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 rise of the smartphone revolution in 2007, the second smart revolution, which is the market of Internet of things devices, has been growing rapidly in recent years. With the increase in income level, considerable attention has been paid to the healthcare industry to improve the quality of life. Accordingly, the demand for wearable devices for real-time monitoring of individual health condition has increased [1]. In particular, the spread of the virus such as COVID-19 has also increased the demand for wearable devices in the healthcare industry.

Photoplethysmogram (PPG) is the most widely used signal for health monitoring. It is based on noninvasive and inexpensive photovoltaic measurement. However, PPG is small and often corrupted with various types of artifacts and interferences. Thus, improving the quality of PPG signals is necessary.

In this paper, we firstly suggest a two-step method for an accurate and efficient reduction and elimination of noise: 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 employing two peak algorithms to determine how much the number of matching peaks has increased following noise reduction. Second, we evaluate and compare the performance with matching learning-based model to predict the presence of stress.

II. Methodology

[Figure 1] presents the process of decreasing noise in terms or frequency [2]. When analyzing signals from the perspective of frequency, discrete Fourier transforms are used. First, the signal was divided into segments of N length. The larger the N, the higher the frequency resolution. However, it triggers higher amount of computation. Thus, a frequency resolution of at least 0.1Hz has been adopted. Due to the high dependence of the frequency components of PPG signals on signal characteristics between individuals, we set different bandwidths for each person.

To eliminate the noise components, the frequency cut-off was adaptively determined by extracting the length of 0.1-Hz good-quality signals. The lower cut-off frequency was computed as L = (HR/60) - 0.2 Hz, where HR denotes heart rate. The higher cut-off frequency was computed using fast Fourier transform spectra. We chose the last frequency component, after which all magnitudes were below the threshold value of 15% of the maximum.

After reducing the signal noise in terms of frequency, we eliminated the signals which include high noise level in terms of time, as presented in (b) of [Figure 1] [3]. Signals were divided by 10 cycles with valley detection. We measured the standard deviation, kurtosis, and asymmetry for each block. The measurement method is as follows:

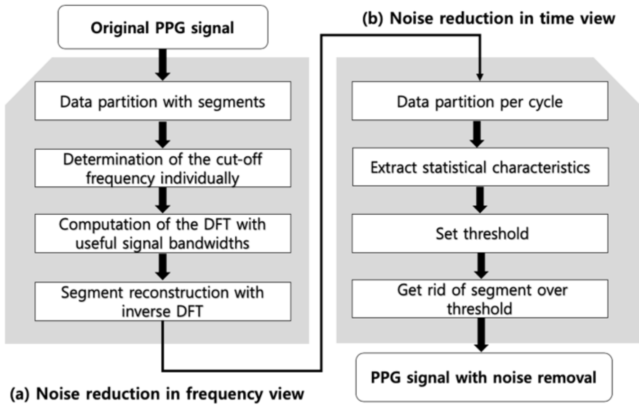

Figure 1. Noise removal algorithm

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

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

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

where std denotes standard deviation and $\bar{x}$ the mean of x. When three statistical values were beyond the threshold, blocks were removed from the signal component. The threshold was 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 extracted the part of good-quality signals from the whole signal. $\bar{\sigma}, \bar{k}, \bar{s}$ denote the average of the values of standard deviation, kurtosis, and skewness. For a_1, a_2, a_3 values, we used the reasonable values, depending on the condition of the signal, as the use of excessively small values may also remove good-quality signals.

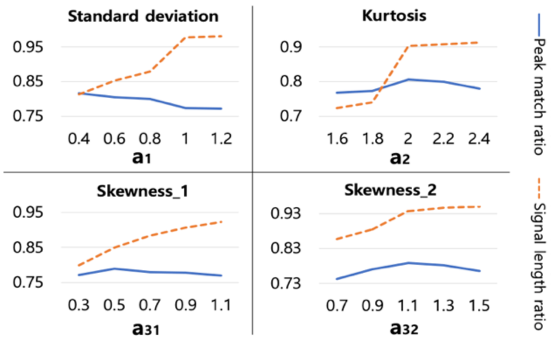

Figure 2. The peak match ratio and signal length ratio correspond to the threshold

III. Experiment and result

In this paper, Wearable Stress and Affect Detection (WESAD) datasets were used [4]. The 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 corresponding to two labels: baseline and stress.

To measure the performance of the proposed method for noise reduction, 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]. We measured the proportion of how many matched peaks have increased by measuring the number of matched peaks between two algorithms.

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

Moreover, a comparative experiment was conducted by setting different good-quality signal ratios that is used in extracting time characteristics. Good-quality signals were extracted from 0.1%, 1%, and 5% of the whole signals. Among those with a signal length ratio of 0.8 or higher, the thresholds with 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 exhibited the best performance. When the good-quality signal ratio was 5%, the peak matching ratio from the original signal was 0.59; the peak matching ratio after noise reduction in frequency, 0.75; and the peak matching ratio after noise reduction in frequency and time, 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 the 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 reduced signals were measured and compared by determining the presence of stress using a machine learning-based model. We used the local minima and maxima peak detection algorithm [7]. Moreover, we added experiments to ensemble five peak detection models [5][6][7][8][9].

We used the oversampling technique to solve imbalances as the data labeled with stress is about 0.57 times less than the data labeled with baseline. We also used leave-one-subject-out cross-validation. [Table 2] represents the result of PPG noise reduction algorithm's performance with random forest, SVM, and gradient boosting model. The table demonstrates that the proposed noise reduction algorithm improves the stress detection performance of the SVM model, that the AUC is increased by 0.1, and that the F1 score is increased by 0.12 compared with the baseline algorithm of the moving average filter. When using 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 the SVM model.

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." denotes frequency, "T." denotes times, and "E." denotes ensemble. Applied moving average filter for baseline.

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 and increase 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 offers us the possibility to monitor our health in real time using only PPG signals. In the future, we expect that the performance can be remarkably improved with the application the noise reduction method in an end-to-end deep learning model.

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