Laser Frequency-Offset Locking Over a 1577 km Fiber Link Based on LSTM Neural Network

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***Summary*—We demonstrated a digital frequency offset locking system based on long short-term memory (LSTM) neural network and locked two free-running lasers at 1550.12 nm with 291.25 MHz offset after transferring through a 1577 km fiber link. Within 1.63 hours of locking, the root-mean-square (RMS) error of frequency offset is 47.1592 kHz. Compared to traditional digital locking systems using proportional-integral-derivative (PID) control, our locking system can effectively resist frequency offset drifting between lasers caused by temperature variation and requires no complicated parameter tuning process.**

***Keywords*—LSTM neural network, fiber link, frequency offset, locking system, transferring**

I. Introduction

Laser frequency offset locking is indispensable in many commercial and research applications that range from precise time and frequency transfer, quantum optics, cold atomic physics, and off-resonant light–atom interfaces [1], through frequency comb stabilization to precision spectroscopy [2]. Especially in bidirectional time and frequency transfer based on fiber, due to the variation of relative wavelength between lasers, there is a jitter in the delay difference of bidirectional signal, reducing transfer accuracy. To reduce this jitter, locking the frequency offset of lasers on a signal source with higher stability is usually a good way. In a digital frequency locking system, when the frequency has a significant fluctuation, conventional PID control barely obtains desired locking precision by tuning parameters [3]. Neural network is an adaptive system that changes its structure based on external or internal information that flows through the network [4], so it is more suitable for the non-linear and uncertain control system [3]. As a kind of neural networks, LSTM neural network is well-suited to processing and making predictions based on time series data [5]. In this note, the frequency offset between lasers is a typical time series data, so we used the LSTM model to learn and predict laser frequency offset and show its performance of experiment.

II. METHODS/RESULTS

Our locking scheme includes a measurement system and a locking system. In the measurement system (Fig.1), the output signal of laser1 enters into a fiber link consisting of 1577 km fiber and 19 erbium-doped fiber amplifiers (EDFA) for transferring. The whole measurement system is in a room, and we controlled the room temperature periodic-like variation. We collected frequency offset data of laser1 and laser2 in 16 hours and trained the LSTM model with this data. Fig.2 shows the variation of frequency offset and temperature at the same time range of 16 hours. The blue line represents the frequency offset between laser1 and laser2, and the orange line represents room temperature. We can observe that the variation trend of frequency offset is approximately consistent with the room temperature, demonstrating that the primary influence of frequency offset variation is temperature fluctuation in this experiment. The frequency offset of lasers under a free-running state varies from 19 MHz to 72 MHz, which is too large and is not available in many applications.

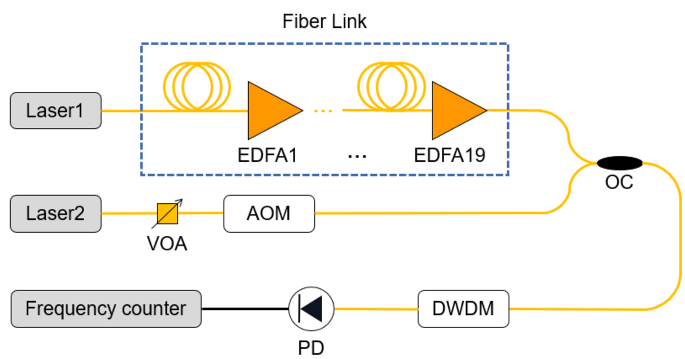

Fig. 1. The measurement system of laser frequency offset in the free-running state. Laser: single frequency fiber laser, OC: optical coupler, PD: photo-detector with 6 GHz bandwidth, EDFA: erbium-doped fiber amplifier, DWDM: dense wavelength division multiplexing, VOA: variable optical attenuator, AOM: acoustic optical modulator, Fiber Link: totally 1577 km fiber and 19 EDFAs, the length of fiber between two EDFAs is about 83 km.

The schematic of the locking system based on the LSTM model is shown in Fig.3. The locking system is in the same room as the previous measurement system and is also influenced by temperature fluctuation (in Fig.2). The trained LSTM model is stored in micro-control unit (MCU). When locking, MCU calculated compensation frequency at the present moment according to the predicted frequency offset of the LSTM model at the next moment and then pre-compensated the frequency offset variation by driving acousto-optic modulator

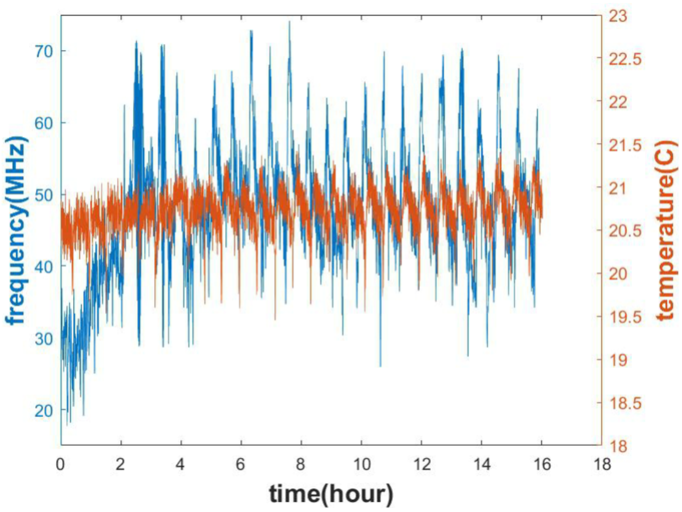

Fig. 2. The variation of laser frequency offset and environment temperature in 16 hours.

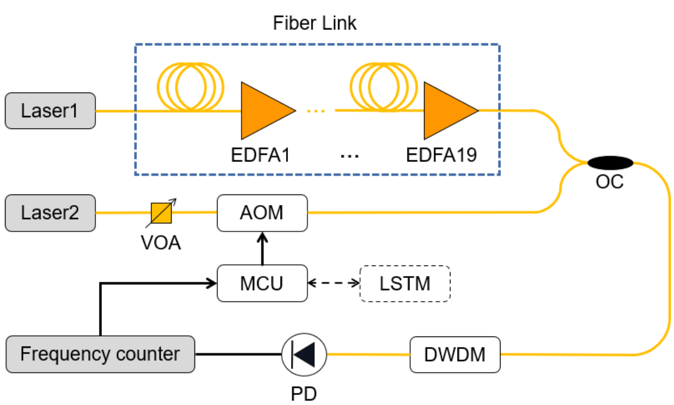

Fig. 3. Laser frequency offset locking system based on LSTM model. Laser: single frequency fiber laser, OC: optical coupler, VOA: variable optical attenuator, PD: photo-detector with 6 GHz bandwidth, EDFA: erbium-doped fiber amplifier, DWDM: dense wavelength division multiplexing, AOM: acoustic optical modulator, MCU: micro-controller unit, LSTM: long short-term memory, Fiber Link: totally 1577 km fiber and 19 EDFAs, the length of fiber between two EDFAs is about 83 km.

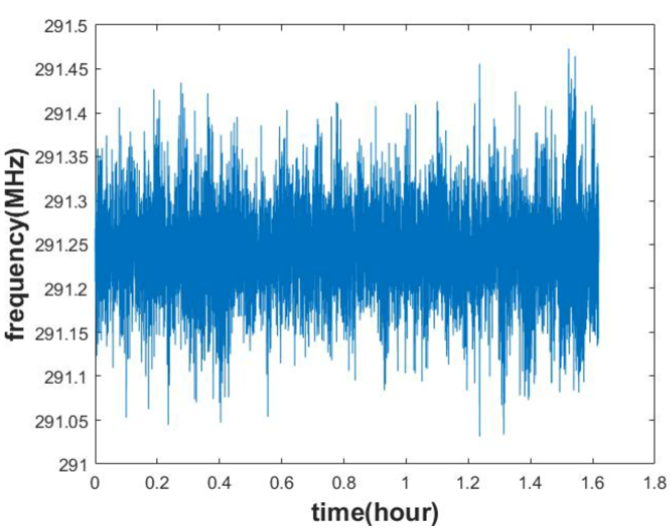

Fig. 4. The variation of laser frequency offset after locking in 1.63 hours.

(AOM). Fig.4 shows the locking result of the frequency offset. In 1.63 hours of locking, the RMS error of frequency offset is 47.1592 kHz, and the maximum frequency variation is 0.5 MHz.

III. DISCUSSION/INTERPRETATION

The result demonstrates that the LSTM model we used in our locking system can learn and predict laser frequency offset variation trends in the case of temperature fluctuation, so our locking system can effectively resist the influence of temperature variation on lasers and the long fiber link. Because the LSTM neural network is an adaptive system that changes its structure based on laser frequency offset data flowing through the network, it is more suitable for nonlinear, uncertain, and complex control systems than PID control. In addition, we avoided fine-tuning PID parameters by training the LSTM neural network model, which reduced the difficulty of locking. Overcoming conventional PID control drawbacks of hysteresis, our locking system can compensate for frequency drifting in advance, reducing system dynamic deviation and adjustment time, thus improving the locking precision.

IV. CONCLUSIONS

We demonstrated a digital frequency locking system based on an LSTM neural network and locked two free-running fiber lasers after transferring through a 1577 km fiber link. Introducing LSTM neural network model, this locking system can effectively reduce the influence of the environment temperature on laser and a long-distance fiber link while requiring no fine parameter tuning. Because the locking system is robust and adaptive, it can be used in some complicated situations, such as long-distance time and frequency transfer with large environmental temperature fluctuations. In addition, it can also be used to lock repetition rate and offset frequency of optical frequency comb and any situation requiring locking frequency. In the future, we will lock lasers of different wavelengths complying with DWDM channel spacing and optimize the LSTM model to realize long-term high-precision locking.

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