DEEP LEARNING FOR LOCATION BASED BEAMFORMING WITH NLOS CHANNELS
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As opposed to previously proposed methods, it allows to handle the H2020 project Hexa-X (Grant Agreement no. 101015956). However, the main drawback of LBB with respect to CSI based communications and enhances the physical layer security [10].

For such approaches, the location of users is directly used to determine precoders. This allows to spare a lot of resources for CSI acquisition (CSI or beam training procedures [6]). Both approaches induce a consequent overhead and limit overall system efficiency.

Is CSI or beam training absolutely needed for a massive MIMO system to operate? Not necessarily, since appropriate precoders could be chosen at the base station based on other sources of information about users. In particular, channel estimation and beamforming in the context of massive MIMO systems have benefited from ML [3, 4, 5]. Although such approaches are very promising, their main drawback is that most need pilot symbols to be sent in order to estimate channel state information (CSI) or beam training procedures [6]. Both approaches induce a consequent overhead and limit overall system efficiency.

Related work. Location based beamforming has been proposed a decade ago [7]. In its original formulation, it relies only on the main angle of departure (estimated by sending pilots) in order to synthesize an estimated single path channel which is then used to determine a precoder (without any learning). Such an approach is inherently limited to LOS channels, or at least channels comprising a dominant path. LBB Methods that were subsequently proposed [10, 8, 9] introduce refinements to the original idea but do not get rid of this inherent limitation. The method proposed in this paper overcomes this limitation to LOS channels since it directly learns the location/precoder mapping, but as a counterpart, it requires a training phase to calibrate this mapping. The proposed approach pertains to integrated sensing and communication (ISAC) [12], and more specifically to sensing-assisted communication which aims at leveraging sensors at the base station to enhance communication [13].

RFFs [11] are a crucial element of the proposed neural network. Their usage in neural networks stems from the impossibility to learn mappings containing high frequencies with classical neural networks such as the multilayer perceptron (MLP) [14].
mapping starting from a very low-dimensional space particularly benefit from RFFs [14]. RFF based neural networks have been applied successfully to 3D scene reconstruction [15], where the network learns the mapping linking the 3D location and orientation to the radiance and density (which can be seen as the light channel).

2. PROBLEM FORMULATION

The method proposed in this paper applies to a wide variety of multi-user massive multiple input multiple output (massive MIMO) wideband systems [16, 17, 18], operating indifferently in time division duplex (TDD) or frequency division duplex (FDD), where the antennas at the base station are indifferently colocated or not (in which case it is a distributed MIMO system).

Let us consider $A$ base station antennas and a single subcarrier, and denote $h \in \mathbb{C}^A$ the downlink channel vector between the base station and any given user, and $l \in \mathbb{R}^D$ its location, where $D$ can be two or three, depending on whether or not the elevation of users is considered relevant. Moreover, the proposed method can be directly transposed to systems comprising several subcarriers, but is presented here for a single subcarrier for ease of exposition.

Based on a labeled database of $N$ downlink channels associated with the corresponding user locations

$$\{ h_i; l_i \}_{i=1}^N,$$  \hspace{1cm} (1)

the objective in this paper is to build a location based precoding function (or simply precoding function), whose function is to focus energy on the intended user location. It is mathematically defined as

$$\mathcal{P}: \mathbb{R}^D \rightarrow \mathbb{C}^A$$

$$l \mapsto w \triangleq \mathcal{P}(l),$$  \hspace{1cm} (2)

where $w$ is the predicted precoding vector (of unit norm).

**Performance measure.** In order to evaluate precoding functions, the normalized correlation between the precoder $w$ and the channel $h$ is used. It is expressed as

$$\eta \triangleq \frac{|w^H h|^2}{\|h\|_2^2}.$$  \hspace{1cm} (3)

It is between zero and one (for a perfect precoder), and is tightly linked to the downlink channel capacity (considering a single user), whose expression is

$$\log(1 + \eta \cdot \text{SNR}_{\text{opt}}),$$

for received signal of the form $y = \sqrt{P}w^H h s + n$ where $n \sim \mathcal{N}(0, \sigma^2)$ is additive noise, $s$ is the sent symbol and $P$ the transmit power. In that setting, $\text{SNR}_{\text{opt}} \triangleq \frac{P\|h\|^2_2}{\sigma^2}$ is the highest achievable signal to noise ratio (SNR) [19]. In summary, the correlation is a single number between zero and one allowing to determine the maximum achievable downlink spectral efficiency for any transmit power and noise variance considering a given precoder.

3. PROPOSED SOLUTION

**Neural precoding function.** Deep neural networks are known to be universal function approximators [20, 21] and have led to great practical successes [22]. It is proposed here to implement the precoding function $\mathcal{P}$ as a deep neural network. However, it has been shown that classical neural networks known as multilayer perceptrons (MLP) [23] are in practice unable to learn functions of high frequency [14]. This phenomenon is known as spectral bias [24, 25] and has been characterized with help of the theory of neural tangent kernels (NTK) [26].

In order to remedy this fundamental weakness, it has been proposed [14] to use random Fourier features [11] to help the neural network building high frequencies. This line is followed in this paper, motivated by the fact that the optimal precoder may vary fast with respect to the user’s location, due to fading. This results in a neural network whose first layer is fixed and corresponds to random Fourier features expressed as

$$\gamma(l) = [\cos(2\pi B l), \sin(2\pi B l)]^T,$$

where $B \in \mathbb{R}^{R \times D}$ contains $R D$-dimensional (spatial) frequencies drawn randomly as

$$B \sim \mathcal{N}(0, s^2 I),$$

where the variance parameter $s^2$ controls the frequency range (the higher $s^2$ the more high frequencies are likely to appear). It is proposed to concatenate this RFF layer with a classical MLP using fully connected layers and rectified linear units (ReLU) activation functions [27] of width $M$ (number of neurons per layer) and depth $Q$ (number of layers). The last layer is of width $2A$, which corresponds to the real and imaginary parts of the predicted precoder $w$ stacked together. The structure of the proposed neural network is shown on Fig. 1. Simply put, the role of the RFF layer is to pre-build high frequencies in order to ease learning for the subsequent MLP.

In order to calibrate the weights, the cost function to minimize is expressed as

$$\text{CF} \triangleq 1 - \frac{1}{N} \sum_{i=1}^N \left| \mathcal{P}(l_i)^H h_i \right|^2 \frac{\|h_i\|_2^2}{\|h_i\|_2^2}.$$  \hspace{1cm} (4)

It measures the misalignment of the predicted precoders with respect to the training channels and is between 0 (if the precoders are perfectly aligned with the channels) and 1 (if the precoders are orthogonal to the channels).

**Practical setup.** Two distinct phases are to be distinguished for the proposed method to operate in a real system:

- **Training phase:** At first, the database $\{ h_i; l_i \}_{i=1}^N$ has to be built. To do so, the base station can send pilots and estimate channels using any classical method. Moreover, it has to access users’ locations, using either a GNSS, video cameras or also pilots. The neural network can be trained with the built database in order to calibrate the precoding function $\mathcal{P}$. 
The experiments are carried out using simulation settings. The proposed method is compared with two baselines: a classical LBB approach and a deep learning approach using a simple MLP (without RFFs). The architecture of the MLP is exactly the same as the one of the proposed method, except the first layer (RFF computation) that is replaced by a simple fully connected layer. This baseline is here to show the interest of RFFs.

Results. The performance of the three compared methods on a test set of 10000 channels (not used for training) is shown on Fig. 2. The cumulative distribution function (CDF) of the correlation is plotted (with an ideal precoder it would be equal to zero for all values of \( x < 1 \) and to one for \( x = 1 \)). The plot clearly shows the great improvement brought by the proposed method. Indeed, in such an urban environment where a LOS path is not available for every location, the classical LBB approach yields a median correlation of 0.708. This is explained by the fact that the approach is inherently biased towards LOS channels. Using a deep learning approach with a simple neural network (without RFF) yields a slight improvement (median of 0.714). This very simple neural network is prone to too much variance. However, the proposed method using RFFs allows to attain a median of 0.946, which is a lot better than what is attained by the two aforementioned baselines, because of a better bias/variance trade-off.

It is also interesting to look at the spatial distribution of the attained correlation. This is depicted on Fig. 3 (for the classical LBB approach) and Fig. 4 (for the proposed approach). On these figures, the colors (blue to yellow) denote the obtained correlation for 50000 test channels, and the base station location is denoted by a red cross. Note that on both figures, black areas on the left correspond to zero-norm channels. Comparing these figures, it is obvious that the classical LBB approaches (Fig. 3) yield good precoders (yellow) for areas where user are in line of sight with respect to the base station, but very bad precoders elsewhere (blue areas). On the opposite, the proposed approach (Fig. 3) yields good precoders everywhere on the considered area, even in locations that are in non-line of sight with respect to the base station. This clearly shows the benefit of the proposed method, which allows...
Fig. 3: Spatial performance of direction based LBB [7, 8]. Only LOS regions are well covered.

In order to obtain good precoders in areas where classical LBB approach fails, again owing to the incapacity of handling NLOS channels.

In order to assess the applicability of the proposed method, it is interesting to vary the number of training channels $N$ in order to determine which density of training channels is required. To that aim, the results in terms of average and median correlation are shown as a function of $N$ on Fig. 5. From this figure, it can be seen that, obviously, the greater $N$ the greater the test correlation. However, one can see that the proposed method starts to perform well (on test data) for $N > 3000$. The area in which users can be located spans a total surface of $20520 \text{m}^2$, which means that the proposed method requires approximately one training channel every $\frac{20520}{3000} \approx 7 \text{m}^2$ on average to perform well. Such an empirical result is important in order to determine the time duration of the training phase in which both channels and locations have to be collected in order to build the database used to train the neural network.

5. CONCLUSION

In this paper, a location based beamforming method was proposed. It is based on a neural network comprising RFFs allowing to learn functions of high spatial frequency. The method was empirically assessed on realistic synthetic channels, yielding very promising results. Indeed, it is able to handle both LOS and NLOS channels whereas previously proposed methods perform well only for LOS channels. This shows the capacity of the proposed structure to interpolate well between training points thanks to RFFs which inject prior information on the learned mapping.

In the future, the method could be extended in several ways. First of all, the distribution of frequencies used to build the RFFs could be optimized to further enhance performance. It would also be interesting to aim at predicting not only an appropriate precoder but directly the channel vector. This would amount to summarize the whole propagation environment in the weights of a neural network, and could serve many applications, such as channel mapping [31, 32] (in space) or radio environment compression.

6. REFERENCES

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