from the estimated channel as (2), our proposal is to maximize C_{LB} of (7).

As for the optimization method, the greedy algorithm is available as well as the case of (2). In the case of criteria (2), the greedy algorithm can be implemented with significantly small computations by utilizing the Sherman-Morrison formula[4]. However, in the case of C_{LB}, generally we cannot simplify the computation like that due to the additional term of Φ^{-1}.

Let us discuss the special case when $\boldsymbol{R}_k$ is expressed as a diagonal form. In this case, denoting $\boldsymbol{R}_k = \mathrm{diag}[r_1\, r_2\, \cdots\, r_{N_{\mathrm{Rx}}}]$ yields,

$$C_{\mathrm{LB}} = \log_2\det\left(\boldsymbol{I}_{N_{\mathrm{RF}}} + \boldsymbol{A}_{\tau_k}\widetilde{\boldsymbol{H}}_k\widetilde{\boldsymbol{H}}_k^{\mathcal{H}}\boldsymbol{A}_{\tau_k}^{\mathcal{H}}\right) \quad (8)$$

$\widetilde{\boldsymbol{H}}_k$ is defined as

$$\widetilde{\boldsymbol{H}}_k \triangleq \begin{bmatrix} [\widehat{\boldsymbol{H}}_k]_{1,:} / \sqrt{r_1 + \sigma_n^2} \\ [\widehat{\boldsymbol{H}}_k]_{2,:} / \sqrt{r_2 + \sigma_n^2} \\ \vdots \\ [\widehat{\boldsymbol{H}}_k]_{N_{\mathrm{Rx}},:} / \sqrt{r_{N_{\mathrm{RF}}} + \sigma_n^2} \end{bmatrix}. \quad (9)$$

where r_i is i-th diagonal element of $\boldsymbol{R}_k$. (8) is exactly the same form as (2) except that $\widehat{\boldsymbol{H}}_k$ is replaced by $\widetilde{\boldsymbol{H}}_k$. This implies that the maximization of C_{LB} can be achieved by exactly the same method as a number of conventional antenna selection methods proposed so far. For example, applying the fast antenna subset selection[4] can save much computational costs. Additional calclations required for (9) is only a division of row vectors by corresponding effective noise.

Intuitively, (9) can be interpreted that the antenna elements which have larger estimation error tend not to be selected as compared to the other elements.

V. Fast Antenna Subset Selection in the case of ML Channel Estimation

In this section we show that $\boldsymbol{R}_k$ becomes diagonal if the ML channel estimation was employed under a block fading channel.

A. Channel Observation Model under a Block Fading Channel

We assume for each fading block, training is repeated N_m times with changing the antenna connection as $\boldsymbol{\xi}_p\,(1 \leq p \leq N_m)$. Let $\boldsymbol{s}_1^{(p)}, \boldsymbol{s}_2^{(p)}, \cdots, \boldsymbol{s}_{T_p}^{(p)} \in \mathbb{C}^{N_{\mathrm{Tx}}}$ be normalized training symbols, each of them being launched from Tx side in number order at fading block k. And let T_p denote the length of training symbols for the p-th measurement. They are normalized such that $\|\boldsymbol{s}_i^{(p)}\|^2 = 1$ i.e. $\|\boldsymbol{S}_p\|_F^2 = T_p$ where $\boldsymbol{S}_p \triangleq [\boldsymbol{s}_1^{(p)}\, \boldsymbol{s}_2^{(p)}\, \cdots\, \boldsymbol{s}_{T_p}^{(p)}]$. Launched symbols are caught at the Rx side with its RF switches connected as $\boldsymbol{\xi}_p$. Then, the received sequences are written as

$$\boldsymbol{Y}_p = \boldsymbol{A}_{\xi_p}\boldsymbol{H}_k\boldsymbol{S}_p + \boldsymbol{N}_p\,. \quad (10)$$

where $\boldsymbol{Y}_p \triangleq [\boldsymbol{y}_1^{(p)}\, \boldsymbol{y}_2^{(p)}\, \cdots\, \boldsymbol{y}_{T_p}^{(p)}]$ and $\boldsymbol{N}_p$ are $N_{\mathrm{RF}} \times T_p$ matrices each of them consisting of received vectors and noise

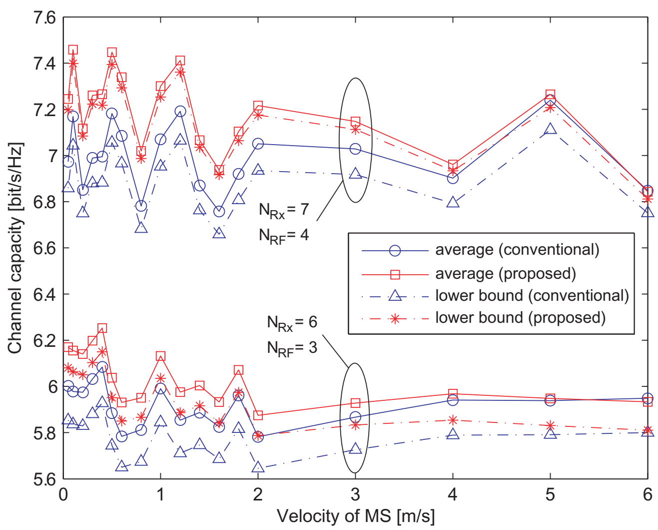

Fig. 2. Channel capacity for different velocity of MS ($\alpha = 0.8$, SNR=8dB)

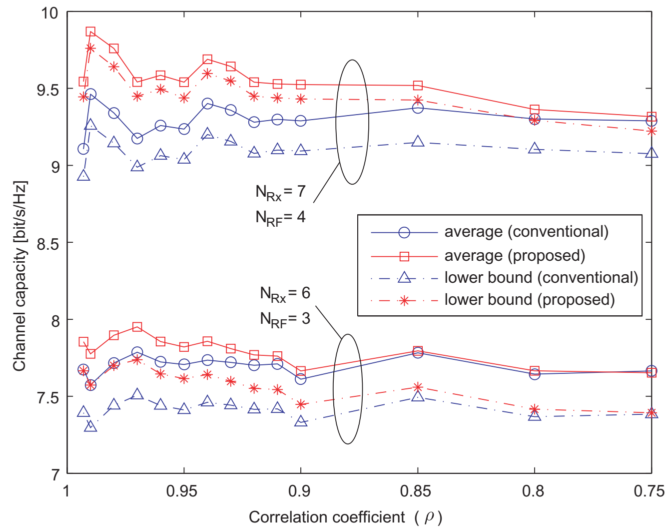

Fig. 3. Channel capacity for different ρ ($\alpha = 0.8$, SNR=8dB)

vectors, respectively. $\boldsymbol{y}_i^{(p)}$ is the received vector corresponding to the transmitted vector $\boldsymbol{s}_i^{(p)}$. Applying vec operator on both sides of the above equation yields,

$$\operatorname{vec} \boldsymbol{Y}_p = \left(\boldsymbol{S}_p^{\top} \otimes \boldsymbol{A}_{\xi_p} \right) \operatorname{vec} \boldsymbol{H}_k + \operatorname{vec} \boldsymbol{N}_p \,. \tag{11}$$

Now, our aim is to obtain the best estimate of $\boldsymbol{H}_k$ from the set of received signals $\boldsymbol{Y}_1, \boldsymbol{Y}_2, \cdots, \boldsymbol{Y}_{N_m}$.

B. ML Channel Estimation

If a spatial correlation characteristics of channel is not available, and also a noise is white gaussian, it has been proven that the best linear estimate of a channel is obtained by pseudoinverse of $\left(\boldsymbol{S}_p^{\top} \otimes \boldsymbol{A}_{\xi_p} \right)$in conjunction with orthogonal training sequence ($\boldsymbol{S}_p \boldsymbol{S}_p^{\mathcal{H}} = T_p / N_{\mathrm{Tx}} \boldsymbol{I}_{N_{\mathrm{Tx}}}$) [9]. Such estimation is called the maximal likelihood (ML) estimation [6][7]. In this case, the origin of channel estimation error is only additive noise term $\boldsymbol{N}_p$ of (11). Therefore $\boldsymbol{P}_k$ of (4) is

$$\boldsymbol{P}_k = \sigma_n^2 N_{\mathrm{Tx}} \boldsymbol{I}_{N_{\mathrm{Tx}}} \otimes \operatorname{diag} \left[\frac{1}{\beta_1} \cdots \frac{1}{\beta_{N_{\mathrm{Rx}}}} \right] \tag{12}$$

where β_i means the total length of received training symbols at the i-th Rx element in the k-th fading block. If β_i equals to zero, the term $1/\beta_i$ should be replaced by zero. A derivation of (12) is omitted due to limitations of space. For any positive semi-definite matrices $\boldsymbol{A}$ and $\boldsymbol{B}$, if $\boldsymbol{X}$ obeys $\operatorname{vec} \boldsymbol{X} \sim \mathcal{CN}(\boldsymbol{0}, \boldsymbol{A} \otimes \boldsymbol{B})$, it holds that $\mathrm{E}_{\boldsymbol{X}} \boldsymbol{X} \boldsymbol{X}^{\mathcal{H}} = (\operatorname{tr} \boldsymbol{A}) \boldsymbol{B}$. By utilizing this relationship, we can obtain the $\boldsymbol{R}_k$ in (6) as follows:

$$\boldsymbol{R}_k = \sigma_n^2 N_{\mathrm{Tx}}^2 \operatorname{diag} \left[\frac{1}{\beta_1} \, \frac{1}{\beta_2} \, \frac{1}{\beta_3} \cdots \frac{1}{\beta_{N_{\mathrm{Rx}}}} \right] \tag{13}$$

Since $\boldsymbol{R}_k$ is diagonal, the optimization with respect to the criteria C_{LB} is tractable with much smaller computations. In this case, r_i in (9) is expressed as $r_i = \sigma_n^2 N_{\mathrm{Tx}}^2 / \beta_i$.

VI. Simulation

A. Verification by 3GPP SCM

We verified an effectiveness of proposed method by numerical simulation. In order to generate a temporally correlated channel, we resort to the 3GPP Spatial Channel Model[10]. A scenario is selected to "Urban micro", and all other parameters are default settings except a number of antenna elements, sampling interval, and velocity of the mobile station.

The Fig.2 depicts an ensemble average of channel capacity and the lower-bound of capacity for different velocity of the mobile station. A channel capacity was calculated with changing initial channel state 80 times, and correlated channels are generated 80 times for each initial channel state. The results are obtained by averaging over them. In the conventional method, we let $\alpha = 0.5$, and antenna subset is selected not considering estimate error as (2). In the proposed medhod, in order to exploit the temporal correlation, we let $\alpha = 0.8$, and utilized the selection criteria of (8). For fair comparison, a number of channel measurements per unit time is chosen to the same value. From the graph, we can see as the velocity of the mobile station becomes slower, the capacity is enhanced.

B. Analysis by Simple Channel Model

In order to obtain more comprehensible results, we also investigated by using a simple single tapped Gauss-Markov model. The updating equation is

$$\boldsymbol{H}_k = \rho \boldsymbol{H}_{k-1} + \sqrt{1 - \rho^2} \boldsymbol{X} \tag{14}$$

where ρ $(0 \leq \rho \leq 1)$ is a temporal correlation coefficient between adjacent fading blocks, and $\boldsymbol{X}$ is a random matrix which obeys $\operatorname{vec} \boldsymbol{X} \sim \mathcal{CN}(\boldsymbol{0}, P_r / N_{\mathrm{Tx}} \boldsymbol{I}_{N_{\mathrm{Tx}} N_{\mathrm{Rx}}})$.

The Fig.3 depicts an ensemble average of channel capacity and the lower-bound of capacity for different temporal correlation(ρ) where $N_t = 20$. The Fig.4 depicts the capacity for different N_t where $\rho = 0.95$. For both simulation, other configurations are same as the case of Fig.3.

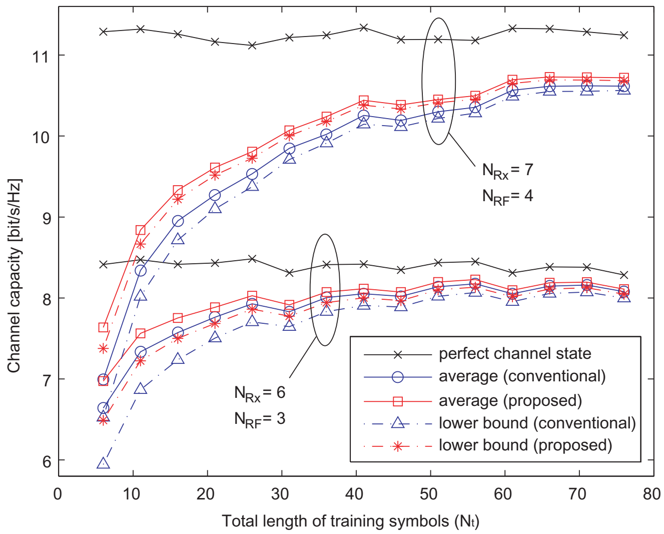

Fig. 4. Channel capacity for different N_t ($\alpha = 0.8$, SNR=8dB)

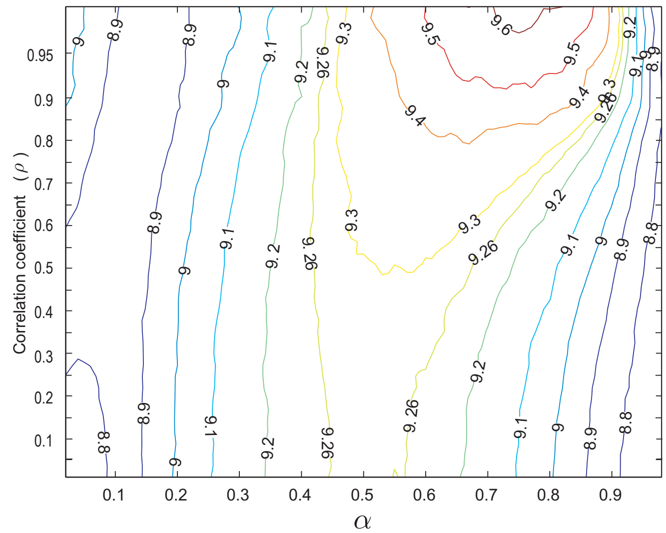

Fig. 5. Lower-bound of channel capacity for different ρ and α (SNR=8dB, $N_t = 20$) Scale of ρ from 0.9 to 1 is magnified by two times than other area.

As the temporal correlation becomes higher, the proposed method achieves better than the conventional method. We can observe 3 to 5 percent improvement for both ensemble mean and lower-bound of capacity.

From the Fig.4, as the length of training symbols becomes larger, the effectiveness of proposed method becomes weaker. As for the average SNR, more improvement of capacity was observed in the lower SNR conditions (less than 8dB). An effectiveness of this method depends on channel conditions such as ρ and SNR.

C. Optimal Choise of α

The Fig.5 depicts the lower-bound of capacity for different temporal correlation and α. We can find that as the temporal correlation of channel becomes higher, the larger α is suitable. Even at extremely high temporal correlation, the optimal α appears to be at most 0.75. The reason for this is that using too large α results in inhibition of change of antenna combination. This is because, in such situation, the channels estimated in the coarse estimation stage become too coarse to be selected. Therefore, too large α spoils merits of antenna selection systems.

On the other hand, $\alpha = 0.5$ is suitable for the lower temporal correlation. This makes sense because we cannot predict in advance which antennas are selected in that case.

From the figure, small difference of α from its optimal value does not yield much degradations in capacity. It is advantageous for us, because choosing α has robustness. This implies that a precise estimation of temporal correlation is not necessary in order to determine α.

VII. Concluding Remarks

We proposed a novel channel estimation scheme for MIMO antenna selection systems as well as a new antenna selection criteria dedicated for the method. The simulation revealed that the proposed method works more effectively when shorter length of training sequence is used under the lower average SNR. Though an improvement of channel capacity is few percent, the implementation of the scheme requires only a small modification to a conventional antenna selection systems.

As future tasks, a easy method which measures a degree of temporal correlation by small computation should be investigated in order to implement this scheme.

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