Generated Adversarial Network for Data Augmentation in Photonic-based Microwave Frequency Measurement

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***Abstract*— Deep learning is a powerful tool for enhancing performance and increasing the functionalities of a system. However, it is challenging to use deep learning to enhance hardware-based photonic systems because a large dataset that covers the whole operation range of each device is needed for achieving an accurate model. However, not all devices in a system can be controlled automatically, making the data collection process challenging and time consuming. In this letter, we use an instantaneous microwave frequency measurement (IFM) system to demonstrate the use of generated adversarial network (GAN) in deep learning platform for data augmentation. With GAN, only 75 sets of experimental data are needed to collect manually from the IFM system. The GAN augments the 75 sets of experimental data into 5000 sets of data for training the model, effectively reduces the amount of experimental data needed by 98.75%, and reduces frequency estimation error by 10 times.**

Keywords—Microwave Photonics, Instantaneous Frequency Measurement (IFM), Deep Learning, Deep Neural Network (DNN), Generated Adversarial Network (GAN), Multilayer Perceptron (MLP).

I. Introduction

In recent years, there has been rapid growth and development in the field of smart photonics, where machine-learning algorithms are used to enhance various types of photonic systems in terms of functionalities and performance, including designing optical components [1], studying optical transmission [2], designing of microwave photonic filters [3], and measuring of instantaneous microwave frequency [4], to name a few. One major hurdle to utilizing machine learning in experiments related to photonics and microwave photonic systems is the need for a large training dataset. In photonic system experiments, those training datasets are usually related to a large number of variables that cannot be generated from simulation and the dataset have to be captured manually one by one through experiment. An insufficient number of training datasets would result in inaccurate training of the machine learning model [5]. Therefore, the need for a large number of training datasets hinders the practical use of machine learning in photonics and microwave photonic systems.

Instantaneous frequency measurement (IFM) is an effective way to quickly detect the frequency of the signal of interest. Therefore, it is an essential component in air defense and military applications including electronic warfare [6], radar and satellite communications [7], deceptive intelligent systems, missile systems, and counterintelligence systems [8], to name a few. However, electronic-based IFM has several disadvantages such as being prone to electromagnetic interference, narrow bandwidth, and low frequency resolution [9]. Photonic-based IFM system has proven to surpass its electronic counterpart in the above aspects [10]. However, the photonics-based IFM systems may not have the accuracy that satisfies frequency-sensitive applications. Recently, machine learning has been used to improve the frequency measurement accuracy [4] and frequency error to the order of tens of MHz for operation range up to 20 GHz. Unfortunately, just like any machine learning-assisted microwave photonic system, a large amount of experimental dataset that covers a large range of parameters is needed to be captured experimentally for achieving an accurate machine learning model. This process is challenging and time-consuming because not all the parameters can be controlled and collected automatically. Consequently, significant degradation of the microwave photonic system performance would result if an insufficient number of datasets is used during the training of the machine learning model.

In this paper, a generated adversarial network (GAN) [5] is proposed for use in microwave photonic systems to augment real experimental dataset. A photonic-based microwave instantaneous frequency measurement system is used as the platform to investigate the efficiency of GAN for overcoming the challenges of utilizing machine learning in photonics-based experiments. According to our study, the number of training datasets needed to be experimentally captured decreases from 6000 to 75 (98.75% decrease), because GAN is capable to augment the 75 experimentally captured datasets to 5000 for training, validation, and testing of the DNN model. Frequency prediction error of only 5% (5 MHz over the range of 1 GHz to 16 GHz) and mean square error <588 kHz are resulted, essentially decreasing the frequency estimation error by 10 times compared with the non-GAN deep learning neural network [4].

II. Generated Adversarial Network and Deep Learning Neural Network for Data Augmentation in Microwave Frequency Estimation

We propose and design a GAN to assist deep neural network (DNN) for data augmentation in an experimental microwave photonic system, as shown in Fig. 1(a). The GAN consists of two sections (i) Generator - a recurrent neural network (RNN) based on long short-term memory (LSTM) and bidirectional long-short term memory (Bi-LSTM) (ii) Discriminator - a 2D convolutional neural network (CNN). The optimized hyperparameters that are used in the GAN and DNN are summarized in Table. 1 at the last part of the paper. Multi-layer perceptron (MLP) is used for the DNN with 3 hidden layers and each layer has 50 neurons, as depicted in Fig. 1(b). With the GAN, 5000 datasets can be generated based on just 75 experimental datasets.

The datasets consist of variations of RF power, frequency of the signal of interest, as well as free spectral range (FSR), and extinction ratio (ER) of the optical filter pair. The 5000 datasets generated from GAN are used for training (2500 datasets), validation (1500 datasets), and testing (1000 datasets) of the DNN model.

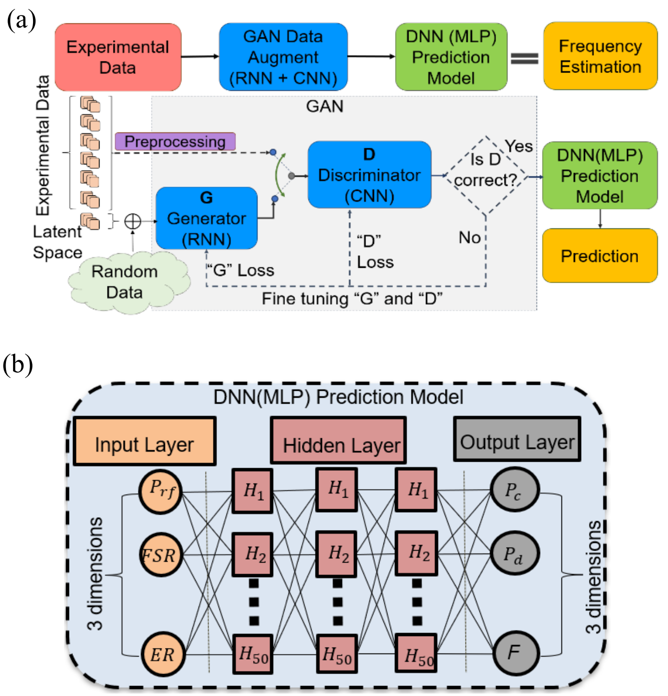

Fig. 1. (a) GAN assisted DNN architecture for data augmentation in experimental microwave photonic systems. (b) DNN MLP architecture for estimating unknown RF frequency.

III. Photonic Based Instantaneous Microwave Frequency Measurement

The photonics-based instantaneous microwave frequency measurement setup that we use for studying the GAN is a complementary optical power measurement approach, as shown in Fig. 2(a) [4]. The unknown microwave signal-of-interest is modulated onto a single wavelength optical carrier (LD), Fig. 2(b)(i), via an electro-optic intensity modulator (EOM). The modulator is biased at the null point such that carrier suppressed double sideband (CS-DSB) modulation is resulted, as illustrated in Fig. 2(b)ii. The CS-DSB signal is then sent to an optical comb filter pair with complementary spectral responses, i.e. one with a negative slope response (constructive interference) and one with a positive slope response (destructive interference). As a result, the microwave frequency of the signal-of-interest can be determined by evaluating the filtered optical power at the filter pair using optical power meters [4], as illustrated in Fig. 2(b)iii-iv. The filter pair could have a sinusoidal or triangular filtering profile, but that triangular profile is used in this experiment to improve the linearity and dynamic range of the measurement system. An RF signal-of-interest that is sweeping from 1 to 16 GHz with a step of 200 MHz is used. 75 datasets are captured experimentally by setting the RF power at 0 dB, ER = 20 dB, and FSR = 50 GHz, as shown in Fig. 2(c). In a non-GAN-based DNN system, 6000 datasets are needed for machine learning [4], while the proposed GAN-based DNN only needs 75 experimentally captured dataset, resulting in a 98.75% decrease in experimental data needed.

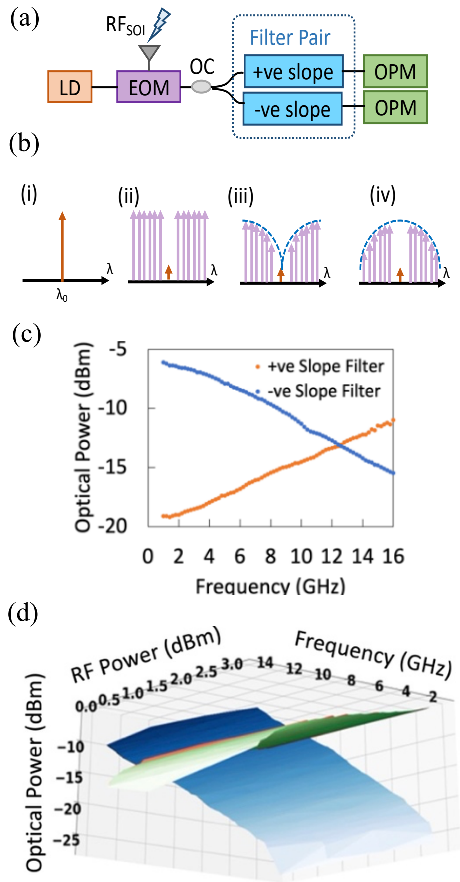

Fig. 2. (a) Schematic illustration of the photonics-based microwave frequency estimation system. (b) Illustration of optical spectra at a different stage of the frequency estimation system. (c) 75 datasets are obtained experimentally for use in GAN for data augmentation. (d) A portion of the 5000 datasets (only datasets with ER = 15 dB, FSR = 40GHz is shown) generated from GAN based on the 75 experimental data in (c).

IV. Implementing GAN and DNN in Photonic Based Instantaneous Frequency Measurement Experiment

The 75 datasets that are collected experimentally from the photonics-based frequency measurement system are launched to the GAN for data augmentation such that 5000 datasets are generated. The GAN-generated dataset has RF power between 0 – 3 dBm with 1 dB step size, FSR between 40 – 60 GHz with 5 GHz step size, and ER between 15 – 30 dB with 5 dB step size as plotted in Fig. 2(d), as shown by the blue and green surfaces for positive slope and negative slope filter outputs, respectively. Training, testing, and validation are performed in PyTorch (Jupyter notebook Python 3.0) with 1000-50000 epochs. The number of training, validation, and testing dataset are 2500, 1500, and 1000, respectively. The GAN has a critic loss of 0.0497, minimax loss of 0.059, and generator loss of 0.56. The training of the DNN is stable according to the loss vs epochs plot of subplot Fig 3(a). The comparison between the predicted and actual measured (orange circle) is on the y = a*x + c line, which means that the predicted values and the actual value are similar, i.e. an accurate DNN model is achieved.

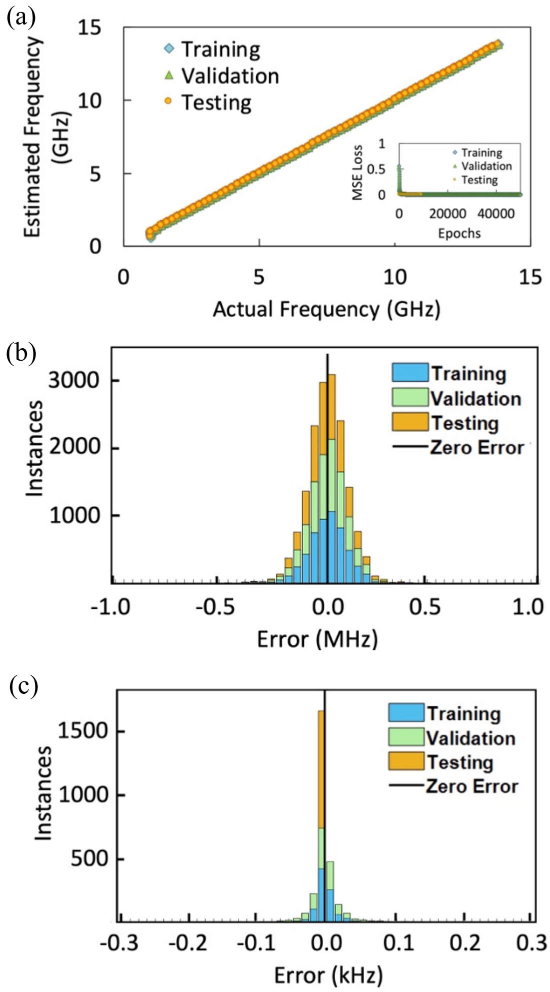

Fig. 3. (a) MLP regression-based comparison between estimated RF frequency and actual RF frequency. Insert: MSE loss vs epoch for training, validation, and testing. (b) Histogram of the absolute frequency error of testing dataset without GAN using DNN MLP. (c) Histogram of the absolute frequency error of testing dataset with GAN using DNN MLP.

To evaluate the performance of the trained model, a histogram of the absolute frequency error between the predicted and actual RF frequency during testing is plotted in Fig. 3(b) and (c). Fig. 3(b) represents the histogram without GAN, 6000 experimental datasets are needed to achieve an MSE loss of 50 MHz and absolute error of 1 MHz [4]. While Fig. 3(c) represents the histogram of the DNN model trained by the GAN augmented datasets, which shows an absolute error of less than 5MHz, and a mean square error < 588 kHz, i.e. 10 times improvement in MSE loss is achieved with the use of GAN. The majority of instances of error are mainly within the -0.1 to 0.1 kHz range as shown in Fig. 3(c). The use of GAN not only improves the accuracy of frequency estimation but also reduces the need for intensive manual capturing of a large amount of experimental data for training the DNN model. Also, both processes show a stable error with normal distribution in terms of the statistical perspective of the data. The GAN technique could be applied to various photonic and microwave photonic experiments for practical use of machine learning to enhance performance and increase functionality.

Finally, to test the GAN-based frequency estimation process, a series of random unknown incoming RF signals with different power is taken from the experiment and is applied as a series of new real-time testing dataset that the DNN model has not seen before. The estimated frequency and comparison with the actual frequency are shown in Fig. 4(a). The unknown incoming RF signal has a frequency range from 0 to 16 GHz, and RF power range between 0 to 3 dBm as shown in Fig. 4(b). The resultant measured optical power at the optical filter pair is between -5 dBm to -30 dBm, as shown in Fig. 4(c). The testing dataset not only has different RF frequencies, but each dataset also has different RF power. The corresponding power of the RF signal series is shown in Fig. 4(b). The purple data points in Fig. 4(a) correspond to the estimated frequency, which matches very well with the actual frequency in green crosses. The results in Fig. 4 prove that the proposed GAN-based machine learning assisted frequency estimation system works well for real-time frequency estimation even when the frequency and RF power are changing rapidly over time.

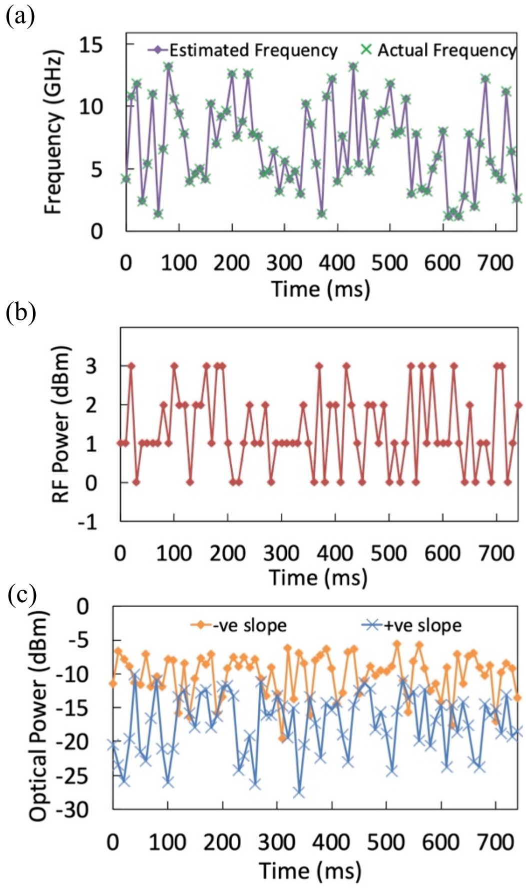

Fig. 4. Performance evaluation with RF signal-of-interest with different frequency and RF power. (a) Estimated frequency and actual frequency. (b) RF power for the incoming unknown frequency. (c) Corresponding optical power measured at the positive and negative slopes.

TABLE I. ARCHITECTURAL DETAILS OF THE DEEP LEARNING MODELS

The optimized hyperparameters for the GAN and DNN		
Parameter	***Data Augmentation***	***Prediction***
Data algorithm	GAN Generator (G): RNN Bi-LSTM Discriminator (D): CNN 2D Conv 3x3	MLP
Hidden layers	G: 3, D: 3	3
Neurons in hidden layers	G: 50 D: 64, 128, 256	50
Batch size	200	48
Dropout rate	G: 20%, D: 10%	10%
Activation function	G: Tanh() D: ReLU()	ReLU()
Optimizer	SDG(), RMSprop(), Adam()	Adam()
Input normalization	GAN (G-FFT)	-
Layer normalization	G: L1, L2 D: Batch	MLP
Loss function	Absolute Error, MSE, Critic, and Minmax	MSE
Learning rate	0.001	0.0001
Number of epoch	5 (10000 steps/epoch)	1 - 50000
Number of generated Feature	100	4
Input noise (Gaussian)	G: 20%	-
# of units in a cell	G: 100, D: 100	-
# of features in a cell	G: 100, D: 100	-

V. CONCLUSION

Although machine learning has shown promising results in enhancing the performance of various photonics and microwave photonic systems, the need for a large amount of training data to obtain an accurate neural network model hinders the full exploration of machine learning in the field of photonics. In this paper, generated adversarial network (GAN) is introduced for augmenting real experimental data to reduce the need for intensive manual capturing of data in photonic systems as well as to improve frequency estimation accuracy in a photonics-based microwave frequency measurement system. The amount of experimental datasets needed to be captured significantly decreases from 6000 to 75, and the GAN is capable of augmenting the 75 datasets into 5000 datasets for the neural network. Frequency measurement error is significantly improved by 10 times with error <5MHz over the 1 GHz to 16 GHz frequency range.

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