Eliminating Motion Artifacts in PPG

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Abstract--In this study, independent component analysis was employed to separate the independent components (i.e., PPG signals and noise) from the raw signals with motion artifacts. Subsequently, independent components containing PPG signals were selected and the locations of the PPG signal components on the frequency spectrum were analyzed. Next, the raw signals passed through a multi-bandpass filter specifically designed for this study to eliminate motion artifacts. For the experiment, motion artifacts were created using four types of finger movements: vertical finger movement, horizontal finger movement, rapid finger shaking, and random finger shaking. The study results included an independent component analysis of the independent components, the waveforms of the filtered PPG signals in the time and frequency domains, and the heart rate measurements.

I. INTRODUCTION

The equipment for measuring and instantaneously monitoring physiological information for PPG is superior to that of ECG because it is convenient and easy to use. However, PPG measurements are susceptible to the effects of motion artifacts, causing PPG waveform interferences and incorrect detection of physiological information. Thus, misjudgments often occur. To accurately measure physiological information, the properties and composition of PPG signals must be clearly understood. In addition, the types of signals with motion artifacts and the causes of the motion artifacts must be analyzed to separate or remove the interfering signals.

II. METHODOLOGY

In which fast Fourier transform, singular value decomposition, and ICA were used to obtain the noise reference signals of the adaptive filters. The results of analysis indicated that noise reference signal filters generated using the ICA method produced relatively superior results.

A. Composition of PPG Signal Waveform

PPG signals comprise two waveforms [1], created during systole and diastole. For the first waveform, the increase in the blood flow volume causes a pressure change in the blood vessel. The corresponding waveform in Fig.1.



Fig. 1. Composition of the PPG Signal Waveform

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B. Motion Artifacts

When measuring PPG signals, physiological signals are prone to interference (motion artifacts) from external factors. The types of motion artifacts vary, but can primarily be divided into poor contact with sensing elements, interference from surrounding lights, and interference to measuring instruments caused by participant movement (shaking) during measurements [2], the last of which was the most significant.

III. RESEARCH METHODS FOR ELIMINATING MOTION ARTIFACTS

The objective of this study was to solve the problem of PPG measurements being susceptible to the effects of motion artifacts. The degree of artifacts varied as the movement methods and level of shaking varied. To eliminate motion artifacts, a series of methods was designed in this study. The process architecture is displayed in Fig 2.



Fig. 2. Process Architecture of the Research Method

A. Basic Definition of Independent Component Analysis

The ICA is able to separate the raw signal s(t) from the mixed signal x(t) when x(t) is known. The basic model equation for ICA is shown as (1):

$$\mathbf{x}(\mathbf{t}) = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ \vdots \\ x_m \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & a_{13} & \dots & a_{1n} \\ a_{21} & a_{22} & a_{23} & \dots & a_{2n} \\ a_{31} & a_{32} & a_{33} & \dots & a_{3n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & a_{m3} & \dots & a_{mn} \end{bmatrix} \begin{bmatrix} s_1 \\ s_2 \\ s_3 \\ \vdots \\ s_n \end{bmatrix} = \mathbf{As}(\mathbf{t}) (1)$$

Which is represented by the (2) mathematical equation:

$$s(t) \approx Wx(t) = \begin{bmatrix} w_{11} & w_{12} & w_{13} & \dots & w_{1m} \\ w_{21} & w_{22} & w_{23} & \dots & w_{2m} \\ w_{31} & w_{32} & w_{33} & \dots & w_{3m} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ w_{n1} & w_{n2} & w_{n3} & \dots & w_{nm} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ \vdots \\ x_n \end{bmatrix} = u(t)(2)$$

The conceptual diagram of ICA is shown in Fig. 3.



Fig.3. The ICA conceptual diagram

B. Optimization Algorithm

In this study, the ICA algorithm that was introduced by Aapo Hyvärinen [3-4] was used to revise the previously defined objective function. Assuming that a weight vector w is able to correct the objective function and that the independent component u to be solved is $u = w^T x$, the equation can be changed to (3).

$$J(w^{T}x) \propto [E\{G(w^{T}x)\} - E\{G(V)\}]^{2}$$
(3)

This equation is called Gram-Schmidt orthogonalization (4).

$$w_{n+1} = w_{n+1} - \sum_{j=1}^{n} (w_{n+1}{}^{T} w_{j}) w_{j} \qquad (4)$$

The decorrelation vector w can then be normalized using the (5).

$$w_{n+1} = w_{n+1} / \sqrt{w_{n+1}^T w_{n+1}}$$
(5)

C. Multi-Bandpass Filter

The finite impulse response (FIR) digital filter was used in this study. Unlike infinite impulse response, FIR does not possess a feedback loop; therefore, the input frequency response of the pulse signals approach zero, which demonstrates superior system stability.

D. Heart Rate Detection Algorithm

The crest detection algorithm employed in this study was created in reference to the Bigger Fall Side method proposed by Navakatikyan (2002) [5] and the improvement methods proposed by Chen (2004) [6]. The relevant procedure is shown in Fig. 4.



Fig. 4. Crest-Trough Detection Procedure

IV. EXPERIMENT SCENARIOS AND RESULTS OF ANALYSIS

The average heart rates measured using the ECG were set as the reference. Next, the average heart rates obtained from the PPG signal experiment analysis were compared with the reference, as shown in Table I.

Table I						
COMPARISON BETWEEN THE AVERAGE HEART RATES MEASURED USING THE						
ECG AND THOSE OBTAINED FROM THE PPG SIGNAL EXPERIMENT ANALYSIS						

Comparisons Between the Measurement Methods Experiment scenarios		Average heart rate (bpm) measured by the ECG	Average heart rate (bpm) measured by the PPG	Difference in the average heart rate (bpm) between the ECG and the PPG	Difference as a percentag e (%)
Vertical	E1	82.3	81.5	-0.8	0.97
finger movement	E2	82.8	82	-0.5	0.6

V. CONCLUSION

PPG is used in a wide range of applications. In general, PPG must remain stationary when analyzing physiological information. When movements are inevitable during PPG measurement, PPG is prone to interference. Furthermore, the resulting waveforms are affected, causing analysis to be difficult. For example, damages to waveforms cause inaccurate detection of heart rate, the most crucial physiological information. In certain scenarios, analyses are severely damaged, rendering waveform analysis impossible. Therefore, a research method for eliminating motion artifacts was proposed in this study.

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Reference

- Chen Y.X., "Correlational Research on Heart Rate, PPG, and Non-Invasive Pulse Wave Signal." Master Thesis, Department of Automatic Control Engineering, Feng Chia University, June 2005.
- [2] Cai Q.Z., "PPG Motion Artifact Detection and Signal Reconstruction," Master Thesis, Department of Automatic Control Engineering, Feng Chia University, Aug. 2009.
- [3] Aapo Hyvarinen, "Independent Component Analysis by Minimization of Mutual Information," Department of Computer Science and Engineering Laboratory of Computer and Information Science, Aug. 1997.
- [4] Aapo Hyvarinen and Erkki Oja, "Independent Component Analysis: A Tutorial," Department of Computer Science and Engineering Laboratory of Computer and Information Science, Apr. 1999.
- [5] Michael A. Navakatikyan, Carolyn J. Barrett, Geoffrey A. Head, James H. Ricketts , and Simon C. Malpas, "A Real-Time Algorithm for the Quantification of Blood Pressure Waveforms," IEEE transactions on biomedical engineering, vol. 49, no. 7, pp. 662-670, July 2002.
- [6] Chen J.X. "Assessing the Changes in Diastolic Blood Pressure of Surgery Patients Using Non-Invasive Plethysmography Signals." Master Thesis, Department of Mechanical and Electromechanical Engineering, National Sun Yat-sen University, June 2004.