DEFORM: A Practical, Universal Deep Beamforming System

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ABSTRACT
We introduce, design, and evaluate a set of universal receiver beamforming techniques. Our approach and system DEFORM, a Deep Learning (DL)-based RX beamforming achieves significant gain for multi-antenna RF receivers while being agnostic to the transmitted signal features (e.g., modulation or bandwidth). It is well known that combining coherent RF signals from multiple antennas results in a beamforming gain proportional to the number of receiving elements. However in practice, this approach heavily relies on explicit channel estimation techniques, which are link specific and require significant communication overhead to be transmitted to the receiver. DEFORM addresses this challenge by leveraging Convolutional Neural Network to estimate the channel characteristics in particular the relative phase to antenna elements. It is specifically designed to address the unique features of wireless signals complex samples, such as the ambiguous 2π phase discontinuity and the high sensitivity of the link Bit Error Rate. The channel prediction is subsequently used in the Maximum Ratio Combining algorithm to achieve an optimal combination of the received signals. While being trained on a fixed, basic RF settings, we show that DEFORM’s DL model is universal, achieving up to 3 dB of SNR gain for a two-antenna receiver in extensive experiments demonstrating various settings of modulations, bandwidths, and channels. The universality of DEFORM is demonstrated through joint beamforming-relaying of LoRa (Chirp Spread Spectrum modulation) and ZigBee signals, achieving significant improvements to Packet Loss/Delivery Rates relatively to conventional Amplify-and-Forward (LoRa PLR reduced by 23 times and ZigBee PDR increased by 8 times).

1 INTRODUCTION
The success of wireless communications was accompanied by a dramatic crowding of the RF spectrum. Beamforming is a widely used spatial filtering technique to steer RF emissions towards/from other devices. It enables array and diversity gains of multiple-input-single-output (MISO) systems [8, 30], and canceling interference from unwanted sources. Beamforming was extensively investigated in a variety of applications such as in radars, sonars, acoustics, astronomy, and even medical devices design [20]. Beamforming and more advanced MIMO techniques are widely used in systems targeting high throughput and spectral efficiency such as cellular systems since the third generation 3GPP 3G, and IEEE 802.11n.

Extensive research was conducted on beamforming [5, 21, 31, 33, 37]. However, beamforming in today’s systems requires explicit mechanisms such as sounding and feedback in 802.11. Demodulation Reference Signal (DMRS) in 5G, training sequences, etc. This approach introduces critical limitations: Firstly, it results in significant overhead to transmit reference signals and estimate the channel. Secondly, accurate channel estimation typically exhibits long delay that is undesirable in fast-changing channels. Thirdly, it requires compatibility between the transmitter and receiver (to agree on when, what, and how reference signals are transmitted).

Therefore, a universal beamforming scheme is highly desirable as it not only reduces the overhead but can also be used as a technology-agnostic component on the RF front end, and enable new applications such as relaying arbitrary signals. A universal beamformer can support the increasing heterogeneity of wireless technologies operating over the same spectrum. An example of application is a drone equipped with a technology-agnostic relay enabling communications between devices without line-of-sight in scenarios of disaster recovery bringing connectivity to first-responders and other ad hoc communications. Another application is a universal beamforming-relay to extend the range and bridge IoT devices operating on the same frequency. Most IoT devices are low-cost and not equipped with beamforming capabilities.

Recently, Machine Learning techniques were explored in support of beamforming. For instance, ML schemes were developed for selecting a beamforming scheme out of two possibilities maximum ratio transmission (MRT) or zero-forcing (ZF) beamforming [18]. Beamforming with Deep Learning was also recently investigated specially for OFDM systems, and without our goals of universality [35]. Furthermore, the vast majority of prior is limited to analytical and simulations results. In this work, we introduce a set of techniques, and their extensive experimental evaluations demonstrating the feasibility and practicality of universal beamforming for wireless receivers using Deep Learning. Our approach and system denoted DEFORM, is agnostic to the specifics of transmitted signals such as modulation, bandwidth or standard. DEFORM is designed around a deep convolutional neural network (CNN) augmented with a Maximum Ratio Combiner (MRC). It is specifically designed to address the unique features of wireless signals complex samples, such as the 2π phase ambiguous discontinuity. Also, RF links targeting low Bit Error Rates (e.g., below $10^{-4}$) are sensitive to the typical variations and outliers in the continuous-valued estimations of neural network models [4]. DEFORM addresses these challenges successfully achieving the optimal beamforming gain using only two receiving antennas even in multi-path environments. Existing systems addressing multi-path effects typically require more antennas, or extensive support from other sensing hardware. Furthermore, our universal beamforming-relay approach based on DEFORM significantly outperforms the conventional Amplify-and-Relay, for enhancing LoRa (modulated by Chirp Spread Spectrum) and ZigBee. This work also opens the field to DL applications of multi-antenna systems for interference cancellation and multi-user communications. Our contributions can be summarized as follows:

• A design, model, and algorithm for a novel Deep Learning-based universal receiver beamformer (DEFORM). To the best of our knowledge, our work is the first in the literature that leverages DL to enable multi-antenna receivers for beamforming RF signals.
irrespective of modulations, bandwidths, or wireless channels (and not requiring any explicit mechanisms such as sounding).

- A two-antenna Software Defined Radio receiver prototype leveraging DEFORM that supports arbitrary and unseen modulations, bandwidths and channels. The training of DEFORM is performed only on a fixed basic RF settings (single modulation (BPSK) and bandwidth (1 MHz) in a cable environment) and bolstered with efficient RF dataset collection process with phased augmentation to improve dataset diversity.
- DEFORM is extensively evaluated (BPSK, QPSK, 8-PSK, 16-QAM, GMSK with various bandwidth settings), first using RF coaxial cables (for reproducibility) emulating channel effects, then in over-the-air setups. DEFORM achieved the optimal 3 dB gain of a two antenna receiver.
- DEFORM is demonstrated for relaying LoRa and ZigBee signals connecting two devices unable to establish direct communication. We show that DEFORM achieves LoRa Packet Loss Rate of up to 23 times lower and ZigBee Packet Delivery Rate of 8 times higher than the single-antenna Amplify-and-Forward method.

## 2 Problem and Approach

Receiver (RX) beamforming aims to optimally combine the received signals from multiple antennas to maximize the Signal-to-Noise Ratio (SNR). In this section, we identify and formulate the RX beamforming problem and present the key ideas of DEFORM.

### 2.1 Theory and Challenge

Consider a transmitter and a receiver communicating through a slow fading channel. The receiver has $N$ antenna elements, where we model the signal $R_i$ received by antenna $i$ consisting of the transmitted signal $S$ adjusted by the channel gain $h_i$ and the additive Gaussian noise $N_i$:

$$ R_i = h_i S + N_i = s_i + N_i $$

(1)

Receiver beamforming aims to leverage the diversity of the independent wireless channels between the transmitting and receiving antennas by combining the receiving branches with the adequate complex beamforming weights:

$$ R_{\Sigma} = \sum_{i=1}^{N} a_i R_i = \sum_{i=1}^{N} (a_i s_i + a_i N_i) $$

(2)

The beamforming weights $a_i$ are chosen to maximize the combining Signal-to-Noise Ratio (SNR), which is given by:

$$ SNR_{\Sigma} = \frac{\left(\sum_{i=1}^{N} a_i s_i \right)^2}{N_0 \sum_{i=1}^{N} |a_i|^2} $$

(3)

where we assume the noise in each branch is independent and has the same Power Spectral Density (PSD) $N_0$. The maximization of $SNR_{\Sigma}$ is solved using the Cauchy-Schwartz inequality [8] and yields the optimal weights:

$$ \hat{a}_i = \frac{s_i^*}{\sum_{j=1}^{N} |s_j|} \quad \forall j \in 1, ..., N $$

(4)

where the denominator is the scaling factor for the weights. Substitute to Equation (3), we now have the combining SNR:

$$ SNR_{\Sigma} = \frac{\sum_{i=1}^{N} s_i^2}{N_0} = \frac{N}{\sum_{i=1}^{N} |s_i|^2} $$

(5)

The optimal combining SNR is the sum of the SNRs from all receiving branches. In the best case scenario when all branches have the same SNRs, this beamforming technique (also known as Maximal-Ratio Combining [8]) can achieve a final SNR of $N$ times the SNR acquired from a single branch. For instance, with a two-antenna receiver we gain twice the SNR (corresponding to a 3 dB gain).

The main challenge to achieving the optimal combiner is how to estimate the optimal weight $\hat{a}_i$ for each receiving branch $i$. In Equation (4), $\hat{a}_i$ is dependent on $s_i$ ($s_i = h_i S$), which is unknown to the receiver. Conventional techniques, which are still extensively used in OFDM or MIMO systems [29], have to insert mutually-known data such as a training sequence or pilot symbols into the transmitted signals that causes significant communications overhead. Meanwhile, phased-array systems [30] do not require channel estimation, but are especially inaccurate against multi-path effects which add up the channel gains from multiple paths and distort the channel characteristics of the direct path.

### 2.2 Approach

We design the receiver beamforming system with the goal to estimate the optimal beamforming weights $\hat{a}_i$ accurately. We first reformulate $\hat{a}_i$ from Equation (4) in the polar representation:

$$ \hat{a}_i = \frac{|s_i|}{\sum_{j=1}^{N} |s_j|} e^{-j \theta_i} \quad \forall j \in 1, ..., N $$

(6)

To find $\hat{a}_i$, we need to estimate the amplitude $A_i = \frac{|s_i|}{\sum_{j=1}^{N} |s_j|}$ and the phase $\theta_i$. First, we present a simple approach to estimate the amplitude. Out of $N$ receiving branches, we pick an arbitrary branch $k$, and approximate $A_i$ for every branch $i$ with the transformation:

$$ A_i = \frac{|s_i|}{\sum_{j=1}^{N} |s_j|} \approx \frac{|R_i|}{\sum_{j=1}^{N} |R_j|} $$

(7)

where the ratio $\frac{|s_i|}{|R_i|}$ is approximated by the amplitude ratio of received signals $\frac{|s_i|}{|R_i|}$ for every $i \neq k$ (if $i = k$, the ratio is 1). It is easy to see that the approximation is correct when $|s_i| = |s_k|$. Nonetheless, as $|s_i|$ gets significantly bigger than $|s_k|$, the approximation error increases. The worst case scenario is when $|s_k| \gg |s_i|$ and at the same time, the signal power $|s_k|^2$ is close to the noise PSD $N_0$. Fortunately, there are two reasons that justify the approximation in the scenarios we consider. Firstly, $|s_i| \gg |s_k|$ is equivalent to $|R_i| \gg |R_k|$, and both make $A_i$ very close to zero. In this extreme case, the beamforming can only provide the SNR as good as the
best receiving branch, since the other branches have beamforming weights of zero and do not impact the combining signal $R_Y$. Secondly, in practice, many wireless communications typically require a sufficiently high SNR to operate, for example, at least 20 dB is required for Wi-Fi technologies to achieve high data rates [6]. Moreover, as we will discuss in later sections, a SNR of 10 dB is the minimum requirement for the RX to achieve a target Bit Error Rate of less than $10^{-4}$. With a sufficiently large SNR on each antenna (e.g., 10 dB), the approximation error is negligible (less than 5%) even when the SNR on the other antenna is substantially high (e.g., 30 dB).

Estimating the phase $\theta_i$ is more challenging, especially in the absence of explicit information from the transmitter (e.g. reference signal or sounding mechanism). This is due to the effect of multi-path propagation, in which the constructive and destructive phase combining of multiple copies of the signal traversing the space is typically unpredictable. At the same time, estimating the phase is a critical requirement for the optimal beamforming weights to make the receiving branches co-phased in the combined signal. Without this, the branch signals will not add up coherently and the workflow of DEFORM is depicted in Figure 1, where the branch which makes the received signal from branch $\bar{e}_i$ (e.g., $\bar{e}_i$) resulting in the output signal which is sent to the decoder to decode the data. The design and optimization of the most important module - phase estimation, will be presented in details in Section 3.

3 PHASE ESTIMATION FOR UNIVERSAL RX BEAMFORMING

In this section, we present the design of DEFORM’s phase estimation module, which leverages a Convolutional Neural Network (CNN) to accurately estimate the relative phases (which is critical for DEFORM to calculate the beamforming weights), supported by optimization techniques specially designed to address the unique features of wireless signals complex samples. We have considered several neural network architectures and choose CNN because it is very powerful to extract relevant low-level features embedded in data of various types [3, 14, 23, 28]. It is natural to leverage such capabilities to disentangle the signal components and provide accurate phase estimations.

3.1 Neural Network Design

Goals. We define three goals for the design of the CNN model. Firstly, the model should be able to process the continuous stream of I/Q data efficiently. Feeding a very long stream of samples to the CNN would significantly increase the size of the network as well as the computation cost. Secondly, the model should output the real-valued relative phase with the smallest estimation error as possible. Finally, the network estimation needs to be fast and computationally efficient. We note that there is a natural trade-off between the second and third goals, therefore we aim to find the best model that achieves optimal accuracy and speed throughout the training and validation processes.

CNN Architecture. To reduce the computational cost of the network, a long stream of RF samples is divided into equal chunks of $M$ samples ($M = 128$ in our implementation). As complex RF samples are composed of In-phase and Quadrature components, it is intuitive to view a block of $M$ samples as a matrix of size $2 \times M$ where each entry is an In-phase ($1^{\text{st}}$ row) or Quadrature ($2^{\text{nd}}$ row) value. The matrices of $N$ antennas ($N = 2$ in our current system) are stacked along the third dimension, which consequently form a $2 \times M \times N$ tensor of real-valued elements for each input data.

After having done a network structure search, we converge on an optimized structure that achieves good performance in both processing speed and estimation correctness. We find that as the network gets deeper, the estimation error generally decreases. However, after reaching a certain depth, the improvement becomes less significant. As one of our goals is estimation efficiency, we choose the fastest model that can achieve comparable performance with deeper models. We justify our selection by comparing with popular
3.2 Rotational Double-Output

Theoretically, the neural network is required to provide one estimation for one relative phase between two receiving branches. Nonetheless, while investigating various models, we find that the phase estimation exhibits abrupt variations as the relative phase gets very close to the boundaries of phase values (i.e., upper and lower bounds of the ranges $[-\pi, \pi]$ or $[0, 2\pi]$). More specifically, the behavior is described as follows:

- If the network estimates the phase in $[-\pi, \pi]$, then the estimation abruptly fluctuates when the true value is either in $[-\pi, -\pi+\epsilon]$ or $[\pi - \epsilon, \pi]$.

- If the network estimates the phase in $[0, 2\pi]$, then the estimation abruptly fluctuates when the true value is either in $[0, \epsilon]$ or $[2\pi - \epsilon, 2\pi]$.

where $\epsilon = 0.2\pi$ based on our investigation during the validation process. We believe that such behavior is related to the discontinuity of the phase when it travels beyond the boundaries, for example, above $\pi$ and below $-\pi$ for $[-\pi, \pi]$. Because of the rotational characteristics (i.e., $2\pi + \theta = \theta \mod 2\pi$), the phase will be shifted backward by an angle of $2\pi$. This confuses the estimation model because those values are far apart (by a distance of $2\pi$) in the numerical axis.

To overcome this problem, we enhance the CNN model with what we call a rotational double-output feature, which incorporates two estimation outputs $E_1$, $E_2$ (as depicted in Figure 2) for the relative phase converted in $[-\pi, \pi]$ and $[0, 2\pi]$, respectively. We note that the two estimations do not experience abrupt variations simultaneously. Therefore, if we know which output is experiencing errors and not usable, we can select the other output. The double-output selection is described in Algorithm 1, where we define $SELECT_1$ and $SELECT_2$ to imply the correctness of the respective outputs $E_1$ and $E_2$. If both indicators are True, the algorithm selects the predictions with a smaller Standard Deviation (STD) in a history windows of $K = 10$ elements. In the last case, the average value of two outputs is taken. We note that eventually, $E_2$ should be converted to $[-\pi, \pi]$ to avoid inconsistencies of the selections:

$$E_2 = \begin{cases} E_2 - 2\pi & E_2 > \pi \\ E_2 & \text{else} \end{cases}$$

(9)

where $E_2$ is the mean of $K = 10$ last predictions in $[0, 2\pi]$. With this feature, our CNN is trained to minimize the modified Mean Squared Error:

$$\mathcal{L}_0 = (\Delta \theta_0 - E_1)^2 + (\Delta \theta_0 - E_2)^2$$

(10)

where $\Delta \theta_0$ and $\Delta \theta_0$ are the conversions of the true relative phase $\Delta \theta$ in $[-\pi, \pi]$ and $[0, 2\pi]$, respectively.

3.3 Stabilizing The Estimations

When the DEFORM beamforming system directly uses the continuous-valued phase estimations to compute the beamforming weights, it becomes susceptible to variations and outliers as typically seen in neural network models [9]. Meanwhile, practical wireless communication systems and standards require not only a high precision, but also the stability in the estimations as they target a Bit Error Rate in the orders of $10^{-4}$ for a proper operation. Short-term changes on some samples have significant and lasting impacts on the whole packet decoding and easily aggravate the Bit Error Rate. To address this problem, we propose two different methods for stabilizing the phase estimations, described as follows.

**Temporal smoothing.** Because wireless channels typically change with a much slower rate than the incoming rate of RF samples (128 RF samples collected at 1Msamp/s is only 0.128 ms long), we can stabilize the prediction at a given instant by combining with
estimations from the recent past. We stabilize the estimation and improve the robustness of the RX beamforming by using the exponential smoothing function:

$$E^T = E_{cur} \lambda + E^{T-1}(1 - \lambda)$$  \hspace{1cm} (11)$$

where the final phase estimation at the current time period $T$ is computed using the estimation from previous period $T - 1$ and the current CNN output estimation acquired from Algorithm 1. Parameter $\lambda$ controls the smoothness of the result, and is chosen with the best value $\lambda = 0.2$ through the validation process. It should be noted that if the offset between $E^{T-1}$ and $E_{cur}$ is significant (exceeding a certain threshold $a$, i.e. $a = 1.5\pi$), we should select the instantaneous estimation $E_{cur}$ instead. This behavior is typically seen when the channel changes from being vacant to being occupied by the transmitter. In this case, a drastic change of the phase estimation indicates the beginning of a packet that we should account for.

Multi-trial averaging. Temporal smoothing requires multiple chunks of RF samples to achieve a stabilized prediction. In cases when the number of samples is limited but higher computation power is available (e.g., offline processing), we can instead stabilize the prediction by processing the same samples multiple times (thus multi-trials). The algorithm is described in Algorithm 2. To avoid repeatedly getting the same estimation, in each trial, we augment the RF samples by artificially adjusting the phases with a random $\theta_{rand}$. We note that after being processed by the CNN, the current estimation $E_{cur}$ needs to be re-adjusted to account for the prior augmentation. To deal with possible drastic changes, we categorizes the estimations across $N$ trials into two clusters based on their values: We keep the average estimations $E^{T}_{C_1}$ and $E^{T}_{C_2}$ for the clusters at time period $T$. An estimation $E_{cur}$ for any trial is categorized into cluster $C_1$ if $|E_{cur} - E^{T}_{C_1}| < a$ where $a = 1.5\pi$ is the categorization threshold, otherwise cluster $C_2$. Finally, after $N$ trials, we count and compare the number of elements in each group, and choose the average estimation where the corresponding cluster has more elements, as the final estimation for current period.

Algorithm 2: Multi-trial averaging

**Data:** $N$, RF samples in period $T$

**Result:** $E^T$

**repeat** $N$ times

1. Artificially adjust the phases with a random $\theta_{rand}$.
2. Compute instantaneous $E_{cur}$ using Algorithm 1;
3. Update $E_{cur}$ to original value with $\theta_{rand}$;
4. Categorize $E_{cur}$ into two clusters $C_1, C_2$;

**end**

- Count cluster elements $COUNT_{C_1}, COUNT_{C_2}$;
- Calculate average estimations $E^{T}_{C_1}, E^{T}_{C_2}$;
- if $COUNT_{C_1} > COUNT_{C_2}$ then
  - $E^T \leftarrow E^{T}_{C_1}$
- else
  - $E^T \leftarrow E^{T}_{C_2}$

**end if**

4 EXPERIMENTAL EVALUATION

We conduct extensive experiments to validate the universality of DEFORM for different modulations, bandwidths, and wireless channels. To train the DL model, we use the techniques described in Section 3.4 and collect a dataset of over 167 million complex RF samples transformed into 654,553 real-valued tensors of size $2 \times 128 \times 2$, each corresponds to a total of 256 samples collected by the two RX
antennas. For this dataset, we use an Ettus USRP B210 software-defined radio (SDR) with the TX implemented using GNU Radio [1] to transmit BPSK signals (SNR ranging from 0 to 35 dB) to the RX through two identical coaxial cables with a fixed TX bandwidth of 1 MHz. The RX bandwidth is maintained at 1 MHz for the whole dataset. The dataset is split into training, validation, and test sets with ratio 0.64 : 0.16 : 0.2, respectively. While being trained with a fixed set of RF settings, DEFORM still performs very well on other unseen and more sophisticated settings of modulations, bandwidths, and channels. To the best of our knowledge, our work is the first universal RX beamforming system in the literature that is designed using Convolutional Neural Network (CNN) and extensively evaluated for practical, universal RF beamforming capabilities.

4.1 DL Model Comparison

To validate our design of neural network and highlight the benefits of our model for the specific task of phase estimation, we evaluate and compare the CNN model with three popular CNN architectures: VGG16 [28], ResNet18 [10] and MR-CNN [23] using the test set of our beamforming dataset. All models are implemented using PyTorch library [24], then trained and tested on a NVIDIA GeForce GTX 1080 GPU using Adam Optimizer [15] and ReduceLRonPlateau Learning Rate Decay scheduler [36] with initial learning rate $lr = 0.005$. The evaluation metrics are estimation error and network forward time. Mean Square Error loss function (Equation (10)) is used to calculate the estimation error. We use torch.cuda.synchronize from PyTorch to synchronize CUDA operations before and after the neural network propagation function and calculate the elapsed time of such function accurately. Figure 4 compares the estimation error of models on the test set and the network forward time. It is clear that in terms of estimation correctness, DEFORM outperforms MR-CNN with a test error of 12.6 times lower (0.26 compared to 3.28). Moreover, DEFORM’s CNN is 8 times faster than VGG16 and 12 times faster than VGG16 while having comparable estimation error (equal to ResNet18, and only 0.06 lower compared to VGG16). Compared with these two models, DEFORM is lightweight, more computationally efficient, and can quickly provide a phase estimation with high precision, which makes it more suitable for real-time and embedded systems.

4.2 Over-the-cables Evaluation

First, we evaluate DEFORM’s performance in a relatively idealistic environment where the RF signals propagate through coaxial cables, where multi-path and other fading effects are absent. Data packets are sent from the TX to the two analog inputs of RX (devices are Ettus USRP B210 with SDR) through a pair of identical cables (So the received signals have similar SNRs). TX signal is modulated using differential BPSK, QPSK, 8-PSK, GMSK and 16-QAM techniques, and with a fixed TX bandwidth of 1 MHz and center frequency of 795 MHz. We assess DEFORM’s wideband capability by using different values of RX bandwidths, with a random shift of RX center frequency when the bandwidth is larger than 1 MHz (Figure 5).

Evaluation for Model Optimizations. To highlight the impact of the optimization techniques, we measure and analyze the received Bit Error Rate (BER) in five cases: (1) When beamforming is turned off and one of the two received signals is selected for decoding (Note that in our over-the-cables experiments, received signals have similar SNRs), (2) when beamforming is used with the single-output CNN (BF-SO), or (3) with the rotational double-output CNN (BF-DO), and when DEFORM is enabled with double-output CNN and (4) temporal smoothing (DEFORM-TS) or (5) multi-trial averaging (DEFORM-MT) optimization. To calculate BER, we record TX and RX signals at the SDRs and transfer them to the host computer to compare and count the bit errors. Figure 7 illustrates the evaluation results, where we compare the approaches with BPSK transmissions. For each scenario, RX signal features (relative phase, bandwidth) are artificially adjusted to show the effects of model optimizations: For Figure 7a, because $\Delta \phi$ is far from the phase boundaries, all beamforming settings including the baseline single-output CNN achieve 3 dB gain compared to non-beamforming. When $\Delta \phi = \frac{9\pi}{10}$ which is very close to $\pi$ (where the estimation of the single-output CNN estimating phase in $[−\pi, \pi]$ experiences abrupt variations - Figure 7b), the efficiency of BF-SO decreases to less than 1 dB gain, while BF-DO and further optimization settings maintain the 3 dB gain. When we increase RX bandwidth to 6 MHz (Figure 7c), DEFORM-TS and DEFORM-MT outperform the baseline CNNs with
in Figure 10 that in most cases, DEFORM can achieve 2 dB of SNR gain when compared to the better receiving branch. Interestingly, in some cases the gain is approximately 3 dB, such as for QPSK-6MHz, or GMSK-6MHz at BER = 10⁻². Moreover, when comparing with the worse branch, the gain can reach up to 4 dB, such as in QPSK-1MHz, 8PSK-1MHz and 8PSK-4MHz at BER ≥ 10⁻⁴.

**Over-the-air with no LOS.** In the second over-the-air experiment, we place the multi-antenna RX at the location of the red cross in our testbed floorplan (Figure 9) and move the TX to different locations marked by the blue numbered circles. Figure 9 only shows the basic floor plan/architecture of the office, and omits the presence of numerous large-sized objects, such as computers or lockers. At each predefined TX location, the TX transmits data packets with a randomly selected modulation, and the RX also randomly selected the RX bandwidth to receive the signal. The result of BER analysis is shown in Table 1. It is clear that DEFORM achieves significantly lower BER than any single branch in all measurements. For example, at location #4, the measured BER of DEFORM is 100 times lower than branch 1 and 10 times lower than branch 2. Meanwhile at location #13, DEFORM’s BER is approximately 30 times lower than branch 1 and more than 100 times lower than branch 2. These results demonstrate the universality of DEFORM beamforming system, as it was trained on a single modulation (BPSK) and bandwidth (1 MHz).

### 5 UNIVERSAL RF BEAMFORMING-RELAY

We demonstrate the universality of DEFORM with the beamforming-relay application for LoRa [27] and ZigBee [2] - two popular IoT technologies. In recent years, LoRa and ZigBee have seen significant rise in popularity in enabling the IoT communications thanks to the long range communication capability, low power requirement, and low cost. However, wireless channels are highly dynamic, and the communications can experience significant fading if the direct path is not present. An intermediate relay node that has the Line of Sight (LOS) to the transmitter and receiver can help maintain the communications. Motivated by this, we conduct experiments where DEFORM is deployed as a universal beamforming-relay system when the direct LoRa/ZigBee communications are not possible. The relay system leverages DEFORM with a modification where the combining signal is relayed to the TX chain instead of being sent to the decoder (as in the original workflow in Figure 1). In our
setup, the location of relay node is fixed, while the TX/RX nodes are mobile within a small range around the locations that create a LOS with the relay node, as marked in Figure 11a and pictured in Figure 11b.

First, we report on DEFORM performance in relaying LoRa signal. We note that the original CNN model (trained for differential BPSK modulation) optimized by Temporal Smoothing (Section 3.3) is maintained for all the experiments. DEFORM beamforming system, is agnostic to RF signal characteristics, and its capability to improve the quality of the relay signal from LoRa, a chirp spread spectrum (CSS) modulation, is another strong indicator of its universality. We use Ettus USRP X310 for the relay node to achieve a better TX power, and Heltec ESP32 Development Kit for LoRa devices. It is noted that TX gain is always set to maximum and RX gain is fixed at the relay node. Also, to illustrate the system capability, LoRa’s TX power is configured to the lowest level. We conduct 4 experiments, each consists of 4 measurements of 1 minute: The first measurement determines the Packet Loss Rate of direct TX-RX communications, in which we got 100% for all experiments, confirming that the direct communications are not possible. The next two measurements determine the PLR of Amplify-and-Forward relay from a single antenna, and the last one provides the PLR for beamforming-relay using DEFORM. The result of the measurements shown in Table 2 indicates that the beamforming-relay approach achieves less than 10% Packet Loss Rate (PLR), significantly better compared to typical single-antenna Amplify-and-Forward relay of LoRa communications (PLR is up to 12 and 23 times lower than the stronger and weaker antennas, respectively).

We repeat the same experiments for relaying ZigBee communications. We use two XBee-PRO 900HP equipped with the XBee Grove Development Boards for the TX and RX ZigBee nodes. It is noted that because ZigBee supports shorter communication range than LoRa, we set the TX power of Zigbee node to maximum. Due to such limited capabilities of ZigBee for long-range communications, we focus on the Packet Delivery Rate (PDR) of the direct and relay communications. We acquire measurements for 6 sets of 1-minute experiments in which the direct Zigbee communications are not feasible (with 0% PDR). It is clear to see in the results (Table 3) that the universal beamforming-relay still outperforms the single-antenna Amplify-and-Forward: With DEFORM, We are able to achieve a successful packet reception as high as 93% of the stronger antenna

### Table 2: Packet Delivery Rate (PDR) in LoRa communications

| SNR | logBER | BPSK-6MHz | DEFORM-TS | DEFORM-MT | No BF |
|-----|--------|-----------|-----------|-----------|-------|
| 1   | 2      | 3         | 4         | 5         | 6     |

### Table 3: Packet Delivery Rate (PDR) in ZigBee communications

| SNR | logBER | 8-PSK-6MHz | DEFORM-TS | DEFORM-MT | No BF |
|-----|--------|------------|-----------|-----------|-------|
| 1   | 2      | 3          | 4         | 5         | 6     |

Figure 8: BER analysis of over-the-cables communications for different modulation schemes and RX bandwidths. DEFORM is evaluated with Temporal Smoothing (DEFORM-TS) and Multi-Trial Averaging (DEFORM-MT).

Figure 9: Non-LOS over-the-air testbed environment in a 50 ft. × 100ft. lab office (left) and RF experiment settings (right). TX locations are marked by the blue numbered circles, while the fixed location of RX is marked by the red cross.
Figure 10: BER analysis of over-the-air communications with inherent LOS on different modulations and RX bandwidths.

Figure 11: Testbed environment for beamforming-relay experiments. TX and RX are mobile within a small range from the marked spots on the map. (a) Satellite view map. (b) Viewpoints of relay node’s location from TX (left) and RX (right).

relay (In experiment #3, DEFORM achieves 42.57% successful reception while the stronger antenna only achieves 21.92%), and up to 858% of the weaker antenna relay (Experiment #2).

6 DISCUSSION AND RELATED WORK

It is clearly seen that the Deep Learning-based approach of DEFORM can be extended to larger multi-antenna systems to achieve even higher than 3 dB gain. For a RF receiver system of \( N \) receiving antenna elements, the deep learning architecture can be modified to have \( 2 \times (N - 1) \) outputs in which two estimations are made for each relative phase between the pre-selected antenna and one other antenna. The new requirement of such systems are time synchronization mechanisms for RX radios as typical wireless peripherals have a limited number of antennas (Most of Ettus’s USRPs only support 2 simultaneous RX channels [26]).

Our current system assumes that there is only one user in the observing spectrum at any given time. The problem becomes more challenging when multiple users are simultaneously transmitting on the same frequency band, which results in significant interference that damages the phase structure in the captured RF samples. In this case, the prediction could be accurate for only one user, or even not working for any users. It would be interesting to investigate the CNN’s capability for multi-band spectrum and collision analysis in the future work.

Theoretical aspects of beamforming have been investigated in the literature [5, 21, 31, 33, 37], including some efforts to build the so-called blind beamformers [5, 11, 37], that estimates the channel phase offsets without explicit knowledge from the transmitter. The practicality of those methods and systematic deployment guidelines, however, are still open questions. Popular wireless communications technologies still utilize informed beamformer approaches that estimate the channel using information from the transmitter such as pilot sequence [38] in IEEE 802.11 or reference signal [19] in 5G radios. As discussed, this approach typically requires significant communication overhead, and is limited to specific TX-RX setup and communication techniques.

The capabilities of phased-array systems [30] have been investigated for decades. Popular approaches using phase-array to efficiently extract the phase characteristics of signal in the presence of noise are MUSIC and ESPRIT [30]. Nonetheless, it is widely understood that these approaches are ineffective against multi-path effects, where coherent signals from multiple transmitting path distort the phase patterns at the receiver [25]. Recently, several works in localization areas such as ArrayTrack [34], SpotFi [16], or
Table 1: BER analysis of non-LOS over-the-air experiment. The indexes corresponds to the numbered marks in Figure 9. Cross mark indicates no packets are detected resulted by insufficient SNR. NaN indicates a BER of zero.

| Branch 1          | Branch 2          | DEFORM       |
|-------------------|-------------------|--------------|
| BER (log scale)   | BER (log scale)   | BER (log scale) |
| 1                  | 1                 | 1            |
| -0.43             | -0.74             | -1.15        |
| -0.81             | -0.79             | -1.07        |
| -1.34             | -1.34             | -0.75        |
| -1.11             | -1.11             | -1.07        |
| -0.75             | -0.75             | -1.07        |
| -0.75             | -0.75             | -1.07        |
| -1.07             | -1.07             | -1.34        |
| -0.75             | -0.75             | -1.07        |
| -1.07             | -1.07             | -1.34        |
| -1.07             | -1.07             | -1.34        |
| -1.07             | -1.07             | -1.34        |

Table 2: Comparison of Packet Loss Rate for LoRa direct and relay (RL) communications.

| Index | Direct Antenna 1-RL | Antenna 2-RL | DEFORM-RL |
|-------|----------------------|--------------|-----------|
| 1     | 100                  | 22.33        | 11.65     | 0.97      |
| 2     | 100                  | 4.85         | 20.45     | 2.91      |
| 3     | 100                  | 20.39        | 12.91     | 8.74      |
| 4     | 100                  | 16.67        | 7.84      | 0.98      |

Table 3: Comparison of Packet Delivery Rate for ZigBee direct and relay (RL) communications.

| Index | Direct Antenna 1-RL | Antenna 2-RL | DEFORM-RL |
|-------|----------------------|--------------|-----------|
| 1     | 0                    | 57.53        | 54.11     | 77.4      |
| 2     | 0                    | 63.01        | 8.22      | 70.55     |
| 3     | 0                    | 21.92        | 15.75     | 42.47     |
| 4     | 0                    | 73.97        | 21.23     | 76.03     |
| 5     | 0                    | 26.03        | 0         | 39.73     |
| 6     | 0                    | 47.94        | 28.08     | 75.34     |

Ubicarse [17] have investigated this problem, and achieved some improvements. However, those systems have certain limitations considering the goal of universal beamforming. Firstly, they typically require a lot of antennas [34], or other types sensing hardware such as gyroscope or accelerometer [17]. Secondly, they rely on specific assumptions of radio mobility to easily distinguish between the direct path and reflection paths, and therefore are not universal. Finally, they are designed specially for localization, i.e. finding the Line-of-Sight direction of the transmitter, thus cannot find the optimal beamforming where the reflection paths are constructive and can improve the SNR of the direct path.

Advances in Machine Learning and Deep Learning have emerged as a solution for critical problems in various areas, including wireless communications. In recent years, ML and DL approaches have been extensively utilized in various tasks such as modulation recognition [23], RF technology identification [22], or wireless localization [32]. There are also some efforts to enable ML-driven beamforming. For example, in [35], a Deep Neural Network (DNN) is developed for OFDM channel estimation. In [12], DNN is utilized for downlink MIMO beamforming. Nonetheless, those works are limited by simulated data, and specific assumptions of channel model. Furthermore, they lack the explanation and evaluation for the impact of various RF characteristics, i.e. link modulations, bandwidths, and wireless channels. Compared to those, our work is unique in multiple aspects. First, our CNN-based DL model is trained with real RF data acquired by an efficient dataset collection process. Second, our system is agnostic to different RF settings of modulations, bandwidths, and channels. Despite being trained on a fixed, basic RF settings, we can still achieve the optimal beamforming gain in complex, unseen settings. Third, DEFORM is vital for the universal beamforming-relay application that achieves Packet Loss Rate of 23 times lower for LoRa and Packet Delivery Rate of 8 times higher for ZigBee compared to the conventional Amplify-and-Relay method. Hence, DEFORM can be used as a universal RX beamforming module for existing multi-antenna RF receivers.

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