Data-Driven Complementary Power Measurement for Microwave Instantaneous Frequency Estimation

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***Abstract*— A high-precision photonic based instantaneous frequency measurement system driven by machine learning is proposed and experimentally demonstrated. A three-layer deep neural network is used to tackle device nonlinearity and system noise, resulting in absolute error < 50 MHz and 1.1 MHz root mean square error.**

Keywords—Frequency measurement, Machine learning

I. Introduction

Instantaneous and wideband microwave frequency measurement system is an essential tool for radar detection, electronic warfare, military threats identification, decisive intelligence acquisition, and deceptive counter-measures implementation [1]. However, emerging complex wireless environment brings critical challenges to realize frequency measurement using conventional electronic technologies. Microwave photonics has shown its advantage as a candidate to overcome hurdles faced by electronics due to its ultra-broad bandwidth, high reconfigurability, and immunity to electromagnetic interference characteristics. Microwave photonic based frequency measurement have been demonstrated using frequency-to-time mapping [2], power fading comparison [3], and SBS-assisted phase-to-intensity modulation [4]. Although existing photonic-assisted methods solved some of the challenges in their electronic counterparts, current schemes still suffer from relatively limited reconfigurability, large frequency measurement error, and inability to adapt to dynamic RF systems. At the same time, photonics has been further applied to cognitive radio, which is considered to be an effective machine learning assisted technology to manipulate RF system dynamically [5]. Photonics enabled cognitive radio observes and reacts to complex electromagnetic condition, where artificial intelligence enables the adaptation to dynamic changes.

In this paper, we propose and demonstrate a complementary optical power measurement scheme for instantaneous frequency estimation assisted by deep neural network (DNN). Based on prior experience, the intelligent frequency measurement system is capable of achieving high accuracy measurement and tolerant to device nonlinearity and system noise. The DNN-assisted frequency measurement system can adapt to new RF transmission condition and significantly decreases the resultant frequency measurement error to 50 MHz with a 1.1 MHz root mean square error over a 14 GHz frequency range.

II. Experimental Design and Results

Figure 1(a) shows the experimental setup of the proposed data-driven frequency estimation system which consists of two parts: complementary optical power measurement unit and a deep neural network for frequency estimation. To achieve complementary optical power measurement, a distributed feedback laser (DFB) centered at 1549.275 nm is used as the optical carrier for the RF signals sweeping from 1 to 14 GHz with a step of 200 MHz. Modulation is performed using a 10-Gb/s electro-optic intensity modulator (EOM). The EOM is biased at the null transmission point such that carrier-suppressed double-sideband (CS-DSB) modulation is achieved. The CS-DSB optical signal is then shaped by an optical wave shaper that has two linearly complementary transmission functions (i.e. triangular and inverse triangular shape in log scale) to ensure the difference between the two measured complementary power is

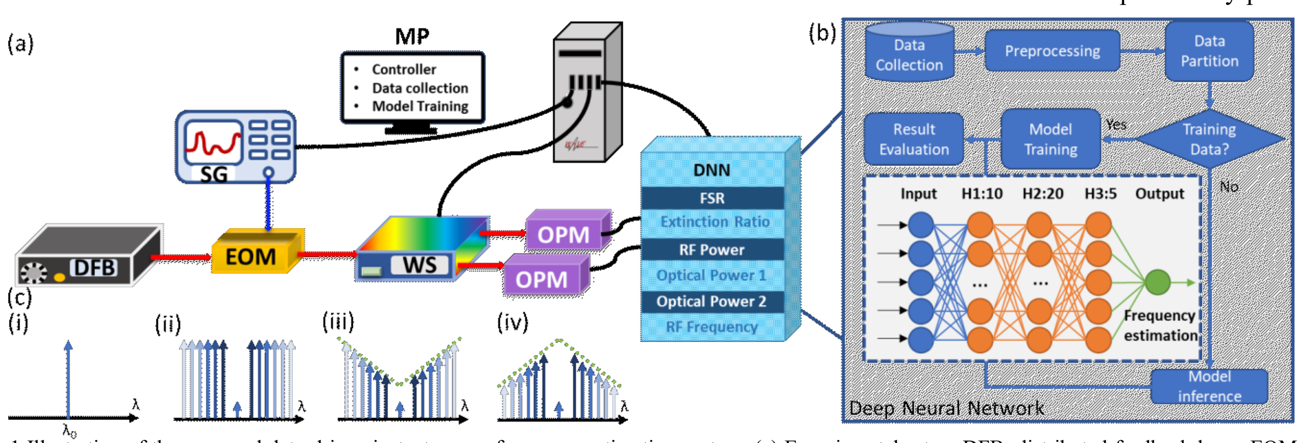

Fig.1 Illustration of the proposed data-driven instantaneous frequency estimation system; (a) Experimental setup. DFB: distributed feedback laser; EOM: electro-optic modulator; SG: signal generator; WS: optical wave shaper; OPM: optical power meter; MP: microprocessor; DNN: deep neural network; (b) the structure of the designed DNN; (c) optical spectra after (i) DFB, (ii) EOM, (iii) WS (inverse triangular transmission), (iv) WS (triangular transmission).

This work is supported by NSF (1653525 and 1917043).

proportional to the signal frequency. Out-of-band transmission is set to close to zero for removing optical noise and undesired high frequency components generated from non-ideal electro-optic modulation. As shown in Fig.1(c)iii-iv, the complementary triangular functions change the power of the CS-DSB signal sidebands depending on the signal frequency. Therefore, the RF signal frequency can be identified by evaluating the power relationship resulted from the complementary triangular transmission functions under a known system setting. In a dynamic scenario, data-driven dynamic frequency estimation can be used. The system is trained using training data obtained from the complementary optical power measurement unit with various transmission functions, modulator bias, and signal power. As shown in Fig. 2(a), the designed optical transmission function has tunable free spectral range (FSR) and extinction ratio (ER). In our experiment, FSR ranges from 40 GHz to 70 GHz with step resolution of 5 GHz is used. A larger FSR supports a wider frequency measurement range with a lower frequency resolution. The resultant low frequency resolution can be compensated by adjusting the ER of the triangular functions. ER ranges from 15 dB to 30 dB with a step of 5 dB can be achieved to satisfy the needs. To enable power transparent frequency measurement, training data with RF power from -10 dBm to 2 dBm with increment of 2 dB is used to train the DNN model. A quasi-linear relationship is observed in the measured complementary optical powers obtained through the two triangular transmission functions, as shown in Fig. 2(b).

Next, DNN is uniquely designed to assist the frequency measurement, where $Y_i^{W,b}$ stands for the RF frequency under weight W and modulator bias b. To precisely estimate the unknown microwave frequency, the parameters of interest used for the estimation are FSR X_{FSR} and ER X_{ER} of the complementary transmission functions, input RF power $X_{RFpower}$, measured optical powers at complementary transmission functions, X_{opt1} *and* X_{opt2}. Thus, the nonlinear transmission model can be expressed as,

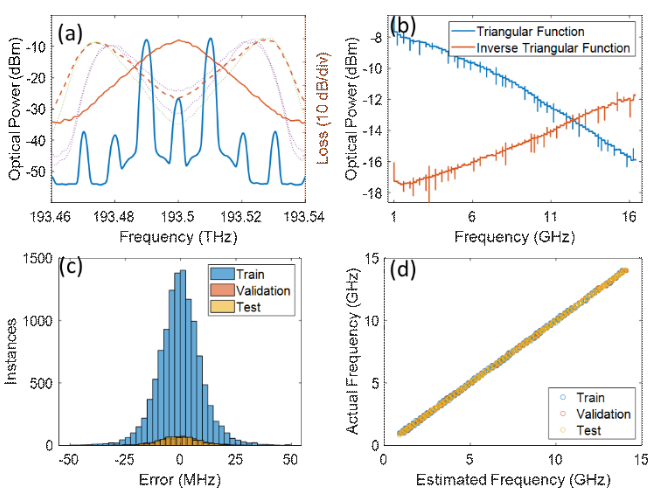

Fig.2 Examples of various measurement using one setting: (a) Measured optical spectra of CS-DSB signal (blue); complementary triangular transmission curves (orange solid and dash), transmission curves with tunable FSR and ER (dotted curves); (b) measured optical power of different RF frequency at RF power = 0 dBm, ER = 15dB and FSR = 0.05THz; (c) The model error distribution among train, validation and test data; (d) model evaluation with R2 equal to 0.9994.

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$$Y_i^{W,b} = F\left(X_{FSR-i}, X_{ER-i}, X_{RFpower-i}, X_{opt1-i}, X_{opt2-i}\right) + \sigma_i^2 \quad (1)$$

where σ_i^2 denotes the unknown system error for i-th observation that caused by the unknown system noise or nonlinearity. To train the DNN, the collected data are partitioned into three parts, 90% for training, 5% for validation, and 5% for testing. The designed DNN is optimized by adjusting the weights and bias with Levenberg Marquardt regularization such that $RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(Y_i^{W,b} - Y_i^{real}\right)}$ is minimized. The proposed data-driven DNN is then trained using a processer with an Intel Xeon CPU E5 3.5 GHz and two NVIDIA Geforce-Quadro-P4000 GPUs. The trained dataset consists of 12936 observations, which is applied to the designed three hidden layer DNN, including 10, 20, and 5 neurons, respectively. To test the performance of the trained model, histogram of the absolute error between the predicted and actual RF frequency is shown in Fig. 2(c), which is less than 50 MHz, as shown by the yellow bars. The histogram of the training and validation processes are also shown in blue and orange in Fig. 2(c) for comparison. In addition, the calculated RMSE is 1.1 MHz, which is only 0.5% of the RF frequency sweeping step resolution. The regression performance plot between predicted and the actual RF frequency with respect to the training, testing and validation dataset is also shown in Fig. 2(d). The calculated R2 value is 99.94% among all groups of data, which indicates a goodness of fit of the proposed DNN model. The DNN-assisted frequency measurement system works well even under dynamic user-specified parameter settings with unknown data.

III. Conclusion

We proposed and experimentally demonstrated a data-driven instantaneous frequency estimation system based on complementary optical power measurement. The absolute measurement error is significantly reduced to 50 MHz with a RMSE of 1.1 MHz. The designed DNN-assisted frequency estimation system could solve the accuracy issues resulting from system noise and device nonlinearity, as well as overfitting problem by most conventional frequency measurement methods. Unlike conventional frequency measurement scheme, the proposed frequency estimation model works well for both pre-known and un-known data. With the DNN training, the measurement error is significantly improved through the training and validation process, which also results in adaptability to unknown complementary optical powers.

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