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Deep CNN based precoder and combiner design in mmwave MIMO system

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Abstract: Hybrid beamformer design is a crucial stage in millimeter wave (mmWave) MIMO systems. For millimeter wave (mmWave) massive multiple-input multiple-output (MIMO) systems, hybrid processing architecture is usually used to reduce the complexity and cost, which poses a very challengingissue in channel estimation. In thiswork, we propose a convolutional neuralnetwork (CNN) framework for the joint design of precoder and combiners. Inthis work, deep convolutional neural network (CNN) is employed to address this problem. We first propose a spatial frequency CNN (SF-CNN) based channel estimation exploiting both the spatial and frequency correlation, wherethe corrupted channel matrices at adjacent subcarriers are input into the CNN simultaneously. Then, exploiting the temporal correlation in time varying channels, a spatial-frequency-temporalCNN (SFT-CNN) based approach isdeveloped to further improve theaccuracy. Moreover, we design a spatial pilot-reduced CNN (SPR-CNN) to save spatial pilot overhead for channel estimation, where channels in several successive coherence intervals are grouped and estimated by a channel estimation unit with memory.

Numerical results show that the proposed SF-CNN and SFT-CNN based approaches outperform the non-ideal minimum mean squared error (MMSE) estimator but with reduced complexity, and achieve the performance close to theideal MMSE estimator that is verydifficult to be implemented in practical situations. They are also robust to different propagation scenarios.

The proposed network accepts the input of channel matrix and gives the output of analog and baseband beam-formers. Previous works are usually based on the knowledge of steering vectors of array responses which is not always accurately available in practice. The SPR-CNN based approach achieves comparable performance to SF-CNN and SFT-CNN based approaches while only requires about none third of spatial pilot overhead at the cost of complexity. Our work clearly shows that deep CNN can efficiently exploit channel correlation to improve the estimation performance for mmWave massive MIMO systems.

Keywords: *mmWave, MIMO, Hybrid beamforming,Deep learning, Convolutional neural network, Channel estimation.*

I. INTRODUCTION

Hybrid beamforming is a promising architecture to be used in next generation millimeter wave (mmWave) MIMO(Multiple Input Multiple Output) systems where robust beamforming performance is provided with smaller cost and less number of fully-digital beamformers. Several methods are proposed to design the hybrid beamformers. In a greedy-based approach, orthogonal matching pursuit (OMP), is proposed where the analog precoder and combiners are selected from a dictionary of transmit and receive array responses. This algorithm requires the knowledge of the user direction-of-arrival/aperture (DOA/DOD) angles to construct such a dictionary.

Using the connection between the optimum and the hybrid beamformers, proposes an alternating minimization approach to estimate the analog and baseband beamformers based on phase extraction.

Millimeter wave (mmWave) communications can meet the high data rate demand due to its large bandwidth. Its high propagation loss can be well compensated by using massive multiple- input multiple-output (MIMO) technique. However, Due to the limited physical space with closely placed antennas and prohibitive power consumption in mmWave massive MIMO systems, it is difficult to equip a dedicated radio frequency (RF) chain for each antenna. To reduce complexity and cost, phase shifter based two-stage architecture, usually called hybrid architecture, is widely used at both the transmitter and the receiver to connect a large

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number of antennas with much fewer RF chains.

The above works provides optimization-based and greedy based solutions for hybrid beam-forming problem. However achieving the optimum solution and the computation time are the main drawbacks of the above techniques. In order to circumvent this issue, we consider deep learning (DL)- based techniques for the hybrid beam-forming problem. DL has several advantages such as low computational complexity when solvingoptimization-based or combinatorial/greedy search problems and the ability to extrapolate new features from a limited set of features contained in a training set. A great deal of attention is received for DL-based techniques in communications society for the problems such as channel estimation DOA estimation, antenna selection, and analog beam selection.

II. METHODOLOGY

Convolutional Neural Network

In deep learning, a convolutional neural network (CNN, or ConvNet) is a class of artificial neural network, most commonly applied to analyze visual imagery. They are also known as shift invariant or space invariant artificial neural networks (SIANN), based on the shared-weight architecture of the convolution kernels or filters that slide along input features and provide translation equivariant responses known as feature maps. CNNs are regularized versions of multilayer perceptrons. Multilayer perceptrons usually mean fully connected networks, that is, each neuron in one layer is connected to all neurons in the next layer. The "full connectivity" of these networks make them prone to overfitting data. Typical ways of regularization, or preventing overfitting, include: penalizing parameters during training (such as weight decay) or trimming connectivity

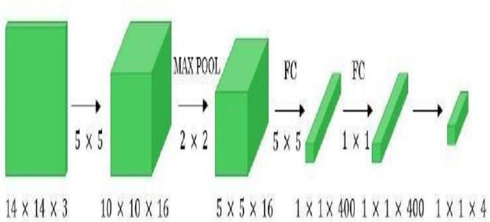

Fig1 Softmax Layer.

A. Convolution Layer

A Convolution neural network has one or more convolutional layers and are used mainly for image processing, classification, segmentation etc. convolution is essentially sliding a filter over the input rather than looking at an entire image at once to find certain features it can be more effective to look at smaller.

This layer consists of a set of learnable filters that we slide over the image spatially, computing dot products between the entries of the filter and the input image. The filters should extend to the full depth of the input image.

B. Pooling Layer

Pooling is a form of non-linear down- sampling. The goal of the pooling layer is to progressively reduce the spatial size of the representation to reduce the amount of parameters and computation in the network, and hence to also control overfitting. There are several functions to implement pooling among which max

pooling is the most common one. Pooling is often applied with filters of size 2x2 applied with a stride of 2 at every depth slice. A pooling layer of size 2x2 with stride of 2 shrinks the input image to a 1/4 of its original size.

III. IMPLEMENTATION

An end-to-end communication scenario is modeled in and by using auto- encoders where single-input-single-output (SISO) systems are considered also uses auto-encoders for the channel state information (CSI) feedback problem. Very recently, a DL based hybrid beamforming is considered in where only precoder design is considered whereas joint precoder and combiner design is used in massive MIMO system where the beamforming is required in both end of the communication. The proposed network architecture in is based on multi-layer perceptrons which do not effectively extract the hidden features inherit in the input data. In order to achieve feature extraction and obtain better performance, we propose a convolutional neural network (CNN) framework for mmWave massive MIMO systems.

For mmWave massive MIMO systems with the

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hybrid architecture, channel estimation is a challenging problem. Previously a hierarchical multi-resolution codebook has been designed, based on which an adaptive channel estimation algorithm has been developed by exploiting the channel sparsity. The structured sparsity in angle domain has been utilized to estimate the wideband channel for multi-user mmWave massive MIMO uplink. A channel estimation approach has been developed for mmWave massive MIMO orthogonal frequency division multiplexing (OFDM) systems with low-precision analog-to-digital converters (ADCs). For the mmWave MIMOOFDM downlink, a channel parameter estimation for the angles, time delays, and fading coefficients has been proposed, resorting to the low-rank tensor decomposition. Instead of estimating the mmWave MIMO channel directly, the method for singular subspace estimation has been proposed, based on which a subspace decomposition algorithm has been further developed to design the hybrid analog-digital architecture. Deep learning (DL) has been successfully used in joint channel estimation and signal detection of OFDM systems with interference and non-linear distortions.

An iterative channel estimation has been proposed for the lens mmWave massive MIMO systems, where denoising neural network (NN) is used in each iteration to update the estimated channel. To reduce the CSI feedback overhead of the frequency duplex division (FDD) massive MIMO system, DL has been employed to compress the channel into a low dimensional codeword and then to perform recovery with high accuracy. Exploiting temporal correlation of the channel, long short-term memory (LSTM) based deep NN (DNN) has been introduced to develop a more efficient channel compression and recovery method for the CSI feedback. DL has been applied to estimate channels in wireless power transfer systems, which outperforms the conventional scheme in terms of both estimation accuracy and harvested energy. In supervised learning algorithms have been used to acquire the downlink CSI for FDD massive MIMO systems with reduced overheads for pilot and CSI feedback. The supervised learning has been exploited to perform blind detection for massive MIMO systems with low- precision ADCs. The conventional channel estimation methods usually perform unsatisfactorily in the more practical massive MIMO-OFDM systems. To exploit the correlation among channels at adjacent subcarriers in OFDM,

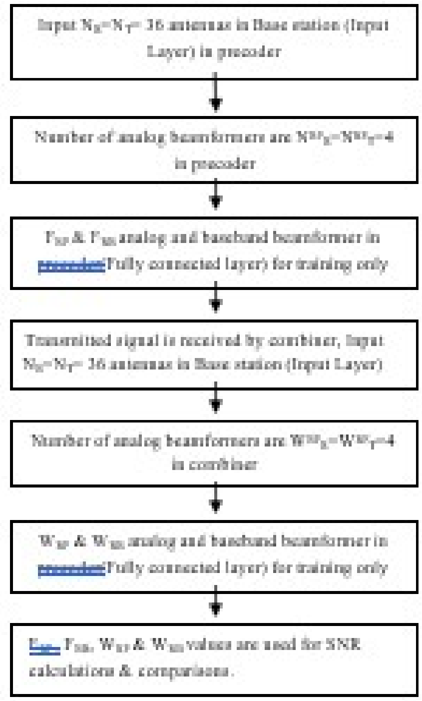

Fig 2 Flowchart of CNN Based Preorder and Combiner Design

We consider a mmWave massive MIMO-OFDM system as in Fig.2, where the transmitter is with NT antennas and NTRF RF chains and the receiver is with NR complicated channel model and also suffer antennas and N ^{RF} RF chains. Phase from high complexity. In contrast, the deep convolutional NN (CNN) is more capable to extract the inherent characteristics underlying the channel matrix from the large amount of data and provides the potential to estimate the channel more accurately with lower complexity by using the efficient parallel computing methods. In this paper, we use the deep CNN to address channel estimation for mmWave shifters are employed to connect a large number of antennas with a much fewer number of RF chains at both the transmitter and the receiver sides. We therefore assume NT>> N_T^{RF} & N_R>> N_R^{RF}.

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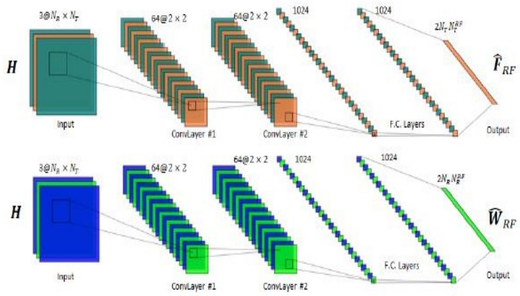

Fig3 CNN Layer Of Precoder (at Tx) and Combiner (at Rx).

The $N_R \times N_T$ channel matrix between the receiver and the transmitter in the delay domain is given by

$$\mathbf{H}(\tau) = \sqrt{\frac{N_T N_R}{L}} \sum_{l=1}^{L} \alpha_l \delta(\tau - \tau_l) \mathbf{a}_R(\varphi_l) \mathbf{a}_T^H(\phi_l),$$

where L is the number of main paths, α1 –given bywhere fs denotes the sampling rate and K is the number of OFDM subcarriers. To estimate Hk, the transmitter activates only one RF chains to transmit the pilot on one beam in each channel use while the receiver combines the received pilot by using all RF chains associated with different beams. In more detail, the transmitter transmits pilots, Xk;u, using MT beamforming vectors. For the transmit pilot signal corresponding to each beamforming vector, fk;u, the receiver employs MR combining vectors, to respectively process it. Since the receiver is equipped with N^R (< M) RF chains, it $CN(0,\sigma^2\alpha)$ is the propagation gain of the lth
can only use N^R combining vectors in a path, τ1 is the delay of the lth path, ϕ1 and ϕ1 ϵ[0 to 2π], are the azimuth angles of arrival and departure (AoA/AoD) at the receiver and the transmitter, respectively. For uniform linear array (ULA), the corresponding response vectors can be expressed as

$$\mathbf{a}_R(\varphi_l) = \frac{1}{\sqrt{N_R}} \left[1, e^{-j2\pi\frac{d}{\lambda}\sin(\varphi_l)}, \ldots, e^{-j2\pi\frac{d}{\lambda}(N_R-1)\sin(\varphi_l)}\right]^T,$$

$$\mathbf{a}_T(\phi_l) = \frac{1}{\sqrt{N_T}} \left[1, e^{-j2\pi\frac{d}{\lambda}\sin(\phi_l)}, \ldots, e^{-j2\pi\frac{d}{\lambda}(N_T-1)\sin(\phi_l)}\right]^T$$

$$\mathbf{H}_k = \sqrt{\frac{N_T N_R}{L}} \sum_{l=1}^{L} \alpha_l e^{-j2\pi\tau_l f_s \frac{k}{K}} \mathbf{a}_R(\varphi_l) \mathbf{a}_T^H(\phi_l),$$

where d and λ denote the distance between the adjacent antennas and carrier wavelength, respectively. According to the channel model, the frequency domain channel of the kth subcarrier in OFDM is channel use. Then, if the receiver uses all MR combining vectors to process a beamforming vectorcarrying pilot, the required channel uses will be [MR / N^R]. So the total channel uses for processing all beamforming vectors will be MT [MR / N^R] Then the pilot signal matrix associated with the kth subcarrier at the baseband of the receiver can be written as

$$\mathbf{Y}_k = \mathbf{W}_k^H \mathbf{H}_k \mathbf{F}_k \mathbf{X}_k + \tilde{\mathbf{N}}_k,$$

XK is an MT × MT diagonal matrix with its uth diagonal element being xk;u. N ˋ = WkH.NK denotes the effective noise after combining and NK is additive white Gaussian noise (AWGN) with *CN*(0, 1) elements before combining. We consider the pilot insertion in both frequency and time domain. Specifically, adjacent Q^K(Q ≥2) subcarriers respectively place pilots with the same length at the beginning of a coherence interval to form a pilot subcarrier block and the rest of time slots in each coherence interval are used for data transmission. Two pilot subcarrier blocks are separated by Q_d ($Q_d \geq 0$) subcarriers dedicated to data transmission. Pilots are utilized to estimate the channels of corresponding time-frequency positions. Based on the estimated channels, interpolation can be applied to get the channels at the positions without pilots. It is clear that the accuracy of interpolation is dependent on the accuracy of the estimated channels and the variation of channels. Therefore, we will focus on improving the accuracy of the pilot based channel estimation in this paper so that more reliable reference values can be provided for interpolation.

Block Diagram of Proposed System

A. SF – Channel

Fig 4 Block Diagram of SF-CNN.
(Please refer last page of this article.)

we first propose a spatial-frequency CNN (SF-CNN) based channel estimation, where the tentatively estimated channel matrices at adjacent subcarriers are input into the CNN simultaneously.

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B. SFT – Channel

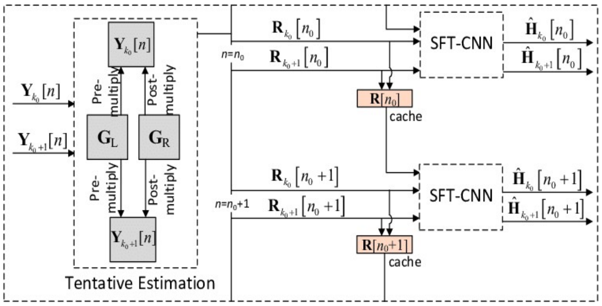


Fig 5 Block Diagram of SFT-CNN.

To further exploit the temporal correlation, a spatial-frequency temporal CNN (SFT- CNN) based channel estimation is developed, where the channel information of the previous coherence interval is utilized when estimating the channel matrices of the current coherence interval. The SFT-CNN based approach incorporates all types of channel correlation in a simple way and yields remarkable performance gains that can be used to significantly save the spatial pilot overhead due to large scale arrays.

Fig 6 Block Diagram of SPR-CNN.
(Please refer last page of this article.)

Therefore, we propose a spatial pilot-reduced CNN (SPR-CNN) based channel estimation, where channels in several successive coherence intervals are grouped and estimated by a channel estimation unit (CEU) with memory.

IV. RESULTS

Fig 7 SF-Channel SNR Graph shows losses according to trained epoch and test data.

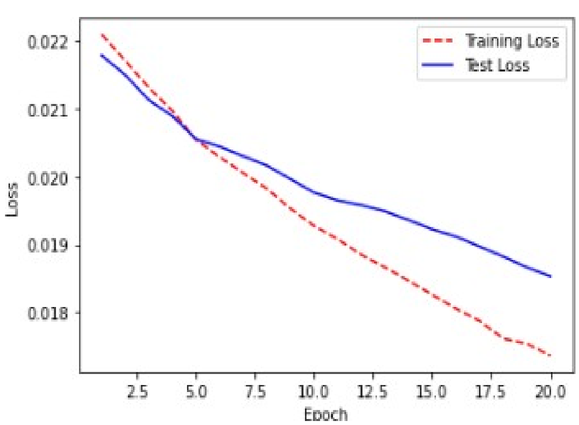


Fig 8 SFT-Channel SNR Graph shows losses according to trained epoch and test data

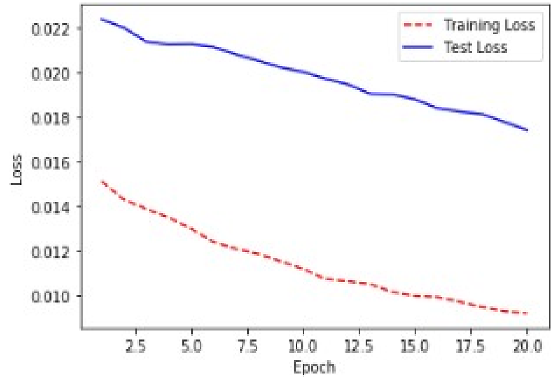
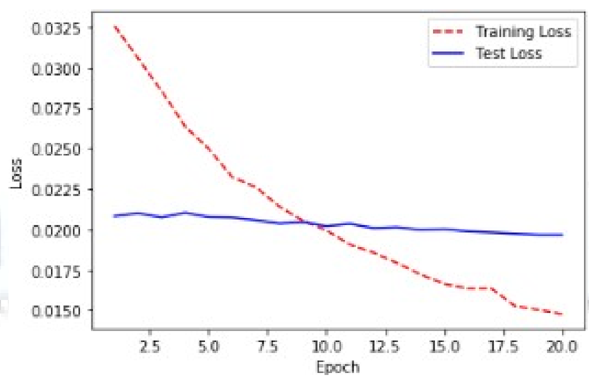


Fig 9 SPR-Channel SNR Graph shows losses according to trained epoch and test data



V. CONCLUSION

In this work, a CNN framework is proposed for the joint estimation of precoder and combiners in hybrid beamforming problem. We show that the proposed network architecture provides better spectral efficiency as compared to the optimization-based and greedy-based algorithm.

From the numerical results, the proposed SF-CNN and SFT-CNN based approaches outperform the non-ideal minimum mean squared error (MMSE) estimator and achieve the performance very close to the ideal MMSE estimator that is very difficult to be implemented in practical systems. They are also with lower complexity than the MMSE estimator and exhibit the unique robustness to maintain the fairly good performance when facing different channel statistics. The SPR-CNN based approach achieves comparable performance to SF-CNN and SFT-CNN based approaches by using only about one third of spatial pilot overhead and moderately increased complexity. In this project, we propose a CNN-based framework with two CNNs, each of which is dedicated to estimate the analog precoders and combiners respectively.

In future work, we reserve the case when the training data is small where transfer learning-like approaches can be developed.

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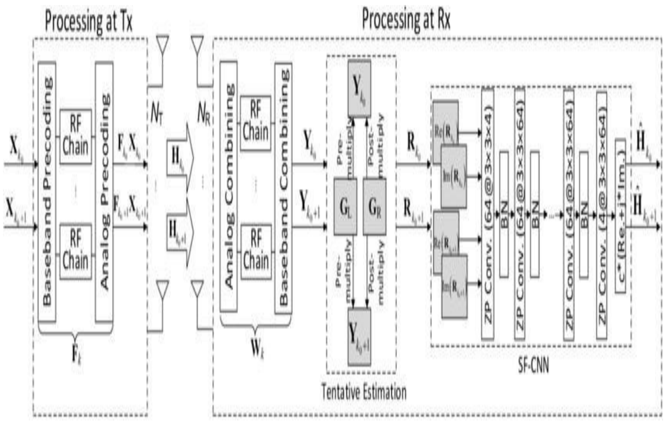

Fig 4 Block Diagram of SF-CNN.

Fig 6 Block Diagram of SPR-CNN