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# A Low Complexity Channel Estimation Algorithm for Massive MIMO System

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***Abstract***

*Massive MIMO can boost the capacity and increase the coverage, however the pilot overhead of its channel estimation will linearly increase with the antenna increasing. In order to reduce pilot overhead and improve the quality of channel estimation, a multi-dimension Wiener filtering channel estimation algorithm was put forward. First we analyzed Massive MIMO system model and channel model in which Base station configured a two-dimension antenna array; then accomplished channel estimation applying the correlation function of time, frequency, the row and column of the antenna array, and presented a simple closed-form solution of the space-time-frequency correlation function to reduce the complexity of the algorithm. The proposed algorithm extends one-dimension space filtering to two-dimension, so doesn't need to transmit pilots in every raw of the two-dimension antenna array contrast with 3D-Wiener and can reduce beyond 50% pilot overhead. Based on the simulation results, this algorithm can achieve 8dB performance gain over 2D-Winner and 3dB over 3D-Wiener with same pilot overhead and can acquires the optimal throughput with considering both the channel estimation quality and pilot overhead.*

***Keywords:*** *Massive MIMO, Channel Estimation, Multi-dimension Wiener Filter, Space-time-frequency Correlation*

## 1. Introduction

In the foreseeable future, the requirements of high rate wireless applications and the high density of wireless devices are expected to lead to enormous new challenges in terms of the efficient exploitation of the achievable spectral resources. Among the prospective air-interface techniques, Massive MIMO (known as Large-scale MIMO) in the base station can boost the cell throughput, improve the link quality and decrease the transmission power [1, 2]. Massive MIMO is characterized that Base station can distinguish the objective user not only the position in X/Y planar but also the height in Z axis. To achieve the alignment of three dimensions, it will configure two-dimension rectangle array which has more antenna than the traditional one-dimension array [3]. Massive MIMO can precisely concentrate the transmitting power on the height of the target user so as to improve the link quality and reduce the interference to other users. On the hand Massive MIMO can support spatial multiplexing of multiple users with different heights, so can boost the system capacity.

The most common method to acquire MIMO channel knowledge in the receiver is channel estimation aided by pilots or preambles [4, 5]. The transmitter delivers pilots from every antenna or different beams, and the receiver estimates channel information of the corresponding antenna or beam using LS (Least Squares), LMMSE (Linear Minimum Mean Square Error), 2D-MMSE (Two-dimension Minimum Mean Square Error) or 2D (two-dimension) Wiener filtering algorithms. With antenna and distinguishable beam increasing, the overhead of pilots or preambles will linearly increase and greatly decrease the system

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throughput. For Massive MIMO with more antenna and more precise beams, new channel estimation algorithms should be studied on how to reduce pilot overhead and improve the quality of channel estimation.

The following literatures have studied on how to utilize the channel correlation to reduce pilot overhead and improve the quality of channel estimation. Literature [6] proposed 2D-Wiener channel estimation algorithm which achieved channel estimation interpolation using time-frequency channel correlation. It can significantly reduce pilot overhead and improve the channel estimation quality comparing LS, LMMSE algorithms. The three dimensional Wiener filter (referred to as 3D-Wiener) channel estimation algorithm was considered in the literature [7]. It achieved channel estimation interpolation using the space-time-frequency correlation of MIMO channel and proved that 3D-Wiener is superior to 2D-Wiener of approximately 5dB with same pilot overhead. Literature [8] proposed a three-dimensional MMSE channel estimation algorithm using the channel space-time-frequency correlation. But those literatures were for the conventional one-dimensional antenna array and haven't defined the space correlation of arbitrary two elements for the two-dimension antenna array. As 2D-Wiener don't use spatial correlation of MIMO channel, pilot will deliver from every antenna to estimate channel information and its pilot overhead is linearly increased with the number of antenna. 3D-Wiener and 3D-MMSE don't use two-dimension spatial correlation of MIMO channel, pilot will deliver from every raw of the antenna array to estimate channel information and its pilot overhead is increased with the number of rows. For Massive MIMO, the space-time-frequency correlation of the two-dimension antenna array and new channel estimation algorithm still need more studied.

On the study of the space-time-frequency correlation with the two-dimensional uniform rectangular array, literature [9] presented and simulated the solving of the spatial correlation of uniform rectangular array, but hasn't considered the integrated solving scheme of space-time-frequency correlation function. Literature [10] proposed the space-time-frequency correlation solution with arbitrary antenna arrays, but its solution is very complicate and hard to be applied in the actual channel estimation algorithm. Literature [11] proposed a Massive MIMO channel model for IST-Wiener channel simulation but didn't analyze the channel correlation.

In this paper, we extend one-dimension space filtering of original 3D-Wiener algorithms to two-dimension space filtering and propose a multi-dimension Wiener filter channel estimation algorithm. We achieves the channel estimation interpolation with multi-dimension filtering and gets the optimal Wiener filtering weights using the channel correlation functions of the time, frequency, raw and column of the antenna array. The proposed algorithm doesn't need to transmit the pilot from every antenna element contrast to 2D-Wiener or even every raw contrast to 3D-Wiener and can be significantly reduced the pilot or preamble overhead. At last based on theoretical analysis and simulation results, it's shown that the proposed algorithm has the better quality of channel estimation than 2D-Wiener and 3D-Wiener algorithm with the same pilot overhead. What is more, the proposed algorithm acquires the optimal throughput with considering both the channel estimation quality and pilot overhead.

## 2. System Model and Massive MIMO Channel Model

Based on the literature [3], a typical antenna configuration is used in base station as shown in Figure 1. The transmitter configures a uniform rectangular antenna array (URA) with $N_{row}$ raw and $N_{col}$ column, which composes $N$ same omnidirectional antennas with same RF characteristic and $N = N_{row} \times N_{col}$. The spacing of every two adjacent elements is $d_x$ to x-axis and $d_y$ to y-axis. The receiver configures uniform linear array (ULA), as shown in Figure 2, with M antenna elements, which the spacing of every two adjacent units is $d_x$ to x-axis.

Assume that time-frequency resources of MIMO+ OFDM system are divided into a plurality of same resource blocks and every resource block includes K subcarriers, L OFDM symbols and applies the same pilot transmission scheme. In this paper a resource block will be the object to describe the multi-dimension Wiener filter channel estimation algorithms. For the $t^{th}$ OFDM symbol and the $\omega^{th}$ subcarrier, the received signal of a physical resource block is can be expressed as:

$$\boldsymbol{Y}(t,\omega) = \boldsymbol{H}(t,\omega)\boldsymbol{X}(t,\omega) + \boldsymbol{n}(t,\omega) \tag{1}$$

Where $\boldsymbol{Y}(t,\omega)$ is the $M\times 1$ dimension receiving signals and the dimension of $\boldsymbol{Y}$ is $LK\times M\times 1$; $\boldsymbol{H}(t,\omega)$ is the $M\times N$ channel matrix from the transmitter to the receiver and the dimension of $\boldsymbol{H}$ is $LK\times M\times N$. $\boldsymbol{X}(t,\omega)$ is the $N\times 1$ dimension transmitting signal. $\boldsymbol{n}(t,\omega)$ is the $M\times 1$ dimension additive white Gaussian noise (AWGN) with zero mean and variance $\sigma^2$. Assume that the average normalized channel gain $E\left\{\left|\boldsymbol{H}(t,\omega)\right|^2\right\}=1$ and the average signal to noise ratio (SNR) per symbol is $\gamma = \frac{E_s}{\sigma^2}$.

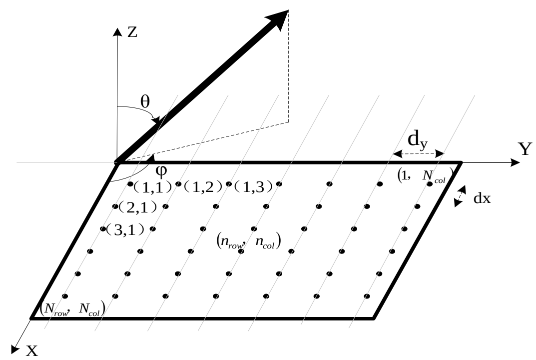


**Figure 1. Antenna Configuration of the Transmitter**

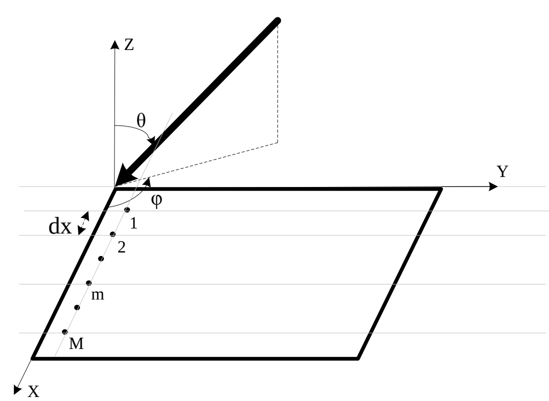


**Figure 2. Antenna Configuration of the Receiver**

 

In this paper we focus on the estimation of the channel impulse response (CIR) without considering the impact of large-scale fading. It is commonly assumed that the distance from the antenna array to scatters a much larger than the antenna spacing. Therefore, propagation waveforms in the scattering environment are plane waves. There are I multi-paths from the transmitter to the receiver which every path is distributed to Rayleigh distribution. For the $t^{th}$ OFDM symbol and the $\omega^{th}$ subcarrier, the channel matrix $\boldsymbol{H}(t,\omega)$ can be expressed as:

$$\boldsymbol{H}(t,\omega)\overset{\Delta}{=}\sum_{i=1}^{I}\boldsymbol{a}_R(\varphi_i,\theta_i)\beta_i(t,\omega)\cdot\boldsymbol{a}_T^T(\varphi_i,\theta_i) \tag{2}$$

Where $[\cdot]^T$ denotes the transpose of the matrix or vector. I is the total number of multi-path, and $\beta_i(t,\omega)$ is CIR of the $i^{th}$ path. $\boldsymbol{a}_T(\varphi_i,\theta_i)$ is the steering vector of URA in the transmitter, $\varphi_i$ is the angel between the x-axis and the direction-of departure (DOD) of the $i^{th}$ path from the transmitter and commonly known as the azimuth angle ; $\theta_i$ is the angel between the z-axis and the DOD of the $i^{th}$ path and commonly known as the elevation angle. $\boldsymbol{a}_R(\varphi_i,\theta_i)$ is the steering vector of the ULA in the receiver. $\boldsymbol{a}_T(\varphi_i,\theta_i)$ is defined as the following formula (3):

$$\begin{aligned}\boldsymbol{a}_T(\varphi_i,\theta_i)&=vec\left(\boldsymbol{a}_{N_{row}}(\mu)\boldsymbol{a}_{N_{col}}^T(\upsilon)\right)\\&=\begin{bmatrix}1,e^{j\upsilon},\cdots,e^{j(N_{col}-1)\upsilon},e^{j(\mu+\upsilon)},\cdots,e^{j[\mu+(N_{col}-1)\upsilon]},\ldots,\\e^{j(N_{row}-1)\mu},\ldots,e^{j[(N_{row}-1)\mu+(N_{col}-1)\upsilon]}\end{bmatrix}^T\end{aligned} \tag{3}$$

Where $\boldsymbol{a}_{N_{row}}(\mu)=\left[1,e^{j\mu},\cdots,e^{j(N_{row}-1)\mu}\right]^T$ and is the raw steering vector of URA. $\boldsymbol{a}_{N_{col}}(\upsilon)$ is the column steering vector and $\boldsymbol{a}_{N_{col}}(\upsilon)=\left[1,e^{j\upsilon},\cdots,e^{j(N_{col}-1)\upsilon}\right]^T$. Further $\mu=2\pi d_x\cos\varphi\sin\theta/\lambda$ and $\lambda$ is the wavelength. $\upsilon=2\pi d_y\sin\varphi\sin\theta/\lambda$. $\boldsymbol{a}_R(\varphi_i,\theta_i)$ is the steering vector of the receiving antenna array and the $M\times 1$ dimension vector as formula (4) shown:

$$\boldsymbol{a}_R(\varphi_i,\theta_i)=\left[1,e^{j\upsilon},\cdots,e^{j(M-1)\upsilon}\right]^T \tag{4}$$

## 3. Multi-stage Wiener Filtering Channel Estimation Algorithm

In this paper, pilots are transmitted from the antenna. The $n_0^{th}$ transmitting antenna transmits pilot signals in the $t_0^{th}$ OFDM symbol and the $\omega_0^{th}$ subcarrier, other antennas transmit null signal in the current physical resource element as illustrated in Figure 3, and the receiver will estimate CIR of this antenna based on received pilot signals. Pilot signals are transmitted spacing $d_t$ symbols in the time domain, $d_f$ subcarriers in the frequency domain and $d_s$ antennas in the space domain, which means there is only one antenna to transmit the pilot in every $d_s$ antenna and other antenna don't need to transmit the pilot in any time-frequency resources.

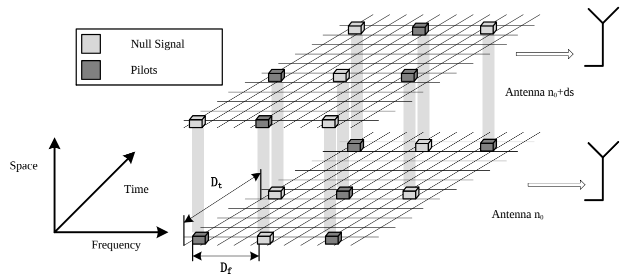


**Figure 3. The Pilot Transmission Scheme**

Assume that $\boldsymbol{X}(t_0,\omega_0,m_0,n_0)$ is the pilot signal transmitted in the $t_0^{th}$ OFDM symbols, the $\omega_0^{th}$ sub-carrier and the $n_0^{th}$ transmitting antennas. CIR can be estimated by LS algorithm to estimate from the receiving signal in this time-frequency resource and is expressed as:

$$\hat{\boldsymbol{H}}(t_0,\omega_0,m_0,n_0)=\frac{\boldsymbol{Y}(t_0,\omega_0,m_0,n_0)}{\boldsymbol{X}(t_0,\omega_0,m_0,n_0)} \tag{5}$$

The channel information of other antenna and other time-frequency resources are obtained by the interpolation using Wiener filtering. Wiener interpolation filter achieve the minimum mean squared error between the filtered output signal $\hat{\boldsymbol{H}}_{m,n}(t,\omega)$ and the desired signal $\boldsymbol{H}_{m,n}(t,\omega)$. The channel information of every receiving antenna is acquired by formula (5), and the output signal of Wiener filter is written as:

$$\begin{aligned}\hat{\boldsymbol{H}}(t,\omega,m,n)&=\boldsymbol{w}_{opt}\cdot\hat{\boldsymbol{H}}(t_0,\omega_0,m,n_0)\\&=\boldsymbol{R}_{dp}\boldsymbol{R}_{pp}^{-1}\hat{\boldsymbol{H}}(t_0,\omega_0,m,n_0)\end{aligned} \tag{6}$$

The channel correlation matrix $\boldsymbol{R}_{dp}$ and $\boldsymbol{R}_{pp}$ are the four-dimensional function, so the proposed algorithm called multi-dimension Wiener filter channel estimation algorithm. $\boldsymbol{R}_{pp}$ is the $LK\times M\times M$ auto-correlation matrix of the estimated CIR at the pilot position. For the $t_0^{th}$ OFDM symbols, the $\omega_0^{th}$ sub-carrier, the $m_0^{th}$ receiving antenna and the $n_0^{th}$ transmitting antenna, the autocorrelation matrix $\boldsymbol{R}_{pp}$ is calculated as follows:

$$\boldsymbol{R}_{pp}(t_0,\omega_0,m,n_0)=E\left[\hat{\boldsymbol{H}}(t_1,\omega_1,m,n_1)\hat{\boldsymbol{H}}^*(t_0,\omega_0,m,n_0)\right] \tag{7}$$

Wherein $(\cdot)^*$ denotes conjugate. $\boldsymbol{R}_{dp}$ is the cross correlation matrix between output values of CIR in data position and the estimated CIR in pilot positions and is calculated as follows:

$$\boldsymbol{R}_{dp}(t,\omega,m,n)=E\left[\hat{\boldsymbol{H}}(t,\omega,m,n)\hat{\boldsymbol{H}}^*(t_0,\omega_0,m,n_0)\right] \tag{8}$$

Wherein $(\cdot)^*$ denotes conjugate. As $\hat{\boldsymbol{H}}(t,\omega,m,n)$ is unknown, we will use the space-time-frequency correlation character of Massive MIMO channel to solve formula (8). It is commonly assumed that CIR is Wide-Sense Stationary Uncorrelated Scattering (WSSUS) model, it means that the time correlation $\rho(\Delta t)$ of all the multi-path is same with the time interval $\Delta t$, and the frequency correlation $\rho(\Delta\omega)$ with subcarrier spacing $\Delta\omega$ is same in the system bandwidth. Where $\rho(\Delta t)$ is denoted the time correlation function between the channel of symbol $t$ and symbol $t+\Delta t$; $\rho(\Delta\omega)$ is denoted the frequency correlation function between the channel of sub-carrier $\omega$ and sub-carrier $\omega+\Delta\omega$.Therefore, $\rho(\Delta t)$ and $\rho(\Delta\omega)$ are irrelevant with the spatial correlation function. We utilize formula (5) to estimate CIR of every receiving antenna, so it is only necessary to consider the spatial correlation of the transmitter. Through the above analysis, formula (8) is the independent product of spatial correlation function, the time correlation function and the frequency correlation function [6-8]:

$$\boldsymbol{R}_{dp} = \boldsymbol{R}_T(n_1, n_2)\rho(\Delta t)\rho(\Delta\omega) \tag{9}$$

Where $\Delta t = t_2 - t_1$ and $\Delta\omega = \omega_2 - \omega_1$. $\boldsymbol{R}_T(n, n_1)$ is the spatial correlation function between the $n^{th}$ transmit antennas and the $n_1^{th}$ transmit antennas.

The time correlation function and is calculated as follows [5, 6]:

$$\rho(\Delta t) = J_0\left(2\pi\Delta t f_{\max} T_{sym}\right) \tag{10}$$

Where $f_{\max}$ is the maximum Doppler shift, $T_{sym}$ is OFDM symbol length, and $J_0(\cdot)$ represents the zero order Bessel function. The frequency correlation function and is calculated as follows [5, 6]:

$$\rho(\Delta\omega) = \sum_{i=1}^{L} P_i \cdot e^{j2\pi\Delta\omega} \tag{11}$$

Where $P_i$ is the expected power of the $i^{th}$ path.

For the transmitting antenna, we assume that the $n^{th}$ antenna is located in the $n_{row}^{th}$ row and $n_{col}^{th}$ column of the transmitting antenna array and the $n_1^{th}$ antenna is located in the $n_{row}^{1th}$ row and $n_{col}^{1th}$ column of the transmitting antenna array, the spatial correlation function of the $n^{th}$ transmitting antenna and the $n_1^{th}$ transmitting antenna can be calculated according to the following formula:

$$\begin{aligned}
&\boldsymbol{R}_T(n_1, n_2) \\
&= \int_{\varphi}\int_{\theta} a_{n_{row},n_{col}}(\varphi,\theta) a^*_{n^1_{row},n^1_{col}}(\varphi,\theta) p(\varphi,\theta) d\theta d\varphi \\
&= C\int_{\varphi_0-\Delta\varphi}^{\varphi_0+\Delta\varphi}\int_{\theta_0-\Delta\theta}^{\theta_0+\Delta\theta} \Big\{ e^{j2\pi/\lambda\left[\left(n_{col}-n^1_{col}\right)d_y \sin\varphi\sin\theta\right]} \cdot \\
&\qquad\qquad e^{j2\pi/\lambda\left[\left(n_{row}-n^1_{row}\right)d_x \cos\varphi\sin\theta\right]} \Big\} d\theta d\varphi \\
&= C\int_{\varphi_0-\Delta\varphi}^{\varphi_0+\Delta\varphi}\int_{\theta_0-\Delta\theta}^{\theta_0+\Delta\theta} \Big\{ e^{j\Delta_y \sin\varphi\sin\theta} e^{j\Delta_x \cos\varphi\sin\theta} \Big\} d\theta d\varphi
\end{aligned} \tag{12}$$

 

Where $p(\varphi,\theta)$ is the joint probability density function of the azimuth angle and the elevation angle. Assume that the azimuth angle is independent distribution with the elevation angle, so $p(\varphi,\theta)=p(\varphi)p(\theta)$. $\Delta\varphi$ is the angel spread of the azimuth angle and $\varphi_0$ is the average azimuth angle, $\Delta\theta$ is the angel spread of the elevation angle and $\theta_0$ is the average elevation angle. If the azimuth angle $\varphi$ is uniform distributed in $[\varphi_0-\Delta\varphi,\ \ \varphi_0+\Delta\varphi]$ and the elevation angle $\theta$ is uniform distributed in $[\theta_0-\Delta\theta,\ \ \theta_0+\Delta\theta]$, we can deduce $C=1/4\Delta\varphi\Delta\theta$. $\Delta_x$ and $\Delta_y$ respectively are phase deviation of x-axis and y-axis.

Let $\Delta=\sqrt{\Delta_x^2+\Delta_y^2}$ , $\gamma=\arg\tan\frac{\Delta_x}{\Delta_y}$ , then formula is denoted as:

$$\begin{aligned}\boldsymbol{R}_T(n_1,n_2)&=\frac{1}{4\Delta\tau\Delta\omega}\int_{\varphi_0-\Delta\varphi}^{\varphi_0+\Delta\varphi}\int_{\theta_0-\Delta\theta}^{\theta_0+\Delta\theta}e^{j\Delta\sin(\varphi+\gamma)\sin\theta}d\theta d\varphi\\&=\int_{\varphi_0+\gamma-\Delta\varphi}^{\varphi_0+\gamma+\Delta\varphi}\int_{\theta_0-\Delta\theta}^{\theta_0+\Delta\theta}\begin{bmatrix}\cos(\Delta\sin\theta\sin\psi)\\+j\sin(\Delta\sin\theta\sin\psi)\end{bmatrix}d\theta d\psi\end{aligned}\tag{13}$$

Based on the well-known representations:

$$\begin{aligned}&\cos(\Delta\sin\theta\sin\psi)=J_0(\Delta\sin\theta)+2\sum_{n=1}^{\infty}J_{2n}(\Delta\sin\theta)\cdot\cos 2n\psi\\&\sin(\Delta\sin\theta\sin\psi)=\sum_{n=1}^{\infty}2J_{2n-1}(\Delta\sin\theta)\cdot\sin(2n-1)\psi\end{aligned}\tag{14}$$

$$\int_0^{2\pi}J_{2n}(2z\sin\theta)d\theta=\frac{\pi}{2}J_n^2(z)\tag{15}$$

Formula (13) can be expressed a simple closed-form solution:

$$\begin{aligned}&\boldsymbol{R}_T(n_1,n_2)=\frac{\pi}{2}J_0^2(\frac{\Delta}{2})+\\&\sum_{n=1}^{\infty}\frac{\pi}{2n}J_n^2\left(\frac{\Delta}{2}\right)[\sin(\varphi_0+\gamma+\Delta\varphi)-\sin(\varphi_0+\gamma-\Delta\varphi)]\\&+j\sum_{n=1}^{\infty}\frac{\pi}{2n}J^2_{n=\frac{1}{2}}\left(\frac{\Delta}{2}\right)[\cos(\varphi_0+\gamma-\Delta\varphi)-\cos(\varphi_0+\gamma+\Delta\varphi)]\end{aligned}\tag{16}$$

We calculate the cross correlation matrix $\boldsymbol{R}_{dp}$ using formula (10), (11), (16), and estimate channel information of every transmitting antenna in the resource block based on formula (6).

## 4. IV Performance Analysis and Simulation Results

In this section we analyzed and evaluated the MSE and Throughput performance of this algorithm. To more clearly evaluate the performance, we compare Multi-dimension Wiener channel estimation algorithm with current 2D-Wiener and 3D-Wiener filter channel estimation algorithm. Simulation parameters are shown in Table 1.

**Table 1. Simulation Parameters**

| Parameters | Values | Parameters | Values |
|---|---|---|---|
| Frequency | 2.4GHz | Bandwidth | 10MHz |
| Scenario | Micro Urban | Sampling duration | 65.1 ns |
| Antenna configurations | Transmitter: 4 × 4 URA,<br>Receiver: 4 ULA. Antenna spacing: λ / 2 | | |
| Channel Model | IST-Wiener Model, B1 NLOS (16 paths) | | |
| Physical Resource Blocks | 12 subcarriers×14 OFDM symbols | | |
| Pilot transmission scheme | Time interval：dt =4, Frequency interval df =3<br>（as shown in Figure 2）<br>Space interval：described in simulation method | | |

MSE of the Multi-dimension Wiener filter channel estimation algorithm is calculated as the following formula (16):

$$\begin{aligned}\sigma_e^2 &= \frac{1}{MNLK}\sum_{\omega=1}^{K}\sum_{t=1}^{L}\sum_{n=1}^{N}\sum_{m=1}^{M}\sigma_e^2[t,\omega,m,n] \\ &= E\left[\|\boldsymbol{H}(t,\omega,m,n)\|^2\right] - \boldsymbol{w}_{opt}^H(t,\omega,m,n)\boldsymbol{R}_{dp}(t,\omega,m,n) \\ &- \boldsymbol{R}_{dp}^H(t,\omega,m,n)\boldsymbol{w}_{opt}(t,\omega,m,n) \\ &+ \boldsymbol{w}_{opt}^H\boldsymbol{R}_{pp}(t,\omega,m,n)\boldsymbol{w}_{opt}\end{aligned} \tag{17}$$

According the solution of formula (6), the latter two can be canceled each other out. Then formula (16) can be simplified as the following formula (18):

$$\begin{aligned}&\sigma_e^2 \\ &= E\left[\|\boldsymbol{H}(t,\omega,m,n)\|^2\right] - \boldsymbol{w}_{opt}^H(t,\omega,m,n)\boldsymbol{R}_{dp}(t,\omega,m,n)\end{aligned} \tag{18}$$

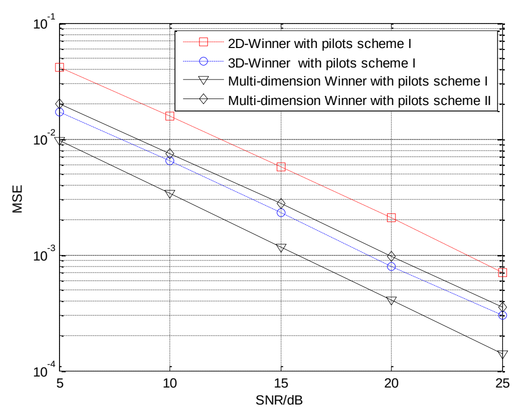


**Figure 4. MSE~SNR Simulation Results**

 

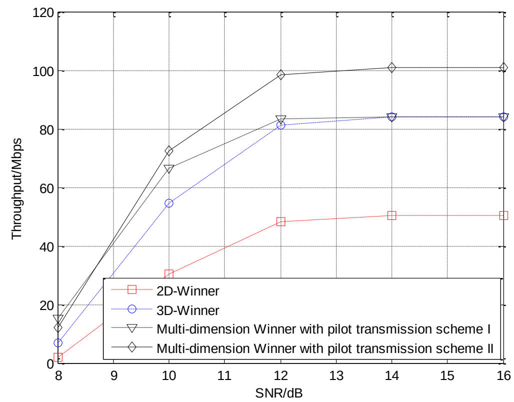


**Figure 5. Throughput ~SNR Simulation Results**

MSE~SNR simulation results of different channel estimation algorithms are shown in Figure 3 (left figure). The multi-dimension Wiener filter channel estimation algorithm configures two pilot transmission schemes. The scheme I is that pilots are transmitted on every antenna same as 2D-Wiener, 3D-Wiener. The scheme II is that pilots are transmitted on every antenna in the odd column of URA. The multi-dimension Wiener filter channel estimation algorithm utilizes the two dimension spatial correlation of the row and column of URA. With the same pilot overhead, it can acquire approximately 8dB performance gains over 2D-Wiener which filtered without the spatial correlation and 3dB gain over 3D-Wiener which filtered with the one-dimension spatial correlation. In particular, pilots overhead of the pilot transmission scheme II is less than scheme I, but as a result of the row and column two-dimensional space filter, the MSE performance is worse about 0.6dB than 3D-Wiener channel estimation algorithm and better 3.6dB than 2D-Wiener.

In order to comprehensively evaluate the quality of channel estimation and pilots overhead, we compare the throughput performance, which specially is that the amount of transmitting bits in simulating physical resources is multiplied by the correct probability and then subtract pilots overhead. In the simulation, we use 1/2 convolutional code and 16QAM modulation, and a single stream beamforming for the data transmission. Pilot transmission scheme is determined by the characteristics of every channel estimation algorithm. 2D-Wiener transmits pilots from every antenna and its pilot overhead is 57%. 3D-Wiener antenna can use the one-dimension space correlation, therefore it transmitted pilots from odd antenna in every raw of URA and its pilot overhead is 28.5%. The multi-dimension Wiener filtering can be implemented using two-dimension space correlation and configures two pilot transmission schemes. Schemes I is same with the scheme of 3D–Wiener. Scheme II transmits pilots only from the odd antenna in odd raws of URA and its pilot overhead is 14%. Shown as Figure 3 (Right), the throughput of the proposed algorithm is optimal and much higher than the 2D-Wiener. At low SNR, the proposed algorithm with the same pilot scheme get higher the throughput than 3D-Wiener, and as the SNR increasing, the quality of channel estimation is improved and pilot overhead determines their throughput, therefore the throughput of the proposed algorithm is same as 3D-Wiener. In Pilot transmission scheme II with minimal pilots overhead, the proposed algorithm takes full advantage of the two-dimension space correlation of URA, the throughput performance of proposed algorithm is superior to 3D-Wiener both in the low or high SNR and can achieve optimal throughput performance.

## 5. Conclusions

In this paper we analyze Massive MIMO channel model and the space-time-frequency correlation of URA and put forward a simple and closed solution of the space-time-frequency correlation function between arbitrary two pairs of transmitting antenna and receiving antenna. Further the multi-dimension Wiener filtering algorithm obtains the optimum filter weights using the above-mentioned correlation function and achieves the channel estimation interpolation with multi-dimensional filtering in the time, frequency, rows and columns domain. This algorithm can reduce by half or three-quarters of pilots overhead while obtaining a good channel estimation performance. Based on simulation results, it is proved that the proposed algorithm can acquire higher system throughput comparing with 3D-Wiener and 2D-Wiener channel estimation algorithm for Massive MIMO system with a uniform rectangular array. This algorithm can be applied in Massive MIMO system with good research and practical value.

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