Deep Learning based Multiple-Beam Transmission for IEEE 802.11ay Beamforming Training

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***Abstract*—In this study, we propose a deep neural network-based scheme that performs efficient multi-user multiple-input-multiple-output (MU-MIMO) beamforming training (BFT) for IEEE 802.11ay wireless local area network (WLAN). It achieves this by accurately estimating link qualities measured when an action frame is transmitted thought multiple concurrent beams.**

***Index Terms*—Beamforming training, 802.11ay, deep learning**

I. Introduction

To realize tens-of-Gbps transmission rates, IEEE 802.11ay supports a downlink MU-MIMO transmission [1]. That means that an access point (AP) can send multiple data streams simultaneously to multiple stations (STAs). The MU-MIMO transmission must be directional and, to this end, the AP performs MU-MIMO BFT with the STAs which have already been defined as an multi-user (MU) group.

The MU-MIMO BFT procedure starts with the single-input-single-output (SISO) phase, followed by the MIMO phase. In the SISO phase, the AP transmits short sector sweep (SSW) frames through different transmit sectors (TSs), or precomputed antenna weight vectors, of each of its transmit antenna arrays. Each STA then measures signal to noise ratios (SNRs) corresponding to the SSW frames. Finally, the AP collects the SNRs from respective STAs, which is referred to as *SISO feedback*. During the MIMO phase, the AP is required to send a significant number of action frames to the STAs to perform the subphases of BF setup, BF training, BF feedback, and BF selection. Determining the TSs used in the transmission of action frames is crucial for mitigating the signaling and latency overhead of the MIMO phase [2], [3]; however, the 802.11ay standard does not specify how the AP determines TSs to transmit an action frame [1].

In this paper, we propose a deep neural network-based transmit antenna configuration (DTAC) scheme for MU-MIMO BFT. Our scheme determines multiple TSs for the transmission of an action frames. To this end, using a deep neural network, our scheme accurately estimates the link qualities measured at the STAs when certain TSs are used simultaneously to transmit an action frame. By simulation, we show that the proposed scheme reduces the duration of the MIMO phase.

II. DTAC for MU-MIMO BFT

A. System Model

IEEE 802.11ay standard defines a transmitter block diagram to transmit the action frames for the MIMO phase. All action frames are transmitted using the control mode defined in [1] over a 2.16 GHz channel. Each radio frequency (RF) chain is connected to only one transmit antenna array. The bit stream of an action frame is transmitted using multiple RF chains by applying a spatial expansion with cyclic shift diversity; the transmitter, i.e., the AP, maps a single bit stream to all RF chains. The bit stream of each RF chain is finally transmitted through an antenna array associated with the RF chain. The receiver, i.e., each STA, uses a quasi-omni pattern to receive the bit stream.

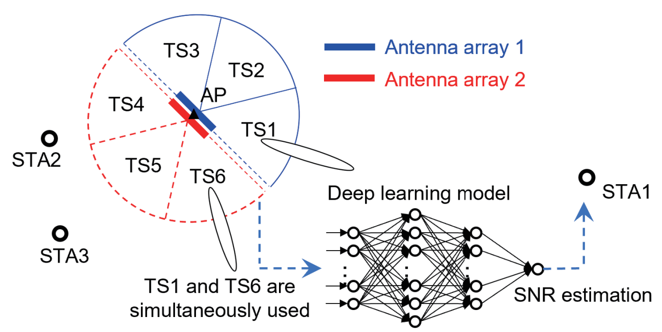

Fig. 1. Deep learning-based estimation of the SNR to be measured at STA1 when multiple concurrent beams, i.e., TS1 and TS6, are used simultaneously.

B. Proposed DTAC Scheme

The SISO feedback contains a list of TSs detected when each STA receives the SSW frames, and SNRs corresponding to the detected TSs. Our proposed DTAC scheme utilizes multiple TSs simultaneously to transmit an action frame for the MIMO phase; to this end, our DTAC scheme estimates the SNR to be measured at each STA for the multiple TSs. The SNR is estimated based on the SNRs measured with every single TS which are known from the SISO feedback.

As shown in Fig. 1, our proposed scheme uses a multilayer perceptron neural network to estimate the SNR of the multiple concurrent beams; each layer, except the last one, is fully connected to the next and there are no connections within a layer. The input layer can be presented as two sets, where the first one is the set of SNRs measured at an STA when the action frame is transmitted through every single TS, and the second one is a set of SNRs corresponding to TSs in a candidate set of multiple TSs. The output layer contains a single node that represents the SNR to be measured at the STA when the action frame is transmitted through the candidate set of multiple TSs simultaneously. Intervening layers are referred as to hidden; each hidden layer can comprise any number of nodes.

In the BF setup and selection subphases of the MIMO phase, the AP repeats the transmission of an action frame with a different set of TSs, such that all STAs in the remaining MU group can receive the action frame. To reduce signaling overhead, whenever each transmission occurs, our scheme determines the corresponding set of TSs with which the transmission reaches the largest number of STAs in the remaining MU group that have not received the action frame yet. Given the corresponding set of TSs, for each STA, our DTAC scheme first estimates the SNR to be measured at the STA using the multilayer perceptron neural network; our scheme then regards the STA as within reach of the transmission if its SNR is greater than a predetermined SNR threshold.

In the BF training subphase, our DTAC scheme determines the sets of TSs to be used for the transmissions of action frames, so that the AP performs BFT with more different subgroups of STAs in the MU group [3]. In the BF feedback subphase, for each STA in the MU group, our DTAC scheme selects a set of TSs where the corresponding estimated SNR is the highest [2], [3].

III. Simulation Results and Discussion

We conducted simulations using MATLAB, ns-3, and python programs [4]. To accurately predict the characteristics of the mmWave channel, we employed the NIST Q-D channel realization software. We considered one AP and eleven STAs, and the channel between the AP and each STA was characterized by the direct and first order reflected multipath components; pathloss, delay, phase shift, angle of arrival, and angle of departure were calculated as the properties of respective multipath components. The indoor scenario of the lecture room with size $(10 \times 19 \times 3)$ m was considered; the AP was located at the coordinates $(1, 3, 1)$ m and the STAs were randomly distributed. The AP had three antenna arrays and each antenna array was associated with nine different TSs. Every STA used one antenna array to realize the quasi-omni receive pattern. To measure the packet error rate of each action frame transmitted through the selected set of TSs, we utilized the encoding and modulation schemes of the control mode implemented in the MATLAB WLAN toolbox. The multilayer perceptron neural network was implemented with python. We set the number of hidden layers to 3; the first, second, and third hidden layers were comprised of 128, 64, and 32 neurons, respectively. The dataset of 801 900 samples was collected and 90 % and 10 % of the samples were used to train and validate, respectively; each sample included the input and output SNRs to be used for our multilayer perceptron neural network. Our ns-3 program conducted the MU-MIMO BFT at every beacon interval of approximately 0.1 s [5].

We evaluated our proposed DTAC scheme and the results of the proposed scheme were compared with those of the existing LNS and ILQE schemes. The LNS scheme in [2] finds the TSs through which the transmission can reach the largest number of STAs and the ILQE scheme in [3] also selects the TSs in the same manner as the LNS scheme; however, unlike the LNS scheme, the ILQE scheme additionally uses channel information to estimate the qualities of the links between the AP and the STAs.

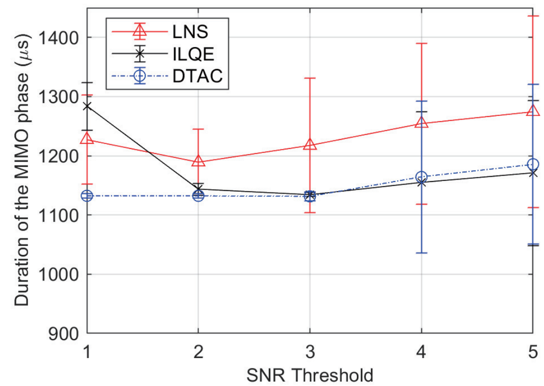

Fig. 2. Duration of the MIMO phase in the lecture room scenario.

Fig. 2 plots the duration of the MIMO phase in the lecture room scenario. We found that the durations of the ILQE and our DTAC schemes were shorter than those of the LNS scheme. The curves in the figure can be attributed to the fact that the ILQE and DTAC schemes were able to transmit fewer action frames than the LNS scheme by identifying more STAs within the reach of each transmission. However, unlike our proposed DTAC scheme, the ILQE scheme requires the additional overhead of collecting the channel information during the SISO phase.

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References

[1] *Enhanced Throughput for Operations in License-exempt Bands above 45 GHz*, IEEE Standard 802.11ay-2021, July 2021.

[2] M-S. Kim, T. Ropitault, S.K. Lee, and N. Golmie, "Efficient MU-MIMO Beamforming Protocol for IEEE 802.11ay WLANs," *IEEE Commun. Lett.*, vol. 23, no. 1, pp. 144-147, Jan. 2019.

[3] M-S. Kim, T. Ropitault, S.K. Lee, N. Golmie, H Assasa, and J. Widmer, "A Link Quality Estimation-based Beamforming Training Protocol for IEEE 802.11ay MU-MIMO Communications," *IEEE Trans. Commun.*, vol. 69, no. 1, pp. 634-648, Jan. 2021.

[4] *A Collection of Open-source Tools to Simulate IEEE 802.11ad/ay WLAN Networks in ns-3.* https://github.com/wigig-tools

[5] H. Assasa, N. Grosheva, T. Ropitault, S. Blandino, N. Golmie, and J. Widmer, "Implementation and Evaluation of aWLAN IEEE 802.11ay Model in Network Simulator ns-3," *in Proc. Workshop Ns-3*, 2021.