IMPACT: International Journal of Research in Engineering and Technology
ISSN (P): 2347–4599; ISSN (E): 2321–8843
Vol. 10, Issue 6, Jun 2022, 9–16

A NOVEL BEAM FORMING ALGORITHM FOR MASSIVE MIMO SYSTEM USING KALMAN FORMULATION WITH DEEP LEARNING

Fasna. K V[1], Dr. N. Kaleeswari[2], N. Arun Prasath[3] & Karthika. C M[4]

[1]*PG Student, EASA College of Engineering and Technology, Coimbatore, Tamilnadu, India*

[2]*Professor, Department of ECE, EASA College of Engineering and Technology, Coimbatore, Tamilnadu, India*

[3]*Senior Assistant Professor, Department of ECE, EASA College of Engineering and Technology, Coimbatore, Tamilnadu, India*

[4]*Assistant Professor, Department of ECE, EASA College of Engineering and Technology, Coimbatore, Tamilnadu, India*

Received: 07 Jun 2022 **Accepted:** 07 Jun 2022 **Published:** 07 Jun 2022

ABSTRACT

Deep learning (DL) techniques have lately been widely applied to telecommunication systems, and they have been shown to be an excellent tool for solving complicated non-convex optimization issues. In large-scale millimetre wave (mmWave) MIMO systems, hybrid pre coding (-beam forming) is the most promising solution for reducing high hardware costs and high power consumption. In the near-optimal analogue and digital precoders have been constructed multi-user environment, hybrid precoding combines large-dimensional analogue precoding (or beamforming) using kalman based formulation with deep learning technique for decomposition of the channel matrix. This work used a deep learning technique to create a hybrid precoding system with a low level of complexity and better spectral efficiency.

KEYWORDS: *Massive MIMO, Hybrid Beamforming, Beam Training, Deep Learning, Unsupervised Learning*

INTRODUCTION

Wireless communication refers to the transfer of data over a long distance without the need of wires, cables, or other electrical conductors. Wireless communication is a wide term that encompasses all procedures and ways of connecting and communicating between two or more devices via wireless communication technologies and devices employing a wireless signal. Wireless communication is the transfer of data between two or more points without the use of a physical link. Wireless communication provides various advantages due to the lack of any "physical infrastructure. Often, this entails compressing distance or space. The utilisation of connection wires is required for wired communication. Communication through wireless networks does not necessitate a complex physical infrastructure or routine maintenance. As a result, the cost is lowered. To send and receive messages, you do not need to be in an office or a telephone booth.. Miners in the outback can rely on satellite phones to call their loved ones, and thus, help improve their general welfare by keeping them in touch with the people who mean the most to them [1],[2].

The huge Multiple-Input Multiple-Output (MIMO) technology has been touted as one of the most promising possibilities for the Fifth Generation (5G) standard of mobile communication in recent years, and the Third Generation Partnership Project is working to standardise it (3GPPIn a large MIMO system, each Base-Station (BS) has tens to hundreds of antennas, each of which is connected to its own Radio Frequency (RF) chain, allowing it to serve tens of User

Equipments (UEs) at the same time-frequency resource. In this way, huge gains could be realised. One of the most significant advantages is that such systems may considerably increase capacity and energy efficiency at the same time due to their ability to produce a very large array gain and aggressive spatial multiplexing [10]-[13].

HYBRID BEAMFORMING

Hybrid beamforming is a promising method for reducing the complexity and cost of enormous multiple-input multiple-output (MIMO) systems while maintaining a high data rate. The hybrid precoder design, on the other hand, is a difficult undertaking that necessitates CSI feedback and the solution of a sophisticated optimization issue. To design hybrid beamforming in massive MIMO systems, this work provides a unique RSSI-based unsupervised deep learning algorithm. We also present I a method for designing the synchronisation signal (SS) in initial access (IA) and ii) a way for designing the codebook for the analogue precoder [3]-[5]. The synchronization signals need to be detected with a complete detection rate. This cause residual errors and will only give rise to small performance degradation and system complexity.

HYBRID PRECODING USING KALMAN

Fully digital techniques are infeasible with large antenna arrays due to hardware constraints at such frequencies, while purely analog solutions suffer severe performance limitations. When applied to a multi-user environment, hybrid analog/digital beamforming is a promising approach. Three major contributions are made in this paper: 1) For hybrid analog/digital precoding in a multi-user environment, a Kalman-based formulation with deep learning is proposed; 2) an analytical expression of the error between transmitted and estimated data is formulated, so that the Kalman algorithm at the base station does not require information on the estimated data at the mobile stations and instead relies only on the precoding/combining matrix; and 3) an iterative solution for the hybrid precoding sc.

Hybrid precoding designed by minimizing the error between the transmitted and estimated data due to its ability to better adjust the precoding matrix in hybrid architectures using kalman formulation and reduced system complexity. The proposed system is shown in Fig. 1.

Beamforming

The beam forming algorithms conducted at the digital baseband in MIMO communication systems with a large number of antennas, often known as massive MIMO systems, can become very complex. Furthermore, if all beam forming takes place in baseband, each antenna will require its own RF feed. This can be quite expensive at high frequencies and with a large number of antenna elements, increasing system loss and complexity. Hybrid beam forming has been proposed as a solution to these problems.

Kalman Based Precoder

The mean-phase-error would likewise be reduced using the Kalman filter. The unscented Kalman filter, which does not require the computation of the gradient and can handle nonlinearity, can now be used to estimate precoding in this model. We also propose an iterative Kalman-based multi-user hybrid solution that minimises the error between the preamble transmitted by the BS and the estimated received data at the MS, because the unscented Kalman filter minimises the mean-square of the state error-vector directly, regardless of the observation variable. The error formulation is mathematically defined as a function of simply the precoding, combining, and channel matrices. The algorithm does not require any explicit data estimation in this way.

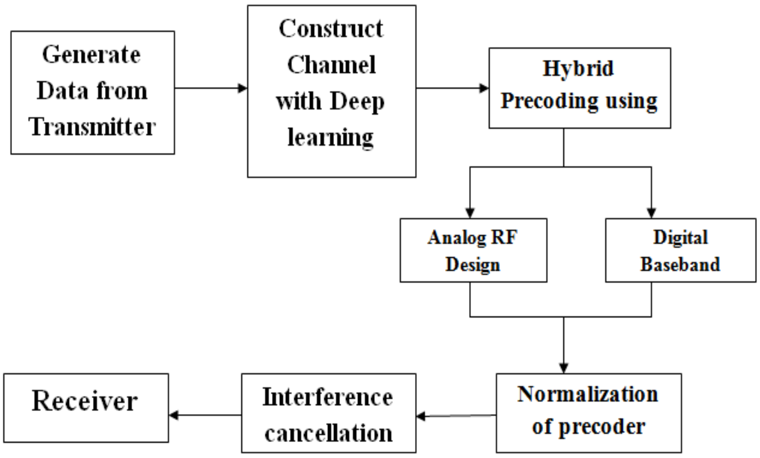

Figure 1: The Proposed Architecture of Hybrid Precoding using Kalman.

Then, a two step procedure is carried out: first, the RF analog precoding/combining step is performed as in single-user systems based on energy maximum principle; then an iterative Kalman-based approach is applied to estimate the digital baseband precoder at the BS in order to reduce inter-user interference.

Steps in kalman Formulation

- Initialize system parameters
- Initialize Cannel parameters
- Generate Channel matrix using deep learning
- Compute weight matrix for each mobile station
- Compute hybrid analog and digital precoding matrix
- Normalize the precoding matrix

Kalman Based Precoder Model

A is a matrix, a is a vector, a is a scalar, and A is a set. kAkF is the Frobenius norm of A, whereas AT , AH, 1/A are its transpose, Hermitian, and inverse respectively. I is the identity matrix, and N(m;R) is a complex Gaussian random vector with mean m and covariance R. E is used to denote expectation. The network architecture is a mmWave-based massive MIMO cellular system where the BS is sending Nb streams through NBS antennas and Nt RF chains for serving M mobile stations (MS), each with NMS antennas and one RF chain, with Nb < Nt < NBS. At the downlink, the BS sends a synchronization message applying both the baseband precoder FBB, with size NtxNb, and the analog precoder FRF , with size NBS xNt, so that the sampled transmitted signal is:

x = FRF FBBs (1)

where s is the Nb x1 transmitted symbol vector, P the transmitted power and Nb =M. We assume that P is equally allocated among different users’ streams.

For simplicity we adopt a narrowband blockfading channel.

Thus, the received signal at MS-m is:

rm = Hm FRF FBBs + nm (2)

where Hm is the NMS x NBS matrix of the mmWave channel between the BS and the MS-m, and N is the Gaussian noise vector.

The received signal rm in can be rewritten showing the desired contribution and the interference as follows:

rm = Hm FRF fBBmsm +Hm FRF fBBj sj + nm (3)

Where FRF fBBm is the BS precoding vector for MS-m, fBBm is the column m of the matrix FBB. and sj is the jth element of s.

We compute the analogue combining wm matrix for each mobile station and the hybrid analogue and digital precoding FRF and FBB matrices at the BS in the hybrid multi-user system. We now want to use the Kalman-based technique to construct the hybrid mmWave precoding matrix by reducing the error defined in:

$$\begin{aligned} \underset{\mathbf{F}_{RF},\mathbf{F}_{BB}}{\text{minimize}} \quad & E\|\mathbf{s}-\hat{\mathbf{s}}\|^2 \\ \text{subject to} \quad & \|\mathbf{F}_{RF}\mathbf{F}_{BB}\|_F^2 \leq P \\ & \mathbf{F}_{RF} \in \{\mathbf{f}_1, ..., \mathbf{f}_L\} \end{aligned} \qquad (4)$$

The optimization formulation does not involve any data transmission/estimation s(n) and ^s(n) but only the precoding/combining matrices, i. e., FBB, FRF , and the collection of wm contained in He, that is the equivalent channel matrix defined as

He = [h1; :::; hM]H in which hH (5)

m = wHm

HmFRF represents the effective downlink channel to MS-m. The problem is nonconvex due to the multiplication of the variables FRF, FBB, and wm. However, if we fix FRF and wm, we can solve the optimization problem and calculate FBB.

RF Precoding and Combining Matrix

We determine first the RF beamforming/combining matrices for each BS-MS link independently, similarly to, and then continue with the baseband precoding to reduce the multi-user interference. In the first step, the BS and each MS-m calculate the RF beamforming and combining vectors, fRFm and wm, by maximizing the signal power for the MS-m. RF beamforming solutions can be used on this purpose, in order to design the RF beamforming/combining vectors without explicit channel estimation and maintain a low training overhead Once the combining vectors wm are determined for all MSs, as well as the the analog precoder FRF at the BS, the digital baseband precoder FBB is computed based on algorithm 1.

Algorithm 1 Kalman based hybrid beamforming

Input: BS RF codebook $\mathcal{F}$, MS RF codebook $\mathcal{W}$

Output: $\mathbf{F}_{BB}$, $\mathbf{F}_{RF}$, and $\mathbf{w}_m$ $\forall m = 1, ..., M$

Step 1 - RF Analog design: Single-user $\mathbf{F}_{RF}$ and $\mathbf{w}_m$ $\forall m$

BS and MS-m select $\tilde{\mathbf{v}}_m, \tilde{\mathbf{g}}_m \forall m$ so that

$$\tilde{\mathbf{g}}_m, \tilde{\mathbf{v}}_m = \underset{\forall \mathbf{g}_m \in \mathcal{W}, \forall \mathbf{v}_m \in \mathcal{F}}{\arg\max} \|\mathbf{g}_m^H \mathbf{H}_m \mathbf{v}_m\|$$

BS sets $\mathbf{F}_{RF} = [\tilde{\mathbf{v}}_1, ..., \tilde{\mathbf{v}}_M]$ and MS-m sets $\mathbf{w}_m = \tilde{\mathbf{g}}_m \forall m$

Step 2 - BB Digital design: Multi-user $\mathbf{F}_{BB}$

MS-m estimates $\bar{\mathbf{h}}_m^H \doteq \mathbf{w}_m^H \mathbf{H}_m \mathbf{F}_{RF}$ and quantizes $\bar{\mathbf{h}}_m$ using a codebook $\mathcal{H} \forall m$

MS-m calculate and sends to BS $\hat{\mathbf{h}}_m$ $\forall m$ where

$$\hat{\mathbf{h}}_m = \underset{\hat{\mathbf{h}}_m \in \mathcal{H}}{\arg\max} \|\bar{\mathbf{h}}_m^H \hat{\mathbf{h}}_m\|$$

BS sets $\mathbf{H}_D = \hat{\mathbf{H}}_e = [\hat{\mathbf{h}}_1, ..., \hat{\mathbf{h}}_M]^H$

At BS: **for** $n \leq N$ **do**

$$\epsilon(n) = \frac{\mathbf{I} - \mathbf{H}_D \mathbf{F}_{BB}(n|n-1)}{\|\mathbf{I} - \mathbf{H}_D \mathbf{F}_{BB}(n|n-1)\|_F^2}$$

$$\mathbf{F}_{BB}(n|n) = \mathbf{F}_{BB}(n|n-1) + \mathbf{K}(n)\epsilon(n)$$

$$\mathbf{K}(n) = \mathbf{R}(n|n-1)\mathbf{H}_D^H[\mathbf{H}_D \mathbf{R}(n|n-1)\mathbf{H}_D^H + \mathbf{Q}_n]^-1$$

$$\mathbf{R}(n|n) = [\mathbf{I} - \mathbf{K}(n)\mathbf{H}_D]\mathbf{R}(n|n-1)$$

Normalize $\mathbf{F}_{BB} = \sqrt{P} \dfrac{\mathbf{F}_{BB}}{\|\mathbf{F}_{RF}\mathbf{F}_{BB}\|_F}$

Deep Learning for Channel Matrix

As illustrated in Fig.2, Convolutional Neural Networks (CNN) are employed in a variety of tasks and have excellent performance in a variety of applications. One of the earliest applications in which CNN architecture was effectively used was the recognition of handwritten numbers. Since the inception of CNN, networks have been continuously improved with the addition of new layers and the use of other computer vision algorithms. In the Challenge, Convolutional Neural Networks are typically employed with various combinations of sketch datasets. Few of the researchers have shown a comparison between the human subject and a trained network's detection abilities on datasets.

- **Input Layer:** The first layer of each CNN used is 'input layer' which takes data, resize them for passing onto further layers for feature extraction.
- **Convolution Layer:** The next few layers are 'Convolution layers' which act as filters for data, hence finding out features from data and also used for calculating the match feature points during testing.
- **Pooling Layer**: The extracted feature sets are then passed to 'pooling layer'. This layer takes large data and shrink them down while preserving the most important information in them. It keeps the maximum value from each window, it preserves the best fits of each feature within the window.
- **Rectified Linear Unit Layer**: The next 'Rectified Linear Unit' or ReLU layer swaps every negative number of the pooling layer with 0. This helps the CNN stay mathematically stable by keeping learned values from getting stuck near 0 or blowing up toward infinity.
- **Fully Connected Layer**: The final layer is the fully connected layers which takes the high-level filtered data and translate them into categories with labels.

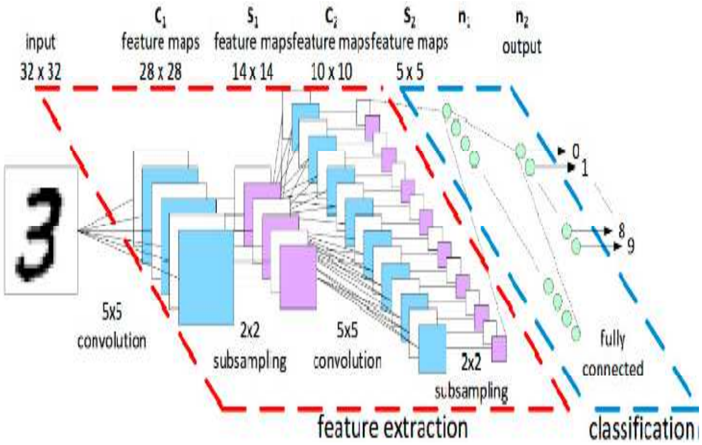

Figure 2: CNN with Layers.

EXPERIMENTAL RESULTS

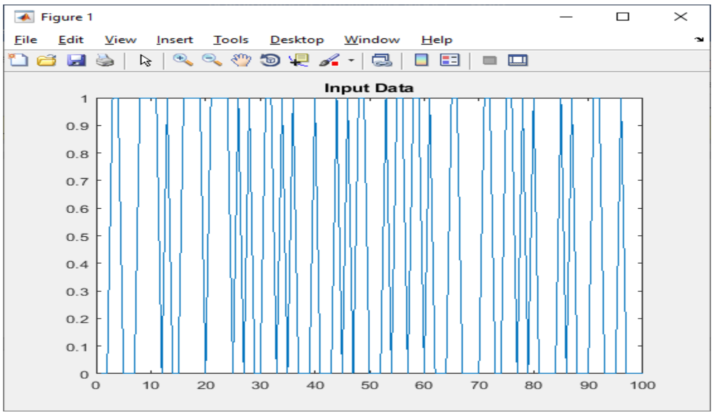

Figure 3: Input Data.

Fig.3 shows the input data signal generated using random data

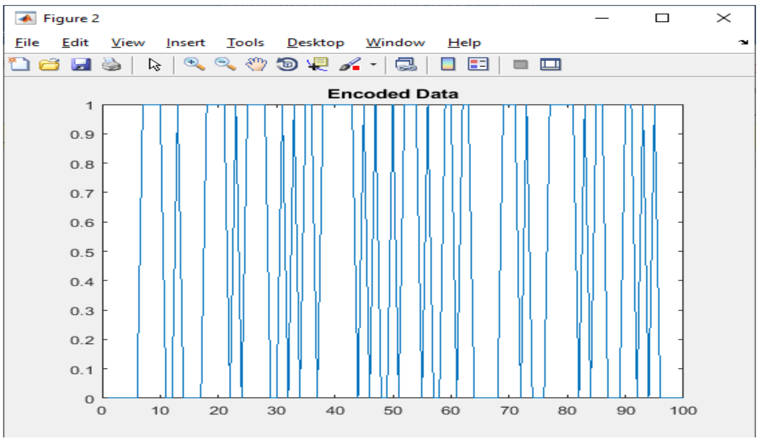

Figure 4: Encoded Data.

Fig.4 shows the data which is modulated and then encoded. For encoding convolutional encoder is used. Received data is the input signal, after completion of decoding, and demodulation. It is shown in Fig.8

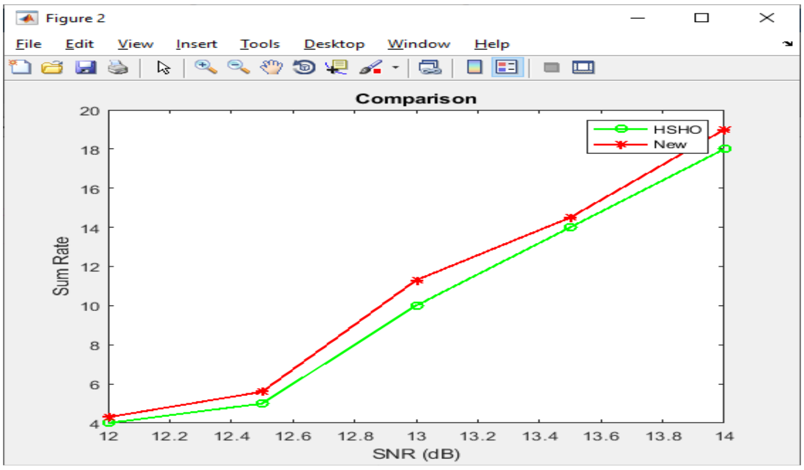

Figure 5: Performance Comparison.

Fig.5 graph shows the performance comparison of existing and proposed. The sum rate at different SNR Conditions. The proposed method gives better sum rate.

CONCLUSION

Broadband beamforming is more applicable in massive MIMO systems than narrowband beamforming owing to its cost-effective means of mitigating bandwidth issues and its power-efficient circuits in smart antenna array design. Finally, an optimal beamforming for massive MIMO systems can be achieved by deploying a combination of analogue and digital beamforming (hybrid analogue/digital beamforming) with optimal algorithms. For the proposed hybrid beamforming, the analog beamforming vectors apply the optimal beam of each MIMO user. Thus hybrid beamforming jointly designing with user scheduling can greatly improve the performance of massive MIMO system.

REFERENCES

1. *H. Li, Z. Wang, Q. Liu, and M. Li, "Transmit Antenna Selection and Analog Beamforming with Low-Resolution Phase Shifters in mmWave MISO Systems," IEEE Communications Letters, pp. 1–1, 2018.*
2. *X. Li, Y. Zhu, and P. Xia, "Enhanced Analog Beamforming for Single Carrier Millimeter Wave MIMO Systems," IEEE Transactions on Wireless Communications, vol. 16, no. 7, pp. 4261–4274, July 2017.*
3. *M. Jasim, J. E. Pezoa, and N. Ghani, "Simultaneous multi-beam analog beamforming and coded grating lobes for initial access in mmWave systems," in 2017 CHILEAN Conference on Electrical, Electronics Engineering, Information and Communication Technologies (CHILECON), Oct 2017, pp. 1–6.*
4. *M. Lee and W. Chung, "Transmitter design for analog beamforming aided spatial modulation in millimeter wave MIMO systems," in 2016 IEEE 27th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC), Sept 2016, pp. 1–6.*
5. *S. Hur, T. Kim, D. J. Love, J. V. Krogmeier, T. A. Thomas, and A. Ghosh, "Millimeter wave beamforming for wireless backhaul and access in small cell networks," IEEE Transactions on Communications, vol. 61, no. 10, pp. 4391–4403, October 2013.*

6. *N.Arun Prasath, N.Kumaresan," Vehicle Speed Measurement and Number Plate Detection using Real Time Embedded System," Networks and Complex Systems (IISTE), Vol.5,Issue 3,pp 15-20,March 2015.*
7. *A. F. Molisch, V. V. Ratnam, S. Han, Z. Li, S. L. H. Nguyen, L. Li, and K. Haneda, "Hybrid beamforming for massive mimo: A survey," IEEE Communications Magazine, vol. 55, no. 9, pp. 134–141, 2017.*
8. *R. Magueta, D. Castanheira, A. Silva, R. Dinis, and A. Gameiro, "Non linear space-time equalizer for single-user hybrid mmWave massive MIMO systems," in 2016 8th International Congress on Ultra Modern Telecommunications and Control Systems andWorkshops (ICUMT), Oct 2016, pp. 177–182.*
9. *J. Zhang, A. Wiesel, and M. Haardt, "Low rank approximation based hybrid precoding schemes for multi-carrier single-user massive MIMO systems," in 2016 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), March 2016, pp. 3281–3285.*
10. *S. Han, C. I, Z. Xu, and C. Rowell, "Large-scale antenna systems with hybrid analog and digital beamforming for millimeter wave 5G," IEEE Communications Magazine, vol. 53, no. 1, pp. 186–194, January 2015.*
11. *L. Zhao, D. W. K. Ng, and J. Yuan, "Multi-User Precoding and Channel Estimation for Hybrid Millimeter Wave Systems," IEEE Journal on Selected Areas in Communications, vol. 35, no. 7, pp. 1576–1590, Jul. 2017.*
12. *C. Huang, L. Liu, C. Yuen, and S. Sun, "Iterative Channel Estimation Using LSE and Sparse Message Passing for MmWave MIMO Systems," IEEE Transactions on Signal Processing, vol. 67, no. 1, pp. 245–259, Jan. 2019.*
13. *N.Arun Prasath, N.Kumaresan," A Novel Approach on Greedy Maximal Scheduling Algorithm on Embedded Networks," Networks and Complex Systems (IISTE), Vol.5,Issue 3,pp 15-20,March 2015*
14. *P. Dong, H. Zhang, G. Y. Li, I. S. Gaspar, and N. NaderiAlizadeh, "Deep CNN-based channel estimation for mmWave massive MIMO systems," IEEE J. Sel. Topics Signal Process., vol. 13, no. 5, pp. 989–1000, Sep. 2019.*
15. *A. M. Elbir, "CNN-based precoder and combiner design in mmWave MIMO systems," IEEE Commun. Lett., vol. 23, no. 7, pp. 1240–1243, Jul. 2019.*