IJAREEIE

e-ISSN: 2278-8875
p-ISSN: 2320-3765

International Journal of Advanced Research

in Electrical, Electronics and Instrumentation Engineering

Volume 11, Issue 8, August 2022

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

Impact Factor: 8.18

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering (IJAREEIE)

| e-ISSN: 2278 – 8875, p-ISSN: 2320 – 3765| www.ijareeie.com | Impact Factor: 8.18|

||Volume 11, Issue 8, August 2022||

|DOI:10.15662/IJAREEIE.2022.1108006 |

5G MIMO OFDM Channel Sounding using Neural Networks

Shweta Singh Jat[1], Pankaj Shrivastava[2]

PG Student (M.E. CCN), Dept. of ECE, M.P.C.T. College, Gwalior (M.P.), India[1]

Professor, Dept. of ECE, M.PC.T. College, Gwalior (M.P.), India[2]

ABSTRACT: The quality of channel estimation (CE) is critical to the performance of wireless communication systems. In addition to the conventional model based CE methods appeared in the past few decades, deep learning (DL) based CE methodswhich is introduced to learn the statistical characteristics of wireless channels, has emerged as a promising methods in recently years. For analysis, we consider two very common and widely adopted time-varying fading scenario. In these fading scenarios, it is generally challenging to analytically tackle the channel estimation problem due to its nonlinearity and non-convexity. To intelligently and effectively address this issue, deep learning is exploited in this paper. First, in this fading scenario, we propose a novel learning scheme for joint channel estimation and pilot signal design by constructing a deep autoencoder via a convolutional neural network (CNN). Through extensive numerical simulations, we demonstrate effectiveness and superior performance of the proposed schemes.

KEYWORDS: Massive MIMO, MIMO-OFDM, Deep Learning, Channel Estimate, 5G.

I. INTRODUCTION

Massive multiple-input multiple-output (MIMO) has many advantages in terms of spectral and energy efficiency and has been envisioned as one of the key enabling technologies in the fifth generation of wireless communication systems [1,2]. However, the realization of the potential gains of massive MIMO systems heavily relies on the availability of accurate channel state information (CSI). In time-division duplex (TDD) systems, only the uplink channel needs to be estimated thanks to the channel reciprocity [3] and the training overhead scales linearly with the number of users, which is usually acceptable. However, in frequency-division duplex (FDD) systems, the downlink CSI needs to be estimated and fed back to the base station (BS) by the users, where the downlink training and uplink feedback overhead scales linearly with the number of antennas at the BS and can substantially deteriorate the system efficiency. Since the challenge mainly comes from the large number of antennas, dimension reduction is a natural idea that comes to mind. In practice, the BS is usually located in high altitude with few surrounding scatters [4], so the angular spread of incident signals of each user at the BS is narrow. Consequently, the channel covariance matrix (CCM) possesses low-rank characteristics. To exploit this, the original channels are approximated with a few main eigenvalues and eigenvectors in [5,6] to reduce the effective channel dimensionality. However, the involved eigen-decomposition operation requires high computational complexity and the acquisition of accurate CCM in massive MIMO systems also requires extra overhead. An alternative method is to exploit the basis expansion model (BEM), which reduces the number of parameters to be estimated by exploiting the channel sparsity in specific domains [7,8]. In [7], a spatial BEM has been proposed to transform the problem of estimating channel impulse responses to that of estimating spatial basis function weights, which are sparse due to the physical scattering characteristics. The spatial and frequency wideband effects are considered in [8], where the channel sparsity in the angle and the delay domains is exploited, and angular and delay rotations are used to further enhance the sparsity level. Although more computationally efficient, the BEM methods inevitably introduce approximation error to channel estimation due to the imperfect model. A comprehensive overview of low-rank channel estimation methods for massive MIMO systems can be found in [9].

In conventional massive MIMO systems, each antenna is equipped with a dedicated radiofrequency (RF) chain, which leads to high hardware and energy cost when the number of antennas is large. To tackle this issue, the so-called hybrid analog-digital (HAD) architecture has been proposed, where the multi-antenna array is connected to only a limited number of RF chains through phase shifters in the analog domain [10,11]. However, the channel estimation problem becomes more difficult in the context of HAD since now the received signals at the BS are not the original signals at

| e-ISSN: 2278 – 8875, p-ISSN: 2320 – 3765| www.ijareeie.com | Impact Factor: 8.18|

||Volume 11, Issue 8, August 2022||

|DOI:10.15662/IJAREEIE.2022.1108006 |

antennas, but only a few of their linear combinations. In this situation, the conventional least-square (LS) estimator becomes inefficient with dramatically increased overhead [12]. In [13], the complete channels are obtained by LS in the preamble stage and directions-ofarrival (DoAs) of channel paths are estimated first. Since the DoAs change slowly and can be used for a relatively long period, only channel gains of each path need to be re-estimated. Usually, the number of paths is much smaller than that of antennas in millimeter wave systems, therefore greatly reducing the estimation overhead. An alternative method is to adopt the compressive sensing (CS) methods to directly recover the sparse channels all at once, such as orthogonal matching pursuit (OMP) [14], sparse Bayesian learning (SBL) [15], etc. Through embedding the structural characteristics of channel sparsity, several improved CS algorithms have been further proposed, including structured SBL [16] and structured variational Bayesian inference (S-VBI) [17]. However, the performance of the CS algorithms heavily relies on the channel sparsity and the computational complexity is relatively high.

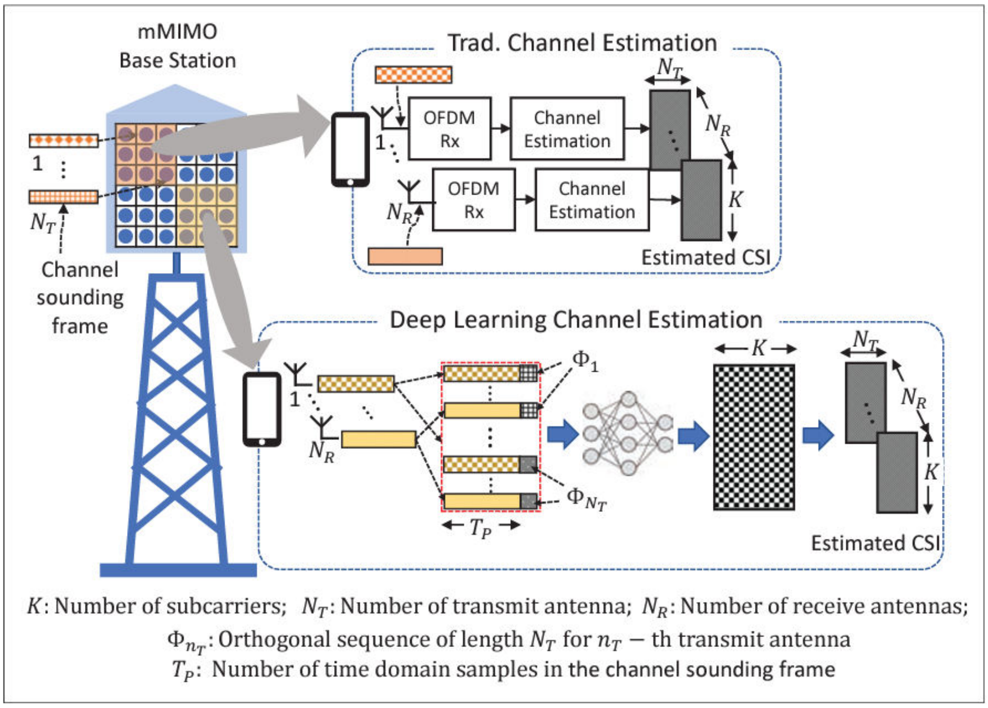


Fig. 1: Tradition and neural network based channel estimation

The main objective of the work is developing a deep neural network for channel estimation in OFDM massive MIMO systems. Adopting the autoencoder architecture, the region-specific measurement matrix is jointly4 learned with the channel estimator. The learned measurement matrix significantly improves the signal measurement efficiency than the conventional one, and the learned channel estimator has stronger estimation capability than the state-of-the-art CS algorithms, as well as lower computational complexity.

II. RESEARCH METHODOLOGY

This section deals with the methodology used by us to do the channel estimation. Here, we use deep learning techniques to perform channel estimation. For example, by viewing the resource grid as a 2-D image, we can turn the problem of channel estimation into an image processing problem, similar to denoising or super-resolution, where CNNs are effective.

Using Matlab's 5G Toolbox, we can customize and generate standard-compliant waveforms and channel models to use as training data. Using Matlab's Deep Learning Toolbox, we use this training data to train a channel estimation CNN. This paper shows how to generate such training data and how to train a channel estimation CNN. The work also shows

| e-ISSN: 2278 – 8875, p-ISSN: 2320 – 3765| www.ijareeie.com | Impact Factor: 8.18|

||Volume 11, Issue 8, August 2022||

|DOI:10.15662/IJAREEIE.2022.1108006 |

how to use the channel estimation CNN to process images that contain linearly interpolated received pilot symbols. The work concludes by visualizing the results of the neural network channel estimator in comparison to practical and perfect estimators.Figure 2 represents the methodology that are being used to simulate the work described in this paper.

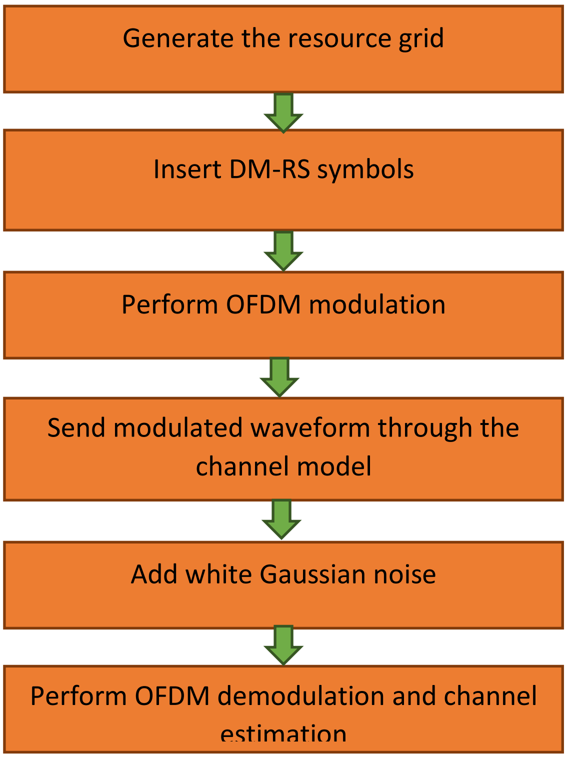


Fig. 2: Research Methodology flow chart

In this work, The DM-RS symbols in the grid are used for channel estimation. This example does not transmit any data, therefore, the resource grid does not include any PDSCH symbols. To flush the channel content, append zeros at the end of the transmitted waveform. These zeros take into account any delay introduced in the channel, such as multipath and implementation delay. The number of zeros depends on the sampling rate, delay profile, and delay spread. Send data through the TDL channel model. Add additive white Gaussian noise (AWGN) to the received time-domain waveform. To take into account sampling rate, normalize the noise power. The SNR is defined per resource element (RE) for each receive antenna (3GPP TS 38.101-4). For an explanation of the SNR definition that this example uses, see SNR Definition Used in Link Simulations. Perform perfect synchronization. To find the strongest multipath component, use the information provided by the channel. OFDM-demodulate the received data to recreate the resource grid.

III. RESULT AND DISCUSSIONS

After successful implementation, we have tested the proposed method using software simulation. For software simulation, we have used Matlab environment with deep learning and 5G toolboxes. For clearity and to show the effectiveness of the work, we have compared the obtained result with some standard OFDM MI O channel estimation schemes. Here we perform and compare the results of perfect, practical, and neural network estimations of the same channel model. To perform perfect channel estimation, use the nrPerfectChannelEstimateMatlab function using the value of the path gains provided by the channel. To perform practical channel estimation, use the nrChannelEstimate function from Matlab 5G toolbox. This function will estimate the channel with taking into account some standard errors

| e-ISSN: 2278 – 8875, p-ISSN: 2320 – 3765| www.ijareeie.com | Impact Factor: 8.18|

||Volume 11, Issue 8, August 2022||

|DOI:10.15662/IJAREEIE.2022.1108006 |

and noises during the transmission. To perform channel estimation using the neural network, we must interpolate the received grid. Then split the interpolated image into its real and imaginary parts and input these images together into the neural network as a single batch. Use the predict (Deep Learning Toolbox) function to make predictions on the real and imaginary images. Finally, concatenate and transform the results back into complex data. Fig. 3 represents the training statistics of the proposed neural network. From this figure, it is clear that the training completes in 5 epochs and we get a validation accuracy of 16.168. The total training time taken by the network while being trained is 3 minutes and 56 seconds.

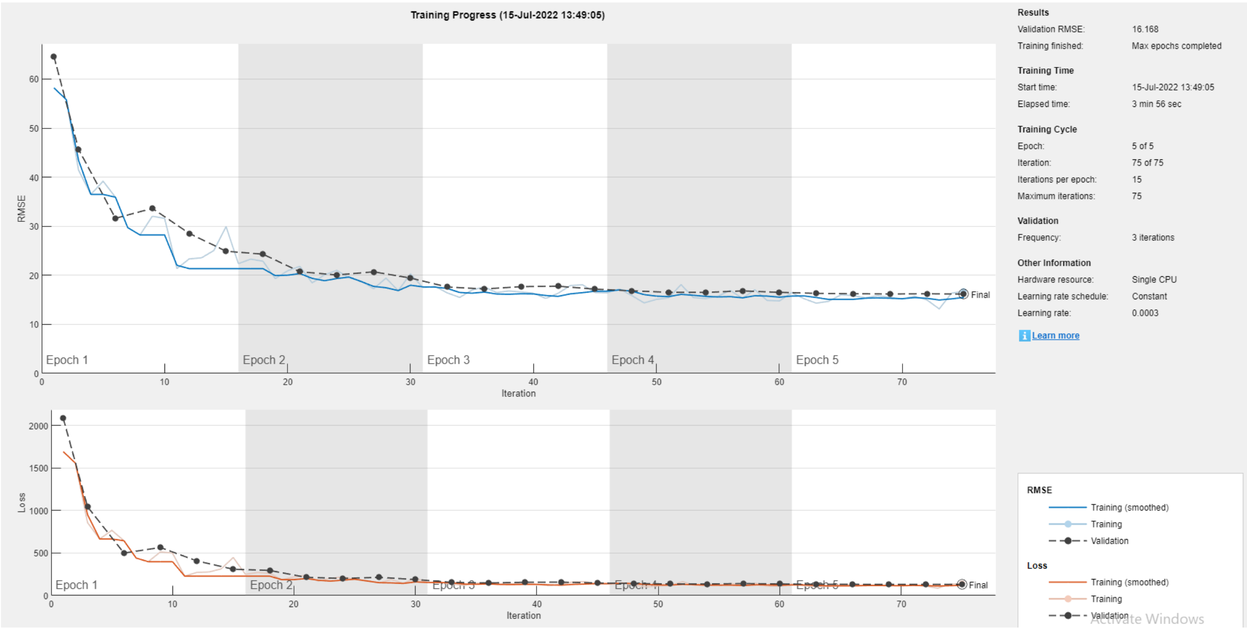


Fig. 3: The training statistics of the proposed neural network.

Fig 3 represents the result of channel estimation with (a) linear interpolation method (b) Practical estimator method, (C) neural network based proposed method and (d) the actual channel. Here from this figure, it is clear that the linear interpolation method shows a MSE of 0.17904, MSE of practical estimator is 0.034578 and the MSE of the proposed neural network based method is 0.019588 which is the lowest among all three. Fig. 4 represents the bit error rate vs SNR for a transmitter-receiver system having the proposed model as a channel estimation method with some other channel estimation methods such as Least Square Estimate (LSE) method and theoretical method. Here the DNN based our approach shows similar BER than the theoretical method. Fig. 5 represents the Mean square error (MSE) while estimating channel vs SNR for proposed method as well as other channel estimation methods. From this figure. It is clear that we are getting the minimum mean square error for the channel estimation using the proposed DNN based channel estimation method.

| e-ISSN: 2278 – 8875, p-ISSN: 2320 – 3765| www.ijareeie.com | Impact Factor: 8.18|

||Volume 11, Issue 8, August 2022||

|DOI:10.15662/IJAREEIE.2022.1108006 |

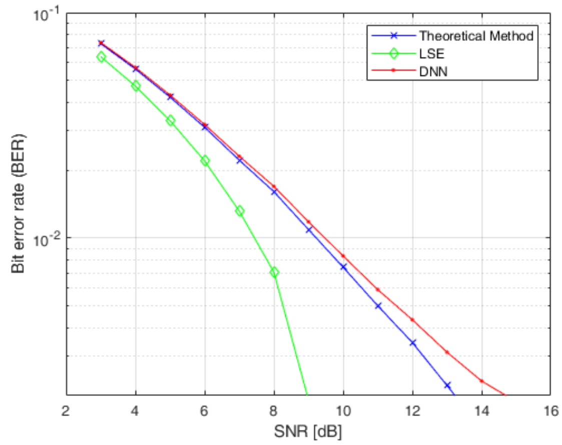


Fig. 4: Bit error rate vs SNR for channel estimation with the proposed method as well as some conventional methods.

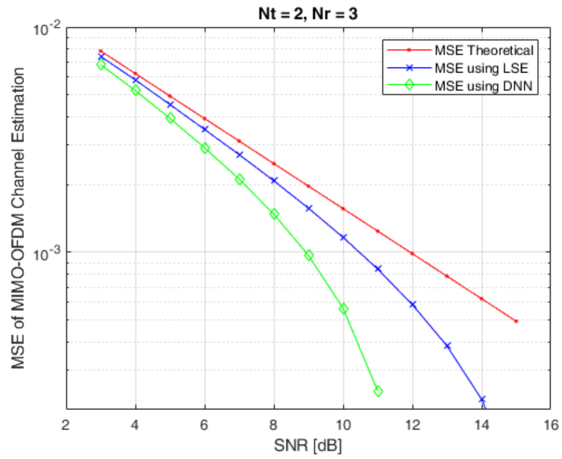


Fig. 5: Mean square error (MSE) while estimating channel vs SNR for proposed method as well as other channel estimation methods.

IV. CONCLUSION

In this paper, we studied the deep learning based channel estimation for the MIMO system with received SNR feedback in the quasi-static block-fading and time-varying fading scenarios. In this, we developed the novel technique for the joint MIMO channel estimation and pilot signal design by constructing the deep autoencoder with the CNN. In the time-varying scenario, the new channel estimation technique was proposed by combining the RNN and CNN. For the two fading scenarios, we construct the effective GAN and CGAN, respectively, to generate the artificial channel samples, and the training procedures using the artificial channel samples were also presented. The effectiveness and the superior performance of the proposed schemes were demonstrated through the numerical results.

REFERENCES

[1] F. Rusek et al., "Scaling up MIMO: Opportunities and challenges with very large arrays," IEEE Signal Process. Mag., vol. 30, no. 1, pp. 40–60, Jan. 2013.

[2] E. G. Larsson, O. Edfors, F. Tufvesson, and T. Marzetta, "Massive MIMO for next generation wireless systems," IEEE Commun. Mag., vol. 52, no. 2, pp. 186–195, Feb. 2014.

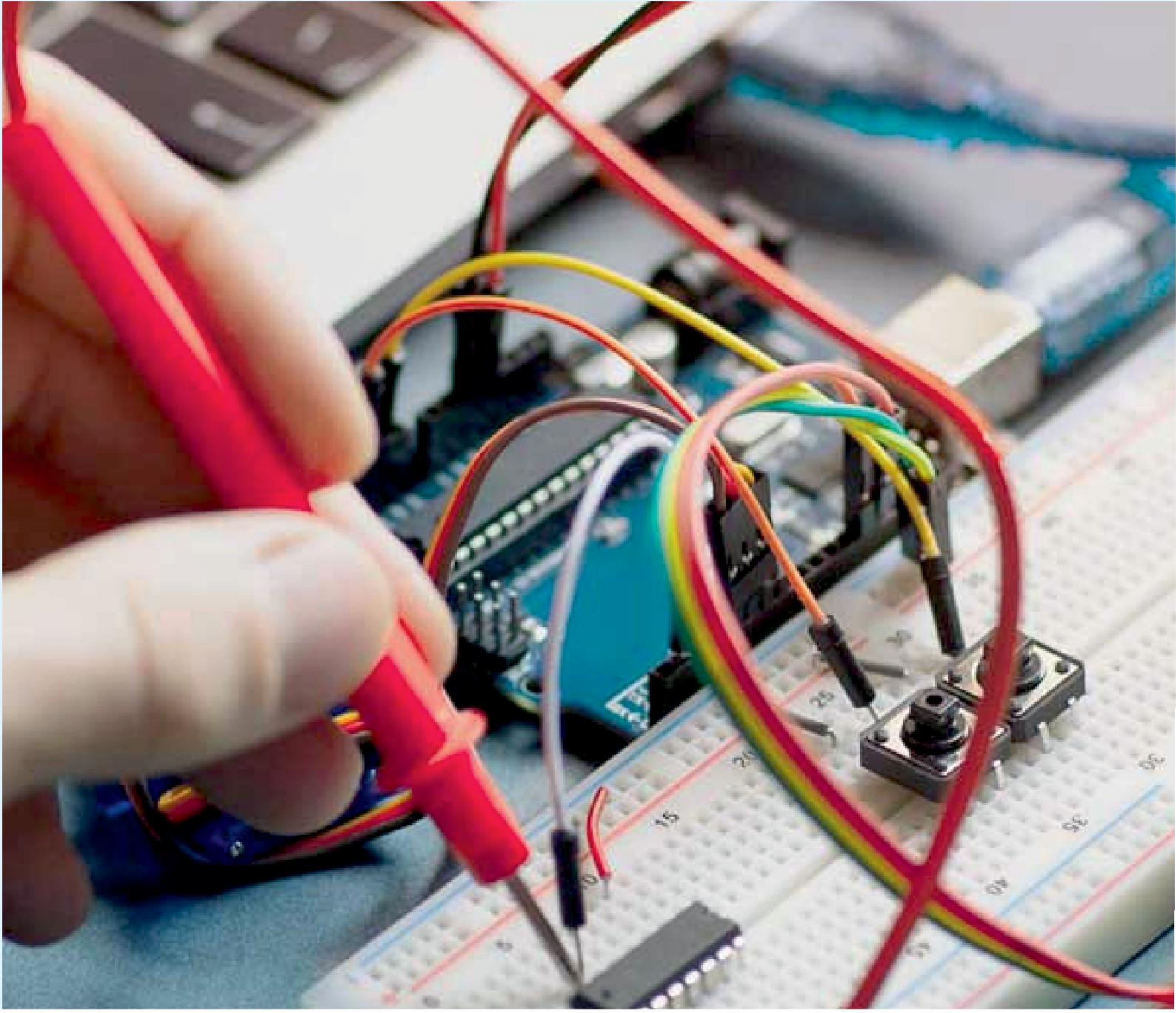
[3] G. Barriac and U. Madhow, "Space-time communication for OFDM with implicit channel feedback," IEEE Trans. Inf. Theory, vol. 50, no. 12, pp. 3111–3129, Dec. 2004.

| e-ISSN: 2278 – 8875, p-ISSN: 2320 – 3765| www.ijareeie.com | Impact Factor: 8.18|

||Volume 11, Issue 8, August 2022||

|DOI:10.15662/IJAREEIE.2022.1108006 |

[4] A. Al-Hourani, S. Kandeepan, and A. Jamalipour, “Modeling air-to-ground path loss for low altitude platforms in urban environments,” in Proc. IEEE Global Commun. Conf., Austin, TX, 2014, pp. 2898–2904.
[5] Adhikary, J. Nam, J. Ahn, and G. Caire, “Joint spatial division and multiplexing–the large-scale array regime,” IEEE Trans. Inf. Theory, vol. 59, no. 10, pp. 6441–6463, Oct. 2013.
[6] Sun, X. Gao, S. Jin, M. Matthaiou, Z. Ding, and C. Xiao, “Beam division multiple access transmission for massive MIMO communications,” IEEE Trans. Commun., vol. 63, no. 6, pp. 2170–2184, June 2015.
[7] H. Xie, F. Gao, S. Zhang, and S. Jin, “A unified transmission strategy for TDD/FDD massive MIMO systems with spatial basis expansion model,” IEEE Trans. Veh. Technol., vol. 66, no. 4, pp. 3170–3184, April 2017.
[8] Wang, F. Gao, S. Jin, H. Lin, and G. Y. Li, “Spatial- and frequency-wideband effects in millimeter-wave massive MIMO systems,” IEEE Trans. Signal Process., vol. 66, no. 13, pp. 3393–3406, July 2018.
[9] H. Xie, F. Gao and S. Jin, “An overview of low-rank channel estimation for massive MIMO systems,” IEEE Access, vol. 4, pp. 7313–7321, Nov. 2016.
[10] F. Sohrabi and W.Yu, “Hybrid digital and analog beamforming design for large-scale antenna arrays,” IEEE J. Sel. Topics Signal Process., vol. 10, no. 3, pp. 501–513, Apr. 2016.
[11] A. F. Molisch et al., “Hybrid beamforming for massive MIMO: A survey,” IEEE Commun. Mag., vol. 55, no. 9, pp. 134–141, Sep. 2017.
[12] Y. Ding, S. E. Chiu, and B. Rao,“Bayesian channel estimation algorithms for massive MIMO systems with hybrid analogdigital processing and low-resolution ADCs,” IEEE J. Sel. Topics Signal Process., vol. 12, no. 3, pp. 499–513, Jun. 2018.
[13] Fan et al., “Angle domain channel estimation in hybrid millimeter wave massive MIMO systems,” IEEE Trans. Wireless Commun., vol. 17, no. 12, pp. 8165–8179, Dec. 2018.
[14] J. Lee, G. Gil, and Y. Lee, “Channel estimation via orthogonal matching pursuit for hybrid MIMO systems in millimeter wave communications,” IEEE Trans. Commun., vol. 64, no. 6, pp. 2370–2386, Jun. 2016.
[15] S. Ji, Y. Xue, and L. Carin, “Bayesian compressive sensing,” IEEE Trans. Signal Process., vol. 56, no. 6, pp. 2346–2356, Jun. 2008.
[16] Y. Wang, A. Liu, X. Xia, and K. Xu, “Learning the structured sparsity: 3D massive MIMO channel estimation and adaptive spatial interpolation,” IEEE Trans. Veh. Technol., vol. 68, no. 11, pp. 10663–10678, Nov. 2019.
[17] X. Xia, K. Xu, S. Zhao, and Y. Wang, “Learning the time-varying massive MIMO channels: Robust estimation and data-aided prediction,” IEEE Trans. Veh. Technol., vol. 69, no. 8, pp. 8080–8096, Aug. 2020.



INNO SPACE

SJIF Scientific Journal Impact Factor

Impact Factor: 8.18

doi crossref

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

निस्केयर NISCAIR

International Journal of Advanced Research

in Electrical, Electronics and Instrumentation Engineering

9940 572 462 6381 907 438 ijareeie@gmail.com

Scan to save the contact details

www.ijareeie.com