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L. Wei

University of Wollongong

Joe F. Chicharo

University of Wollongong, chicharo@uow.edu.au

Yanguang Yu

University of Wollongong, yanguang@uow.edu.au

Jiangtao Xi

University of Wollongong, jiangtao@uow.edu.au

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Pre-Processing of Signals Observed from Laser Diode Self-mixing Interferometries using Neural Networks

Lu Wei, Joe Chicharo, Yanguang Yu, Jiangtao Xi

School of Electrical, Computer and Telecommunications Engineering, University of Wollongong, Northfields Ave, Wollongong, NSW, 2522, Australia

Corresponding Author, Tel: +61-2-4221-3412, Fax: +61-2-4221-3236

E-mail: jiangtao@uow.edu.au

Abstract — This paper presents a novel neural network signal interpolation technique in order to eliminate the noise and disturbance associated with the self-mixing signal observed from optical feedback self-mixing interferometry (OFSMI). The proposed technique aims to improve the accuracy for displacement and moving track measurement of a target. The performance of the proposed approach is evaluated by both simulation and experimentation, with simulation revealing a measuring accuracy of $\lambda/25$ for weak feedback and $\lambda/20$ for moderate feedback.

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I. INTRODUCTION

Laser feedback self-mixing interferometry has been explored soon after the invention of lasers and has become a well-established technique in both laboratory and industry to measure the velocity, vibration, and displacement of a moving target. Nowadays self-mixing interferometry with semiconductor lasers (SL) has attracted significant attention due to its low-cost, energy efficiency and high reliability.

Optical feedback self-mixing (OFSM) occurs when a fraction of the laser beam emitted from a semiconductor laser is reflected or backscattered by an external target and allowed to reinject into the laser cavity, resulting in amplitude and frequency modulation of the electric field. A typical OFSM sensor comprises of a laser diode, basic collimating optics and a reflector such as a mirror or corner cube. When the reflective target is subject to a

form of vibration, the optical path length in laser external cavity will vary and cause fluctuation in the laser intensity. The laser intensity variation is then detected by a photo diode enclosed at the rear of a typical SL package and referred to as a self-mixing signal, which is fed into signal acquisition unit and converted into digital data. Analysis of the self-mixing signal will yield information about the target displacement.

OFSM effect for semiconductor lasers has been studied for more than two decades[1-4]. Three different feedback regimes are classified according to the value of a parameter known as feedback level factor (C) based on the strength of reinjected signal. When $C < 1$, defined as weak feedback, the self-mixing signal appears as a slightly deformed sinusoidal waveform with 2π periodicity and is a single valued function. When $1 < C < 4.6$, the OFSM system operates at moderate feedback where the self-mixing waveform is characterized by a saw-tooth like shape with abrupt transitions at each 2π interval. Bistability is exhibited in this regime due to the presence of three values for some time intervals but only two of them are stable thus will be excited. For $C > 4.6$, feedback is regarded as high with multistability predicted by the theory [4]. The target displacement has been retrieved under moderate feedback in a variety of works based on the fringe counting technique[4-8] as every 2π change in the laser phase corresponds to a target displacement of $\lambda/2$. Generally a differentiation circuit is employed to count the number of transitions in the self-mixing waveforms in order to estimate the target displacement.

A more straightforward way of calculating target displacement is by applying experimental

data into the theoretical model directly. However this is hindered by the fact that the observed self-mixing signals are usually distorted due to the influence of noise and disturbance inherent to the OFSMI systems and signal acquisition process. Hence the observed self-mixing signals must be processed before they are employed for achieving displacement or movement measurement. However, this issue has yet to be demonstrated in detail in the literature.

In this paper, we present an approach to eliminate the noises by means of neural network curve fitting technique whereby the distorted self-mixing signal is input to a radial basis network trained to output a nondistorted signal which best fits the input signal. The pre-processed signal is then used to reconstruct target displacement as well as moving track with an algorithm derived from the theoretical model. The proposed method is extremely simple with no additional component and since it does not rely on a counting circuit, it is suitable for both weak feedback and moderate feedback regimes.

II. THEORY

The well-known Lang-Kobayashi theoretical model for the OFSM system takes the form as follows:[1, 4]

$$\phi_F(\tau) = \phi_0(\tau) - C \cdot \sin[\phi_F(\tau) + \arctan(\alpha)] \quad (1)$$

$$P(\tau) = P_0[1 + mF(\tau)] \quad (2)$$

$$F(\tau) = \cos(\phi_F(\tau)) \quad (3)$$

where $\phi_0(\tau)$ and $\phi_F(\tau)$ are the laser phases without and with feedback respectively. $\tau = 2L/c$, is the round trip time between the LD and the external target. C is called feedback level factor. $P(\tau)$ and P_0 denote the laser power with and without feedback respectively. m is called modulation index (typically $m \approx 10^{-3}$). $F(\tau)$ is defined by Eq.(3) and is a periodic function of period 2π . Seemingly, once $P(\tau)$ is measured in an OFSM experimental setup, the unperturbed laser phase $\phi_0(\tau)$ can be retrieved from solving Equations (1)-(3) as

$$F(\tau) = [P(\tau)/P_0 - 1]/m \quad (4)$$

$$\phi_F(\tau) = \arccos[F(\tau)] \quad (5)$$

$$\phi_0(\tau) = \phi_F(\tau) + C \cdot \sin[\phi_F(\tau) + \arctan(\alpha)] \quad (6)$$

According to the relationship $\phi_0(\tau(t)) = 4\pi L(t)/\lambda_0$, the target instant distance $L(t)$ from LD is easily obtained, hence the target displacement if the equilibrium position of the target is known. Whereas, since $\phi_F(\tau)$ is computed from an inverse cosine function in Eq. (5) which always produces values in the interval $(-\pi, \pi]$, it has to be unwrapped to its real values. As is illustrated in Fig.

1, the true phase can be recovered from the algorithm as follows:

$$\phi_F(\tau) = (-1)^{M_1} \arccos(F(\tau)) + M_2 \cdot 2\pi \quad (7)$$

Where M_1 accumulates by 1 each time $F(\tau)$ reaches peaks and valleys. M_2 is added by 1 each time $F(\tau)$ reaches the valleys when ϕ_F is increasing, and -1 when ϕ_F is decreasing. The trend of ϕ_F , whether it is increasing or decreasing can be determined by observation of the abrupt upward and downward transitions of the self-mixing signal. However, in practice, the experimental data is usually contaminated with random noise and sparkles, it is hardly possible to locate the peak and valley points in $F(\tau)$ directly, or equivalently in the self-mixing signals. As a result, data preprocessing is entailed by means of signal processing techniques to eliminate the added noises.

III. NOISE ELIMINATION WITH RADIAL BASIS NEURAL NETWORK

Traditionally noise removal will involve some form of filtering depending on the nature of particular noises. A quick observation of experimental SMS signals as shown in Fig. 7 reveals that they comprises of mainly two sorts of noises, one presenting significant incoherence with the neighbourhood signal values (referred as impulsive noises or sparkles) and the other taking the form of random noises. An efficient way of removing the impulses would be utilizing a non-linear median filter. It is important to note, however, the length of a median filter should be chosen with care to ensure it is not either too short which will result in filter inefficiency, nor too long which consequently alters the signal traits badly. In our case, the filter length of 5 points will yield satisfactory outcome for weak feedback and 19 points for moderate feedback. On the other hand,

Fig 1. Illustration of laser phase and self-mixing waveform
(a) Phase without external feedback
(b) Phase with external feedback (c) Self-mixing waveform

one way of removing the fast varying random noises in contrast to the SMS signal fringe frequency could be through a low-pass filter. However, since the desirable denoised signal is monotonic within each increasing or decreasing intervals, the performance of a low-pass filter can be somewhat limited. Hence, a more appropriate denoise technique is needed to address this problem.

Recent development of neural network has recognized itself a powerful tool in a range of disciplines such as system modeling, pattern recognition and signal processing etc [9]. It represents a computing paradigm that learns through experience which differs from the conventional algorithmic approach by mimicking the operation of human brains. The basic processing element of a neural network is known as a neuron. A neural network employs a massive weighted interconnection of neurons that are organized in the form of layers. Each layer of neurons is associated with a so-called activation function, which introduces nonlinearity into the network and thus makes it more powerful.

Radial Basis Functions (RBF) is a category of functions that are particularly efficient for interpolation and smoothing of data [10] and is consequently selected to be used for our work. The Gaussian bell function is the most commonly used basis function. A typical radial basis network comprises of a hidden layer of neurons with radial basis function and a linear output which is a sum of the weighted output from hidden layer as shown in Fig. 2.

If we define $X \in (x_0 \dots x_n)$ as network input which is the distorted self-mixing signal, the network output $\hat{y}$ can be expressed as

$$\hat{y} = \sum_{j=1}^N w_{2j} \sum_{i=1}^N w_{1i} g_i(X) \quad (8)$$

Where w_{1i} and w_{2i} are the weights of the network, g_i is the radial basis function for hidden neurons. Mathematically g_i can be described by equation

Figure 2. Illustration of a neuron network

$$g_i(X) = -\exp\left(-\sum_{j=1}^n \frac{|x_j - c_{ij}|^2}{2\sigma_{ij}^2}\right) \quad (9)$$

Where $c_i^T = [c_{i1}, c_{i2}, \dots, c_{in}]$ is the centre of the receptive field and σ_{ij} is the width of the Gaussian function.

The network is then trained using a set of data containing N input-output pairs (x_i, y_i) ($i = 1, 2, \dots, N$) with y_i representing the desired undistorted self-mixing fringes such as the theoretical calculated output for a controlled target movement. Often it is convenient to use the root-mean-square error (RMSE) when evaluating the quality of the network, that is

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2} \quad (10)$$

During training, the network weights and parameters together with the number of hidden neurons are updated in a way so that $RMSE$ is minimized. With enough hidden neurons, a radial basis network can fit any function with desired accuracy.

IV SIMULATIONS

The proposed method was tested firstly with computer simulations. The external target is assumed to be subject to a harmonic vibration which can be represented as $L(t) = L_0 + \Delta L \cos(2\pi f t + \theta_0)$, where L_0 is the initial distance between the laser front facet and the target, f is the vibration frequency, t is time variable, θ_0 is the initial phase of target movement. The laser phase without feedback is then calculated as

$$\phi_0(t) = \frac{4\pi L(t)}{\lambda_0} = \frac{4\pi L_0}{\lambda_0} + \frac{4\pi \Delta L}{\lambda_0} \cos(2\pi f t + \theta_0) \quad (11)$$

When sampled with frequency of f_s , the discrete version of Eq. (9) can be written as

$$\phi_0(n) = \frac{4\pi L_0}{\lambda_0} + \frac{4\pi \Delta L}{\lambda_0} \cos\left(\frac{2\pi f n}{f_s} + \theta_0\right) \quad (12)$$

If we assume $f = 200 \text{ Hz}$, $f_s = 200 \text{ kHz}$, $L_0/\lambda_0 = 25000$ and $\Delta L/\lambda_0 = 2.6$, $\theta_0 = -\frac{\pi}{2}$, the self-mixing signal can be generated using (1)–(3) and (12) with $C = 0.8$, $\alpha = 4$ for weak feedback and $C = 3$, $\alpha = 4$ for moderate feedback. A small white noise is also added with signal-to-noise ratio (SNR) of 20 dB to emulate the practical situation as

shown in Fig. 3. We then performed fitting and found that the weak feedback curves can be fitted very well with the proposed method. Whereas, the situation for moderate feedback is a bit complex as the network does not perform good fitting for the curves with abrupt transitions. We solved this problem by segmenting the waveforms at the switching points and performed fitting for each segment using the same RBF neural net, and satisfactory outcome were produced as a result.

The curve fitted waveforms are plotted in Fig. 4. In order to evaluate the accuracy of our method, we compare the reconstructed moving track with its real counterpart and the error is plotted in Fig. 5. It can be seen that accuracy of our proposed method can reach $\lambda/25$ in the case of weak feedback and $\lambda/20$ where moderate feedback is presented.

Fig. 3 Simulated SM signals with SNR = 20dB (a) moving track of external target (b)weak feedback with $C = 0.8$ and $\alpha = 4$ (c) moderate feedback with $C = 3$ and $\alpha = 4$

Fig. 4 Curve fitted SM signals (a) Weak feedback (b) Moderate feedback

Fig. 5 The error between recovered target movement track and the real track (a) weak feedback (b) moderate feedback

V EXPERIMENT RESULTS

In the OFSM experimental setup, an SL with the wavelength of 785nm is biased with a dc current of 80mA. A metal plate is used as the target, which is made to vibrate harmonically by placing it close to a loudspeaker driven by a sinusoidal signal. Temperature is controlled at $25 \pm 0.1^\circ C$. The SMS is detected by the monitor photodiode (PD) and is amplified by a trans-impedance amplifier, as shown in Fig. 6 [5].

Fig. 6 OFSM experimental setup

The neural network training took approximately 1000 presentations of data to reach the convergence criterion. It was shown that testing waveforms are fitted very well with the neural network and the target moving tracks are recovered correctly based on the unwrapped phases. The waveforms of the SMS in weak feedback and moderate feedback are shown in Fig. 7. Sparkles and random noise are significant in both signals.

Fig. 8-a, b show the median filter processed one period SMS signal of the harmonic movement of the target in weak feedback and moderate feedback respectively. The filter length for weak feedback and moderate feedback are 5 and 19 respectively. It can be found that the random noise present in the moderate feedback SMS is still significant. Fig. 8-c, d shows further neural network processed SMS signals for weak feedback and

moderate feedback respectively. It is clearly seen that the noises have been effectively eliminated.

Fig. 9 shows the target moving track recovered from SMS waveforms. It is approximately harmonic, which reveals a good recovery of the real movement of the target. The ripples along the recovered moving track for moderate feedback is due to the broadened transition sections in the measured SMS waveforms.

Fig. 7 Experimental SMS waveforms for (a) weak feedback and (b) moderate feedback

Fig. 8 Self-mixing waveforms before and after neural network processing (a) Median filter processed SMS for weak feedback (b) Median filter processed SMS for moderate feedback (c) Neural network processed SMS for weak feedback (d) Neural network processed SMS for moderate feedback

Fig. 9 Recovered target moving track (a) weak feedback (b) moderate feedback

VI. CONCLUSION

Neural network interpolation has been employed to remove noises from self-mixing signals after median filtering. Radial Basis network is found very effective in fitting the noisy SMS data into a smooth waveform while maintaining good accordance between the input data and the fitted curve. With the proposed phase unwrapping algorithm, target moving trajectory and displacement has been recovered with good accuracy of $\lambda/25$ for weak feedback and $\lambda/20$ for moderate feed back according to computer simulation. The method was proven to be reliable by the experimental recovery of the sinusoidal movement of the target in both weak and moderate feedback regimes.

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