Swish-Driven GoogleNet for Intelligent Analog Beam Selection in Terahertz Beamspace MIMO

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Abstract—In this paper, we propose an intelligent analog beam selection strategy in a terahertz (THz) band beamspace multiple-input multiple-output (MIMO) system. First inspired by transfer learning, we fine-tune the pre-trained off-the-shelf GoogleNet classifier, to learn analog beam selection as a multi-class mapping problem. Simulation results show 83% accuracy for the analog beam selection, which subsequently results in 12% spectral efficiency (SE) gain, upon the existing counterparts. Towards a more accurate classifier, we replace the conventional rectified linear unit (ReLU) activation function of the GoogleNet with the recently proposed Swish and retrain the fine-tuned GoogleNet to learn analog beam selection. It is numerically indicated that the fine-tuned Swish-driven GoogleNet achieves 86% accuracy, as well as 18% improvement in achievable SE, upon the similar schemes. Eventually, a strong ensembled classifier is developed to learn analog beam selection by sequentially training multiple fine-tuned Swish-driven GoogleNet classifiers. According to the simulations, the strong ensembled model is 90% accurate and yields 27% gain in achievable SE, in comparison with prior methods.

Index Terms—Terahertz (THz) band, beamspace, multiple-input multiple-output, analog beam selection, GoogleNet, Swish, ensembled classifier.

I. INTRODUCTION

Over the recent years, beamspace technology [1] has attracted a major attention in high-frequency bands, as an alternative to the conventional massive multiple-input-multiple-output (MIMO) architecture. In latter case, each antenna element requires a specific radio frequency (RF) chain which makes this architecture inefficient in practice, owing to a massive number of required RF chains. In beamspace technology nevertheless, the scattered signals of divergent paths (beams) can be concentrated upon a limited number of dominant beams and the spatial domain channel is thereby transformed into the beamspace domain channel. To this reason, from a massive number of beams, merely a limited number is adopted, which in turn necessitates few RF chains for a reliable beam steering.

The hybrid analog-digital beamspace MIMO is consequently a reasonable system in terms of energy, cost, and complexity, provided that the analog beam selection is efficiently performed. Unfortunately, this sets out new challenges due to the massive number of beams. While on one hand, the prior optimization-based analog beam selection efforts such as those in [2] impose expensive computational burden to the transceivers, the low-complexity machine/deep learning approaches like [3] and [4] on the other hand, suffer from accuracy loss in this regard. According to the statistics in [5], trained on environmental samples (e.g., the line-of-sight (LoS) and non-line-of-sight (NLoS) beams), two well-known classifiers i.e., the linear SVM [3] and the decision tree [4] are only 33% and 55% accurate, respectively, which in turn brings about a non-trivial performance loss for the beamspace architecture.

The main contribution of this paper is to relieve the precision fall in prior learning-aided works on analog beam selection, by proposing a fine-tuned deep learning technique, along with an ensemble learning technique as follows.

- First we account for the analog beam selection problem as a multi-class classification task. To this aim, we retrain the pre-trained off-the-shelf GoogleNet classifier [6] based on the concept of transfer learning [7], so as to learn the analog beam selection. Simulation results verify that the retrained GoogleNet exhibits some 83% accuracy for the analog beam selection and achieves by up to 12% gain in achievable spectral efficiency (SE) upon the counterparts, when signal-to-noise-ratio (SNR) is 30dB.
- We fine-tune the GoogleNet classifier for a beyond classification precision, by replacing its conventional activation function i.e., the rectified linear unit (ReLU) with the Swish activation function [8]. It is numerically shown that retraining the fine-tuned GoogleNet achieves some 86% accuracy, as well as 18% achievable SE gain upon the counterparts, at SNR = 30dB.
- In addition, the performance of the proposed analog beam selection scheme is further enhanced by sequentially incorporating multitude of the fine-tuned GoogleNets (each one is known as a weak learner) into an ensembled model (known as a strong learner) [9]. The proposed strong learner according to the simulations outperforms the achievable SE of the prior counterparts, by up to 27%, while yielding 90% accuracy, when SNR = 30dB.

In remaining of the paper, Sections II and III describe the system setup and the solution approach, whereas the simulation results and conclusions are presented in Sections IV and V, respectively.
II. SYSTEM SETUP

A. Hybrid Analog-Digital Architecture

Consider a downlink THz communication, where the transmitter employs \(N_t(N_t^{RF})\) transmit antennas (transmit RF chains) for serving a receiver, equipped with \(N_r(N_r^{RF})\) receive antennas (receive RF chains). The system multiplexing gain or equivalently, the number of simultaneously communicated data streams is \(N_s = \min(N_t^{RF}, N_r^{RF})\) and the power-normalized transmit symbols, are denoted by \(s \in \mathbb{C}^{N_s \times 1}\), where \(E[ss^H] = I_{N_s}\). The transceivers enjoy a hybrid analog-digital beamspace architecture to preserve the system flexibility, as well as the efficiency in hardware cost and energy consumption [1]. As demonstrated, in Fig. 1 a baseband digital matrix \(F_{BB} \in \mathbb{C}^{N_t^{RF} \times N_s}\) is leveraged at the transmitter, followed by an analog beam selection network, denoted by \(S_t \in \mathbb{R}^{N_t \times N_t^{RF}}\) in matrix form for mapping \(N_t^{RF}\) transmit RF chains into a subset of \(N_t\) transmit antennas/beams. Eventually, a lens antenna array is deployed at the transmitter, including an energy-focusing electromagnetic lens, where its focal surface is equipped with a large-scale antenna array.

At the receiver side reversely, once the lens antenna array receives the signals, a mapping is performed between the predominant receive antennas/beams and the receive RF chains through the receive analog beam selection network \(S_r \in \mathbb{R}^{N_r \times N_r^{RF}}\), where a baseband digital combining matrix \(W_{BB} \in \mathbb{C}^{N_r^{RF} \times N_r}\) is embedded afterwards to obtain the transmit symbols. Thus, the discrete-time received baseband complex signal is given by \(y = W_{BB}^H S_r^H H_b x + W_{BB}^H S_r^H n\), wherein \(n \sim N(0, \sigma^2 I_{N_r})\) is the additive white Gaussian noise (AWGN) with a noise power \(\sigma^2\) and \(H_b\) denotes the THz beamspace channel.

B. Communicating THz Channel

According to the well-known Saleh-Valenzuela geometric model [11], a ray-based clustered THz channel is assumed with \(N_{cl}\) cluster of scatterers, each contributes \(N_{ray}\) propagation rays. Also, a limited angle-of-departure/arrival (AoD/AoA) spread is supposed for a typical cluster \(l\), denoted by \(\psi_{l}^{i}\) and \(\psi_{l}^{r}\), respectively. For a typical cluster/ray \(l/u\), the complex-valued gain is denoted by \(\alpha_{l,u}^{i}\), while the physical AoD and AoA for the transmitter and receiver is respectively denoted by \(\theta_{l,u}^{i}\) and \(\theta_{l,u}^{r}\), respectively. Let us denote the antenna element spacing by \(d\), the speed of light by \(c\), the wavelength by \(\lambda = c/f_c\), and the carrier frequency by \(f_c\). Then, the spatial AoD/AoA can be represented by \(\phi_{l,u}^{i} = (d/\lambda)\sin\theta_{l,u}^{i}\) and \(\phi_{l,u}^{r} = (d/\lambda)\sin\theta_{l,u}^{r}\), respectively. Accordingly, the narrowband discrete-time spatial domain THz channel \(H \in \mathbb{C}^{N_r \times N_t}\) is expressed as

\[
H = \gamma \sum_{i=1}^{N_{cl}} \sum_{u=1}^{N_{ray}} \alpha_{l,u} \Phi_{l,u}^{i} \Phi_{l,u}^{T} \Phi_{l,u}^{r} \Phi_{l,u}^{T}
\]

with the normalization factor \(\gamma = \sqrt{N_r N_t/N_{cl} N_{ray}}\). Following the uniform linear array (ULA), the antenna array responses at the transmitter/receiver, are represented by

\[
a_l(\phi_{l,u}^{i}) = \frac{1}{\sqrt{N_{t}}} \begin{bmatrix} e^{j2\pi \phi_{l,u}^{i}} & \cdots & e^{j2\pi (N_{t}-1)\phi_{l,u}^{i}} \end{bmatrix}^H \in \mathbb{C}^{N_t \times 1}
\]

and \(a_r(\phi_{l,u}^{r}) = \frac{1}{\sqrt{N_{r}}} \begin{bmatrix} e^{j2\pi \phi_{l,u}^{r}} & \cdots & e^{j2\pi (N_{r}-1)\phi_{l,u}^{r}} \end{bmatrix}^H \in \mathbb{C}^{N_r \times 1}\), respectively. Important to note that the THz channel \(H\) in spatial domain is effectively transformed into the equivalent channel in beamspace domain \(H_{bb}\), on the basis of DFT operations in lens antenna array (see [10] for details).

C. Problem Statement

In the considered hybrid analog-digital beamspace massive MIMO system, we focus on achieving analog beam selection for the transmitter and receiver \(S_t, S_r\), under the assumption of given the precoding/combining matrices and given the beamspace channel. This problem can be formally stated as

\[
\begin{align*}
\min_{S_t, S_r} & \quad \|H_b - S_t W_{BB} F_{BB} S_r^H \|^2 \\
\text{s.t.} & \quad S_t \in S_t, \\
& \quad S_r \in S_r,
\end{align*}
\]

where \(S_t\) and \(S_r\) are the analog beam selection candidate sets at the transmitter and receiver, respectively. The optimal solution for acquiring the analog beam selection variables \(S_t\) and \(S_r\) is the exhaustive search method, which is computationally expensive and definitely infeasible for a beamspace massive MIMO system.

III. SOLUTION APPROACH

In this section, the training sample set acquisition, the Swish-driven GoogleNet, transfer learning and ensemble learning are respectively elaborated as our solution approach to (1).

A. Sample Set Acquisition

We consider the network parameters path gain, transmit power, AoA and AoD constituting \(4N_{cl} \times N_{ray} + 2\) random real-valued features with one feature for the transmit power of the transmitter, one feature for the path gain, \(2N_{cl} \times N_{ray}\) features for the AoDs/AoAs of the transmitter/receiver, and as such \(2N_{cl} \times N_{ray}\) features for the real and imaginary parts of the complex-valued gain to form a data sample. In following, we conduct a normalization process, a Gaussian mixture model (GMM) fitting, and a labeling operation over the samples.

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Fig. 1: The hybrid analog-digital beamspace MIMO architecture at the transmitter.
1) **Normalization:** Due to the diversity in sample ranges (e.g., the transmit power is based on dB, while AoDs are within [0, 2π]), a normalization pre-processing needs to be accomplished for each feature of samples as $\hat{a}_{ij} = \left[a_{ij} - \text{Mean}(a_{ij})\right] / \left[a_{ij}^{\text{max}} - a_{ij}^{\min}\right]^{-1}$, where $a_{ij}^{\text{max}}$ indicates the value of $f$th feature in $m$th sample and $\text{Mean}(a_{ij})$ is the mean of all $a_{ij}^{m}$. Besides, $a_{ij}^{\text{max}}$ and $a_{ij}^{\text{min}}$ denote the maximum and minimum values of the $f$th feature among all samples, respectively. Hence, the $m$th sample as a feature row vector can be characterized as $z_{m} \in \mathbb{C}^{K \times (4N_{cl} \times N_{rays} + 2)}$ with $4N_{cl} \times N_{rays} + 2$ normalized features.

2) **GMM Fitting:** Since the beamspace channel features $\phi_{t}$, $\phi_{r}$, and $\alpha$ follow a Gaussian distribution [13], we adopt a GMM for appropriately fitting the beamspace channel. In doing so, we have $\hat{H}_{b} = A \times \left(\sum_{k=1}^{K} w_{k} \exp\left(-\frac{\left(\phi_{t} - \mu_{\phi_{t}}^{k}\right)^{2}}{2\sigma_{\phi_{t}}^{2}}\right) - \frac{\left(\phi_{r} - \mu_{\phi_{r}}^{k}\right)^{2}}{2\sigma_{\phi_{r}}^{2}}\right)$, with the GMM-fitted beamspace channel $\hat{H}_{b}$, the GMM amplitude $A$, and $K$ Gaussian components, where $w_{k} \in [0, 1]$ is the weight of the Gaussian component $k$ and $\sum_{k=1}^{K} w_{k} = 1$. Note that in $\hat{H}_{b}$, the central coordinates are $(\mu_{\phi_{t}}, \mu_{\phi_{r}}, \alpha)$, whereas $\sigma_{\phi_{t}}, \sigma_{\phi_{r}}$, and $\sigma_{\alpha}$ indicate their corresponding standard deviation. In vector representation, the Gaussian component $k$ can be expressed as $q_{k} = [w_{k}, \mu_{\phi_{t}}, \mu_{\phi_{r}}, \alpha, \sigma_{\phi_{t}}, \sigma_{\phi_{r}}, \sigma_{\alpha}]$. Equivalently, the spatial features of the samples based on all of the Gaussian components can be given by $q = [A; q_{1}; q_{2}; \ldots; q_{K}]^{T} = [A, \mu_{\phi_{t}}, \mu_{\phi_{r}}, \alpha, \sigma_{\phi_{t}}, \sigma_{\phi_{r}}, \sigma_{\alpha}, \mu_{\phi_{t}}, \mu_{\phi_{r}}, \alpha, \sigma_{\phi_{t}}, \sigma_{\phi_{r}}, \sigma_{\alpha}, \mu_{\phi_{t}}, \mu_{\phi_{r}}, \alpha, \sigma_{\phi_{t}}, \sigma_{\phi_{r}}, \sigma_{\alpha}, \ldots, \mu_{\phi_{t}}, \mu_{\phi_{r}}, \alpha, \sigma_{\phi_{t}}, \sigma_{\phi_{r}}, \sigma_{\alpha}]^{T}$. Finally, the optimal vector $q$, which is used to model the beamspace channel distribution can be determined according to [14].

3) **Labeling:** The cost function for evaluating the analog beam selection decisions (i.e., labeling) is the objective in [11], which equivalently optimizes the achievable SE [12]. The labeling phase is a multi-class mapping operation that determines the optimum (beam, RF) candidates obtained from [15], wherein each RF chain is a class label to which, analog beams are assigned to.

### B. GoogleNet Architecture

As an off-the-shelf pre-trained network, GoogleNet has been trained by the well-known datasets (e.g., ImageNet) beforehand, while its weights, biases, and other training parameters have been already set. According to Fig. 4, the network has 22 layers with an input layer of size $224 \times 224 \times 3$ for receiving a two-dimensional (2D) image of width and length 224 and 3 channels of RGB (i.e., red, green, and blue). The main parts in GoogleNet architecture are its inception modules that incorporate multiple convolutions, kernels, and max-pooling layers, simultaneously within a single layer. The main activation function in GoogleNet is ReLU, which is computationally cheap and embedded upon a filter concatenation layer within the inception module (see Fig. 4) for improved training performance. By going deeper in GoogleNet architecture as observed in Fig. 4, the linear layer of size 1000 is followed by a dropout layer with 40% ratio of dropped outputs and connected to a Softmax activation function with 1000 classes.

### C. Swish-driven GoogleNet

Despite its accurate classification capability, the performance of GoogleNet can still be improved by minor architectural modifications. For instance, the authors in [16] proposed to substitute the ReLU activation functions in GoogleNet with the Leaky-ReLU (an extension of the conventional ReLU) for faster convergence. In [17], the large convolutional filters in GoogleNet were factorized into smaller ones, and this modification benefited for the middle layers of GoogleNet. In this paper, we modify the ReLU activation functions in filter concatenation layer of the inception modules (see Fig. 4) in GoogleNet architecture by the Swish [8]. The latter is a self-gated, smooth, and non-monotonic activation function recently proposed by Google Brain Team. By definition, the Swish activation function for any input $x$ can be given by $f(x) = x \cdot \text{Sigmoid}(x) = \frac{x \cdot e^{x}}{1 + e^{x}}$. The numerical results in [8] indicate that the Swish is more precise than the ReLU (and its alternative extensions, such as Leaky-ReLU) with a
similar level of computational complexity, especially in very deep architectures.

D. Transfer Learning

To fit the size of samples into the input layer of the fine-tuned Swish-driven GoogleNet, certain modifications need to be necessarily accomplished in accordance with Fig. 4. First, we extend the dimensionality of a typical sample $z_m$ of size $(4N_{cl} \times N_{ray} + 2)$ into a matrix form of size $(4N_{cl} \times N_{ray} + 2) \times 224 \times 224$ as a 2D image. Next, we preform an image resizing through the interpolation technique to transform each sample into the size of $224 \times 224$. Specifically, we use bicubic interpolation that can preserve the quality of the primary image by extracting the most determinant properties (which correspondingly are related to the most dominant features of the sample in our case). The $224 \times 224$ resized 2D image of $z_m$ is eventually extended into a three dimensional (3D) image by using zero-valued rescaling. To do so, the RGB color triplet for each pixel is set to zero, thus leading to a 3D RGB image corresponding to the most dominant features of the image by extracting the most determinant properties (which are mainly fixed).

We further fine-tune the final linear layer of the GoogleNet by setting $N_{RF} + 1$ classes for the transmitter (or $N_{RF} + 1$ for the receiver), which trains the GoogleNet to map any sample (beam) into the correct class (RF chain). During the training process, the beamspace channel feature space is processed through the layers of the GoogleNet, while its main features (energy-focused features of the beam) are extracted. The Softmax classifier eventually learns a multi-class mapping based on the labeled samples obtained from $\{\mathcal{X}_m\}$. The probability of the $i$th RF chain being selected by the Softmax function is

$$\delta(N_{RF})_i = [e(N_{RF})_i] \times \left( \sum_{i=1}^{N_{RF}} e(N_{RF})_i \right)^{-1}.$$

Finally, as observed in Fig. 4, a modified version of the GoogleNet is trained by fine-tuning its linear layer and activation functions. This approach is known as transfer learning, whereby the main layers of a pre-trained network are directly imported into the new application, while other layers remain unchanged. By doing so, the fine-tuned GoogleNet learns analog beam selection at the transceivers based on the beamspace channel feature space, while its internal weights, biases, and other parameters are mainly fixed.

E. Enhancing Accuracy via Ensemble Learning

We further improve the accuracy of the proposed procedure for analog beam selection through the ensemble learning technique, which puts forward to train a strong ensemble model, that combines the predictions of distinct weak learners (e.g., the Swish-driven GoogleNet modules in this paper) to achieve a more precise model. To do so, a gradient boosting (gradBoost) mechanism [9] is adopted, wherein we sequentially train the weak learners.

Towards forming an ensembled model as in Fig. 3, we adopt $M_1$ random subsets $Z_m(m \in M_1)$ of the whole training sample set $Z$, where the weak learners are trained upon different subsets. For any sample $z_m \in Z_m$ of size $C \times (4N_{cl} \times N_{ray} + 2)$, the weak learner performs a classification and assigns a specific class from $\omega_m \in \Omega = \{0, ..., N_{RF}^{cl}\}$.

The goal in each step is boosting the training accuracy of the current weak learner through focusing on the misclassified observations made by the previous ones. The misclassified samples are injected forward to train the next weak learner more efficiently. The strong ensemble learner thereafter adopts a majority voting mechanism based on a weighted summation of $M_1$ weak learners. To this goal, a voting counter $\Psi(\omega) \in \mathbb{N}^{1 \times 1}$ indicates the number of classifiers, which adopted the RF chain class $\omega$. The weighted summation is given by $\Psi^{ens}_m = \sum_{\omega=1}^{M_1} c_m \Psi^{\omega}_m(\omega)$, where $c_m$ denotes the weight of the $m$th Swish-driven GoogleNet, indicating the performances of this weak model. Indeed, the better a weak learner performs, the more it contributes to the strong ensembled model. The strong ensemble learner thus, is generally less biased than the weak learners, since the misclassified observations are efficiently propagated and learned along the ensembling chain. The challenge here, is to select the optimal order of the classifiers to be trained within the ensembling chain, i.e., obtaining the optimal order of $\Psi^{ens}_m$ is complicated, especially for a long ensembling chain.

Instead of optimizing this order globally, we are seeking for the best possible pairs of $(c_m, \Psi(\omega))$ to be locally built and iteratively added in a sub-optimal approach. The strong ensemble model can be recurrently indicated by $\Phi^{ens}_m = \Phi^{ens}_{m-1} - c_m \nabla \Phi^{ens}_{m-1} E(\Phi^{ens}_{m-1})$, whereby the best possible pair $(c_m, \Psi(\omega))$ can be obtained as $(c_m, \Psi(\omega)) = \arg \min_{\omega \in \Omega} E(\Phi^{ens}_{m-1} + c \Psi(\omega))$, with $E(\cdot)$ denoting the strong ensemble learner fitting error. Finally, the RF chain class $\omega$, which maximizes the voting counter $\Psi(\omega)$ by contributing $M_1$ weak learners and their impacts, is adopted by the strong ensemble learner as $\omega^* = \arg \max_{\omega \in \Omega} \frac{1}{M_1} \sum_{\omega=1}^{M_1} c_m \Psi(\omega)$.

IV. SIMULATION RESULTS

We consider a clustered THz channel with $N_{cl} = 4$ clusters and $N_{ray} = 2$ propagation rays in each cluster. The signal wavelength is $\lambda = 1.36$, the AoAs and the AoDs are uniformly distributed within $[-\frac{\pi}{4}, \frac{\pi}{4}]$, while the complex-valued gain follows $CN(0, 1)$. Simulations are performed for a lens-aided MIMO system equipped with $N_t = 64$, $N_i = 256$ and
TABLE I: GoogleNet configurations

| Parameter        | Value     |
|------------------|-----------|
| TrainingSize     | 70%       |
| ValidationSize   | 30%       |
| MiniBatchSize    | 128       |
| MaxEpochs        | 6         |
| Shuffle          | every epoch |
| InitialLearnRate | 1e-3      |
| ValidationFrequency | 3          |

For the simulations related to the GoogleNet as indicated in Table I, we used 70% of the sampling data for the training and the rest are for the validation. Moreover, the “MiniBatchSize” shows the number of images used at each iteration of training/validation. The maximum number of training epochs is indicated by “MaxEpochs” and the “Shuffle” field is every epoch, which randomly initiates a new datastore with the same training/validation data. The initial learning rate “InitialLearnRate” slows down the learning process, in the transferred layers owing to its adopted small value and the “ValidationFrequency” field specifies that the validation is performed every three iterations during training.

The analog beam selection baseline strategies MLP, k-NN, and SVM with the same internal configurations in [3], the conventional ReLU-driven GoogleNet, the modified Swish-driven GoogleNet, and the ensemble learning schemes are investigated for comparison in terms of achievable SE. Additionally, the fully digital zero-forcing (ZF) strategy by using the whole beams at the transceivers, is the optimal benchmark baseline.

First, we assess the convergence accuracy and loss ratios for the training/validation process of the proposed Swish-driven GoogleNet scheme in Figs. 4(b) and 4(d), respectively. Clearly, the training/validation process is inaccurate in first iterations. That is because the weights and biases of the input layer and the linear layer are not well fine-tuned with the sampling data. Gradually as the iterations progress, the training/validation accuracy improves (tends to 100%), while the training/validation loss degrades (tends to 0).

Next, we analyze the performance of our proposed schemes in a comparative fashion. The benchmark fully-digital ZF strategy with $N_t^{RF} = 256$ and $N_r^{RF} = 16$ RF chains obviously, has the largest achievable SE in Fig. 4(a) and Fig. 4(c) at the expense of severe system complexity, energy consumption, and hardware cost. Fig. 4(a) with varying SNR in 0dB–30dB and $N_s = 4$, indicates that by increasing the SNR, the achievable SE improves for all the baselines. According to Fig. 4(c) with varying $N_s$ in 4–10, where $N_t^{RF} = N_r^{RF} = N_s$, where $N_s = 4$, indicates that the achievable SE improves for more number of simultaneous data streams. Our proposed ensemble learning scheme is the most superior amongst others and is the closest scheme to the benchmark due to a better accuracy. This scheme according to Fig. 4(a), improves the achievable SE of the analog beam selection baseline strategies MLP, k-NN, and SVM with the same internal configurations in [3], the conventional ReLU-driven GoogleNet, the modified Swish-driven GoogleNet, and the ensemble learning schemes are investigated for comparison in terms of achievable SE.
MLP scheme [3] at SNR = 30dB, by up to 27%. Similarly at SNR = 30dB, the proposed Swish-enabled GoogleNet and the conventional ReLU-driven GoogleNet schemes achieve a better performance than other strategies MLP, SVM, and k-NN, by exhibiting 18% and 12% achievable SE gain compared to the MLP scheme [3], respectively.

In Fig. 5 under the same configurations in Fig. 4(c) with $N_t = 4$, the accuracy of the analog beam selection strategies is assessed. The ensemble learning strategy with 90% accuracy is the best, while the Swish-driven GoogleNet and the conventional ReLU-driven GoogleNet schemes with 86% and 83% on average, are the second and third best strategies for analog beam selection. The reason is that retraining/modifying the pre-trained networks such as GoogleNet based on transfer learning for the classification tasks (e.g., analog beam selection) is more accurate than training a deep network such as MLP [3] from scratch. Inspired by the transfer learning method, the parameters in a pre-trained deep structure are mostly kept unchanged, while few certain parameters are fine-tuned based on samples. We further examine the accuracy of the conventional ReLU-driven GoogleNet, as well as the fine-tuned Swish-driven GoogleNet schemes by applying different training functions e.g., root mean square propagation (RMS-PROP), adaptive moment estimation (ADAM) and stochastic gradient descent method (SGDM), as demonstrated in Table II. One can observe that the Swish-driven GoogleNet scheme trained by the SGDM can achieve the best analog beam selection accuracy.

V. CONCLUSIONS

In this paper, we proposed a novel deep learning technique framework to address the analog beam selection problem in a THz beamspace MIMO system. Specifically, we retrained the pre-trained off-the-shelf GoogleNet for learning the analog beam selection based on the concept of transfer learning. Then, we fine-tuned the GoogleNet enabling the Swish activation function, for a better analog beam selection precision. Finally, an ensemble learning technique presented for boosting the precision beyond a conventional fine-tuned GoogleNet. Simulations revealed a remarkable enhancement in accuracy, as well as in achievable SE.

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REFERENCES

[1] J. Brady, N. Behdad, and A. M. Sayeed, “BeamSpace MIMO for millimeter-wave communications: system architecture, modeling, analysis and measurements,” IEEE Trans. Antennas Propag., vol. 61, no. 7, pp. 3814-3827, Jul. 2013.

[2] I. Orikumhi, J. Kang, H. Jwa, J. H. Na and S. Kim, “SINR Maximization Beam Selection for Millimeter-Wave Beamspaces MIMO Systems,” IEEE Access, vol. 8, pp. 185688-185697, 2020.

[3] C. Anton-Haro and X. Mestre, “Learning and data-driven beam selection for Millimeter-Wave communications: an angle of arrival-based approach,” IEEE Access, vol. 7, pp. 20404-20415, 2019.

[4] X. Ma, Z. Chen, Z. Li, W. Chen and K. Liu, “Low Complexity Beam Selection Scheme for Terahertz Systems: A Machine Learning Approach,” IEEE Int. Conf. Commun. Workshops (ICC Workshops), Shanghai, China, pp. 1-6, 2019.

[5] A. Klautau, P. Balista, N. Gonzalez-Prelcic, Y. Yang and R. W. Heath, “SG MIMO data for machine learning: application to beam selection using deep learning,” Proc. ITA, pp. 1-9, 2018.

[6] C. Szegedy et al., “Going deeper with convolutions,” IEEE Conf. Comp. Vis. Patt. Recog. (CVPR), Boston, MA, 2015, pp. 1-9, 2015.

[7] Pratt, L. Y. and T. Sebastian, “Machine learning,” Special issue on inductive transfer, July, 1997.

[8] P. Ramachandran, B. Zoph, and Q. V. Le, “Swish: A self-gated activation function,” arXiv preprint, arXiv:1710.05941, Oct. 2017.

[9] T. Hastie, R. Tibshirani, J. H. Friedman, “10. Boosting and Additive Trees”, The Elements of Statistical Learning (2nd ed.), Springer, pp. 337–384, Nov., 2009.

[10] W. Shen, X. Bu, X. Gao, C. Xing and L. Hanzo, “BeamSpace Precoding and Beam Selection for Wideband Millimeter-Wave MIMO Relying on Lens Antenna Arrays,” IEEE Trans. Signal Process., vol. 67, no. 24, pp. 6301-6313, Dec., 2019.

[11] A. A. M. Saleh and R. Valenzuela, “A statistical model for indoor multipath propagation,” IEEE J. Sel. Areas Commun., vol. 5, no. 2, pp. 128-137, Feb. 1987.

[12] M. Wang, F. Gao, S. Jin and H. Lin, “An Overview of Enhanced Massive MIMO With Array Signal Processing Techniques,” IEEE J. Sel. Top. Signal Process., vol. 13, no. 5, pp. 886-901, Sept. 2019.

[13] X. Wei, C. Hu, L. Dai, “Knowledge-Aided Deep Learning for Beamspace Channel Estimation in Millimeter-Wave Massive MIMO Systems”, arXiv preprint, arXiv:1910.12455, Jan., 2020.

[14] G. Celeux, S. Chr’etien, and F. Forbes, “A component-wise EM algorithm for mixtures,” Journal of Computational and Graphical Statistics, no.4 pp. 697—712, Jan., 2012.

[15] P. Amadori and C. Masouros, “Low LF-complexity millimeter-wave beamspace-MIMO systems by beam selection,” IEEE Trans. Commun., vol. 63, no. 6, pp. 2212-2222, Jun., 2015.

[16] L. Balagourouchetty, J. K. Pragatheeswaran, B. Pottakkat and G. Ramkumar, “GoogLeNet-Based Ensemble FCNet Classifier for Focal Liver Lesion Diagnosis,” IEEE J. Bio. Hlth. Inf., vol. 24, no. 6, pp. 1686-1694, June 2020.

[17] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens and Z. Wojna, “Rethinking the Inception Architecture for Computer Vision,” IEEE Conf. Comput. Vis. Patt. Rec. (CVPR), Las Vegas, NV, 2016, pp. 2818-2826.