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Data augmentation using a generative adversarial network for a high-precision instantaneous microwave frequency measurement system

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In this Letter, an unsupervised-learning platform—generative adversarial network (GAN)—is proposed for experimental data augmentation in a deep-learning assisted photonic-based instantaneous microwave frequency measurement (IFM) system. Only 75 sets of experimental data are required and the GAN can augment the small amount of data into 5000 sets of data for training the deep learning model. Furthermore, frequency measurement error of the estimated frequency has improved by an order of magnitude from 50 MHz to 5 MHz. The proposed use of GAN effectively reduces the amount of experimental data needed by 98.75% and reduces measurement error by 10 times.

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Machine learning has provided significant assistance to the fields of photonics and microwave photonics for enhancing their functionalities and performance, including designing optical components [1], studying RF and optical transmissions [2], designing optical and microwave subsystems [3], and measuring unknown RF and microwave signal frequency [4]. Among all the machine learning techniques, meta-learning, big data, unsupervised learning, and reinforcement learning have been the majority contributors due to their capability to solve human-level problems such as object detection in videos and natural language processing. However, one major hurdle to using machine learning platforms in experiments on photonic and microwave photonic systems is the need for a large training dataset. Unlike using machine learning in a simulation setting, microwave photonic experiments require the training datasets to be captured one by one experimentally, which necessitates the manual control of a large number of varying parameters of all the devices in the experiment. An insufficient number of training datasets would result in inaccurate training of machine learning models. Therefore, the need for a large number of training datasets hinders the practical use of machine learning in photonic and microwave photonic systems. Looking into different machine learning techniques, an unsupervised learning framework—generative adversarial network (GAN)—can gradually generate realistic and intrinsic high-quality data from a small dataset, which could be a promising and practical solution to apply machine learning in photonic experiments. Adversarial training is proposed because it can produce more discrete and sharper outputs than platforms.

Instantaneous frequency measurement (IFM) is a critical subsystem for applications including electronic counter warfare and air defense [5], radar and satellites [6], as well as deceptive intelligent system and counterintelligence [7–9]. A photonic-based IFM system [10] surpasses its electronic counterpart because it is immune to electromagnetic interference and supports wideband measurement. However, a photonics-based IFM system has a relatively large frequency error, which may not be accurate enough for 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 an operation range up to 20 GHz. Unfortunately, just like any machine learning assisted microwave photonic system, a large amount of the experimental dataset that covers a wide range of parameters is needed to be captured experimentally for accurate frequency estimation. 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 training datasets is used during the training of the machine learning model.

In this Letter, a generative adversarial network (GAN) [11,12] is introduced to a deep neural network (DNN) [13] assisted microwave photonic system to augment a real experimental dataset. What makes GAN an attractive solution is that it is based on unsupervised learning that does not need any labeled data, or any other data annotation process. A photonic-based microwave instantaneous frequency measurement system is used as the platform to investigate the efficiency of GAN for overcoming the challenges of using machine learning in photonics-based experiments. According to our study, the number of training datasets needed to be experimentally captured decreases significantly from 6000 to 75 (98.75% decrease), while GAN is capable to augment the 75 experimentally captured datasets to 5000 sets for training, validation, and testing of the DNN model. A frequency estimation error of less than 5% is achieved, i.e., <5 MHz of frequency error during training and <1 MHz of frequency error during validating over the range of 1 GHz to 16 GHz, as well as a mean square error < 588 kHz is achieved during the testing phase. The assistance of GAN essentially decreases the frequency estimation error by 10 times and reduces the complexity

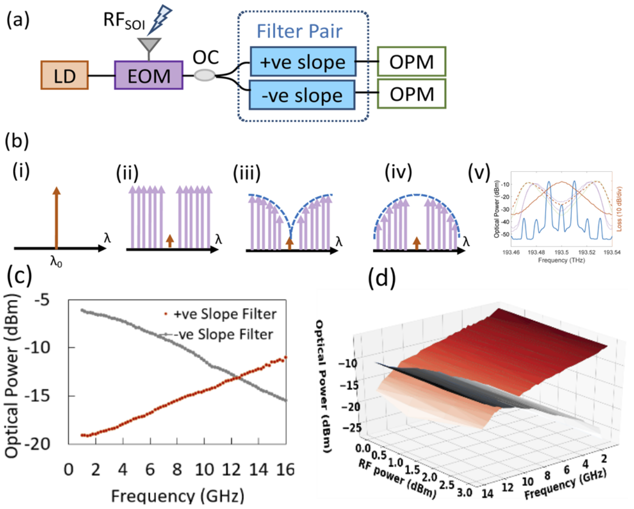

Fig. 1. (a) Schematic illustration of the photonic based microwave frequency estimation system. (b) Illustration of optical spectra at a different stage of the frequency estimation system. (c) Seventy-five datasets obtained experimentally for use in GAN for data augmentation. (d) Part of the 5000 datasets (only datasets with ER = 15 dB, FSR = 40 GHz are shown), generated from GAN based on the 75 experimental data in panel (c).

of the data acquisition process compared with DNN without the GAN [4].

The photonics-based instantaneous microwave frequency measurement system [4] that we use for studying the GAN is a complementary optical power measurement approach, as shown in Fig. 1(a). The unknown microwave signal-of-interest (RF_{SOI}) is modulated onto a single wavelength optical carrier [LD, Fig. 1(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 achieved, as illustrated in Fig. 1(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 [Fig. 1(b)(iii), destructive interference at the carrier] and one with a positive slope response [Fig. 1(b)(iv), constructive interference at the carrier]. Figure 1(b)(v) shows the experimentally measured optical spectra of the CS-DSB signal and the optical filter pair in blue and orange, respectively. As a result, the microwave frequency of the signal-of-interest can be determined by evaluating the filtered optical power relationship at the filter pair using optical power meters [8], as illustrated in Figs. 1(b)(iii) and 1(b)(iv). The filter pair could have a sinusoidal or triangular filtering profile, but a triangular profile is used in this experiment to improve the linearity and dynamic range. The extinction ratio (ER) and free spectral range (FSR) of the triangular optical filter pair can be changed to meet the requirement of the measurement range and frequency resolution. An RF signal sweeping from 1 to 16 GHz with a step of 200 MHz is used as the RF_{SOI}. Datasets are captured experimentally by setting the RF power = 0 dBm, ER = 15 dB, and FSR = 40 GHz, as shown in Fig. 1(c). During the experiment, only 75 datasets are captured experimentally, which is a 98.75% decrease in experimental data needed compared with a non-GAN-based DNN system where 6000 experimental datasets are being captured [4]. The 75 experimental datasets are launched to the GAN for data augmentation, then the augmented data are used for training in the MLP DNN for prediction.

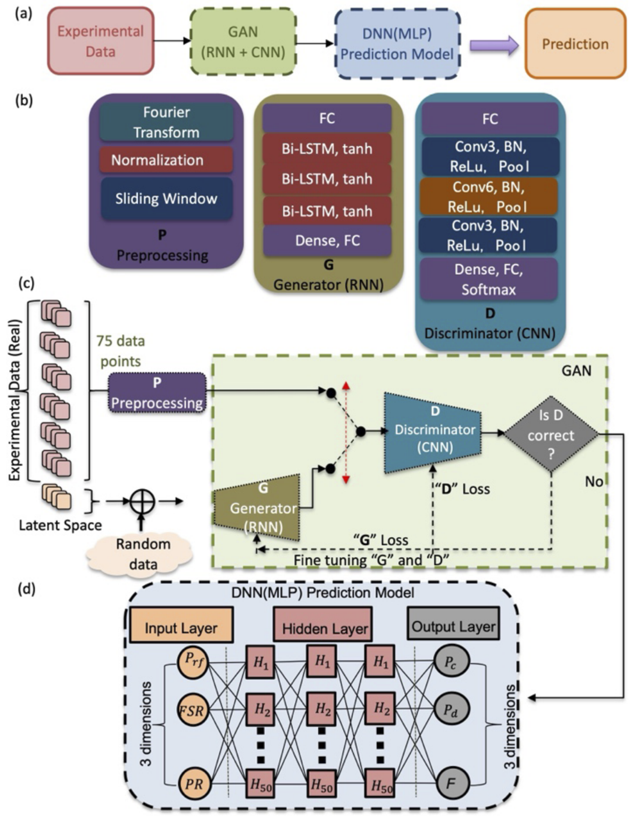

Fig. 2. (a) Overall GAN/DNN assisted IFM model architecture, (b) Three GAN components for data augmentation in experimental microwave photonic systems. FC, fully connected; BN, batch normalization; Pool, Max pooling. (c) Detail architecture of GAN. (d) DNN model for frequency estimation. PR, optical power ratio.

The overall process for estimating the unknown frequency is described in Fig. 2(a), which includes data preprocessing (P), data augmentation (GAN), and data prediction (MLP). The GAN that we proposed and designed for data augmentation in the microwave photonic system is shown in the green shaded area in Fig. 2(b), which consists of two parts: (1) Generator—a recurrent neural network (RNN) based on long short-term memory (LSTM) and bidirectional long-short term memory (Bi-LSTM); (2) Discriminator—a 2D convolutional neural networks (CNN)). The generator, indicated as G in Fig. 2(b), takes random data, and combines it with the latent space to generate a time series RNN (Bi-LSTM) output. As shown in the inset of Fig. 2(b), the generator has three Bi-LSTM hidden layers, where nonlinearity based on Tanh() is introduced between each layer. There are also two fully connected (FC) layers, where one of them is a 1D dense layer. Experimental data captured from the instantaneous microwave frequency measurement system are pre-processed through Fourier transformation, normalization, and sliding window, as illustrated in Fig. 2(b). The switching path between the generated time series data and preprocessed experimental data is used for classification and feature extraction at the discriminator (D). CNN is used as the discriminator since CNN is highly capable of performing classification tasks [12]. As illustrated in Fig. 2(b), the discriminator has three hidden layers and two outer layers. Each hidden layer consists of kernel 3 × 3 convolution (Conv3), batch normalization (BN), and ReLu(). The two outer layers are FC with pooling, SoftMax(), and a dense

Table 1. Architectural Details of the Deep Learning Models

Parameter	Data Augmentation	Prediction
Algorithm	GAN Generator (G): RNN Bi-LSTM Discriminator (D): CNN 2D Conv 3 × 3	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 of Epochs	5 (10,000 steps/ epoch)	1–50,000
Generated Features	100	4
Input Noise (Gaussian)	G: 20%	-
Number of Units	G: 100, D: 100	-
Number of Features	G: 100, D: 100	-

layer. The optimized GAN (RNN + CNN) hyperparameters are summarized in Table 1. For prediction, a multi-layer perceptron (MLP) DNN with three hidden layers, three input parameters, and three output parameters is used, as shown in Fig. 2(c).

After data augmentation, the GAN has a critic loss of 0.0497, minimax loss of 0.059, generator loss of 0.056, and discriminator loss of 0.041, and all these loss values are below 0.1, which means that the augmented data from GAN has similar properties as the original experimental data and the augmentation process is successful. The datasets generated consist of a wide variation parameter, including RF power between 0 and 3 dBm with 1-dB step size, FSR between 40 and 60 GHz with 5-GHz step size, and ER between 15 and 30 dB with 5-dB step size. The 5000 datasets generated from GAN are used for training (2500 datasets), validation (1500 datasets), and testing (1000 datasets) of the DNN model. Figure 1(d) shows a portion of the 5000 datasets (i.e., only datasets with ER = 15 dB, FSR = 40 GHz are shown) generated from GAN based on the 75 experimental datasets [Fig. 1(c)].

The 75 datasets that are collected experimentally using the frequency measurement system are launched to the GAN for data augmentation such that 5000 datasets are generated. Training, testing, and validation are performed in PyTorch (Jupyter notebook Python 3.0) with 1000–50,000 epochs. The number of training, validation, and testing datasets are 2500, 1500, and 1000, respectively. The training of the DNN is stable according to the loss versus epochs plot in Fig. 3(a). The estimated and actual measured RF frequency for training (blue diamond),

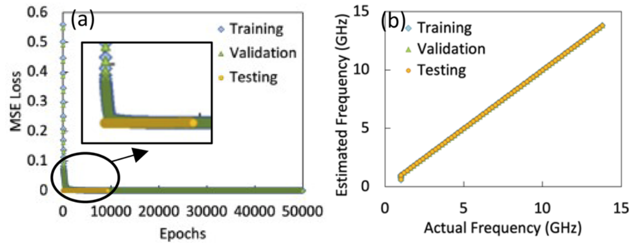

Fig. 3. (a) MSE loss versus epoch for training, validation, and testing. (b) Comparison between estimated RF frequency and actual RF frequency.

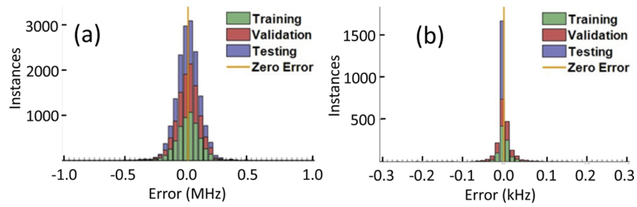

Fig. 4. Absolute frequency error of training, validation, and testing of the DNN (a) without GAN (b) with GAN.

validation (green triangle), and testing (orange circle) are overlaid in Fig. 3(b), the three sets of data points are aligned on the $y = m*x + c$ line, which means that the predicted values and the actual value are similar, i.e., an accurate DNN model is obtained.

To evaluate the performance of the trained model, histograms of the absolute frequency error between the predicted and actual RF frequency during testing are plotted in Figs. 4(a) and 4(b) for the DNN model without and with data augmentation using GAN, respectively. Without GAN, 6000 experimental datasets are needed to achieve an MSE loss of 50 MHz and an absolute error of 1 MHz [4], as shown in Fig. 4(a). However, the GAN-assisted frequency measurement system results in an absolute error of less than 5%, i.e., <5 MHz of frequency error during training and <1 MHz frequency error during validating over the range of 1 GHz to 16 GHz, as well as a mean square error < 588 kHz is achieved during the testing phase. With the use of GAN, not only is a 10 times improvement in accuracy achieved but also a reduced need for intensive manual capturing of a large amount of experimental data for training the DNN model. This GAN technique could be applied to various photonic and microwave photonic experiments for practical use of machine learning to enhance performance.

Finally, we apply a series of new incoming random unknown RF frequency datasets for a 700-ms duration that the DNN model has not seen before to perform frequency estimation in real time. The comparison between actual frequency and estimated frequency is shown in Fig. 5(a). It is worth noticing that the random testing dataset has a variety of RF frequencies, RF power [blue curve in Fig. 5(b)), FSR [purple curve in Fig. 5(c)], and ER [green curve in Fig. 5(c)]. The orange data points in Fig. 5(a) correspond to the estimated frequency, which matches very well with the actual frequency, as shown by the purple crosses. The resultant error is also plotted in green in Fig. 5(a). The corresponding FSRs and ERs of each data point are plotted in Fig. 5(c), while the RF power and the corresponding optical power at the +ve and −ve slope are plotted in Fig. 5(b) in blue, red, and gray, respectively.

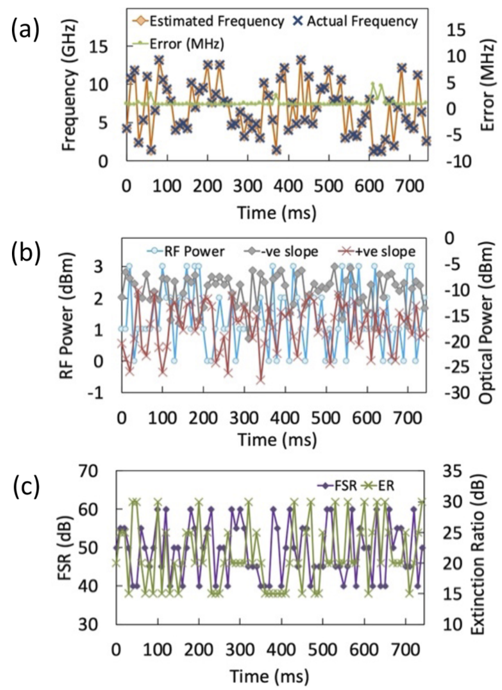

Fig. 5. Real-time frequency detection evaluation with RF signal-of-interest with different parameters for 700 ms incoming unknown frequency. (a) Estimated frequency and actual frequency. Green, corresponding frequency error. (b) Corresponding RF power, +ve, and −ve slope optical power. (c) Corresponding FSRs and ERs of the RF signal in panel (a).

Although machine learning has shown promising results in enhancing the performance of various photonic and microwave photonic systems, the need for a large amount of experimentally captured training data to obtain an accurate neural network model hinders the full exploration of machine learning in the field of photonics. In this Letter, a generative adversarial network (GAN) is introduced for augmenting real experimental data to reduce the need for intensive capturing of experimental data in photonic systems as well as to improve estimation accuracy in a photonics-based microwave frequency measurement system. The number 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 a mean square error < 588 kHz over the 1–16 GHz range during the testing phase.

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Data availability. Source codes used to generate the results presented in this paper are available at [14].

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