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Investigation of Sparse M-MIMO Channels in Time-Space Correlation Domains in Frequency Division Duplexing

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ABSTRACT:
Massive Multiple-Input Multiple-Output(M-MIMO) systems are one of the mainstays of the new generation of wireless communications and have the potential to increase data throughput, reduce energy consumption and increase the security of communication lines. In this paper, we intend to investigate channel estimation, which is one of the most common parts of telecommunication systems and is considered as the main cause of disturbance in M-MIMO systems and needs to be compensated. Therefore, first of all, considering that systems with a large number of antennas as well as high bandwidth represent a thin multi-path structure, the sparse domains of M-MIMO systems in frequency, time, angle and we describe the hybrid model of these domains and then we deal with temporal and spatial correlations in this type of channels and finally we simulate the spatial correlation in this type of sparse channels which the results show less pilot overhead is required if using this method.

Keywords: Sparsity, Spatial correlation, Temporal correlation, M-MIMO.

INTRODUCTION:

In recent years, the rate required to send data has increased significantly due to the use of smartphones, tablets and other communication devices. According to forecasts, this need will increase in the future. The evolution of cellular telecommunication network generations can be attributed to the growth in the number of wireless devices, higher data rate demand and higher quality experience.

In addition to the growing number of devices connected to the Internet, as shown in Figure (1), data traffic is growing exponentially. The fifth generation (5G) network is projected to account for 12% of mobile traffic in 2022. Also in 2022, the average 5G connection is expected to be nearly three times higher than the average 4G connection. In summary, some of the parameters considered in the fifth generation are: connection of more than 100 billion devices to the Internet, a delay of one millisecond (in the third generation network, this number was equal to 100 milliseconds and in the fourth generation, equal to 50 milliseconds) and Data rate of 10 gigabits per second (Barnett et al, 2015).

The introduction of new solutions to meet these needs has led to the idea of fifth generation cellular telecommunications by introducing its own new technologies. In 5G networks, five new technologies and orientations will emerge, one of which is the mass multi-input-multi-output system (Boccardi et al, 2014). Mass multitasking technology will be an important part of 5G networks that will be widely used in the not too distant future.

Massive multiple-input multiple-output technology is a promising approach for the future of 5G communications due to its spectral efficiency and high energy efficiency. An accurate channel estimate is necessary to realize its potential performance. Channel estimation in M-MIMO systems is one of the most influential parts that is one of the limitations of using this technology.

Article Structure:

We continue the article in the following order: First, in the second part, we examine the spatial domains in M-MIMO systems, in which we describe the frequency domain, time domain, angle domain, and the combined model of the transmission in the domain. It combines angle and DFT. Then, in the third section, we examine and describe the temporal and spatial correlations in thin channels, and review the up-to-date work done in this area. Continuation of the spatial correlation simulation scheme used and finally concluding the work done.

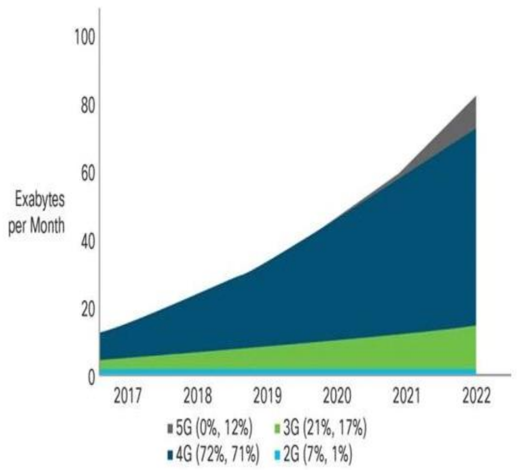


Figure 1 - Monthly traffic of mobile phones by type of network connection [1].

Investigation of sparsity domains in M-MIMO systems:

Studies (Bajwa et al., 1991) show that systems with a large number of antennas as well as high bandwidth represent a sparse multi-path structure. The results of practical experiments show that in M-MIMO systems, specific channel views can be presented sparsely. The presence of a large number of antennas gives a degree of freedom in the system Although in scattering environments, most channel coefficients are small, in other words, many of the coefficients that describe the multi-channel behavior of M-MIMOs are zero or are too small to be ignored. Research has shown that channels in the frequency domain can be represented almost sparsely and converted to other domains will also be sparse (Wunder et al, 2015). As a general model, the channel can be described as follows.

$$\boldsymbol{H} = \boldsymbol{Z}\boldsymbol{H}_S\boldsymbol{V} \tag{1}$$

Where and are unitary matrices that are a linear transformation of the H matrix with the aim of creating a sparse matrix. Due to its sparse structure, H estimation is possible using intensive measurement. Much work has been done on the use of channel conversion to show the property of sparsity in various domains such as time domain (Masood et al, 2015), (Chen et al, 2016), in the field of frequency of channel vectors after conversion, in frequency Different cells will be sparse (Wen et al, 2015). In the virtual angle domain, where the obtained channel vectors after conversion are sparse in different directions. It has also been observed that in many cases the vectors of the obtained channels after the conversion pattern represent the same sparsity.

Frequency domain:

The use of a large number of antennas makes it possible to observe the approximate sparsity behavior in the frequency display of channels. In fact, the channel frequency response can be assumed to be sparse. The channel impulse response is sparse due to the limited number of scatterings, and the frequency conversion will almost retain the sparsity properties. For example, in a multi-carrier transmission system, especially OFDM, such as the following equation,

$$\boldsymbol{y} = \boldsymbol{H}\boldsymbol{x} + \boldsymbol{w} \tag{2}$$

Where the vector with length L contains the transmitting OFDM symbols. The channel matrix with dimensions and vector corresponding to the received signal in length is equal to the number of subcarriers and w is equal to the white noise vector in length. The matrix H has the property that most of its components are small in size and most of the signal energy is concentrated in the original diameter and this energy decreases as the elements move away from the original diameter (Berger et al, 2010). Demonstration of matrix sparsity can be expressed as follows.

$$\mathbf{y} = (\boldsymbol{x}^T \otimes \boldsymbol{I}_L) vec(\boldsymbol{H}) + \boldsymbol{w} \tag{3}$$

Which in the equation $\boldsymbol{I}_L$ is an unitary matrix with $L \times L$ dimensions and $vec(\boldsymbol{H})$ vector H matrix.

Time domain:

The characteristics of a wireless multi-channel channel can be expressed sparse in time. Sparsity in time is due to the existence of a limited number of scatterings that are distributed in space. These scattering generates a limited number of paths that the transmitted signal can transmit from transmitter to receiver. The sparse vector can model the channel impulse response vector in our time domain between a user antenna and an antenna across the base station. The equivalent of the frequency representation can be obtained by taking the Fourier transform as follows:

$$\boldsymbol{h} = \boldsymbol{Q}_F\boldsymbol{h}_S \tag{4}$$

Where $\boldsymbol{Q}_F$ is a single discrete Fourier transform L × L matrix in which ($k.l$)th element is obtained as follows,

$$q_{k.l} = \frac{1}{\sqrt{L}} e^{-jkl\frac{2\pi}{L}} \tag{5}$$

By making changes, the display in the frequency domain proposed in (Masood et al, 2015), (Chen et al, 2016), the obtained model is as follows,

$$\boldsymbol{y} = \boldsymbol{P}\boldsymbol{h} + \boldsymbol{w} \tag{6}$$

Where $\boldsymbol{y} \in \mathbb{C}^{N_c \times 1}$ is the received signal with N_c sub-carrier on the antenna. $\boldsymbol{P} \in \mathbb{C}^{N_c \times N_c}$ is a diagonal matrix also includes the training sequences used and $\boldsymbol{h} \in \mathbb{C}^{N_c \times 1}$displays the frequency domain of the channel impulse response. The property of sparsity in broadband systems can be obtained by using the inverse DFT on the channel impulse response of channel, $\boldsymbol{h}$.

$$\boldsymbol{h}_S = \boldsymbol{Q}_F^H\boldsymbol{h} \tag{7}$$

In this case, $\boldsymbol{h}_s$ is the display of sparse conversion in the time domain related to the impulse response of the channel h.

$$\boldsymbol{y} = \boldsymbol{P}\boldsymbol{Q}_F\boldsymbol{h}_s + \boldsymbol{w} \tag{8}$$

Therefore, using DFT, it is possible to display the sparsity properties of the channel by means of a discrete time channel vector model.

Angle domain:

The angle representation can be expressed in the base station from uniform linear arrays in which signals are received from fixed directions in the angle domain. These directions can be expressed as the inverse Fourier analysis of the channel,

$$\boldsymbol{H} = \boldsymbol{Q}\boldsymbol{H}_S\boldsymbol{U}^T \tag{9}$$

Which in Equation (9), H_S includes the mixed gain of each path, including transmit and receive. Also, $\boldsymbol{Q} \in \mathbb{C}^{n_r \times n_r}$and $\boldsymbol{U} \in \mathbb{C}^{n_t \times n_t}$the unit matrices in the transmission domain of beam are due to the transmission between the receiver and the transmitter.

Hybrid model:

(Bajwa et al, 2010) presents a hybrid model that combines angle transfer and DFT. This model is used in frequency-selective channels to extract channel representations with sparse lines.

$$\boldsymbol{Y} = \sqrt{\frac{\xi}{n_t}}\boldsymbol{H}_S\boldsymbol{P}_F + \boldsymbol{W} \tag{10}$$

In which $\mathbf{Y} \in \mathbb{C}^{n_r \times L}$ is discretized by the transmission matrix in the angle domain. $\mathbf{Q} \in \mathbb{C}^{n_r \times n_r}$ and $\boldsymbol{P}_F \in \mathbb{C}^{n_r \times L}$ the Fourier transform of $\boldsymbol{B}^H\boldsymbol{P}$ and $\boldsymbol{W} \in \mathbb{C}^{n_r \times L}$is the noise matrix.

Work done in the domains of time and space:

Channels between transmitter and receiver can have spatial, temporal, or frequency correlations. Spatial correlation occurs when different user channel matrices have common backups, meaning that a number of non-zero domains in their matrices are the same. Having a number of common scatterers in signaling to all users will create such a feature. The reason for the temporal correlation is the slow changes in the propagation environment, which in turn cause the matrix supports to change slowly over successive time frames. On the other hand, there is more frequency correlation in the OFDM scenario where the channel matrix has different supports between different frequency carriers. sparsity is more common in frequency-selective fading channels, and the main reason for this is the limited scattereres in the propagation environment, with the difference that the channel is modeld based on a number of paths with a specific delay and gain. Assuming a large delay spread, the channel impulse response matrix will have a sparse display in the time domain. Once the sparse channel matrix display is obtained, it is possible to estimate the channel with a smaller number of pilots using compressive sensing methods. In this regard, the methods of sparse signal recovery in the field of compressive sensing divided into three general categories: greedy, convex and repetitive optimization methods have been used. However, in addition to specific compressive sensing algorithms, some papers have provided control methods for adjusting the required pilot in a adaptive manner to find the best number of pilots in a adaptive manner and to improve channel estimation (Lau et al., 2016), (Liu et al, 2016). In the following, we review the articles that show the sparsity of massive multiple-input-multiple-output systems in both time and space, and analyze the different channel estimation techniques used in the field of compressive sensing, and finally we describe our case model.

Temporal correlation:

In the paper (Chandra et al, 2014) the channel is estimated in the presence of flat fading and taking into account the slow changes of the propagation environment over time and the use of the temporal correlation feature. Therefore, it is assumed that the user's channel matrix has common supports over consecutive time frames. He then proposed a greedy algorithm for channel recovery that was able to take advantage of the sparsity of the channel matrix and common supports in consecutive timeframes, ultimately reducing the amount of pilot required. In the article (Lau et al, 2016), as in (Rao and Lau, 2015), a scenario with flat fading is used. Assuming that the channel sparsity order is not available and has introduced a new algorithm that is stable to sparsity order changes. For this purpose, he used the closed-loop technique to adjust the pilot number based on the quality of the estimate. In addition, the paper (Minn et al, 2006) has shown that by using channel time correlation, the pilot required to estimate channels associated with several OFDM symbols can be further reduced.

In a situation where the pilot overhead of the downlink channel estimation consumes a large amount of communication resources, especially for the FDD massive multiple-input multiple-output systems, the paper (Zhang et al, 2018), to solve this problem, A downlink channel estimation method using Distributed Compressive Sensing(DCS) has proposed to slow the changes of the statistical characteristics of the channel in successive frames and to note that the sparse channel information and the support set for consecutive time intervals without The change remains in addition to fully exploiting the common spatial distribution across several subchannels in the frequency domain. This paper deals with the previous support information with respect to the temporal correlation of consecutive channel frames in order to reduce the pilot overhead. The paper (Zhang et al, 2018), in particular, proposes a hybrid structure to examine the channel in the current frame based on the previous frame support information, using slow changes in the statistical characteristics of the channel. Using the common spatial sparsity and previous support information of the previous frame, it divided the estimated channel in each subcarrier into the current frame into two parts: a dense section containing elements indexed by the previous support and a sparse section containing elements indexed support complement set in previous frame. The DCS-assisted channel estimation algorithm then combines the DCS and LS methods, which are used to estimate the dense and sparse sections of the angle-domain channel coefficients between different subcarriers, respectively. In addition, the uplink-downlink angle response is used to obtain the previous support information effectively to obtain the uplink initial backup estimate. This method can reduce the pilot overhead compared to downlink.

The paper (Huang et al, 2020) proposes a channel estimation algorithm called gBAMP. In this algorithm, using time block-time-frequency multi-input-multi-output block systems, the selected index sets are optimized in the algorithm iteration process to improve the algorithm stability. Then, in the absence of the threshold parameter, the condition for stopping the adaptive repetition using the residual is determined based on the Frobinius norm and proves the effectiveness of the method.

The paper (Zhao et al, 2020) proposes a low complexity estimation algorithm based on compact measurement for multi-antenna mobile terminals to reduce the terminal computational overhead. In this design, the mobile terminal estimates the downlink massive multi-input multi-output channel and uses the spatial sparsity properties of the massive multi-input multi-output channel to reduce the overhead. Since the different antennas of a terminal have the same set of support, this algorithm estimates several indices in each iteration and collects the estimated indices of the different antennas at the end of each iteration. As a result, it reduces the total number of iterations of the algorithm. It then obtains a stop condition for a greedy algorithm that stops the iteration process due to the residual energy.

Spatial correlation:

In this section, we review articles that have based their channel estimation on massive multi-input multi-output systems based on different spatial correlation modes, and explore the different techniques under consideration.

The paper (Rao and Lau, 2014) considers the channel with flat fadind and imagines the spatial representation of the space using the angular domain for the M-MIMO channel matrix. Considering the multi-user scenario for its model, it uses spatial correlation between different users and proposes an algorithm for estimating the channel using greedy recovery methods in the field of compressive sensing, which can be a common support feature use between users's channel matrix as well.

The paper (Sadeghi and Azghani, 2021) proposes a sparse-based algorithm for more efficient channel estimation. For this purpose, a problem modeling is proposed to exploit the spatial correlation between different BS antennas as well as the similarity between the user of the channel support set. A repetition-based threshold method has been proposed to approximate the channel matrix, which has been effective in estimating the channel due to the large number of base station antennas and consequently the large number of channel paths.

Also in line with the idea of using channel estimation in M-MIMO systems, FDD-based channel estimation (Björnson and Ottersten, 2009) using spatial correlation of channels has shown that the pilot needed to evaluate The canal can be reduced by rice distributing. References (Gao et al, 2014) and (Qi and Wu, 2014) have used spatial and sparse correlation of latency channels to estimate channels with reduced required pilot, but assuming channel sparsity in The user is an unrealistic assumption.

In order to use compressive sensing to reduce the pilot overhead cost for channel estimation in wireless communication systems, (Kuai, et al, 2019), have used structured turbo compressive sensing, which is a framework for structured sparse signal recovery to provides reduced computational complexity. This paper addresses the problem of estimating OFDM-based M-MIMO channels in a FDD system. Using structured frequency-angle domain and angle-delay domain delay of OFDM-based M-MIMO systems, under structured turbo compressive sensing framework using frequency-angle and angle-delay domain probabilistic models and the design of channel estimators based on message transmission shows the channel. In the following paper, several structured turbo compressive sensing algorithms for channel estimation of OFDM-based massive multi-input multi-input systems are proposed using a structured sparsity with fast convergence speed and low error performance. The following article (Akbarpour-Kasgari and Ardebilipour, 2019) also proposes a structured turbo compressive sensing algorithm that manage effectively channel sparsity in various areas, including the angle domain, the frequency domain as well as the delay domain. It also determines the performance of the proposed algorithm by state evolution. The paper (Zeng et al, 2021) proposes a channel state information feedback method based on sparse learning in an compressive sensing framework for massive multi-input multi-output systems. He goes on to say that the key point is to consider the sparse structure of the channel state information through the least squares return algorithm and to process the sparse base with a continuous update. Based on this, a comparative dictionary characteristic of sparse channel state information is constructed, which shows that it is highly accurate in channel recovery.

The paper (Jingzhi et al, 2021) proposes a dual-choice channel estimation method based on distributed compressive sensing for massive multi- input multi-output system. In the first step, it formulates the problem of estimating dual-choice channels within a distributed compressive sensing framework. He then theoretically proved the combined sparsity of the dual select channel by showing that the channel coefficients in the converted domain have a spatial correlation between adjacent antennas. He then reconstructed the channel coefficients with a distributed compressive reconstruction algorithm using a combined sparsity of the converted domain coefficients related to the channel between the different sending and receiving antennas.

The paper (Nouri et al, 2020) introduces a new compressive sensing algorithm that considers the benefits of correlation between incoming and outgoing signals for iterative estimation. For this purpose, it uses the intersection between the paired users and then selects the ones that minimize the remaining norm while keeping the number of non-zero elements to a minimum.

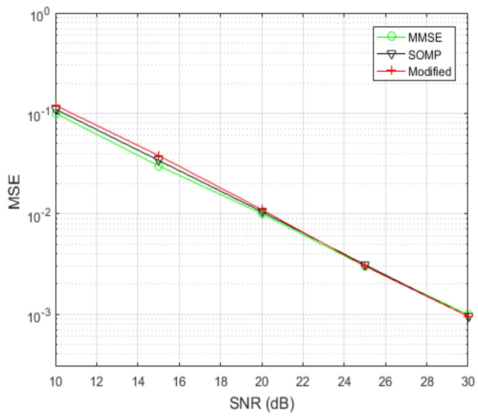
Due to the fact that the articles have shown that wireless communication in the delay domain tends to have a sparse channel impulse response. In line with the channel estimation strategy using sparsity in massive multi-input multi-output channels based on the added assumptions on the joint support between uplink channels, the paper (Lahbib et al, 2019) proposes a general approach that specifies in different channels beyond any additional assumptions. To achieve this goal, he proposed a training sequence, also known as a pilot sequence, and compressive sensing channel impulse response estimation techniques for uplink sparse massive multi-input multi-output channels. The simulations also show that the performance improvement of the proposed algorithm was between 5 and 10 for NMSE and 1 to 9 for BER.

The channel matrix of massive multi-input-multi-output systems is scattered in the delay domain. Channel estimation based compressive sensing uses the sparsity of the channel matrix to improve the accuracy of channel estimation and reduce the pilot overhead. With this in mind, the paper (Kang et al, 2019) proposes the block-compressive sensing adaptive tracking channel estimation algorithm (B-CoSaMP). The proposed algorithm combines the spatial correlation of multi-input-multi-output channels due to the propagation of multiple antennas, short-range antennas at the base station and creates a block response based on block sparsity to improve the channel estimation performance.

For conventional broadband wireless communication systems, delay channels are inherently sparse in nature due to the limited number of scatterers in the media and the large latency range (Dai and Wang, 2013). Meanwhile, for MIMO systems with an antenna array with a common location in the BS, channels between a single user, and different transmission antennas in the BS, very similar path delays due to the similarity of the highly scattered components in the environment. Diffusion channels indicate that the latency channels between the user and the different transmission antennas in the BS show a common sparsity when the antenna array aperture is not very large. This common feature is called spatial sparsity. Given the spatial correlation mentioned in the articles, in this dissertation we intend to draw our attention to this feature of MIMO channels, which is a kind of spatial sparsity of systems, and this correlation is the basis of our work.

SIMULATION RESULTS:

Next, in order to provide a spatial correlation in the sparse channels of massive multi-input-multi-output systems and the use and non-use of knowing the channel sparsity on the transmitter side and using an algorithm whose sparsity is obtained comparatively, we estimated the channel. And we have proposed the structured SOMP algorithm. The estimation specifications are in accordance with (Abedi et al, 2025) and respectively, the system carrier frequency, $f_c = 2GHz$, system bandwidth $f_c = 10MHz$, DFT size was N = 4096, and protective guard length was Ng = 64, which can have a maximum delay propagation of 6.4 µs. we have considered. The flat antenna array is(4 ×16) M = 64(We also consider a criterion for comparing performance, an LS algorithm, assuming a known channel support sequence on the user-side, and an algorithm similar to the proposed algorithm, the proposed modified algorithm, assuming a narrow channel level on the user's side. Figure (2) compares the performance of MSE with the proposed channel estimation and the MMSE algorithm (Zhai et al, 2019). It should be noted that the proposed scheme has a significant reduction in pilot requirements compared to the MMSE algorithm, because the MMSE algorithm only works well when equation (2) is correctly defined or exceeded.



Figure(2): Comparison of MSE and MMSE performance with the proposed channel estimation schemes of M-MIMO FDD systems.

CONCLUSION:

In this study, after discussing the need to facilitate channel estimation in M-MIMO systems and the problems in enjoying the benefits of these systems such as spectral efficiency, we addressed the existing solutions in better channel estimation in these systems and We investigated and described the sparse channel estimation in the frequency, time, angle, and hybrid domain domains that combine transmission in the angle and DFT domains, and showed that depending on the modeling conditions, each of these models could estimate the channel. To facilitate. In the following, we reviewed the work done in the domains of using spatial and temporal correlations for structured estimation and enumerated and identified their differences. Finally, using spatial correlation and proposing a structured algorithm to the advantage of this We have discussed the algorithm in estimating the optimal channel.

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