PPG signal preprocessing and comparison study with learning-based model for stress detection

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Abstract

PPG signals are widely used to measure and provide personalized health information in wearable devices. However, PPG signals are often corrupted by different artifacts, and the corrupted signals lead to a deterioration in the performance of downstream studies. To improve the quality of PPG signals, we propose a simple but effective two-step noise reduction algorithm. First, the algorithm uses Discrete Fourier Transform to suppress noise components in terms of frequency. Then, it removes remaining noises in terms of time. Consequently, we confirm that the proposed PPG noise reduction method increases the PPG peak matching ratio and eventually improves the stress detection performance of learning-based models, such as random forest, support vector machines, and gradient boosting. As the demand for wearable devices increases and the growth of the healthcare industry continues, we expect that more accurate health management would be available through the proposed PPG noise reduction method.

I. Introduction

Since the advent of the smartphone revolution in 2007, the second smart revolution, the market of IoT devices has been growing rapidly in recent years. In addition, as income level increases, the healthcare industry has been attracting strong interest to improve the quality of life. Accordingly, the demand for wearable devices which monitors individual health condition in real time has increased[1]. In particular, as the spread of the virus has raised interest in health, the demand for wearable devices for healthcare has increased more.

PPG (Photoplethysmogram) is the most widely used signal for health monitoring. This is based on non-invasive and inexpensive photovoltaic measurement. However, PPG signal is small and often corrupted with various types of artifacts and interferences. It is important to improve the quality of PPG signals.

In this paper, we firstly suggest two-step method for reducing and eliminating noise accurately and efficiently: analyze the signal in terms of frequency, and reconstruct the signal by removing the remaining noise signals in terms of time. To identify the effectiveness of our proposed method, we use two verification methods. First, we measure the number of matching peaks using two peak algorithms to determine how much the number of matching peaks has increased after noise reduction. Second, we compare and evaluate performance with matching learning-based model to predict the presence of stress.

II. Methodology

[Figure 1] shows the process of decreasing noise in terms or frequency[2]. When analyzing signals from a frequency perspective, Discrete Fourier Transforms (DFT) are used. First, the signal is divided into segments of N length. The larger the N, the higher the resolution of frequency, but it triggers higher amount of computation. Thus, frequency resolution of at least 0.1Hz has adopted. Because the frequency components of PPG signals are highly dependent on signal characteristics between individuals, we set different bandwidth each person.

The frequency cut-off is adaptively determined to eliminates the noise components. We extract the length of 0.1Hz good-quality signals to determine the cut-off frequency. The lower cut-off frequency is computed as L = (HR/60) - 0.2 Hz, where HR means heart rate. The higher cut-off frequency uses Fast Fourier Transform (FFT) spectra. We choose the last frequency component after which all magnitudes are below the threshold value of 15% of the maximum.

After reducing the noise of the signal in terms of frequency, we eliminate the signals which includes high noise level in terms of time, as shown in (b) of [Figure 1] [3]. Signals are divided by 10

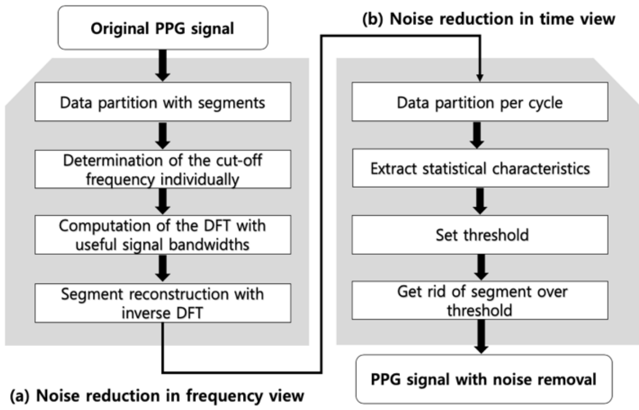

Figure 1. noise removal algorithm

cycles with valley detection. We measure the standard deviation, kurtosis, and asymmetry for each block. The measurement method is as follows:

$$\text{Standard deviation} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})^2} \quad (1)$$

$$\text{Kurtosis} = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})^4}{std^4} \quad (2)$$

$$\text{Skewness} = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})^3}{std^3} \quad (3)$$

where std means standard deviation and $\bar{x}$ means mean of x. When three statistical values are over threshold, blocks are removed from the signal component. The threshold is set as follows:

$$T_\sigma = \bar{\sigma} + a_1 \quad (1)$$

$$T_k = \bar{k} + a_2 \quad (2)$$

$$T_{s1} = \bar{s} + a_{31} \quad (3)$$

$$T_{s2} = \bar{s} + a_{32} \quad (4)$$

We extract the part of good quality signals from the whole signals. $\bar{\sigma}$, $\overline{k}$, $\overline{s}$ represent the average of the values of standard deviation, kurtosis, and skewness. For a_1, a_2, $a_3$values, we use the reasonable values depending on the condition of the signal, as using excessively small values may remove good-quality signals too.

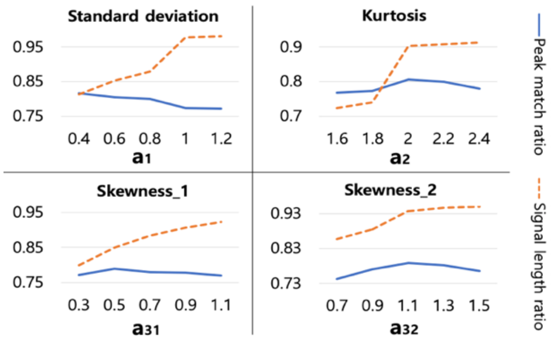

Figure 2. Peak match ratio and signal length ratio correspond to threshold

III. Experiment and result

In this paper, WESAD datasets are used[4]. Datasets were measured in 64Hz from 15 subjects, and the signal was measured in the baseline, pleasure, stress, meditation, and recovery circumstances. We used signals correspond to two labels, baseline and stress.

To measure the performance of the proposed noise reduction methods, two peak detection algorithms were applied to the original PPG signals, PPG signals after noise reduction in terms of frequency, and PPG signals after noise reduction in terms of frequency and time[5][6]. By measuring the number of matched peaks between two algorithms, we measured the proportion of how many matched peaks has increased respectively.

First, a variety of thresholds were applied to find the optimal thresholds. Good quality signals for threshold setting were used by extracting 1% of the whole signal. [Figure 2] is the result of the ratio of peak matching to each threshold settings, and the ratio of reduced signal length to the original signal length. As the signal length ratio increases, the peak matching ratio tends to increase and decrease from certain points.

In addition, a comparative experiment was conducted by setting different quality signal ratios that is used in extracting time characteristics. Good quality signals were extracted 0.1%, 1%, and 5% of the whole signals. Among those with a signal length ratio of 0.8 or higher, the thresholds which have the highest peak matching ratio were used($a_1 = 0.4$, $a_2 = 2.0$, $a_{31} = 0.5$, $a_{32} = 1.1$). The extraction ratio of 5% has showed the best performance. When the good quality signal ratio was 5%, peak matching ratio from original signal was 0.59, peak matching ratio after noise reduction in frequency was 0.75, and peak matching ratio after noise reduction in frequency and time was 0.84, which increased by 0.25. The results are as follows [Table 1].

Good quality signal ratio	Peak matching ratio			Signal length ratio
	Original signal	NR. in frequency view	NR. in time view	
0.1%	0.5945	0.7532	0.8196	0.6526
1%	0.5945	0.7532	0.8374	0.7026
5%	0.5945	0.7532	0.8378	0.7554

Table 1. Results according to extracted rate of good quality signal. The "NR." Represents noise reduction, and the signal length ratio represents noise reduced signal length divided by original signal length

Finally, the original signals and noise removed signals were measured and compared by determining the presence of stress with machine learning based model. We used local minima and maxima peak detection algorithm[7]. We also added experiments to ensemble five peak detection model[5][6][7][8][9].

We applied over-sampling to solve imbalance problems as data labeled with stress is about 0.57 times less than data labeled with baseline. We also used leave-one-subject-out cross validation. The following [Table 2] is the result of PPG noise reduction algorithm's performance with Random forest, SVM, and Gradient

Model		Noise reduction method			
		Baseline	F.	F. & T.	F. & T. & E.
Random forest	AUC	0.5584	0.6225	0.6317	0.6749
	F1	0.4348	0.4974	0.5437	0.5230
SVM	AUC	0.5782	0.6469	0.6812	0.7241
	F1	0.4955	0.5951	0.6131	0.6395
Gradient boosting	AUC	0.5901	0.5997	0.6067	0.6271
	F1	0.5422	0.5315	0.5393	0.6866

Table 2. Stress detection results with learning-based models. "F." represents frequency, "T." represents times, and "E." represents ensemble. Applied moving-average filter for baseline.

boosting model. It proves that the proposed noise reduction algorithm improves the stress detection performance for SVM model, the AUC is improved by 0.1 and, the F1 score is improved by 0.12 compared to the baseline algorithm of the moving average filter. When applying the ensemble peak detection method in addition to the proposed noise reduction algorithm, the AUC is increased by 0.04 and the F1 score is increased by 0.03 for SVM model.

IV. Conclusion

In this paper, we propose an effective approach to improve the quality of PPG signals. Both frequency and time based noise reduction method contributes to high quality signals and results in increased peak matching ratio. In addition to the noise reduction, the ensemble-based peak detection further improves the performance of stress detection; the AUC from 58% to 72%, and the F1 score from 50% to 64%.

This paper significantly improves the performance in detecting the presence of stress by suggesting noise reduction algorithm and ensemble peak detection method. This offer us the possibility that we can monitor our health in real time with only PPG signals. In the future, we expect that the performance can be remarkably improved when we apply the noise reduction method in end-to-end deep learning model.

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