A Frequency Modulated Continuous Wave LiDAR System Based on Reservoir Computing

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***Abstract*—A frequency modulated continuous wave (FMCW) light detection and ranging (LiDAR) system based on reservoir computing (RC) is proposed and its reliability is verified through simulations and experiments. Fundamentally different from previous approaches where Fourier analysis is always required to determine distance information, here temporal signal analysis using RC is adopted. The system is robust to nonlinearity in frequency modulation of optical carrier, hence improving the range detection resolution. An intensity-modulated light is injected into a semiconductor laser to deliberately generate a non-ideal nonlinear wavelength scanning light source. The change in distance corresponds to the change in the IF signal over time. The RC classifies the IF signal waveform in the time domain to eliminate the need for linearization, and determines the distance from the classification results. The distance measurement resolution of this method is 1 cm in the 6.1 GHz scanning range, which shows that the method effectively addresses the effect of source nonlinearity due to the scanning wavelength while reducing computational complexity. The method has been demonstrated to reduce calculation cost.**

Keywords—LiDAR, reservoir computing, microwave photonics, semiconductor laser, frequency modulation

I. INTRODUCTION

Frequency-modulated continuous wave (FMCW) LiDAR systems are widely used in remote sensing [1], remote sensing [2] and 3D imaging [3] due to their advantages of high interference immunity, high resolution, high signal-to-noise ratio and low optical power requirements [4].

FMCW LiDAR typically uses an external optical aberration method for coherent detection. The signal light is coupled to the reference light and an IF signal containing distance and velocity information are generated after PD. A fast Fourier transform (FFT) is then performed on the IF signal to detect very narrow power peaks in the power spectrum, allowing accurate distance and velocity information to be demodulated. Almost all wavelength sources, however, have difficulty achieving perfectly linear sweep. This can significantly affect the FFT peaks and broaden the spectrum, thus significantly degrading the resolution and SNR of LiDAR and even hindering target identification [5].

This work was supported in part by the Engineering and Physical Sciences Research Council of the U.K. (EP/S005625/1), and in part by the National Natural Science Foundation of China (61975248).

So far, the purpose of nonlinear correction has been to remove the spectrum broadening after FFT. However, spectral broadening makes the FFT peaks indistinguishable while complicating the corresponding waveforms in the time domain. Therefore, changing the distance inevitably changes the waveform in the time domain. This change allows accurate distance measurements to be made by distinguishing waveforms at different distances. The reservoir calculation (RC) is suitable for this task. In recent years, based on its fast learning rate and low cost, RC has shown excellent performance in waveform classification, time series prediction, and instantaneous frequency classification [13-15]. RC is a special variant of RNN [16]. Compared to conventional RNN models, RC requires only training the output weights, which provides higher training efficiency and faster computation while maintaining similar recognition performance. RC is also much less computationally intensive than FFT [17-18].

We present an RC-based FMCW LiDAR system that generates wavelength sweeping light by optical injection into a semiconductor laser [19-21]. We then use a Mach-Zehnder interferometer (MZI) and an adjustable delay line to simulate the change in distance to an object: the two arms of the MZI represent the reference and signal light, respectively. The reference and signal light are connected via a 3 dB coupler and detected by a PD to obtain a time-domain IF waveform. The different waveforms can then be quickly classified by RC to determine the measurement distance. The proposed method avoids the negative effects caused by the non-linearity of the light source by identifying the waveforms.

II. PRINCIPLE

As shown in Fig. 1, the overall structure of the proposed system consists of two main parts. The first part aims to extract the waveform of the IF signal together with the distance information in the time domain. As shown in Fig. 1(a), the system uses a light source with a fully nonlinear wavelength sampling process as the wavelength sampling source, and the IF signal is obtained at . Due to the nonlinearity, the frequency difference between the two beams is not constant in continuous time, and the IF signal is scattered as shown in Fig. 1(b). As the distance changes, even small changes in the frequency range cause changes in the waveform as shown in Fig. 1(c).

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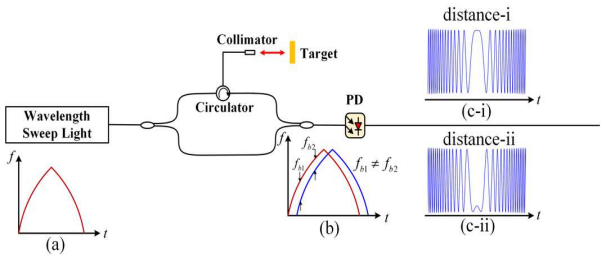

Fig.1. Schematic of the FMCW LiDAR system.

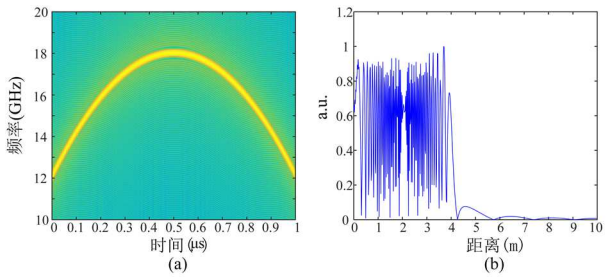

Fig. 2. (a) Instantaneous frequency of FMCW signal. (b) Spectrum broadening due to nonlinearity.

The second module aims to classify the waveforms of IF signals acquired at different distances using RC. The distances can be determined from the classification results.

A typical RC model has an input layer, a storage layer and an output layer, which are trained by summing the state vectors of the reservoir in response to the training data; due to the nature of RC, only the output weights need to be trained, so the input weights and internal state weights are randomised according to the size of the reservoir's water layer should be generated. Thereafter, the updated states of the nodes in the stock water layer need only be stored:

$$s_j = tanh(w_{in}x_j + w_{hat}s_{j-1}) \tag{1}$$

where x_j is the jth sample of the input data,s_{j-1} is the previous state vector, w_{in} is the input matrix, w_{hat} is the memory weight matrix and tanh is the tangential activation function. s_j is the current state vector.

The next training uses the training output weight matrix W_{out} with the ridge regression algorithm:

$$W_{out} = (X^T X + \lambda I)^{-1} X^T X \tag{2}$$

where X is the input matrix, X^T is the transfer matrix of X, Y is the corresponding output matrix, I is the unit matrix, and λ is the degree of normalization. The purpose of the degree of normalization is to control the complexity of the model and prevent overfitting. The larger the value, the larger the penalty of the normalization term in the model, the lower the complexity of the model and the worse the fit in the training set, but the better the generalization to the test set. Conversely, the smaller the value, the greater the complexity of the model, the better the fit to the training set, but the worse the generalization to the test set.

We use $pred_y$ to represent the output of the ESN network. The formula is as follows

$$pred_y = softmax(\bar{y}) \tag{3}$$

where $\bar{y}$ is the output obtained after the ridge regression algorithm, which is calculated as follows

$$\bar{y} = SW_{out} \tag{4}$$

Softmax is an activation function that takes a vector as input and returns the ratio of the exponent of each element to the sum of the elements. In this paper softmax is calculated as

$$softmax(z_j) = \frac{e^{z_j}}{\sum_{i=1}^{K} e^{z_i}} \tag{5}$$

where z_j denotes the jth element of the input vector and K denotes the length of the input vector. This function compresses each element to between [0,1] and makes the sum of all elements equal to 1.

III. Simulation and Experiment Results

The effect of non-linearity on the accuracy of distance measurements was investigated by simulation. Using an LFMCW signal with a sampling range of 6 GHz as the sampling source, the distance variation was simulated using MZI, with a relative time delay of 10 ns for the two MZI arms, a refractive index of 1.4502 for the fibres and the fibre length expressed as:

$$l = \frac{n\tau}{c} \tag{6}$$

where, n represents the refractive index of fiber, τ the represents the relative time delay of two arms of MZI.

When τ is changed to simulate the distance change. Based on the bandwidth of the detected signal and the frequency of the IF signal, the distance d is obtained as follows:

$$d = \frac{cf_o}{2nB} \tag{7}$$

where, c is the speed of light, f_o is the frequency of IF signal, and B is the sweep range of the wavelength sweep light source.

To validate the method proposed in this work, a FMCW signal with a nonlinear sweep bandwidth of 6 GHz was used as the sweep source, as shown in Figure 2(a). The length of the fibre used in the simulation is the same as before. As shown in Figure 2(b), the spectrum widens significantly and the accuracy of the measurement decreases significantly, making it impossible to measure the fiber length accurately.

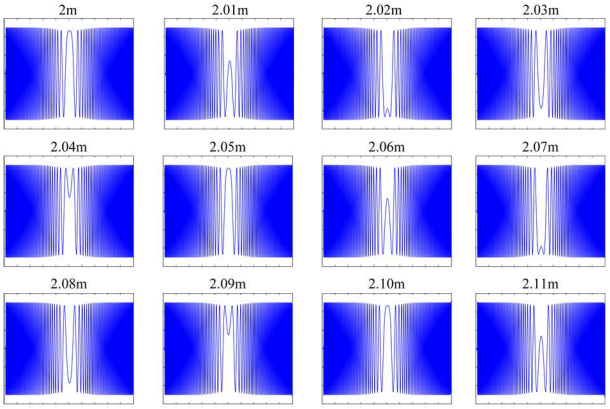

Fig.3. Waveforms of IF signals from 2m to 2.11m with an interval of 1 cm.

However, the non-linearity of the sampling source causes spectral broadening as well as differences in the IF waveform. Next, the relative delay of the MZI was increased from 10 ns to 10.75 ns in 0.05 ns steps, corresponding to distances from 2 m to 2.11 m. Time domain waveforms were generated at different distances in 1 cm steps, as shown in Figure 3.

As can be seen in figure 3, the IF signals have different waveforms. By gradually increasing the measurement distance, the waveform changes cyclically every 5 cm in the low frequency band. However, this does not mean that the waveforms are uniform, as the waveforms in the time domain inevitably become more intense as the frequency of the IF signal increases. Therefore, it is necessary to try to test very similar waveforms.

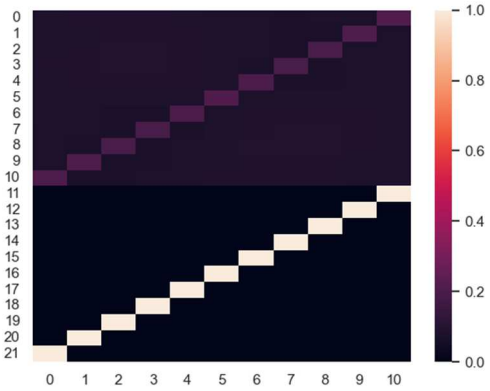

Fig. 4. Results of waveform classification for all the 11 waveforms corresponding to different distances.

The 11 waveform signals were selected from a distance of 2m to 2.1m and trained on the RC in the order of 2m to 2.1m. The test set still uses that set of data but arranges them in reverse order, which is 2.1m to 2 m. In this case, we set the reservoir size to 1000, the spectral radius of the reservoir weight matrix to 0.8, the input scaling to 0.2, the connection threshold between neurons or nodes to 0.3, the normalisation ratio to 500 and the activation function to tan. As shown in Figure 4, the upper half shows the test results and the lower half shows the actual labels; comparing the two results, it can be seen that the peaks in the results match well with the actual labels. This shows that RC successfully classifies waveforms between 2 m and 2.1 m.

The classification results show that RC successfully classifies waveforms from 2m to 2.1m. In addition, waveforms with a high degree of similarity, such as 2m, 2.05m and 2.1m, were successfully classified, indicating that the method has a strong ability to recognise waveforms.

IV. Conclusion

In this study, an RC-based FMCW LiDAR system is proposed and experimentally demonstrated. This scheme uses RC to classify IF signal waveforms, thereby eliminating the non-linear effects of wavelength-scanning light sources and ensuring accurate measurements. Compared to conventional FFT-based schemes, the system complexity is reduced as it does not require the use of an auxiliary interferometer. On the other hand, the RC can be trained quickly and inexpensively, eliminating the need for complex resampling at a later stage. This method has been experimentally validated using simulated data.

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