CHANNEL ESTIMATION FOR MILLIMETER-WAVE VERY-LARGE MIMO SYSTEMS

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ABSTRACT

We present an efficient pilot-assisted technique for downlink channel estimation in Very Large MIMO (VL-MIMO) systems operating in a 60 GHz indoor channel. Our estimator exploits the inherent sparsity of the channel and requires quite low pilot overhead. It is based on a coarse estimation stage that capitalizes on compressed sensing, followed by a refinement stage to find the transmit/receive spatial frequencies. Considering a ray-tracing channel model, the system throughput is evaluated from computer simulations by considering different beamforming schemes designed from the estimated channel. Our results show that the proposed channel estimator performs quite well with very low pilot overhead.

***Index Terms*—** Massive MIMO systems, millimeter-wave communications, compressive sensing, channel estimation.

1. INTRODUCTION

By looking to the future of wireless communications, we always envisage higher data rates. To achieve this goal in a spectrum-scarce scenario, research on VL-MIMO systems, also known as "Massive MIMO", has attracted significant attention in both the academic and industrial sectors. The basic idea behind VL-MIMO systems is to deploy hundreds, or even thousands, of antennas at the access node (AN) to provide a significantly increased data rate and robustness against interference, channel fading and antenna unit failures [1, 2]. In principle, an AN equipped with this amount of antennas is capable to create extremely narrow beamformers, which translates into high spatially selective transmission and simplified receive processing.

VL-MIMO is being considered as a key technology for next-generation millimeter (MM)-wave wireless communications. Although the MM-wave scenario imposes coverage restrictions due to the severe signal attenuation, it enables the use of very small antenna arrays, which are quite suitable for VL-MIMO deployments. Some standards have been proposed to operate in the MM-wave range (e.g. around 60 GHz) such as ECMA-37, IEEE 802.15.3c and IEEE 802.11.ad [3], especially in future indoor communications.

Although coverage restriction appears as key challenge for MM-wave systems, the huge number of antenna elements used on the array allows for a high beamforming gain. In order to exploit such a gain, the AN and the user equipment (UE) must have accurate knowledge of the directions of the main incoming paths to transmit and receive the wireless signals. This information can be obtained through the use of pilot tones. The estimation can be performed either in the uplink or in the downlink. Most studies focus on the uplink case and consider time-division duplexing (TDD). In this case, the channel state information (CSI) is obtained from uplink pilots and the base station (BS) exploits the channel reciprocity to transmit through the downlink channel [1, 4]. However, current wireless standards are dominated by frequency division duplexing (FDD) mode and make a compatible massive MIMO system with the current system is of significant interest. Moreover, in some scenarios FDD is more effective than TDD such as in cases of symmetric traffic and in delay-sensitive applications. Additionally, in TDD the user is not able to estimate the instantaneous downlink channel, since there is no downlink training sequence for CSI estimation [5]. In this paper, we consider the problem of single user downlink channel estimation in FDD VL-MIMO systems.

From a channel modeling viewpoint, in MM-wave communications the electromagnetic wave has similar characteristics to the light, which makes ray-tracing models very attractive in practice, as it has been shown in [6]. Moreover, it is worth mentioning that in indoor environments with transmission in the MM-wave range, the propagation channel is likely to be sparse [6, 7]. Exploiting the inherent channel sparsity appears as a natural way to reduce the number of cell specific pilots.

Approaches to deal with sparse channels have been proposed in the literature by resorting to Compressed Sensing (CS) theory [8, 9]. The traditional Least Squares (LS) estimator imposes a length $K = \mathcal{O}(N_t)$ to the pilot sequence whereas the CS approach results in a length $K = \mathcal{O}(\log N_t)$. This makes possible to create short pilot sequences for downlink channel estimation, avoiding the excess of pilot tones on the wireless network [10]. Few methods exploiting channel sparsity in MM-wave systems have been proposed recently in [7, 11] for channel tracking in VL-MIMO in the downlink case. These methods have only considered single-antenna terminals.

In this paper, we address the problem of estimating beamforming directions on the downlink of a VL-MIMO system operating in a 60 GHz indoor channel. Considering Orthogonal Frequency Division Multiplexing (OFDM), a new pilot-assisted method for channel estimation is proposed, which exploits the inherent sparsity of the channel and requires quite low pilot overhead. The proposed method is based on a coarse estimation stage that capitalizes on CS, followed by a refinement stage to find the transmit/receive spatial frequencies. Assuming a ray-tracing channel model, the system throughput is evaluated from computer simulations by considering three different beamforming/precoding schemes, namely, a wideband precoder (WP), a phase-constrained wideband precoder (PCWP), and a frequency dependent precoder (FP). Our results show that the proposed channel estimator performs quite well with very low pilot overhead.

Notations: Capital bold letters to denote matrices and lower bold letters denote vectors. The superscripts $[.]^H$, $[.]^T$, $[.]^*$ stand for the hermitian, transpose and conjugate, respectively. $[\mathbf{H}]_{m,n}$ represents

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the (m, n)-th entry of $\mathbf{H}$, $\mathbf{I}_M$ is the $M \times M$ identity matrix and $\mathbf{0}_M$ is the $M \times M$ all-zeros matrix. The operators $\mathbb{C}\{.\}$ and $||.||_l$ denote cardinality and norm l, respectively.

2. SYSTEM MODEL

Consider an indoor environment with an AN deployed with N_t antennas and a UE with N_r antennas. At each link end a rectangular array of multiple antennas is considered. We assume that AN and UE are perfectly synchronized and operate according to an FDD protocol. The transmission is performed using OFDM. The received signal vector associated with the k-th discrete time instant and l-th subcarrier, at a given UE, can be written as follows:

$$\begin{aligned} \mathbf{y}_r(k,l) \quad = \quad & \sum_{n=1}^{N_p} \beta_n \mathbf{v}_R(\theta_{R,n}, \phi_{R,n}) \mathbf{v}_T^H(\theta_{T,n}, \phi_{T,n}) \\ & \mathbf{s}(k,l) e^{-\jmath 2\pi \tau_n l \Delta f} + \mathbf{z}(k,l), \end{aligned} \tag{1}$$

where $k \in \mathcal{S}_{time}$ and $l \in \mathcal{S}_{subcarrier}$. These sets have cardinality K and L respectively, and define the frequency and time indices chosen for the transmission of the pilot tones. N_p denotes the number of paths, β_n is the complex factor with Gaussian distribution along the n-th ray, $\phi_{R,n}$ and $\theta_{R,n}$ are respectively the azimuth and the inclination of the incoming rays relative to $x - y$ plane. $\phi_{T,n}$ and $\theta_{T,n}$ denote, respectively, the azimuth and inclination of the rays at the transmitter. The parameter $\tau_n \in [0, \tau_{max}]$ assigns the delay related to the n-th path, T_s is the OFDM symbol period and Δf is frequency distance between two adjacent subcarriers. The $N_t \times 1$ vector $\mathbf{v}_T(\theta_{T,n})$ and the $N_r \times 1$ vector $\mathbf{v}_R(\theta_{R,n})$ are the array steering vectors for the transmitter and receiver, respectively. The vector $\mathbf{s}(k,l)$ contains the pilot symbols used at the k-th time instant and l-th subcarrier. Finally, the term $\mathbf{z}(k,l)$ represents the additive noise whose entries are independent and follow a zero mean complex-valued Gaussian distribution with variance σ^2 [10].

The elements of the steering vectors describe the phase shift of the signal due to the spatial distance among the antenna elements on the array. Generically, we have:

$$[\mathbf{v}_\gamma(\theta_{\gamma,n}, \phi_{\gamma,n})]_i = e^{\jmath(\omega_x x_i + \omega_y y_i)}, \quad \gamma \in \{R, T\} \tag{2}$$

where $\omega_x = \frac{2\pi d}{\lambda} \cos(\theta_{\gamma,n}) \cos(\phi_{\gamma,n})$, and $\omega_y = \frac{2\pi d}{\lambda} \cos(\theta_{\gamma,n}) \sin(\phi_{\gamma,n})$, with x_i and y_i defining the spatial position of the i-th antenna element on the plane $x - y$, d is the inter-element antenna spacing and λ is the wavelength. In this paper, ω_x and ω_y are called spatial frequencies, as they describe the phase variation at each distance unit over the array [14]. The spatial frequency unit is given in radians/mm.

3. CHANNEL ESTIMATION

The channel estimation process starts with the receiver probing the channel in a set of pre-defined pairs of spatial frequencies, $(\omega^p_{R,x}, \omega^p_{R,y}) \in \mathcal{D}, \forall\, p \in \{1, 2, \dots, P\}$. The set $\mathcal{D}$ has cardinality $\mathbb{C}\{\mathcal{D}\} = P$ and the index p identifies the p-th pair of the set $\mathcal{D}$. Each pair defines a given direction where the receiver measures the associated energy. For the p-th spatial frequency pair, there are KL measurements taken on the time-frequency grid given by:

$$r_p(k,l) = \mathbf{w}_p^H \mathbf{y}_r(k,l), \quad p = 1, \dots, P, \tag{3}$$

where $r_p(k,l)$ is the received signal measured on the p-th direction, k-th time instant and l-th subcarrier and $\mathbf{w}_p \in \mathcal{W}$ is the combining vector the signal received from the p-th direction, $\mathbb{C}\{\mathcal{W}\} = P$. By inserting (1) into (3), we can rewrite $r_p(k,l)$ as:

$$r_p(k,l) = \mathbf{s}^T(k,l) \mathbf{V}_T^* \mathbf{F}_p \mathbf{b}(l) + \tilde{z}_p(k,l), \tag{4}$$

where $\mathbf{V}_T = [\mathbf{v}_T(\theta_{T,1}, \phi_{T,1}), \ \dots, \ \mathbf{v}_T(\theta_{T,N_p}, \phi_{T,N_p})]$, $\mathbf{F}_p$ is a diagonal matrix whose n-th diagonal element is given by $[\mathbf{F}_p]_{n,n} = \mathbf{w}_p^H \mathbf{v}_R(\theta_{R,n}, \phi_{R,n})$, $\mathbf{b}(l) = [\beta_1 e^{-\jmath 2\pi \tau_1 l \Delta f}, \ \dots, \ \beta_{N_p} e^{-\jmath 2\pi \tau_{N_p} l \Delta f}]^T$, and $\tilde{z}_p(k,l) = \mathbf{w}_p^H \mathbf{z}(k,l)$. Defining the $K \times 1$ vector $\mathbf{x}_p(l) = [r_p(0,l), \dots, r_p(K-1,l)]^T$ concatenating K time-domain measurements leads to

$$\mathbf{x}_p(l) = \mathbf{S}_l^T \mathbf{V}_T^* \mathbf{F}_p \mathbf{b}(l) + \tilde{\mathbf{z}}_p(l), \tag{5}$$

where $\mathbf{S}_l = [\mathbf{s}(0,l), \ \mathbf{s}(1,l), \ \dots, \ \mathbf{s}(K-1,l)]$ is the $N_t \times K$ pilot matrix, and $\tilde{\mathbf{z}}_p(l) = [\tilde{z}_p(0,l), \ \dots, \tilde{z}_p(K-1,l)]^T$.

A important question about Eq. (5) can be raised at this point. Given that the number N_p of multipaths is much smaller than number of transmit antennas, can we reduce the number K of measurements used for channel estimation? To answer this question, consider a hypothetical case where the arrival angles of the incoming paths are known at the receiver and we choose a beamforming vector $\mathbf{w}_p$ that points towards the direction of the strongest path. Consider also that the spatial frequencies seen by the transmitter are integer multiples of $2\pi/N_t$, i.e. $\omega_{T,x}, \omega_{T,y} \in \{0, \ \frac{2\pi}{N_t}, \ \dots, \ \frac{(N_t-1)2\pi}{N_t}\}$. This assumption implies that $\mathbf{V}_T$ is a 2-D Discrete Fourier Transform (DFT) matrix. Since the DFT matrix is an orthonormal matrix, according to compressive sensing theory $\mathbf{F}_p \mathbf{b}(l)$ can be recovered from (5) with high probability if $K = \mathcal{O}(N_p \log N_t)$ and the elements of $\mathbf{S}$ chosen as i.i.d from a Bernoulli distribution [10].

In our case, the strongest direction is not known at the receiver and must be estimated. Moreover, the spatial frequencies come from the continuum, being very unlikely that they are integer multiples of $\frac{2\pi}{N_t}$. Despite these observations, we could ignore them and apply compressive sensing algorithms by assuming that the spatial frequencies are integer multiples of $\frac{2\pi}{N_t}$. However, this limits the estimation at the space between the frequencies. A similar problem was studied in [11], but the method proposed therein does not consider OFDM and is restricted to a single-antenna receiver.

3.1. Coarse estimation

In reality, we do not know neither the directions of the paths nor the number of paths. Additionally, the real spatial frequencies that synthesize the beamforming vector $\mathbf{w}_p$ and the array response matrix $\mathbf{V}_T$ in Eqs. (3) and (5) respectively, are unknown at the receiver. As a starting point of our estimator, we create a set of discrete spatial frequencies for the x, y axis of both sides of the link, i.e. $\omega_{R,x}, \ \omega_{R,y}, \ \omega_{T,x}, \ \omega_{T,y} \in \{0, \ \frac{2\pi}{P}, \ \dots, \ \frac{(P-1)2\pi}{P}\}$ where $P > \max(N_T, N_R)$ [11]. The estimation of the strongest path starts with receiver searching for the direction that has the highest energy. The search is performed according to the following criterion:

$$\mathbf{w}_o = \arg\max_p \sum_l \sum_k |\mathbf{w}_p^H \mathbf{y}_r(k,l)|^2, \quad \mathbf{w}_p \in \mathcal{W}. \tag{6}$$

The vector $\mathbf{w}_p$ is generated according to the discrete spatial frequencies $\omega_{R,x}^{(p)}$ and $\omega_{R,y}^{(p)}$ as shown below

$$[\mathbf{w}_p]_i = \frac{1}{\sqrt{N_r}} e^{\jmath(\omega_{R,x}^{(p)} x_i + \omega_{R,y}^{(p)} y_i)}, \quad i = \{1, \ \dots, \ N_R\}, \tag{7}$$

where x_i and y_i are the coordinates of the i-th antenna element at the receive array.

Based on $\mathbf{w}_o$, from Eq. (6), the incoming signal along the strongest path during K consecutive time instants is given by:

$$\begin{aligned}\mathbf{y}_{beam}(l) &= [\mathbf{w}_o^H\mathbf{y}_r(0,l),\ \ldots,\ \mathbf{w}_o^H\mathbf{y}_r(K-1,l)]^T \\ &= \mathbf{S}_l^T\mathbf{V}_{D,T}^*\tilde{\mathbf{F}}_o\tilde{\mathbf{b}}(l)+\tilde{\mathbf{z}}_o(l) \end{aligned} \quad (8)$$

where $\mathbf{V}_{D,T}$ is a $N_t \times P$ matrix with each column describing the array response for a possible combination of $\omega_{T,x}^{(p)}$ and $\omega_{T,y}^{(p)}$, $\tilde{\mathbf{b}}(l) = [\tilde{\beta}_1 e^{-\jmath 2\pi\tau_1 l\Delta f},\ \ldots,\ \tilde{\beta}_P e^{-\jmath 2\pi\tau_P l\Delta f}]^T$, and $\tilde{\beta}_1,\ldots,\tilde{\beta}_P$ are independent random variables following a zero-mean unitary-variance Gaussian distribution. $\tilde{\mathbf{F}}_o$ is a $P \times P$ diagonal matrix, with the m-th diagonal element $[\tilde{\mathbf{F}}_o]_{m,m} = \mathbf{w}_o^H\mathbf{w}_m, m = 1,\ldots,P$. We call attention to the difference between Eqs. (5) and (8). The first one is based on the exact number of multipaths, therefore the dimensions of vector $\mathbf{b}(l)$ and matrix $\mathbf{F}_p$ are functions of N_p. The second one is based on the number P of predefined directions taken from the 2-D continuum of spatial frequencies $\omega_{R,x}$ and $\omega_{R,y}$.

We consider the "filtered" vector $\mathbf{b}_{\text{filt}}(l) = \tilde{\mathbf{F}}_p\tilde{\mathbf{b}}(l)$ to identify which one of the P directions best matches to the strongest multipath. This vector is likely to be sparse due to the existence of directions with very low energy coupling. By resorting to CS theory, such a sparsity can be exploited to reduce the number of pilots used for channel estimation [10]. If the receiver had a single omnidirectional antenna, as in [11], $\tilde{\mathbf{F}}_p$ would be an identity matrix and $\mathbf{b}_{\text{filt}}(l) = \tilde{\mathbf{b}}(l)$ and CS estimation performance would depend on the "natural" channel sparsity.

Traditional LS estimation imposes a minimum number $K = \mathcal{O}(N_t)$ of pilots to be used. However, such condition in a VL-MIMO system would result in huge pilot overhead. Compressed sensing can circumvent this problem by exploiting the sparse channel structure to estimate the channel with high probability from $K = \mathcal{O}(\log(N_t))$ random measurements. Based on this observation, in this work we consider the traditional Orthogonal Matching Pursuit (OMP) algorithm to obtain an estimate of $\mathbf{b}_{\text{filt}}(l)$, i.e.:

$$\min ||\mathbf{b}_{\text{filt}}(l)||_1 \quad \text{s.t.} \ ||\mathbf{y}_{beam}(l) - \mathbf{S}_l^T\mathbf{V}_T\mathbf{b}_{\text{filt}}(l)||_2^2 < \sigma^2. \quad (9)$$

The estimation of the strongest direction is performed in a similar way for each subcarrier frequency. The resulting set of vectors $\hat{\mathbf{b}}_{\text{filt}}(1),\ldots,\hat{\mathbf{b}}_{\text{filt}}(L)$ associated with the different frequencies can be arranged in a matrix $\mathbf{B}_{\text{filt}}$ and combined using a function $g : \mathbb{C}^{P\times L} \to \mathbb{R}^{P\times 1}$, $\hat{\mathbf{b}}_{\text{filt}}(l)$ is chosen as

$$g(\mathbf{B}_{\text{filt}}) \doteq \sum_{l=1}^{L} |\hat{\mathbf{b}}_{\text{filt}}(l)|^2, \quad (10)$$

After this combining step, we select the entry of $\mathbf{b}_{\text{filt}}$ whose absolute value is the largest, i.e.:

$$i^* = \arg\max_i [g(\mathbf{B}_{\text{filt}})]_i. \quad (11)$$

The value i^* is associated with the i^*-th direction at the transmitter (i.e. the i^*-th column of $\mathbf{V}_{D,T}$) corresponding to the strongest estimated direction ($\omega_{R,x}^{\text{coarse}}$,$\omega_{R,y}^{\text{coarse}}$). Table 1 summarizes the coarse estimation steps of the proposed algorithm. A similar procedure is performed to coarsely estimate the spatial frequencies of the transmitter side. Therefore, by following the steps shown in Table 1, we can obtain ($\omega_{T,x}^{\text{coarse}}$,$\omega_{T,y}^{\text{coarse}}$).

Table 1. Coarse estimation

Step 1	Quantize the spatial frequencies components: $\omega_{R,x},\ \omega_{R,y},\ \omega_{T,x},\ \omega_{T,y} \in \{0,\ \ldots,\ \frac{(P-1)2\pi}{P}\}$, where, $P > N_t$.
Step 2	Find $\hat{\omega}_{R,x}$ and $\hat{\omega}_{R,y}$ which give the strongest direction. $[\mathbf{w}_p]_i = \frac{1}{\sqrt{N_r}} e^{\jmath(\omega_{R,x}^{(p)}x_i+\omega_{R,y}^{(p)}y_i)}, \quad i = \{1,\ \ldots,\ N_R\}$, $\mathbf{w}_o = \arg\max_p \sum_l \sum_k |\mathbf{w}_p^H\mathbf{y}_r(k,l)|^2, \quad \mathbf{w}_p \in \mathcal{W}$.
Step 3	We calculate $\mathbf{y}_{beam}(l)$ $\mathbf{y}_{beam}(l) = [\mathbf{w}_o^H\mathbf{y}_r(0,l),\ \ldots,\ \mathbf{w}_o^H\mathbf{y}_r(K-1,l)]^T$ $\mathbf{y}_{beam}(l) = \mathbf{S}_l^T\mathbf{V}_{D,T}^*\tilde{\mathbf{F}}_o\tilde{\mathbf{b}}(l)+\tilde{\mathbf{z}}_o(l)$
Step 4	Use OMP, described in [12], to estimate $\mathbf{b}_{\text{filt}}(l) = \tilde{\mathbf{F}}_p\tilde{\mathbf{b}}(l)$ $\hat{\mathbf{b}}_{\text{filt}}(l) = ||\mathbf{b}_{\text{filt}}(l)||_1 + ||\mathbf{y}_{beam}(l) - \mathbf{S}_l^T\mathbf{V}_T\mathbf{b}_{\text{filt}}(l)||_2^2 < \sigma^2$
Step 5	Repeat Steps 3 and 4 for $l \ \in \ \mathcal{P}_{subcarrier}$ $\mathbf{B}_{\text{filt}} = [\hat{\mathbf{b}}_{\text{filt}}(1),\ \ldots,\ \hat{\mathbf{b}}_{\text{filt}}(L)]$
Step 6	Use the function $g : \mathbb{C}^{P\times L} \to \mathbb{C}^{P\times 1}$ to combine the $\hat{\mathbf{b}}_{\text{filt}}(l)\ \forall\, l \in \mathcal{S}_{subcarrier}$ $g(\mathbf{B}_{\text{filt}}) \doteq \sum_{l=1}^{L} |\hat{\mathbf{b}}_{\text{filt}}(l)|^2$
Step 7	Choose the index of $\mathbf{b}_{\text{filt}}$ whose absolute value is the largest. $i^* = \arg\max_i [\mathbf{b}_{\text{filt}}]_i$, where i^*-th column of $[\mathbf{V}_T]_{i^*}$ is the strongest direction that corresponds to the pair ($\omega_{R,x}^{\text{coarse}}$,$\omega_{R,y}^{\text{coarse}}$).

3.2. Refinement of the estimates

After the coarse estimation, an optimization is performed to assign the direction that maximizes a specific cost function. This is a refinement step that consists in adjusting $\omega_{R,x}^{\text{coarse}}$ and $\omega_{R,y}^{\text{coarse}}$ based on the maximization of the energy of the received signal. We consider the following problem:

$$[\omega_{R,x}^{\text{ref}}(l), \omega_{R,y}^{\text{ref}}(l)] = \arg \max_{(\omega_{R,x},\omega_{R,y}) \ \in \ \mathbb{R}^2} J(\omega_{R,x}, \omega_{R,y}, l)$$

$$\text{where} \quad J(\omega_{R,x}, \omega_{R,y}, l) \doteq \sum_{k=1}^{K} |\mathbf{w}^H(\omega_{R,x}, \omega_{R,y})\mathbf{y}(k,l)|^2, \quad (12)$$

and $\mathbf{w}(\omega_{R,x}, \omega_{R,y})$ is the steering vector associated with the pair $(\omega_{R,x}, \omega_{R,y})$, and each element $[\mathbf{w}(\omega_{R,x}, \omega_{R,y})]_i$ follows the same formulation as in (7). The final estimates are given by averaging over the L subcarriers, i.e. $\overline{\omega}_{R,x}^{\text{ref}} = (1/L)\sum_{l=1}^{L}\omega_{R,x}^{\text{ref}}(l)$, and $\overline{\omega}_{R,y}^{\text{ref}} = (1/L)\sum_{l=1}^{L}\omega_{R,y}^{\text{ref}}(l)$.

The algorithm corrects the spatial frequencies, i.e. the beamforming direction, through small steps Δ. This can be done using the so-called "search region" algorithm, which basically consists in evaluating, in a given iteration, the cost function (12) for a set of Δ-spaced points around the one selected in the previous iteration. The method seeks for the largest value of this cost function among the candidate points and selects the one leading to the maximum value. The algorithm stops according the desired granularity. Differently from the coarse estimation step, the refinement step does not take into account the set of predefined directions $\mathcal{W}$. The algorithm takes one predefined direction, ($\omega_{R,x}^{\text{coarse}}$, $\omega_{R,y}^{\text{coarse}}$), and searches for the best pair $(\omega_{R,x}, \omega_{R,y}) \ \in \ \mathbb{R}^2$ that optimizes (12).

Since $\overline{\omega}_{R,x}^{\text{ref}}$ and $\overline{\omega}_{R,y}^{\text{ref}}$ have already been obtained, this information is then used to refine the transmit spatial frequencies. This refinement is based on the maximization of the following

Table 2. Refinement of the transmitter spatial frequencies

Step 1	From the coarse estimation, use the spatial frequencies at the transmitter, $\omega_{T,x}^{\text{coarse}}$ and $\omega_{T,y}^{\text{coarse}}$, as initial values: $\psi_{0,x} = \omega_{T,x}^{\text{coarse}}$ and $\psi_{0,y} = \omega_{T,y}^{\text{coarse}}$ step size: Δ granularity adjustment constant : ϵ $[\mathbf{w}]_i(\overline{\omega}_{R,x}^{\text{ref}}, \overline{\omega}_{R,y}^{\text{ref}}) = \frac{1}{\sqrt{N_R}} e^{\jmath(\overline{\omega}_{R,x}^{\text{ref}} x_i + \overline{\omega}_{R,y}^{\text{ref}} y_i)}$, $i = \{1, \ \ldots, \ N_R\}$
Step 2	Calculate the beam signal coming from the direction $(\overline{\omega}_{R,x}^{\text{ref}}, \overline{\omega}_{R,y}^{\text{ref}})$ $\mathbf{y}_{beam}(l) = [\mathbf{w}^H(\overline{\omega}_{R,x}^{\text{ref}}, \overline{\omega}_{R,y}^{\text{ref}})\mathbf{y}(0,l), \ \ldots, \ \mathbf{w}^H(\overline{\omega}_{R,x}^{\text{ref}}, \overline{\omega}_{R,y}^{\text{ref}})\mathbf{y}(K-1,l)]^T$
Step 3	Update $\psi_{t,x}$ and $\psi_{t,y}$ $\psi_{\Delta+,x} = \psi_{t,x} + \Delta$ $\psi_{\Delta-,x} = \psi_{t,x} - \Delta$ $\psi_{\Delta+,y} = \psi_{t,y} + \Delta$ $\psi_{\Delta-,y} = \psi_{t,y} - \Delta$
Step 4	Assign the new spatial frequency $[\psi_x, \psi_y] = \arg\max_{(\psi_x,\psi_y)} \lvert \mathbf{v}^H(\psi_x, \psi_y)\mathbf{S}_l^* \mathbf{y}_{beam}(l)\rvert^2$, where, $[\mathbf{v}]_i(\psi_x, \psi_y) = \frac{1}{\sqrt{N_t}} e^{\jmath(\psi_x x_i + \psi_y y_i)}$, $i = \{1, \ \ldots, \ N_t\}$ $\psi_x \in \{\psi_{+\Delta,x}, \psi_{-\Delta,x}\}$ and $\psi_y \in \{\psi_{+\Delta,y}, \psi_{-\Delta,y}\}$
Step 5	If $[\psi_{t,x}, \psi_{t,y}] = [\psi_{t-1,x}, \psi_{t-1,y}]$ do $\Delta = \Delta/\epsilon$ and go back to step 2. Otherwise, go forward.
Step 6	If the number of iterations $t < T_o$, set $t = t+1$ and go back to Step 3, otherwise $\omega_{T,x}^{\text{ref}} = \psi_{t,x}$ and $\omega_{T,y}^{\text{ref}} = \psi_{t,y}$

function:

$$[\omega_{T,x}^{\text{ref}}(l), \omega_{T,y}^{\text{ref}}(l)] = \arg \max_{\omega_{T,x},\omega_{T,y}} \lvert \mathbf{v}^H(\omega_{T,x}, \omega_{T,y})\mathbf{S}_l^* \mathbf{y}_{beam}(l)\rvert^2, \tag{13}$$

where $(\omega_{T,x}, \omega_{T,y}) \in \mathbb{R}^2$, $\mathbf{v}(\omega_{T,x}, \omega_{T,y})$ follows the same formulation as in (7), except by the index p and the number of antennas, which is N_T instead of N_R. As for the receive spatial frequencies, the final estimates of $\overline{\omega}_{T,x}^{\text{ref}}$ and $\overline{\omega}_{T,y}^{\text{ref}}$ are obtained by averaging over the L subcarriers.

In principle, the refinement of receive and transmit spatial frequencies could be performed jointly by updating the spatial frequencies at the transmitter and receiver in a iterative process. However, such an approach would imply a higher computational complexity. In this paper, we consider a lower complexity approach, where this refinement is done separately at each link end. According to our results, good performance can be obtained with this approach for line-of-sight (LOS) scenarios. Table 2 summarizes the procedure used in the refinement of the transmit spatial frequencies. A similar procedure is used in the refinement of the receive spatial frequencies, except that Step 2 is not used and Step 4 performs the maximization defined in (6).

4. SIMULATION RESULTS

The proposed algorithms are evaluated using Shannon's capacity formula by considering three beamforming schemes as follows:

- SVD-based beamforming: derived from the right singular vector of the frequency-dependent channel matrix (i.e. each subcarrier has different beamforming weights). Perfect knowledge of the full instantaneous channel matrix is assumed;
- Steering vector-based beamforming: designed from the only knowledge of the estimated spatial frequencies, i.e. $[\mathbf{v}(\omega_{T,x}, \omega_{T,y})]_i = e^{\jmath(\omega_{T,x} x_i + \omega_{T,y} y_i)}$;
- Round-phase beamforming: The design of the steering vector is constrained to four different predefined phases only. Specifically, the phases associated with each entry of the steering vector are rounded to the closest phase among the four ones.

Table 3. Simulation Parameters

Environment	Indoor (LOS)
Carrier Frequency	60 GHz
Multiplexing Scheme	OFDM
Subcarrier Bandwidth	360 kHz
Number of Subcarriers	512
System Bandwidth	0.18 GHz
Number of pilots Subcarriers	32
FFT size	1024
Payload period	1.389 μs
Cyclic prefix	347.22 ns
OFDM symbol period	3.1252 μs
Maximum Tx Power per AN	2 mW
Thermal Noise Level	-174 dBm/Hz
Noise Figure	6 dB
Number of Tx Antennas	64
Number of Rx Antennas	16
Distance Between the Antennas	$\lambda/2$
UE speed	1 m/s

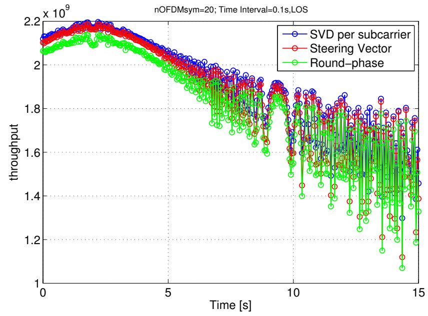

Fig. 1. System throughput (bps) for three types of beamforming. The time interval between two consecutive blocks is 0.1s and the number of OFDM symbols is 20.

The simulations are performed according to the parameters of the Table 3 and channel coefficients are generated according to the ray-tracing model used in [13]. The performance is evaluated in terms of the system throughput considering the transmission of a single data stream.

Fig. 1 shows the system throughput for the three beamforming schemes. Note that the gap between the singular value decomposition (SVD)-based and steering vector-based beamforming solutions is almost negligible. This result indicates that the steering vector approach is preferable due to its much lower complexity compared to the SVD-based beamforming. This has a direct impact on the hardware implementation for VL-MIMO systems.

It is worth mentioning that the SVD-based beamforming results from a linear combination of the rays while the steering vector-based

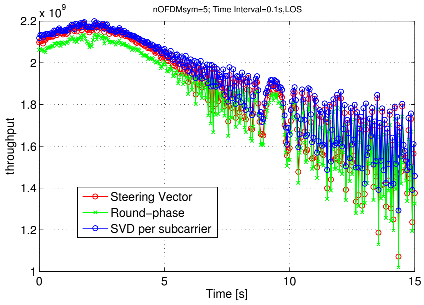

Fig. 2. System throughput (bps) for three types of beamforming.

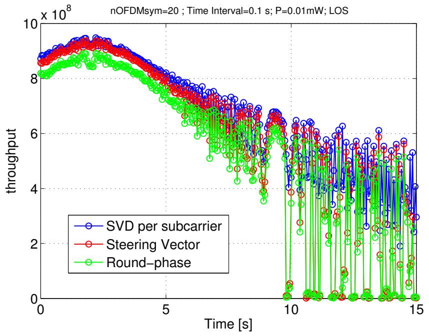

Fig. 3. System throughput (bps) in a very low SNR scenario.

beamforming is designed based on the spatial frequencies of the strongest (LOS) path only. As the LOS path retains most of the received signal energy, transmitting along the LOS direction only is preferable in the considered indoor scenario. Note also that, although SVD-based beamforming may yield a higher throughput in non-LOS scenarios, the frequency dependence of this method makes its implementation challenging, whereas the steering vector-based beamforming does not have such a restriction. Another aspect that deserves attention in Fig. 1 is related to the pilot overhead required to achieve such a performance. For the results shown in this figure, the pilot overhead is 0.0039% only. This observation corroborates the effectiveness of the proposed channel estimation to operate with very few number of pilots in a VL-MIMO context. Fig. 2 shows similar results but now considering only five OFDM symbols as pilots implying a low overhead of $9.74 \times 10^{-4}\%$.

In Fig. 3, we consider a very low signal-noise ratio (SNR) scenario. The system parameters are the same as those used in the previous results, except that the transmitted signal power is two hundred times lower. As can be concluded from this figure, our channel estimation algorithm still operates satisfactorily and starts to fail around a distance of ten meters from the AN.

5. CONCLUSION

We have investigated the overhead reduction of a VL-MIMO system operating in a MM-wave scenario. A two-step channel estimator exploiting the sparse nature of the downlink channel is proposed. Our results show that the proposed method achieves a quite low pilot overhead while ensuring very accurate channel estimates. Our simulations considered an indoor LOS channel and different transmit beamforming schemes, indicating that the steering vector based precoder has a similar throughput performance compared to the SVD-based one, being a good solution from a hardware implementation viewpoint. Perspectives include the extension of the proposed method to the channel tracking problem and a performance evaluation in non-line-of-sight (NLOS) scenarios.

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