

# PROCEEDINGS OF SPIE

[SPIDigitalLibrary.org/conference-proceedings-of-spie](https://SPIDigitalLibrary.org/conference-proceedings-of-spie)

## BCG signal processing based on advanced LMS filter for optical fiber monitor

Liu, Yifan, Xu, Wei, Yu, Changyuan

Yifan Liu, Wei Xu, Changyuan Yu, "BCG signal processing based on advanced LMS filter for optical fiber monitor," Proc. SPIE 11547, Optoelectronic Devices and Integration IX, 115471P (10 October 2020); doi: 10.1117/12.2575310

**SPIE.**

Event: SPIE/COS Photonics Asia, 2020, Online Only

## BCG Signal Processing

### Based on Advanced LMS Filter for optical fiber monitor

Yifan Liu<sup>[1]</sup>, Wei Xu<sup>[2][3]</sup>, Changyuan Yu<sup>\*[1]</sup>

<sup>1</sup>Department of Electronic and Information Engineering, The Hong Kong Polytechnic University, Kowloon, Hong Kong

<sup>2</sup>University of Chinese Academy of Science.

<sup>3</sup>Xi'an Institute of Optical And Precision Mechanics, Chinese Academy of Science

#### Abstract

Heart Rate Variability (HRV) analysis is an important tool for health monitoring. A non-invasive smart health monitoring system based on optical fiber interferometer can get HRV information from the Ballistocardiogram (BCG) signal. For some patients, the HRV can hardly be calculated due to the interferences from breath and other vibrations. In this research, we obtain a stable and high-sensitive BCG signal by a Mach-Zehnder interferometer (MZI) based sensor. In order to reduce the noise in signal, we introduce an advanced least mean squares (LMS) adaptive filter into the procedure. We use the signal processed by a bandpass filter as the 'desired signal' to deal with the raw data and obtain a preferable output for HRV calculation.

**Key words:** BCG, Heart Rate Variability, LMS adaptive filter

#### 1.Introduction

With developing of the aging world, a real-time monitoring of vital signs can efficiently obtain the statuses of body. Vital signs which contain breath and heartbeat signal is a significant tool for human healthcare monitoring and curing<sup>[1]</sup>. Therefore, it has been an acceptable communication index to judge the illness and patients status for longitudinal monitoring, continuous treat which can help the professionals diagnose fast and accurate. A reliable HRV data can interpret the statuses of body and indicate illness of heart, vessels and other organs of a human body<sup>[2,3]</sup>. HRV now is a widely accepted analysis method in vital signs monitoring. Compared with other methodology, an HRV data can help monitor heart rate, blood pressure and other index of vital signs<sup>[4,5]</sup>.

HRV interpreting the variability of heart rate can be calculated by Electrocardiogram(ECG)<sup>[6]</sup> and BCG<sup>[7]</sup> signal. BCG signal has the advantages that it can be used for heart rate, HRV, blood pressure and kinds of features which can further indicate the real-time status of human beings including sleep, fatigue and illness<sup>[8,9]</sup>. Meanwhile, BCG signal has its advantage in long-time monitoring since it can be collected by a non-invasive monitoring system. It can help professionals better get patients vital signs during sleeping or other rest time. Usually, the heart beat provided the dominant part of body vibration. Therefore, enlarging the strong vibration and limiting the small vibration is purpose. A common BCG signal can be described as Fig.1

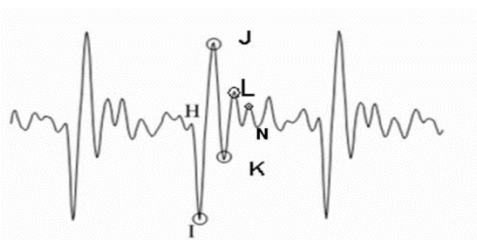


Fig.1 BCG signal

Where a J peak is the dominant vibration by a heartbeat. An I peak and K peak can be found before and after it respectively. It is a basic mode for heartbeat identification.

To obtain a high-quality BCG signal, a sensitive and stable sensor is necessary. Yu<sup>[10]</sup> has presented a sensor based on Mach-Zehnder interferometer (MZI) which can provide a stable and high sensitive BCG signal for HRV calculation.

LMS filter is an FIR filter has advantages in signal strengthen and noise limitation<sup>[11]</sup>. It has been used in BCG processing which has capacity for convergence issues<sup>[12]</sup> and less complex<sup>[13]</sup>. Delayed LMS adaptive Filter (DLMS) and pipelined architecture is used to overcome the path delay<sup>[14]</sup>. In LMS application, a 'desired respond' is hard to obtain. However, the BCG signal and noise have their significant frequency character<sup>[15]</sup> which can be the basic of 'desired respond' obtaining.

## 2.Methodology and Experiment

### 2.1 MZI Sensor

An MZI sensor structure can be described by Fig.1 which is based on a Mach-Zehnder interference.

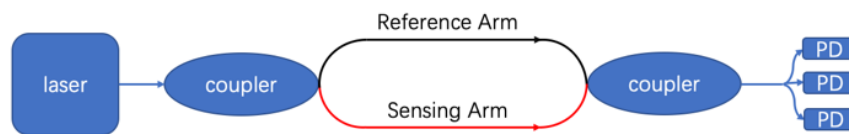


Fig.2 MZI sensor structure

From the structure figure, sensor has a laser light source, two optical couplers, three photodetectors (PDs) and fibers. Especially, the first coupler is a  $1 \times 2$  coupler which separate the light source to two same light. The two light go through the sensing arm and reference arm respectively. After a  $2 \times 3$  coupler, the signal can be detected and changed to electric signal by three PDs that they have a phase difference of  $\frac{\pi}{3}$ .

### 2.2 BCG signal

A common BCG signal can be shown as figure 2.

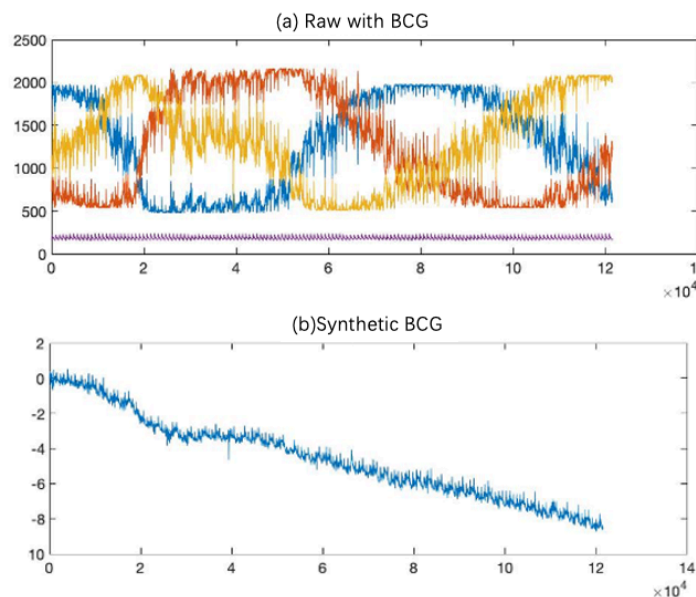


Fig.3. (a)Raw BCG signal collected by 3 PDs, (b)Synthetic BCG signal

In the figure, the blue line, red line and yellow line respectively shows the signal with a settled phase difference. The figure 2(b) is the synthetic BCG calculated by raw data in 2(a). Obviously, it has a strong baseline drift in raw data. Accordingly, a strong baseline drift can be seen in the synthetic BCG signal which will influence the signal processing procedure.

### 2.3 LMS filter

A standard LMS filter flowchart is shown in Fig.3 ,

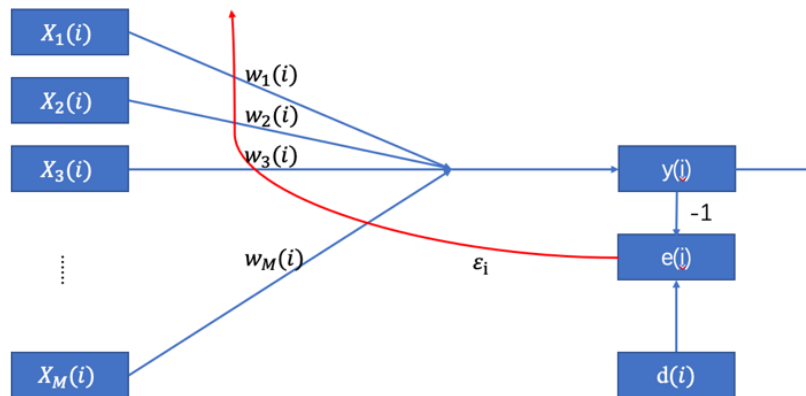


Fig.4 LMS filter

Where  $X_n(i)$  is a series of real discrete-time signals. Then the LMS algorithm can be described as

$$w_{n+1}(i) = w_n(i) + 2\mu\epsilon_i X_n(i) \quad (2.1)$$

Where  $\epsilon_i$  is the error factor which can be calculated by

$$\epsilon_i = d_i - y_i \quad (2.2)$$

Where  $d_i$  is the ‘desired response’, a signal which can better interpret the demand compared with the input signal.

Especially, the vectors  $X_n(i)$  and  $w_n(i)$  respectively represent the input of tapped delay line and the filter weight.

The parameter  $\mu$  need to fulfill the demand

$$0 < \mu < \frac{1}{\lambda_{max}} \quad (2.3)$$

Where  $\lambda_{max}$  is the maximum eigenvalue of autocorrelation matrix of input signals.

### 2.4 Experiment design

In this research, we obtain the input signal by an MZI sensor which has three PDs with a phase difference of  $\frac{\pi}{3}$ . Then we preprocess the signal by a lowpass filter. We obtain the ‘desired response’ by a bandpass filter. The flow chart can be described by fig.4.

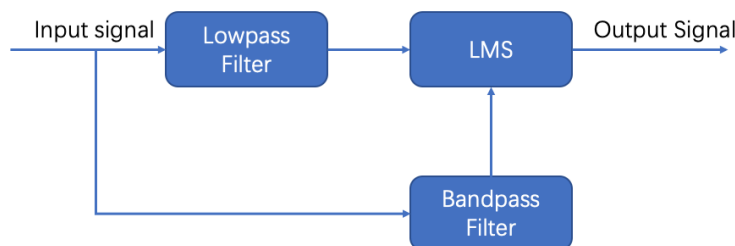


Fig.5 Flowchart of experiment

### 3.Result and discussion

The data is a 60 seconds stable data collected by an MZI cushion sensor with a sample rate of 1000Hz. The raw data is synthesized to a BCG signal and processed by a bandpass filter of 2Hz to 7Hz. Filter tap parameter  $M=3$ , Convergence index  $\mu = 0.002$ . The result is shown in Fig.6

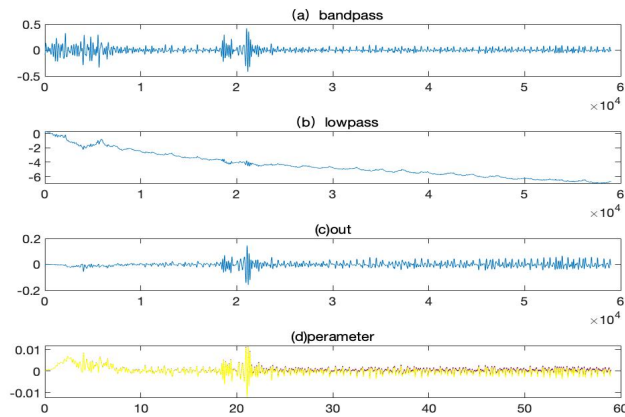


Fig.6 (a)BCG signal processed by a 2Hz to 7Hz bandpass filter.(b) BCG signal processed by a 7Hz lowpass filter.  
(c)Output signal (d)Adaptive filter parameters.

From data in Fig.5(a), the raw signal processed by a bandpass filter can significantly limit the baseline drift which is used to be the ‘desired responds’ as the heart vibrate rate of human being can hardly out of this range. However, a bandpass filter may reduce some significant vibrates less than 2Hz. But the data processed by a lowpass filter can hardly deal with the baseline drift and still maintain some low frequency noise. Therefore, an LMS filter can use a signal passed bandpass filter to iteratively approximate the lowpass signal. The data in 5(c) shows that the new filter can maintain some little vibrates and filter the main noise at same time.

Especially, some details between bandpass signal and LMS filter are shown in Fig.7.

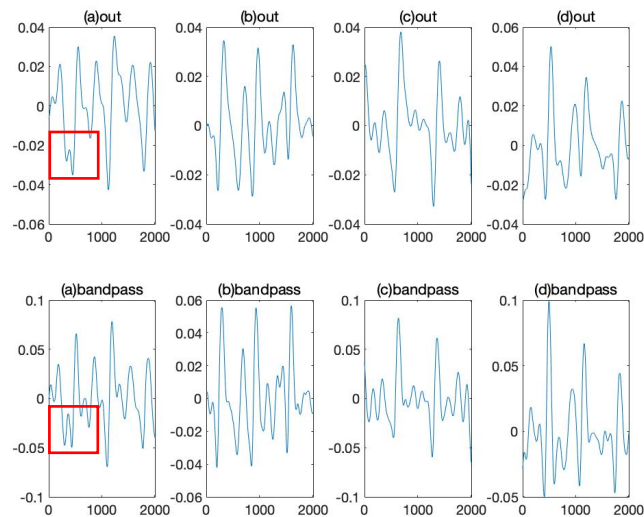


Fig.7 Detail of output signal and ‘desired signal’

From the detail figure, the amplitude of signal processed by LMS filter is narrow. As figure 7(a) shows that LMS filter can reduce the confusion between similar vibration as the red box shows. In figure 7(b), LMS filter can smooth the small vibration. In figure 7(c), LMS filter has advantage in enlarging the stronger vibration. Meanwhile, the figure 7(d) shows that LMS filter can reduce the small vibration.

Meanwhile, we have a further experiment changing the threshold frequency of 'desired responds' which processed by a 1Hz to 7Hz filter. The output signal is showed in Fig.8

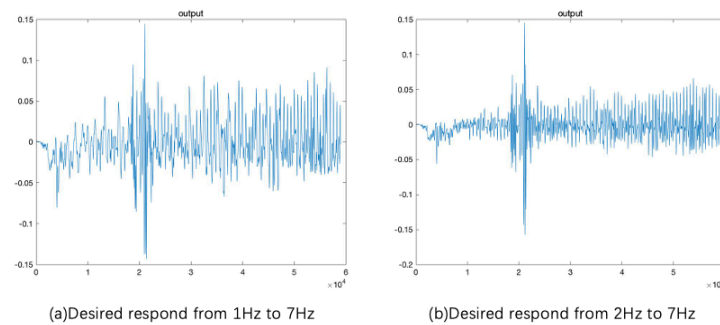


Fig.8 Output signal which 'desired respond' processed by (a)1Hz to 7Hz filter (b)2Hz to 7Hz filter

Compared (a) to (b), the output is disordered and the baseline is not return to zero. Therefore, 'desired respond' chosen can influence the capacity of filter. The raw signal processed by a 2Hz to 7Hz bandpass filter is more preferable.

#### 4.Conclusion

This research uses an LMS filter to process the BCG signal. A raw signal collected from MZI sensor preprocessed by a 2Hz to 7Hz bandpass filter is chosen to be the 'desired respond'. By the processing of LMS filter, the small body vibration can be limited and strong vibration will be enlarged compared with the signal processed by a 2Hz to 7Hz bandpass filter only. Meanwhile, the signal processed by a 2Hz to 7Hz bandpass filter is a better 'desired respond' for the LMS filter.

#### 5.Acknowledgement

This work was supported by Grant 15211317 from HK RGC GRF and 1-ZVHA from HK PolyU.

#### References

- [1] Malik, Marek. "Heart rate variability Standards of measurement, physiological interpretation, and clinical use." *Annals of Noninvasive Electrocardiology* 93.5(1996):1043-65
- [2] Saraswat, Monika, A. K. Wadhwani, and S. Wadhwani . Non-invasive Estimation of HRV Performance for Diabetes Mellitus with Cardiac Disorder on the Basis of Time-Frequency and Poincare Plot Analysis. *Intelligent Computing Applications for Sustainable Real-World Systems, Intelligent Computing Techniques and their Applications*. 2020.
- [3] Tan, Gabriel, et al. "Heart rate variability (HRV) and posttraumatic stress disorder (PTSD): a pilot study." *Applied psychophysiology and biofeedback* 36.1 (2011): 27-35.
- [4] Umetani, Ken, et al. "Twenty-four hour time domain heart rate variability and heart rate: relations to age and gender over nine decades." *Journal of the American College of Cardiology* 31.3 (1998): 593-601.
- [5] Peng, Xiong, et al. "Correlation of heart rate and blood pressure variability as well as hs-CRP with the burden of stable coronary artery disease." *Minerva Cardioangiologica* (2020).

- [6] Siecinski, Szymon, Ewaryst J. Tkacz, and Pawel S. Kostka. "Comparison of HRV indices obtained from ECG and SCG signals from CEBS database." *BioMedical Engineering OnLine* 18.1 (2019): 69.
- [7] Yoshioka, Mototaka, and Souksakhone Bounyong. "Analysis of Pulse Transit Time Derived From Imaging Photoplethysmography and Microwave Sensor-Based Ballistocardiography." *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops*. 2020.
- [8] Divyabharathi, O., et al. "Analysis of Human Physiological Parameters Using Real-Time HRV Estimation from Acquired ECG Signals." *2019 International Conference on Data Science and Communication (IconDSC)*. IEEE, 2019.
- [9] Greco, Alberto, et al. "Assessment of muscle fatigue during isometric contraction using autonomic nervous system correlates." *Biomedical Signal Processing and Control* 51 (2019): 42-49.
- [10] Yu, Changyuan, et al. "Non-invasive smart health monitoring system based on optical fiber interferometers." *2017 16th International Conference on Optical Communications and Networks (ICOON)*. IEEE, 2017.
- [11] Zhang, S., et al. "A normalized frequency-domain block filtered-x LMS algorithm for active vehicle interior noise control." *Mechanical Systems and Signal Processing* 120 (2019): 150-165.
- [12] Meher, Pramod Kumar, and Sang Yoon Park. "Area-delay-power efficient fixed-point LMS adaptive filter with low adaptation-delay." *IEEE Transactions on Very Large Scale Integration (VLSI) Systems* 22.2 (2013): 362-371.
- [13] Douglas, Scott C., and TH-Y. Meng. "Normalized data nonlinearities for LMS adaptation." *IEEE Transactions on Signal Processing* 42.6 (1994): 1352-1365.
- [14] Meher, Pramod Kumar, and Sang Yoon Park. "Low adaptation-delay LMS adaptive filter part-I: Introducing a novel multiplication cell." *2011 IEEE 54th International Midwest Symposium on Circuits and Systems (MWSCAS)*. IEEE, 2011.
- [15] Ngai, Brandon, et al. "Comparative analysis of seismocardiogram waves with the ultra-low frequency ballistocardiogram." *2009 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. IEEE, 2009.