

Measuring Cardiorespiratory Information in Sitting Position Using Multiple Piezoelectric Sensors

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Abstract

We have been studying equipment to easily acquire cardiorespiratory information at home using piezoelectric sensors arranged on the seat surface of a chair. In our previous study, we suggested that the cardiac and respiratory components could be extracted by executing template matching using a two-dimensional cross-correlation function for the signals that were obtained from the piezoelectric sensors. However, there was a difficulty with the signal extraction, depending on the seating position. Therefore, in this study, we examined the measurement of the heartbeat and breathing interval using independent component analysis and multiple piezoelectric sensors. Moreover, the heartbeat and breathing intervals that were obtained from the extracted cardiorespiratory components using our developed automatic decision method were compared with those obtained from electrocardiogram and pneumogram. As a result, it was found that we could achieve better error rates ($0.93\pm 0.44\%$ and $5.23\pm 3.04\%$ for the heartbeat and respiratory intervals, respectively) than in our previous study.

Keywords: heartbeat, breathing, piezoelectric sensor, independent component analysis

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1. Introduction

In recent years, an increase in cardiac and respiratory diseases has become a concern because of the global increase in the percentage of the older population. In addition, people are becoming more health conscious. For determine a person's daily health, it is necessary to measure biological information on a regular basis. Conventionally, scales, thermometers, and blood pressure monitors have been widely introduced to manage our health at home. Although these devices have advantages such as a low initial cost and being simple to use, small, and lightweight, to determine the state of our body more thoroughly, an examination in a medical institution is necessary. However, this has disadvantages not only for us (such as medical expenses and the burden of visiting the medical institution), but also for the medical institution (such as insufficient and overworked medical staff). Therefore, it is unrealistic to visit a medical institution on a daily basis. Moreover, it would not be appropriate to measure biological information at home by introducing the kind of medical equipment used in clinics and hospitals because of the high initial cost and requirement of specialized knowledge for its use.

The heart rate and respiratory rate are widely used as basic vital signs reflecting the state of our body. Moreover, it is known that the heart rate variability (HRV) can be used to determine the activity of the autonomic nervous system (ANS). Thus, it can be of assistance in diagnosing not only cardiac and respiratory diseases but also diseases that influence the ANS. Therefore, measuring cardiac and respiratory information is crucial in managing health. In recent years, various techniques have been developed to replace the conventional medical device used to measure cardiac and respiration information. Gramse et al. [1] developed pajamas with an embedded electrocardiogram electrode and strain gauge (abdominal breathing sensor). Min et al. [2] proposed a simplified structural textile capacitive respiration sensor. On the other hand, a piezoelectric sensor (PES) [3–6], phonocardiograph [7], geophone [8], biological radar [9], and microwave device [10] has been used to record the vibration and noise generated from the cardiopulmonary organ. Most of these have reported monitoring results during sleep. However, there have been few reports on measurements during sitting.

We have been conducting research on equipment that can simply obtain cardiac and respiratory information at home [11]. This is realized by measuring and analyzing the vibrations

that originate from the heartbeat and breathing using a PES placed on the seat surface of a chair. However, there was a problem with difficult signal extraction, depending on the seating position. In this study, we had the goal of measuring the heartbeat and breathing interval regardless of the seating position. Therefore, independent component analysis (ICA) was used to extract the cardiac and respiratory components from the signal obtained with multiple PESs. Then, to examine the usefulness, the precision was determined by comparing the extracted cardiac and respiratory components with the breathing interval obtained from a reference signal.

2. Methods

2.1. Subjects

Ten healthy university students (nine males, 21–24 years old and one female, 22 years old) participated as subjects. Before the experiment, the purpose and content of the experiment was explained to each subject, and they consented to participation.

2.2. Tasks

The subject was instructed to sit in any position on a chair that had eight piezoelectric sensors arranged on the seat surface and remain for 5 min in a resting state. Each subject performed this task twice.

2.3. Recordings

Eight PESs (DT4-028K/L, TE Connectivity, Switzerland) constructed from polyvinylidene difluoride (PVDF) were evenly placed on the seat surface of a chair. In addition to the signals from these PESs, an electrocardiogram (ECG) and a pneumogram (PNG) were obtained as reference signals from a standard limb lead II (PPS-EDA, TEAC, Japan) and an abdominal breathing sensor (TR-512G, Nihonkohden, Japan), respectively. The PES, ECG, and PNG signals were processed using 10 Hz, 40 Hz, and 30 Hz low-pass filters, respectively, and then recorded by an oscilloscope (DL850, Yokogawa, Japan) at a sampling frequency of 1000 Hz.

2.4. Analysis

2.4.1. Independent Component Analysis

ICA was used to separate the cardiac and respiratory components from the PES signals, [12]. ICA separates the signal sources on the basis of the statistical independence between data elements. In this study, fastICA [12] was employed to carry out the component separation (from two to five components, out of 14 components in total) for each PES signal. A fastICA estimation algorithm for multiple independent components is described as follows:

1. Centralize observed signals \mathbf{x} as $E[\mathbf{x}] = 0$.
2. Whiten centralized observed signals \mathbf{x} then let \mathbf{z} be it.
3. Initialize $\mathbf{w}_i (i = 1, \dots, n)$ with random numbers, where $\|\mathbf{w}_i\| = 1$, and orthogonalize matrix W as given below in #5.
4. For all $i = 1, \dots, n$, substitute $E[\mathbf{z}g(\mathbf{w}_i^T \mathbf{z})] - E[g'(\mathbf{w}_i^T \mathbf{z})]\mathbf{w}_i$ for \mathbf{w}_i , where $g(\mathbf{w}_i^T \mathbf{z}) = \tanh(\mathbf{w}_i^T \mathbf{z})$.
5. Symmetrically orthogonalize $W = (\mathbf{w}_1, \dots, \mathbf{w}_n)^T$. Substitute $(WW^T)^{-1/2}W$ for W .
6. If not converged ($W_{t-1}^T W_t \leq R$, $0 \leq R \leq 1$), then go back to #4.

2.4.2. Evaluation for Component Selection

We developed an evaluation method for selecting the most appropriate component from among the 14 components obtained by ICA. First, for the time series of each component, a fast Fourier transform was performed to obtain the power spectrum of each component. Then, the evaluation value was calculated from the power spectrum. Finally, an appropriate component that represented the largest evaluation value was selected as a cardiac or respiratory component. The outline of this evaluation is shown in Figure 1. First, peak values C1 (around 1 Hz) and R1 (0.1–0.7 Hz) were determined as fundamental rhythms derived from the heartbeat and breathing, respectively. Then, peak values C2–C5 were also obtained as the second to fifth harmonics of peak value C1, respectively. Finally, because the separated noise component had a high peak at around 3 Hz, the peak value closest to 3 Hz was removed (zero was substituted instead).

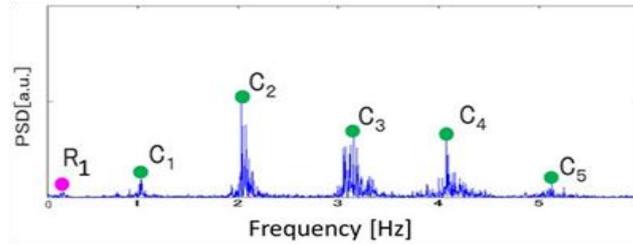


Figure 1. Effects of selecting different switching under dynamic condition

2.4.2.1. Cardiac Component

The evaluation value for cardiac component E_C was calculated using Equation 1:

$$E_C = \frac{1}{\log_{10} R_1} \sum_{i=1}^5 C_i \quad (1)$$

i.e., E_C was determined by calculating the ratio of the sum of C_1 – C_5 (except for the peak value that was closest to 3 Hz) to the common logarithm of R_1 , which was the (first) peak respiratory component.

2.4.2.2. Respiratory Component

The evaluation value for the respiratory component E_R was calculated using Equation 2:

$$E_R = \frac{R_1}{C_1} \quad (2)$$

i.e., E_R was determined by calculating the ratio of R_1 to C_1 , the first peak cardiac component.

2.4.3. Filter Processing

A Butterworth low-pass filter, which had a cut-off frequency of 0.4 Hz, was used on the separated respiratory component.

2.4.4. Verification

2.4.4.1. Error Rate

The i -th heartbeat or breathing interval $I_{est,i}$ which was extracted from the selected component using the previously described evaluation method, was compared with $I_{ref,i}$ which was extracted from the ECG or PNG. To represent the accuracy, error rate E was obtained using the following equation:

$$E = \frac{1}{n} \sum_{i=1}^n \frac{|I_{est,i} - I_{ref,i}|}{I_{ref,i}} \times 100 [\%] \quad (3)$$

2.4.4.2. Selecting Concordance Rate

An examination was conducted to determine whether the selected component was valid. Note that "valid" means the selected component was the same as an ideal component, which represented the minimum error rate, in each measurement. The validity was investigated by calculating the ratio that the selected component concurred with the ideal component.

3. Results

3.1. Recorded Waveforms

Figure 2 shows the first 30 s of the recorded waveforms of subject #1. In the waveforms of channels #4, #5, and #6, it can be confirmed that bursts appear periodically corresponding to the ECG cycle. In addition, burst swing envelopes appear cyclically, corresponding to the PNG period.

3.2. ICA-derived Waveforms

Figure 3 shows the first 30 s of the ICA-derived waveforms of separation numbers 2–5 of subject #1. In component #1 of separation number 2, it can be confirmed that the impulses appear to clearly correspond to the R waves of the compared ECG. Such components can be found in separation numbers 3–5. In component #4 of separation number 4, baseline swings appear to clearly correspond to those of the PNG. This can also be seen in separation numbers 4 and 5.

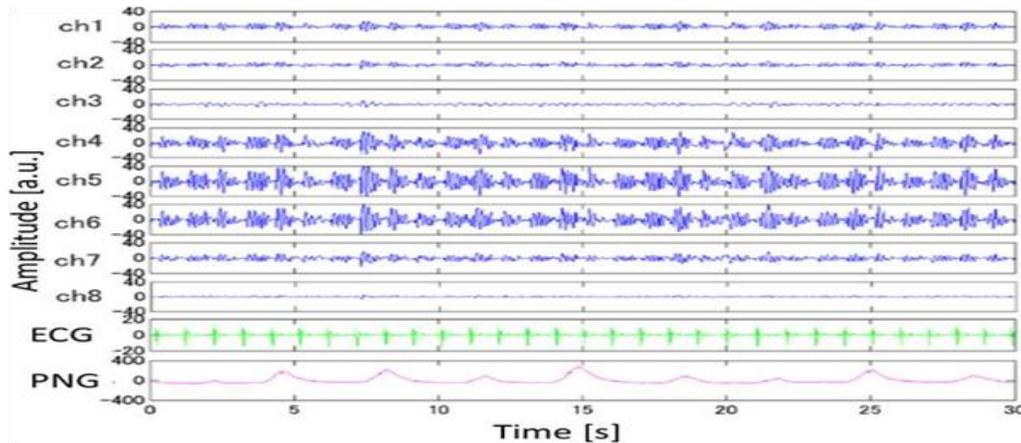


Figure 2. Representative example of recorded waveforms (subject #1, 1st trial)

3.3. Component Selection

Table 1 summarizes the evaluation values for cardiac component E_C in subject #1. The largest evaluation value was observed in component #3 of separation number 4. Therefore, it was selected as the cardiac component. In addition, a summary of the evaluation values for respiratory component E_R in subject #1 is provided in Table 2. The largest evaluation value was observed in component #1 of separation number 5. Therefore, it was selected as the respiratory component.

3.4. Peak Detection

Figure 4 shows the peak detection results of component #1 of separation number 2 and component #4 of separation number 4. The peaks of both the cardiac and respiratory components were reasonably detected corresponding to those of the ECG and PNG.

3.5. Verification

Table 3 summarizes the error rates for the heartbeats and breathing intervals of the selected component for each subject.

Table 1. Evaluation values for cardiac component EC of subject #1 (1st trial)

		Separation number			
		2	3	4	5
Component	#1	610	197	106	47
	#2	110	112	188	332
	#3	-	597	685	241
	#4	-	-	48	109
	#5	-	-	-	662

Table 2. Evaluation values for respiration component E_R of subject #1 (1st trial)

		Separation number			
		2	3	4	5
Component	#1	0.07	0.8	0.8	29
	#2	0.8	0.9	0.08	0.03
	#3	-	0.08	0.05	0.4
	#4	-	-	27	0.8
	#5	-	-	-	0.06

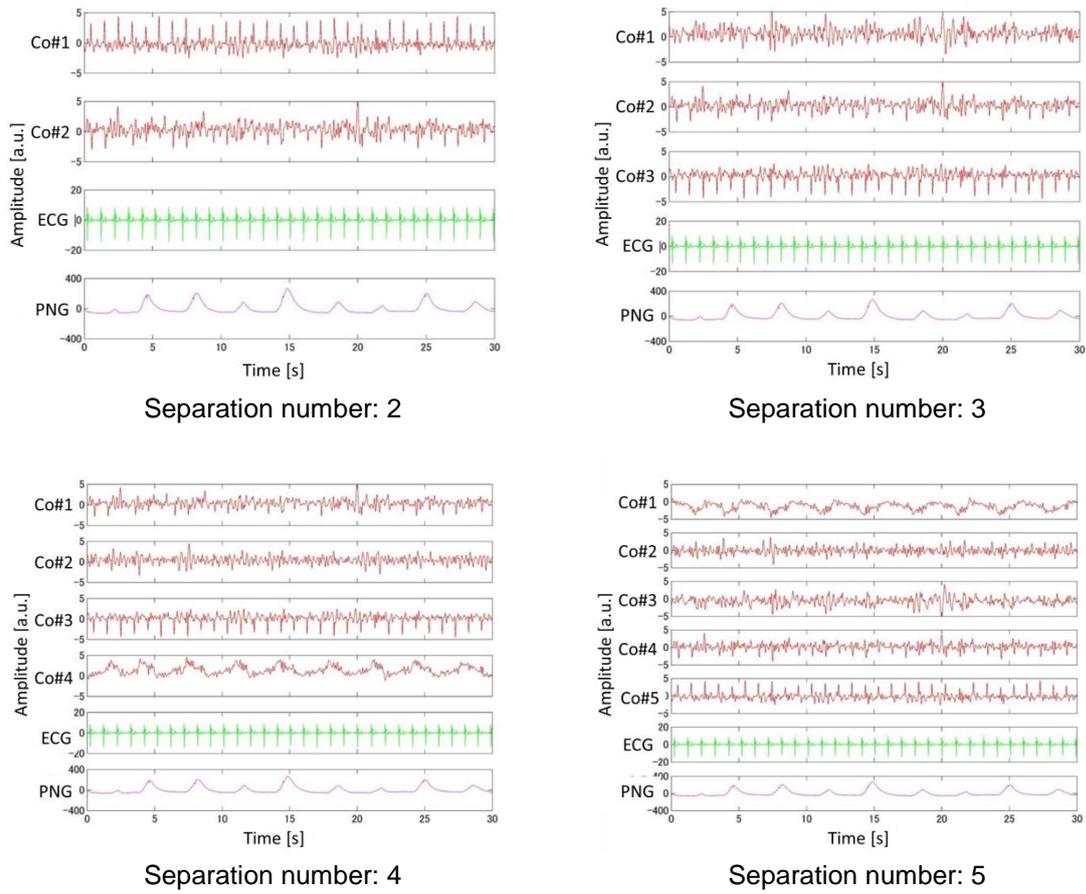


Figure 3. Representative example of ICA performed waveforms (subject #1, 1st trial)

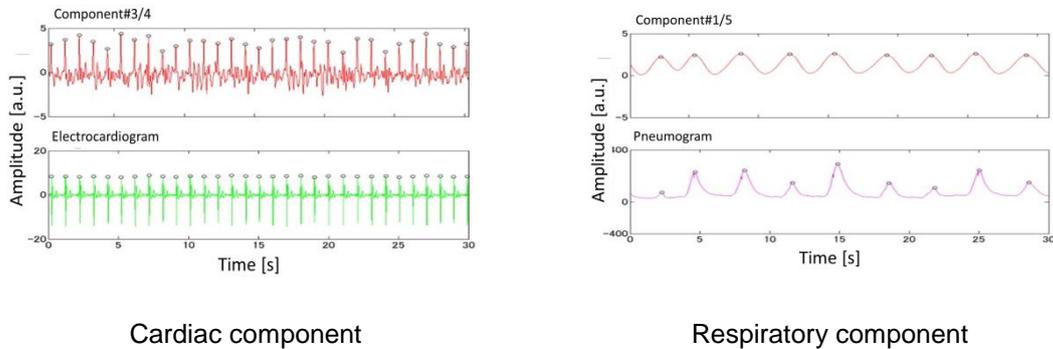


Figure 4. Peak detection using ICA-derived waveforms and reference signals (subject #1, 1st trial)

The overall error rates were $0.93 \pm 0.44\%$ and $5.23 \pm 3.04\%$ for the heartbeat and breathing interval, respectively. In addition, a summary of the error rates for the heartbeat and breathing interval of the ideal component for each subject is provided in Table 4. The overall error rates were $0.78 \pm 0.31\%$ and $4.94\% \pm 2.85\%$ for the heartbeat and breathing interval, respectively. Therefore, the selected concordance rates were 60% and 95% for the cardiac and respiratory components, respectively.

4. Discussion and Conclusion

In this study, we examined a method to measure the heartbeat and breathing interval using ICA and multiple PESs. The overall error rates of the heartbeat and breathing intervals for all the subjects were $0.93 \pm 0.44\%$ and $5.23\% \pm 3.04\%$, respectively. Those in our previous study using two PESs (with a specified seating position) were $2.47 \pm 2.66\%$ and $7.83 \pm 5.48\%$, respectively [7]. Comparing the error rates found in this study with those in our previous study, a significant decrease ($P = 0.036$; t-test) or decreasing tendency ($P = 0.102$; t-test) for the error rate was observed for the cardiac or respiratory component, respectively. Therefore, the cardiac and respiration information could be measured more accurately regardless of the seating position of the subject. Tanaka et al. [7] reported that they measured heartbeat signals for 60 s in a supine position using a phonocardiograph and obtained an error rate of within 1.15%. Our results showed reasonable accuracy despite the fact that the subjects' signals were recorded while they remained for 5 min in a sitting position.

Table 3. Error rates of heartbeat and breathing interval of selected component vs. reference signal [Unit: %]

Subject	Cardiac		Respiratory	
	1st	2nd	1st	2nd
#1	0.6	0.9	4.4	7.3
#2	0.5	0.9	14.3	6.5
#3	0.4	0.5	2.3	2.0
#4	0.6	0.8	3.0	2.7
#5	0.7	0.7	3.0	2.0
#6	1.2	1.6	6.3	3.8
#7	1.8	1.1	3.8	3.4
#8	1.9	0.6	5.7	6.9
#9	1.4	0.7	9.8	5.0
#10	0.6	1.0	4.4	8.0
Overall	0.93 ± 0.44		5.23 ± 3.04	

Table 4. Error rates of heartbeat and breathing interval of ideal component vs. reference signal [Unit: %]

Subject	Cardiac		Respiratory	
	1st	2nd	1st	2nd
#1	0.6	0.9	4.4	7.3
#2	0.5	0.9	14.3	6.5
#3	0.4	0.5	2.3	2.0
#4	0.6	0.8	3.0	2.7
#5	0.6	0.7	3.0	2.0
#6	0.7	1.2	6.3	3.8
#7	1.5	0.9	3.8	3.4
#8	0.8	0.3	5.7	6.9
#9	1.4	0.7	4.0	5.0
#10	0.6	0.9	4.4	8.0
Overall	0.78 ± 0.31		4.94 ± 2.85	

Moreover, an evaluation method to select the most appropriate components from the separated plurality of components was also proposed. The ratios that the selected components matched the ideal components were 60% and 95% for the cardiac and respiratory components, respectively. There was no significant difference in the overall error rates between the selected and ideal components ($0.78 \pm 0.31\%$, $P = 0.222$ for cardiac; $4.94\% \pm 2.85\%$, $P = 0.757$ for

respiratory; t-test). Therefore, it is suggested that multiple PESSs with ICA could be used to obtain reasonable cardiac and respiratory information in a sitting position.

Acknowledgement

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References

- [1] Gramse V, De Groote A, Pavia M. Novel concept for a noninvasive cardiopulmonary monitor for infant: a pair of pajamas with an integrated sensor module. *Ann. Biom. Eng.* 2003; 31(2): 152–158.
- [2] Min SD, Yun Y, Shin H. Simplified structural textile respiration sensor based on capacitive pressure sensing method. *IEEE Sens. J.* 2014; 14(9): 3245–3251.
- [3] Siivola J. New noninvasive piezoelectric transducer for recording of respiration, heart rate and body movements. *Med. Biol. Eng. Comput.*, 1989; 27(4): 423–424.
- [4] Wang F, Tanaka M, Chonan S. Development of a PVDF piezopolymer sensor for unconstrained in-sleep cardiorespiratory monitoring. *J. Intell. Mater. Syst. Struc.* 2003; 14(3): 185–190.
- [5] Choi S, Jiang Z. A novel wearable sensor device with conductive fabric and PVDF film for monitoring cardiorespiratory signals. *Sens. Actuators A Phys.* 2006; 128(2): 317–326.
- [6] Kuboyama K, Wang F, Matsumoto H, Nakazawa N. Real-time detection of respiration and heartbeat signals during sleep using ICA. *J. Jpn. S. Appl. Electrom.* 2013; 21(2): 140–145.
- [7] Tanaka S, Matsumoto Y, Wakimoto K. Unconstrained and noninvasive measurement of heart-beat and respiration periods using a phonocardiographic sensor. *Med. Biol. Eng. Comput.* 2002; 40(2): 246–252.
- [8] Jia Z, Alaziz M, Chi X, Howard RE, Zhang Y, Zhang P, Trappe W, Sivasubramaniam A, *An N. HB-phone: a bed-mounted geophone-based heartbeat monitoring system.* Proceedings of the 15th ACM/IEEE International Conference on Information Processing in Sensor Networks (IPSN). Vienna. 2016: 12.
- [9] Jang BJ, Wi SH, Yook JG, Lee MQ, Lee KJ. Wireless bio-radar sensor for heartbeat and respiration detection. *Prog. Electromagn. Res. C*, 2008; 5: 149–168.
- [10] Suzuki S, Matsui T, Kagawa M, Asao T, Kotani K, An approach to a non-contact vital sign monitoring using dual-frequency microwave radars for elderly care. *J. Biomed. Sci. Eng.* 2013; 6: 704–711.
- [11] Igasaki T, Yoshikawa K, Murayma N. *Fundamental study of measurement of cardiorespiratory signals in a sitting position using piezoelectric sensors.* Proceedings of the 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). Osaka. 2013; 3841–3844.
- [12] Hyvärinen A, Oja E. Independent component analysis: algorithms and applications. *Neural Netw.* 2000; 13(4–5): 411–430.