Article

Comparison of Hybrid Beamforming Precoding Algorithms using Millimeter Waves †

Alexandria K. Ahluwalia [1], Gerardo Melendez Cocoletzi [2], Diego Fernando Carrera [3], and Cesar Vargas-Rosales [4]

1 University of British Columbia; alexandria.ahluwalia@alumni.ubc.ca
2 Tecnologico de Monterrey, School of Engineering and Sciences; a01336692@itesm.mx
3 Tecnologico de Monterrey, School of Engineering and Sciences; dfcarrera@ieee.org
4 Tecnologico de Monterrey, School of Engineering and Sciences; cvargas@tec.mx

† Presented at the 6th International Electronic Conference on Sensors and Applications, 15–30 November 2019; Available online: https://ecsa-6.sciforum.net/

Published: 22 October 2019

Abstract: This study proposes and compares behaviours of different precoding and combining algorithms for beamforming in a 5G millimeter wave (mmWave) scenario to see how the algorithms perform when the channel conditions change randomly. First, a fixed scenario is generated where the devices deployed sense the channel and aid the transmitter in the estimation of the channel coefficients. We then obtain the digital beamforming matrices using optimization, and use this as the optimal algorithm. The second and third methods compared are generated using the same physical setup, but different algorithms to obtain the precoding and combining matrices to hybrid beamform to be able to compensate for the channel gains and phase changes. The second algorithm is the orthogonal matching pursuit and the third algorithm is our proposed method, a singular value selection method. We then compare the calculated spectral efficiencies (SEs) from each of the three different precoding and combining algorithms. Their performances are indicated and compared by using the SE as a function of the signal-to-noise ratio (SNR) with different amounts of data streams.

Keywords: MIMO; mmWave; Beamforming

---

1. Introduction

A global increase in wireless data traffic has led to the development of 5G wireless connectivity to improve data rates, latency, capacity, and service quality. The heightened demand for connectivity and capacity has increased energy cost and consumption across the telecommunications industry, necessitating the use of energy and cost efficient designs. The capacity of wireless communications depends on the cell size, the bandwidth, and the SE [1]. 5G is to use high frequency mm-Wave bands, where smaller wavelengths invite smaller antenna sizes allowing for integrating multiple antennas in small areas.

Antenna arrays are used to overcome path loss and other signal propagation issues. These arrays, and the consideration of the channel as a system, are studied using the Multiple-Input-Multiple-Output (MIMO) system theory. By increasing the number of antennas, we have Massive MIMO systems that have the potential to satisfy the growing demands for higher throughput and reliability. MIMO systems exploit the use of diversity and spatial multiplexing techniques for reliable communication to achieve high data rates and channel capacity without the additional transmit power or bandwidth. In [2], authors include massive MIMO for SE as one of the *big three* 5G issues that need to be addressed along with extreme densification and the use of the mmWave spectrum for increased bandwidth. As a MIMO array becomes larger, the per-antenna transmit energy greatly reduces. Moreover, the random matrix theory reveals that things which are random, become deterministic in large systems, e.g., the singular values of the large MIMO channel matrix. The use of massive MIMO has also been presented as a possible solution to challenges in applications for heterogeneous networks and mmWave systems, [3].

Channel capacity is the maximum achievable transmission rate that a communications channel supports for a given SNR, [4]. To optimize SE, different approaches have been proposed, e.g., MIMO and Massive MIMO systems have been studied from the ergodic capacity point of view in [3], [5], [6] and [7]. It is also well known that with the use of antenna selection techniques, rates are improved, [7], [8]. Antenna selection techniques select a set of antennas out of the whole set so that achievable rate is maximized, [7], and bounds can be determined, [9], [10], [11], [12]. It is also known that SE is optimized when Channel State Information (CSI) is available at the transmitting side, [13], [14], [15]. In [13], authors combine the use of antenna selection techniques and the water filling algorithm to improve ergodic achievable rate for conventional MIMO systems (system that uses equal energy for each of the transmit antennas), and present results based on the resulting number of transmitting antennas selected.

A different technique to be used in 5G, especially in mmWave frequency bands is beamforming, which is used to concentrate transmitting or receiving energy in narrow beams. Multiple antenna arrays are used for beamforming, a process by which the phases and amplitudes of the signal to be transmitted or the signal being received are adjusted through constructive and destructive interference to "steer" the beams in an intended angular direction, [18]. In beamforming, signals are coherently precoded to maximize the SNR, this gain is known as the beamforming gain, [16]. Digital beamforming with fully digital precoding methods with multiple antenna arrays is done by the use of a digital signal processor. This architecture has more flexibility to implement algorithms to beamform through its structural requirement of having a separate RF chain for each antenna element. This requirement results in the complexity of digital beamforming and the related high power costs due to the use of one RF chain per antenna, [16]. In analog beamforming, antenna weights to beamform are applied to the signal by phase shifters or by using time delay elements. Analog beamforming has low complexity, and through that, low flexibility to beamform.

The idea of hybrid beamforming structures is to reduce the hardware and signal processing complexity while simultaneously performing close to digital beamforming. Hybrid architecture is the combination of both analog and digital precoders and combiners. Hybrid architectures are motivated by the hybrid structure having less RF chains than the number of transmit data streams while the beamforming gain is given by the number of antenna elements. Because of this, hybrid beamforming is a suitable architecture for large mmWave MIMO antenna arrays, [16], [20] .

In Section 2 we introduce the model with the beamforming methods and the methodology used for the results. In Section 3 we present the results. Section 4 contains the discussion and Section 5 has the conclusions.

2. System Model

In this section we introduce the concept of beamforming, beamforming techniques used, and the methodology to obtain the results for the comparison.

2.1. Model Description

This section defines the notation and the three methods used for beamforming. We have a MIMO system with a base station with M_T transmit antennas and M_R receive antennas operating on a flat fading channel defined by matrix $\mathbf{H} \in \mathbb{C}^{M_R \times M_T}$ with each of its elements independent zero mean unit variance circularly symmetric complex Gaussian (ZMCSCG). There is CSI at the transmitter, i.e., $\mathbf{H}$ is known. The transmitted signal is the vector $\mathbf{x} \in \mathbb{C}^{M_T \times 1}$, E_s is the total average transmitted signal energy. The signal is transmitted to mobile users that have $M_{R,MS}$ receiving antennas. The received signal is $\mathbf{y} \in \mathbb{C}^{M_R x1}$ and is given by

$$\mathbf{y} = \sqrt{\frac{E_s}{M_T}} \mathbf{H}\mathbf{F_{RF}}\mathbf{F_{BB}}\mathbf{x} + \mathbf{n}, \tag{1}$$

where $\mathbf{n} \in \mathbb{C}^{M_R x1}$ is a vector representing noise whose elements are independent zero mean complex Gaussian with $E\{\mathbf{n}\mathbf{n}^H\} = N_0 \mathbf{I}_{M_R}$, where $\mathbf{I}_{M_R}$ is an identity matrix of order M_R, and $\mathbf{n}^H$ is the conjugate transpose of $\mathbf{n}$. We also assume statistical independence of $\mathbf{x}$ and $\mathbf{n}$. We define the autocorrelation of the transmitted signal as $\mathbf{Q} = E\{\mathbf{x}\mathbf{x}^H\}$.

Since we are considering mmWaves and hybrid beamforming, it is known that in hybrid mmWave MIMO systems, the beamforming at the transmitter and the combining at the receiver can be split into the analog and the digital parts, [20]. These parts are represented by the product of the matrices $\mathbf{F} = \mathbf{F_{RF}}\mathbf{F_{BB}}$, where $\mathbf{F_{RF}}$ is the beamforming matrix and $\mathbf{F_{BB}}$ is the baseband processing matrix, both matrices at the transmitter. At the receiver, we have matrix $\mathbf{W_{RF}}$ as the combining matrix and $\mathbf{W_{BB}}$ the baseband processing matrix. The beamforming and combining matrices for the RF are $\mathbf{F_{RF}} \in \mathbb{C}^{M_T x M_T}$ and $\mathbf{W_{RF}} \in \mathbb{C}^{M_{R,MS} x M_{R,MS}}$, respectively. The beamforming and combining matrices for the digital baseband are $\mathbf{F_{BB}} \in \mathbb{C}^{M_T \times M_T}$ and $\mathbf{W_{BB}} \in \mathbb{C}^{M_{R,MS} \times M_{R,MS}}$. Both $\mathbf{F_{BB}}$ and $\mathbf{W_{BB}}$ are block diagonal matrices.

In a real scenario, a MIMO channel matrix $\mathbf{H}$ changes randomly and the SE is expressed as the expectation with respect to this random matrix as, [5], [7], [17],

$$\overline{C} = \varepsilon \left[\max_{\mathrm{Tr}(\mathbf{Q}) = M_T} \log_2 \left\{ \left| \mathbf{I}_{M_R} + \frac{E_s}{M_T N_0} \mathbf{F_{RF}}\mathbf{F_{BB}}\mathbf{H}\mathbf{Q}\mathbf{H}^H {\mathbf{F_{BB}}}^H {\mathbf{F_{RF}}}^H \right| \right\} \right], \tag{2}$$

Equation (2) defines the channel capacity of a (conventional) MIMO system in units of bps/Hz, [5], and is often referred to as the error-free SE. It is also frequently known as the *Ergodic Channel Capacity*, [11]. The term *conventional* refers to a MIMO system where equal energy is allocated to all the transmit antennas. The SE increases as SNR does, and the SE also increases with the number of M_R and M_T antennas used at the base station.

When the signal arrives at the receiver, it will be processed by a combiner (matrix $\mathbf{W_{RF}}$) that compensates the phase and amplitude changes caused by the channel H. Afterwards, it will go through the detection phase using baseband processing (matrix $\mathbf{W_{BB}}$). The signal processed is then $\tilde{\mathbf{y}} = \sqrt{\frac{E_s}{M_T}} {\mathbf{W_{BB}}}^H {\mathbf{W_{RF}}}^H \mathbf{H}\mathbf{F_{RF}}\mathbf{F_{BB}}\mathbf{x} + {\mathbf{W_{BB}}}^H {\mathbf{W_{RF}}}^H \mathbf{n}$. When beamforming is used, the SE is given by

$$\overline{C} = \varepsilon \left[\max_{\mathrm{Tr}(\mathbf{Q}) = M_T} \log_2 \left\{ \left| \mathbf{I}_{M_R} + \frac{E_s}{M_T N_0} {\mathbf{W_{BB}}}^H {\mathbf{W_{RF}}}^H \mathbf{H}\mathbf{F_{RF}}\mathbf{F_{BB}} \times {\mathbf{F_{RF}}}^H {\mathbf{F_{BB}}}^H \mathbf{H}\mathbf{W_{RF}}\mathbf{W_{BB}} \right| \right\} \right], \tag{3}$$

In the following subsections, we introduced briefly the three methods used and compared in the results.

2.1.1. Optimum Method

When the channel is unknown to the transmitter, assigning equal energy to all transmitting antennas is the logical solution to set up the MIMO link, especially when the system experiences high SNR levels, [5], [17]. On the other hand, channel capacity of the MIMO system, with complete knowledge of CSI at the transmitter, can be considered as the sum of individual capacities of the parallel Single-Input-Single-Output (SISO) channels, [7], [17]. Since all advantages of conventional MIMO are scalable, now we apply water flooding algorithm (WFA) to it, in order to improve SE. WFA changes the ergodic achievable rate by optimizing (2) using the eigenvalues of the channel, and a set of coefficients to modify how the energy is allocated to transmit antennas. Thus, the achievable rate is given by

$$C = \sum_{i=1}^{r} \log_2 \left(1 + \frac{E_s}{M_T N_0} \lambda_i \right), \quad \text{bps/Hz}, \tag{4}$$

where r is the rank of matrix $\mathbf{H}$ (usually $r = \min\{M_T, M_R\}$) and λ_i for $i = 1, 2, \ldots, M_R$ is the i-th eigenvalue of the singular value decomposition (SVD) of matrix $\mathbf{H}\mathbf{H}^H$, [17].

2.1.2. Matching Pursuit

The recovery of signals that have been affected by noise is a fundamental problem in signal processing. One approach to recover of signals that have been affected by noise is the orthogonal matching pursuit (OMP) algorithm. This is an iterative method that selects the column with the most correlated signals at each step [21].

2.1.3. Singular Value Decomposition (SVD) Based Combiner

For the third method, we use the matrices found in the matching pursuit algorithm and try to improve performance by some scaling as follows. Once the matrix $\mathbf{W_{RF}}$ is found using the OMP algorithm, we proceed to obtain the SVD of $\mathbf{W_{RF}}\mathbf{W_{RF}^H}$. We are interested in the eigenvalues that are provided in a diagonal matrix from the SVD operation, because the higher the values are, the better the channel SNR is. We denote such diagonal matrix as $\mathbf{\Omega}$, then, we modify matrix $\mathbf{W_{RF}}$ by scaling it using the diagonal matrix to obtain $\tilde{\mathbf{W}}_{\mathbf{RF}} = \mathbf{\Omega}\mathbf{W_{RF}}$.

Table 1. Iterative design algorithm for the hybrid structure.

Singular Value Selection Method
1. Input: $\mathbf{W_{RF}}$
2. Singular value decomposition of $\mathbf{W_{RF}}\mathbf{W_{RF}}^H$
3. Diagonalize matrix for eigenvalues > 0.1
4. Else; change to 1 to have better eigenvalues for better channels

The simplified algorithm is summarized in **Table 1** above. With this algorithm, the SE in (3) becomes

$$\overline{C} = \varepsilon \left[\max_{\mathrm{Tr}(\mathbf{Q})=M_T} \log_2 \left\{ \left| \mathbf{I}_{M_R} + \frac{E_s}{M_T N_0} \mathbf{W_{BB}}^H \tilde{\mathbf{W}}_{\mathbf{RF}}^H \mathbf{H} \mathbf{F_{RF}} \mathbf{F_{BB}} \times \mathbf{F_{RF}}^H \mathbf{F_{BB}}^H \mathbf{H} \tilde{\mathbf{W}}_{\mathbf{RF}} \mathbf{W_{BB}} \right| \right\} \right], \tag{5}$$

2.2. Methodology

The fixed scenario is generated by defining the transmitting and receiving antenna arrays in a 3-dimensional space. In this, scatters are randomly deployed to generate different channel matrices H. A scatterer describes a single reflection along a NLOS propagation path. A path describes the way that a signal takes from the transmitter to the receiver. In the channel model, there is usually a direct, or LOS path, and several indirect, or NLOS paths [19]. 1000 channel matrices were generated to represent the random channel changes and paths in the scenario to be able to compare the performance of the three different precoding algorithms. The scenario generated uses a hybrid digital and analog antenna array design which allows for beamforming with mm-waves. The scenario defines the transmitting antenna array to have 64 antennas with 4 RF chains at an elevation of 25 meters. The receiver is defined to have 16 antennas, with 1 RF chain and an elevation of 1.5 meters to represent a mobile terminal at a height of a mobile user. The 1000 different propagation channel matrices were generated using Quasi Deterministic Radio Channel Generator, QuaDRiGa [19], with 8 scatterers.

For each propagation channel generated in the previous step, precoding and combining matrices are created to recover the signals. We obtain the optimal precoding and combining weights $\mathbf{F}$ and $\mathbf{W}$ with the *helperOptimalHybridWeights* function and use this as the optimal method in the comparison. For the second method in comparison we obtain the hybrid weights $\mathbf{F_{BB}} \times \mathbf{F_{RF}}$ and $\mathbf{W_{BB}} \times \mathbf{W_{RF}}$ though the OMP algorithm and then calculate the SE with $\mathbf{F_{BB}} \times \mathbf{F_{RF}}$ as $\mathbf{F}$ and $\mathbf{W_{BB}} \times \mathbf{W_{RF}}$ as $\mathbf{W}$. The third method, the *Singular Value Selection Method*, uses the obtained combining weights from the OMP algorithm $\mathbf{W_{RF}}$, and uses those to obtain an updated $\mathbf{W_{RF}}$, $\mathbf{\Omega W_{RF}}$. With that, the SE is calculated with $\mathbf{F_{BB}} \times \mathbf{F_{RF}}$ as $\mathbf{F}$ and $\mathbf{W_{BB}} \times \mathbf{\Omega W_{RF}}$ as $\mathbf{W}$.

3. Results

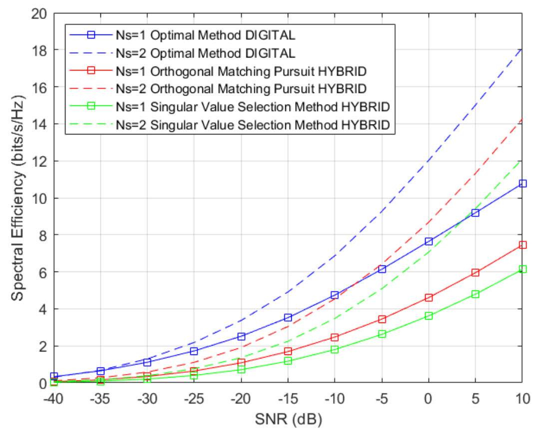

Figure 1. Comparison of spectral efficiency for the three methods and the spectral efficiency improvement when the number of data streams are increased. N_s is the number of data streams.

4. Discussion

It can be understood from the results in Figure 1 that the SE improves significantly from the increase in data streams and that the hybrid methods reduce the use of hardware decreasing the energy consumption. It is worth mentioning that the modification of the matrix $\mathbf{W_{RF}}$ can be carried out in different ways, and this is part of the future research to obtain efficient ways to modify such matrix.

5. Conclusions

The Singular Value Selection Method improves as the number of streams increases, and it approaches the optimum values as the SNR values increase. We need to establish different ways to adjust the values of the beamforming matrices to increase SE.

Author Contributions: Conceptualization, C.V-R. and D.F.C.; methodology and software, G.M-C., A.A. and D.F.C.; validation, A.A. and G.M-C.; writing-original draft preparation, A.A. and G.M-C.; writing review and editing, C.V-R., A.A. and D.F.C.; supervision, C.V-R.; project administration, C.V-R.; funding acquisition, C.V-R.

Funding: This research was supported in part by the SEP-CONACyT Research Project on Spectral Efficiency using Massive MIMO systems for 5G, under Grant 255387.

Acknowledgments: We would like to acknowledge the support from the Telecommunications Research Group, the School of Engineering and Sciences and the International Programs Office at Tecnologico de Monterrey for providing the means to develop this collaborative work.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

MIMO	Multiple-input multiple-output
SE	Spectral Efficiency
mmWave	Millimeter Wave
SNR	Signal-to-Noise Ratio

References

1. M. Agiwal, A. Roy, and N. Saxena. Next Generation 5G Wireless Networks: A Comprehensive Survey. *IEEE Communication Surveys & Tutorials* **2016**, 1617–1655.
2. J. Andrews, S. Buzzi, W. Choi, S. Hanly, A. Lozano, A. Soong, and J. Zhang. What will 5G be?. *IEEE Journal on Selected Areas in Communications* **2014**, *32*, 1065—1082.
3. L. Lu, G. Li, A. Swindlehurst, A. Ashikhmin, and R. Zhang. An Overview of Massive MIMO: Benefits and challenges. *IEEE Journal of Selected Topics in Signal Processing* **2014**, *8*, 742-–758.
4. C. Shannon. A Mathematical Theory of Communication. *The Bell System Technical Journal* **1948**, *27*, 623-–656.
5. D. Tse and P. Viswanath. Fundamentals of Wireless Communications. *Cambridge University Press* **2005**.
6. B. Hochwald, T. Marzetta, and V. Tarokh. Multiple-antenna Channel Hardening and its Implications for Rate Feedback and Scheduling. *IEEE Transactions on Information Theory* **2004**, *50*, 1893-–1909.
7. Cho, Y.S., Kim, J., Yang, W.Y. and Kang, C.G. MIMO OFDM Wireless Communications with MATLAB, *John Wiley & Sons, NY, USA* **2010**.
8. D. G. A. Gorokhov and A. Paulraj. Antenna Subset Selection in MIMO Communication Systems. In *Space-Time Processing for MIMO Communications John Wiley & Sons, NY, USA*, 2005; pp.
9. A. Gorokhov, D. Gore, and A. Paulraj. Performance Bounds for Antenna Selection in MIMO Systems. *Proceedings of the IEEE International Conference on Communications (ICC)* **2003**, 3021-–3025.
10. Tsoulos, G. MIMO System Technology for Wireless Communications. *CRC Taylor & Francis, USA* **2006**.
11. G. Foschini and M. Gans. On Limits of Wireless Communications in a Fading Environment when using Multiple Antennas. *Wireless Personal Communications* **1998**, *6*, 311-–335.
12. A. Gorokhov, D. Gore, and A. Paulraj. Receive Antenna Selection for MIMO Flat-Fading Channels: Theory and Algorithms. *IEEE Transactions on Information Theory* **2003**, *49*, 2687-–2696.
13. J. Cuan-Cortes, C. Vargas-Rosales, and D. Munoz-Rodriguez. MIMO Channel Capacity Using Antenna Selection and Water Pouring. *EURASIP Journal on Wireless Communications and Networking* **2014**.
14. El Gamal, A., and Kim, Y.H. Network Information Theory. *Cambridge University Press, Cambridge, UK* **2011**.
15. Couillet, R., and Debbah, M. Random Matrix Methods for Wireless Communications. *Cambridge University Press, Cambridge, UK* **2011**.
16. I. Ahmed, H. Khammari, A. Shahid, A. Musa, K. S. Kim, E. D. Poorter, and I. Moermann. A Survey on Hybrid Beamforming Techniques in 5G: Architecture and System Model Perspectives. *IEEE Communications Surveys & Tutorials* **2018**, 3060–3097.
17. Telatar, I.E. Capacity of multi-antenna Gaussian channels. *Europ. Trans. on Telecommunications* **1999**, *10* 585–595.
18. B. D. Van Veen and K. M. Buckley. A Versatile Approach to Spatial Filtering. *IEEE ASSP Magazine* **1988**, 4–24.
19. S. Jaeckel, L. Raschkowski, K. Boerner, L. Thiele, F. Burkhardt and E. Eberlein. QuaDRiGa - Quasi Deterministic Radio Channel Generator, User Manual and Documentation. *Fraunhofer Heinrich Hertz Institute* **2017**.
20. S. Mumtaz, J. Rodriguez, L. Dai. mmWave Massive MIMO: A Paradigm for 5G. *Elsevier Science* **2016**, 124.
21. T. Cai and L. Wang. Orthogonal Matching Pursuit for Sparse Signal Recovery With Noise. *IEEE Transactions on Information Theory* **2011**, 4680–4688.