Machine 5G Channel Estimation

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Abstract

As 5G continues to gain more momentum around the world, there are still challenges that need to be addressed in order to capitalize fully on the benefits of the proposed architectures and technologies, that include small cells, advanced OFDM, beamforming, massive MIMO, and millimeter wave. A particular, challenge is 5G channel estimation due to the large and high frequency range involved. In this paper, conventional channel estimation methods such as least square, Minimum Mean Square Error, blind and semi-blind are investigated. Moreover, the application of machine and deep learning in channel estimation has been discussed. We then use the IBM Watson machine learning service for channel estimation using the DeepMIMO dataset which yielded promising results.

Keywords: Lease Square Estimation (LSE), Minimum Mean Square Error (MMSE), Machine Learning (ML), Multiple Input Multiple Output (MIMO), Frequency Division Multiplexing (FDM), Channel State Information (CSI), and Deep Neural Network (DNN).

1 Introduction

The fifth generation of mobile communication (5G) was created to accommodate the exponential increase in data and the need for reliable communications for emerging technologies. The application of IoT in industries, smart cities, connected heath care etc., has contributed to this exponential growth of data (Big data) and due to the nature of the devices used, where high data speed communication with minimal latency is required. The 5G is expected to increase data rate to about 10Gbit/s second or more, reduce the latency by 10 fold, and lower the power consumption. As a result, the millimeter wave band has been considered as the suitable spectrum to deliver on this required results. The mmWave spectrum ranges between 30GHz and 300GHz, with wavelengths between 1mm and 10mm.

In spite of the massive bandwidth, there has been some challenges and concerns when developing communication systems that operate at these high frequencies. Some of the problems include: free-space path loss and attenuation due to atmospheric absorption. Most of the frequencies used in the mmWave band often suffer from free-space path loss (due to short wavelength), but only a few frequencies are affected by atmospheric absorption (mainly 60GHz and 120GHz). In addition to the challenges facing the mmWave band is penetration loss; this is often caused by static and dynamic blockage from objects such as glass, human body, walls, doors etc.

In order to solve these challenges, many technologies and techniques have been employed into the design of mmWave communication equipments so as to maximize the benefits of the 5G. They include massive MIMO, beamforming, Orthogonal Frequency Division Multiplexing (OFDM), and channel estimation. Massive- Multiple Input, Multiple Output (MIMO) is the use of large number of antennas (array) ranging between 16 and 256 antennas at the Base station and user device to increase the capacity of cellular networks. Moreover, MIMO systems are designed to provide multi-path transmission of data which ensures reliable communication by reducing interference in the system. Massive MIMO has been studied for sub-6 GHz systems and has been considered suitable for use in the mmWave band of higher frequencies.

Furthermore, artificial intelligence (AI) has revolutionized many industries- its application in transportation, health care, and manufacturing has yielded remarkable results. One area of AI that has become very popular and flexible to use is Machine Learning (ML). ML divided into two categories- supervised and unsupervised learning. In supervised learning, labeled data are used in training a model to be able to find correlation within the data-set. While In unsupervised learning, unlabeled data is used to train a model or algorithm in order to find meaning within the dataset. Unsupervised learning is sometimes used interchangeably with deep learning.

To better understand the role ML will play in channel estimation, we have established a solid background on some relevant 5G techniques, the challenges faced in conventional channel estimation methods, and the motivation for using ML.

2 Background

Beamforming is another technique employed in 5G architecture to optimize signals received over an array of antennas (in others words, massive MIMO). Beamforming ensures that before signals are transmitted, the amplitude and phase are adjusted towards the direction of interest thereby avoiding areas of interference. Over the years, researchers have recommended various ways of improving beamforming algorithms to accommodate the dynamic changes experienced in radio frequency (RF) transmission. Statistical beamforming is one of the recent techniques introduced to improve beamforming; [15] proposed a novel statistical beamforming technique that will serve a number of users experiencing a peculiar spatial channel correlation in MIMO systems. Their proposal was based on a study of a common phenomenon in 5G where two groups of users, one experiencing a low spatial channel correlation while the other having a higher spatial channel correlation. They addressed this issue by designing the post-beamforming vector to maximize signal to leakage and noise ratio.

In addition to the beamforming technique, OFDM is also considered as an invaluable technique which will better serve the 5G technology and beyond. Orthogonal frequency division multiplexing is a digital-carrier modulation technique that was created to improve the Frequency Division Multiplexing (FDM). This massive improvement was brought about by the introducing "orthogonality" among subcarriers- it is achieved by dividing the pilots into "closely spaced" channels. Each channel or subcarrier is then modulated by one form of digital modulation or the other. For example, the quadrature phase-shift keying (QPSK) can be applied to the channels to produce similar results as though it was applied to a single-carrier channel. In OFDM, large data streams ready to be transmitted are split into parallel data streams which are then supplied to the orthogonal carriers (that is, the subcarriers) at a lower symbol rate [2]. At this lower rate, any of the modulation schemes (e.g. BPSK, QPSK, and QAM) can be applied to the channels to produce the desired results. Although the data rate for each channel is less than the single carrier modulation, its overall data rate, however, is greater. As such, there modulation scheme have since been introduced into WiFi, LTE, and the Ultra Wide Band (UWB) systems.

Having considered the above techniques and technologies used to solve some of the challenges mmWave systems, Channel Estimation in 5G has proven to be challenging. This is because estimating a channel at high frequency is complex and carries many overheads compared to estimating a channel at a low frequency. The channel state information (CSI) which are required to estimate a channel and further assist in beam selection has proven to be challenging in 5G considering not only because of the high frequency, but also due to the amount of antennas involved in the architecture.

Channel estimation is often performed at the receiver end and then relayed to the transmitter. Therefore, the channel state information must be available at the receiver before it can be fed back to the transmitter in order to select the best channel to transmit [9]. Channel state information is ascertained instantaneously or statistically. In instantaneous channel state information, all the link characteristics or properties currently are known to the receiver by deducing the impulse response of the transmitted sequence. Statistical channel state information provides link properties like: channel gain, spatial correlation, fading distribution. CSI are rendered based on how fast or slow channel conditions change.

Least Square (LS) and Minimum Mean Square Error (MMSE) are the two commonly used pilot-based estimation algorithms in a channel. LS estimation requires no CSI to estimate a channel, while MMSE requires some statistical information to estimate the channel, which makes LS to perform faster than MMSE. The major problem with LS, however, is that it does not estimate the channel accurately while MMSE in fact provides more accurate result [8]. MMSE is slow because it takes into account many statistical parameters creating a very large overhead making its performance not only slow, but consumes a considerate amount of resources. For this reason, researchers have started looking into Machine Learning as a suitable application for channel estimation.

The application of machine learning (ML) in many industries have yielded outstanding results over the years. There is no doubt that its use in the telecommunications industry will assist in solving some of its underlying challenges particularly in 5G and beyond [14]. The motivation for ML is using models based on statistical inference obtained from a dataset to make a prediction, where the application of ML to the CSI dataset can provide superior results than the conventional channel estimation algorithms.

Motivated by this, in this paper we shall;

1. Review the performance of conventional channel estimation methods in massive MIMO systems.
2. Present the recent applications of Machine learning/deep learning in channel estimation.
3. Recommend a machine-learning based channel estimation method for application in MIMO-OFDM systems using IBM Watson.

2.1 Conventional Channel Estimation Techniques

There are three major conventional channel estimation techniques, which are: Pilot/train symbol based channel estimation, blind channel estimation, and the semi-blind channel estimation.

In pilot-based channel estimation, pilot symbol are trained to predict the channel impulse response (CIR). The pilot symbol is usually the row of bits that has been previously known to the receiver. This however, changes periodically due to different factors including user mobility and the environment. Therefore, to provide an accurate CSI, the receiver updates these changes to reflect the new pilot signal received. When a receiver receives the pilot symbols, the channel is usually estimated using either the Least Square Error (LSE) or Minimum Mean Square Error (MMSE) [13]. However, the challenge in estimating using pilot symbol is that it creates large overheads that makes performance in MIMO-OFDM system very slow.

Many researchers on the other hand have been trying to come up with solutions that can reduce the overheads in pilot symbol based estimation so as to make it viable for use in massive MIMO system. For example, MM Rana and MK Hosain in [12] proposed the use of a normalized least mean square (NLMS) and recursive least squares (RLS) to achieve an "adaptive estimator" that is capable of updating the channel parameters/characteristics automatically so that storing prior knowledge of the channel by the receiver will no longer be necessary. The only thing their proposed algorithm requires is the received signal. Although, their results showed that the NLMS/RLS based algorithm is faster than the LSE and MMSE, the question of accuracy comes into play when it is deployed on massive MIMO systems.
Additionally, [17] proposed a novel channel estimation method that complements LSE with time domain interpolation. They introduced what is called a pilot-receiver iterative relationship with joint inter carrier interference (ICI) cancellation method that reduces pilot decoding complexity and that enables the LSE computation to yield a more accurate result. Like the proposal made by MM Rana[12], this is also likely to fail in massive MIMO systems but not due to accuracy, rather power consumption. The iterative nature of this algorithm will consume a significant amount of power by the receiver to cancel out the noise in the channel.

In blind channel estimation, statistical properties received from user terminals and the base station are used to deduce the channel coefficients. Since blind channel estimation method does not use pilot signals, the overhead is very low. However, it requires large amount of symbols to infer the statistical properties of the channel. This poses a significant challenge to MIMO-OFDM systems because of the amount of memory required for channel estimation [5]. There are two common method used in channel estimation; subspace-based and recursive-based method.

In subspace-based method, three parameters are extracted from the signal properties to estimate the channel. These parameters are: symbol rate, alphabet structure, and correlation. Usually, when a signal is received, only one of its block is subjected to the subspace-based technique to obtain the CSI. Recursive channel estimation method on the other hand estimate a channel by sampling every instance of data received while applying the recursive technique. As a result of its recursive nature, it will require significant memory to perform efficiently which can pose a serious problem when we are dealing with massive MIMO that can contain hundreds of antennas. As a result, subspace-based channel estimation is preferred to recursive based channel estimation. Importantly, subspace-based channel estimation has what is called an independent component analysis (ICA) that is the base technique used in blind channel estimation.

The ICA is considered a likely option for massive MIMO due to its mode of operation. That is, the channel coefficient are obtained by transforming the vector matrix of the received signal. This is done by calculating the singular value decomposition (SVD) of the covariance matrix, given by $C = E\{YY^T\}$ and $C=UDU^T$ [16]. Where $U \epsilon C^{MxM}$ represents the orthogonal matrix and $D = \{ \lambda_1, \lambda_2, \ldots \lambda_M \}$, U and D are matrices which is used to divide a signal subspace and noise subspace. U matrix is given as $[U_s\, U_N]$ and $D = \begin{matrix} Ds & 0 \\ 0 & Dn \end{matrix}$ [16]

Afterwards the complexity of the received symbols is decreased by projecting the symbols into the subspace domain. The projection is done by what is known as "whitening" (Y_W), which is represented by $Y_w = D_s^{-1/2}U_s^TY$, where $Y_w \epsilon C^{NxN}$. This will then result in the creation of an orthogonal matrix ($W \epsilon C^{NxN}$) that will shrink the vector matrix using its mutual information in order to maximize negentropy [16].

Semi-blind channel estimators combine the use of training symbols and data symbols in order to accurately estimate a channel; i.e. semi-blind algorithms make use of the second-order stationary statistics/process, partial response signaling schemes, and other properties to produce a better spectral efficiency [4]. This concept helps in reducing the channel ambiguity often associated with OFD-MIMO matrix. One of the reasons why semi-blind methods of channel estimation came into play is to solve the pilot contamination that is usually associated with massive MIMO systems that use adaptive or blind channel estimation. Although, semi-blind uses pilot signals, its contamination percentage is greatly minimized.

The mostly widely used semi-blind channel estimation method uses SVD and it has been considered efficient in terms of bit error rate and other computational complexities. UTs left in the subspace of the singular vector covariance matrix are multiplied by the channel vectors $\{h_{1\ldots}h_n\}$ to obtain the normalized channel matrix and the ambiguity matrix. In this context, after the pilot signals are received, the semi-blind channel estimation is estimated by:

$$H_{svd} = U_sU_s^TH_{LS}, \qquad (1)$$

where $U_s \epsilon C^{MxN}$ is the signal subspace of the orthogonal matrix U, $H_{LS} \epsilon C^{MxN}$ is a matrix of the estimated channel coefficients with least square, and $H_{svd} \epsilon C^{MxN}$ is the matrix of the estimated complex channel coefficient (Ture, Garrett, & Tamal, 2017)

The above semi-blind channel estimation method is regarded as the conventional method. However, a proposal was made by [6] to optimize semi-blind channel estimation using time domain. Their results shows a significant reduction of residual error when the receive diversity is used on the time domain. However, their proposal is limited to time invariant channels, and also MIMO systems with available data.

2.2 Machine Learning in Channel Estimation

The application of machine learning in the telecommunication field is progressive; in particular one area where its application increasingly gaining attention is channel estimation. The application of machine learning in channel estimation has yielded positive results, better than conventional channel estimation methods such as the LSE and MMSE. In the research carried out by [1], the researchers used deep learning to create a neural network model for 5G channel estimation of MIMO-OFDM system. They used a 2 x 2 MIMO channel model (that is, a two antenna transceiver) to generate all the data needed to create the deep neural network model (DNN) – which has 5 layers comprising of an input layer, 3 hidden layers, and an output layer. As an input for the DNN, the channel information is attained by applying the LS estimation technique. This is done so as to minimize the mean square error (MSE).

The input realization is process is:

$M_{nt} = \{Re\{ [h^n_{LS}(t)]_0 \}, I_m\{[h^n_{LS}(t)]_0\}, \ldots, \{Re\{ [h^n_{LS}(t)]_3 \}, I_m\{ [h^n_{LS}(t)]_3\} \},$ (2)
where n denotes the n-th realization, Re {.} is the real number, and lm {.} represents the complex number.
The output of the neural network is given as; $O_{nt} = \{Re\{ [h^n_{LS}(t)]_0 \}, I_m\{[h^n_{LS}(t)]_0\}, \ldots, \{Re\{ [h^n_{LS}(t)]_3 \}, I_m\{ [h^n_{LS}(t)]_3\} \}$. Where h^n is the output of the neural network at the n-th realization.

In order to train the DNN model, the researchers used a data set containing 250800 realizations. Of those data set, 70% percent was used for the training, 15% for the validation, and the remaining 15% of the data for testing. To evaluate the performance of the DNN-aided estimation, the results are compared to conventional channel estimation methods such as LS and LMMSE by taking using bit error rate (BER) and the mean square error (MSE) against signal to noise ratio (SNR). After carrying out the evaluation, their proposed DNN model yielded the best MSE performance at low and "mediate" SNR in contrast to LSE and LMMSE. But when the SNR increases by 13dB, the model produces the worst MSE in comparison to the two conventional channel estimators.

In a similar application of deep learning to aid in channel estimation, researchers in [11] proposed a general pipeline known as ChannelNet using deep image restoration technique to estimate a channel. The concept of image recovery from a noisy image was applied to a channel, since both can be reconstructed to represent a vector component. Therefore, their approach is to model the time-frequency grid of the response channel into a 2D image of known pilot positions. The channel grid containing the pilots is considered as the noisy image or the low-resolution (LR) image, while the estimated channel is known as the high-resolution (HR) image. Afterwards, a two phased process is used to estimate the "channel grid". The first phase involves the use of the super resolution (SR) algorithm to enhance the low resolution image of the channel. The second phase is to remove the noise effect of the image by using an image restoration technique or algorithm. The researchers used two convolutional Neural Network (CNN) algorithms (SRCNN & DnCNN) for the super resolution and image restoration networks.
The overview of their proposed pipeline can be elaborated as follows:

1. The estimated channel with noise represented as h^{LS}_p is vectorized as the low resolution input image of the CNN.
2. The noise effect is then removed by denoising the IR network from the super resolution network; i.e. the SRCNN first uses interpolation to find the approximate value of the higher resolution image and further improves the image (channel) in a three layer CNN.

Their proposed deep learning model contained a data set of about 48000, among which, 32000 was used for training, 4000 for testing, and the remaining 4000 for validation. This was obtained from one link comprising transmitter - receiver antenna (basically a Single-input, Single output) pair. The results of the ChannelNet shows that at SNR of 12dB and below, its performance is superior to that of the LSE and MMSE. But at higher SNR, its performance or accuracy begins to drop steadily. This behavior has also been experience by [1], but with a slightly higher SNR.

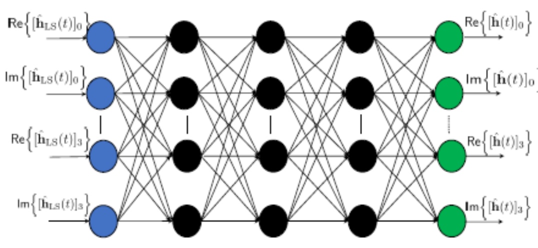

Figure 1: Their proposed DNN structure [1]

Furthermore, machine learning was used by [7] to obtain channel state information by utilizing the temporal channel correlation. Their project was inspired by the recent application of non-linear based machine learning in wireless communication such as the DNN discussed above. They based their theory on the fact that channel state information (CSI) is a time series problem, as such similar techniques used for image recognition can be harnessed and applied for channel estimation. To obtain the CSI, they used a machine learning based timed division duplex (TDD) scheme instead of the conventional pilot-based channel estimators like LS and MMSE. More so, two other machine learning models are used to improve the CSI prediction, namely autoregressive convolutional neural network (AR-CNN) and autoregressive network with exogenous inputs (CNN-RNN). CNN is used to identify the aging pattern of the channel and then AR-CNN or CNN-RNN is used to accurately predict the CSI. A key advantage of this scheme is that channel estimation overheads is massively reduced.

In their analysis, they used a base station with about 128 antennas, and an undisclosed number of users. From the simulated result, their ML-based TDD scheme was able to reduce the channel estimation overhead by about 77% and achieving an MSE below -10dB.

In another research, [10] used deep learning to obtain all the required MIMO channel matrix by processing the incoming signal at a single pass regardless of the number of antenna used in the system. The idea is to estimate each sub-channel in the massive MIMO channel orthogonally. Their proposed deep layer perceptron architecture is able to retrieve a three dimensional CSI matrix – where each dimension corresponds to the number of transmitting antennas, receiving antennas, and sub-carriers. Their DNN model has three hidden layers to achieve the required result, having an input as a time-domain preamble sequence. The model is trained by using a regression algorithm so as to predict each massive MIMO sub-channel in the frequency domain. Their result shows that by training the model on CSI values obtained at high SNR, the model produces the best results compared to the conventional channel estimators at low SNR. Since their DNN model was designed for general use on massive MIMO systems, their proposal suggests that the solution can be used for frequencies above 6 GHz band (mmWave) and even at the THz bands. In other words, their deep learning model can be used for channel estimation in 5G massive MIMO and beyond.

3 Machine Learning-based Channel Estimation Method for MIMO-OFDM using IBM Watson AI

The IBM community have been perfecting its AI services for more than 3 decades now. They have created some advanced tools on their IBM cloud platform that can be applied to various field of studies to achieve AI functionalities. Their machine learning services have yielded outstanding results for several projects . Inspired by this, their deep learning service was applied to channel estimation. The following procedures was addressed:

1. A dataset containing ray tracing scenarios for about a million users was acquired. The dataset can be obtained from [3]
2. The dataset is then imported to IBM ML environment
3. The model is trained using the dataset
4. The result is then analyzed.

The result shows that the IBM model was able to reduce channel estimation overhead to about 80% while achieving an MSE below -10dB. Additionally, the result shows that the model outperforms the LSE and MMSE for low and high SNR. Therefore, the IBM machine learning model could be suitable for channel estimation in 5G applications.

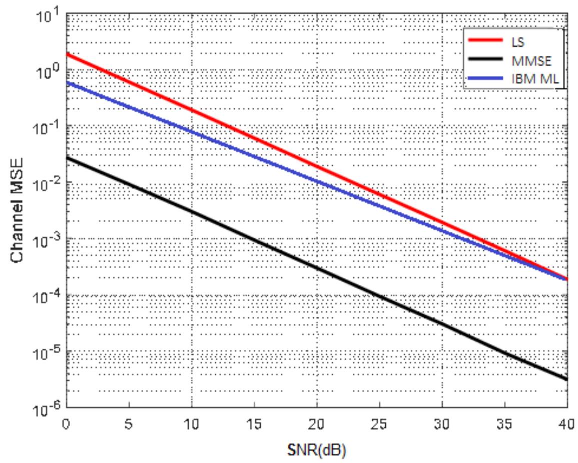

Figure 2: LS, MMSE & Proposed IBM ML performance

4 Conclusion

Channel estimation is one of the most crucial aspect of wireless communications that cannot be overlooked. Conventional channel estimation methods are sufficient for 3G and LTE communication systems, however, these methods might not perform effectively on 5G systems due to the high frequency of operation. In this paper, we have described some machine and deep learning models that could be effective for channel estimation in 5G. But there are still challenges that need to be addressed before it can be deployed on a large scale 5G network. The IBM machine learning has shown promising results, however, however, further research has to be carried out to determine its true potency.

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References

[1] An, L. H., Trinh, V. C., Tien, H. N., Wan, C., & Van, D. N. (2021). Deep Learning-Aided 5G Channel Estimation. IEEE, 1-7.

[2] Dishant, K., Sohni, S., Rashwinder, S., & Sumeet, G. (2018). OFDM Modulation Technique & its Applications: A Review. International Conference on Innovations in Computing (pp. 101-105). CSL Press.

[3] DeepMIMO Dataset. [Online]. Available: http://www.DeepMIMO.net

[4] Ercan, S. Ü. (2016). Compare of Pilot Based and Semi-blind Channel Estimation Techniques in Multiple Input Multiple Output Communication Systems. ResearchGate, 1-4.

[5] Govil, R. (2018). Different Types of Channel Estimation Techniques Used in MIMO-OFDM for Effective Communication Systems. International Journal of Engineering Research & Technology (IJERT), 1-5.

[6] J, K., & Lim, J. (2009). Subspace-based iterative Semiblind channel estimation for MIMOOFDM considering residual error. IEEE Trans. Vehicular Technology Vol.58, 4660-4665.

[7] Jide, Y., Hien, Q. N., & Michail, M. (2019). Machine Learning-Based Channel Estimation in Massive MIMO with Channel Aging. IEEE, 1-6.

[8] Kais, H., Mohammad, M., Marie, Z., & Iyad, D. (2020). Channel Estimation Techniques for Millimeter-Wave Communication Systems: Achievements and Challenges. IEEE Open Journal of the Communications Society, 1-27.

[9] Ko, Y.-C., & Kim, M.-J. (2016). Channel estimation and analog beam selection for uplink multiuser hybrid beamforming system. EURASIP Journal onWireless Communications and Netwoking, 1-14.

[10] Mauro, B., Kunal, S., Carlos, B., Debashri, R., & Kaushik, R. C. (2021). Deep Learning at the Edge for Channel Estimation in Beyond-5G Massive MIMO. IEEE, 1-8.

[11] Mehran, S., Vahid, P., Ali, M., & Hamid, S. (2018). Deep Learning-Based Channel Estimation. ResearchGate, 1-5.

[12] MM, R., & MK, H. (2010). Adaptive Channel Estimation Techniques for MIMO-OFDM Systems. International Journal of Advanced, 1-4.

[13] Muhamad, A., & Indra, W. G. (2011). Channel Estimation Using Least Square Estimation (LSE) Orthogonal Frequency Division Multiplexing (OFDM) System. Applied Electromagnetic Technology (AEMT), (pp. 1-9). Lombok.

[14] Nakao, A. (2020). AI/ML integration for autonomous networking- a future direction for next-generation telecommunications.

[15] Taehyoung, K., & Sangjoon, P. (2020). Statistical Beamforming for Massive MIMO Systems with Distinct Spatial Correlations. Sensors, 1-20.

[16] Ture, P., Garrett, V., & Tamal, B. (2017). Blind channel estimation for massive MIMO. ResearchGate, 1-11.

[17] W, H., R, L., B, V., & Y, L. (2010). A New Iterative Channel Estimation for High Mobility MIMO-OFDM Systems. IEEE Trans. Vehicular Technology Conference , (pp. 1-5).