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Estimation of Blood Pressure Variability Using Independent Component Analysis of Photoplethysmographic Signal

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***Abstract*— The maximum cross-correlation coefficient $\rho_{\max}$ between blood pressure variability and heart rate variability, whose frequency components are limited to the Mayer wave-related band, is a useful index to evaluate the state of the autonomic nervous function related to baroreflex. However, measurement of continuous blood pressure with an expensive and bulky measuring device is required to calculate $\rho_{\max}$. The present study has proposed an easier method for obtaining $\rho_{\max}$ with measurement of finger photoplethysmography (PPG). In the proposed method, independent components are extracted from feature variables specified by the PPG signal by using the independent component analysis (ICA), and then the most appropriate component is chosen out of them so that the $\rho_{\max}$ based on the component can fit its true value. The results from the experiment with a postural change performed in 17 healthy subjects suggested that the proposed method is available for estimating $\rho_{\max}$ by using the ICA to extract blood pressure information from the PPG signal.**

I. INTRODUCTION

To estimate the state of the autonomic nervous system related to the baroreflex function, the authors have previously proposed the maximum cross-correlation coefficient $\rho_{\max}$ between blood pressure variability (BPV) and heart rate variability (HRV) in Mayer wave band [1][2]. However, measurement of continuous blood pressure is required to obtain $\rho_{\max}$. Instead of blood pressure, we have attended to measurement of photoplethysmography (PPG) which is an inexpensive, non-invasive, and easily attachable device. The index $\rho_{\max}$ obtained from a feature variable of PPG includes some physiological components other than BPV [3]. Thus, $\rho_{\max}$ obtained from feature variables of PPG does not always correspond to $\rho_{\max}$ from BPV. Therefore, in this study, we have proposed a new method for obtaining $\rho_{\max}$ with BPV-related information obtained from measurement of PPG. In this study, heart rate is calculated from the foot-to-foot-interval (FFI) of the PPG signal, and BPV-related information is obtained from the parameter extracted by using the independent component analysis (ICA). The adequacy of the proposed method was evaluated on the basis of comparison with the conventional method.

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II. METHODS

A. Maximum cross-correlation coefficient $\rho_{\max}$

Let $u(i)$ and $v(i); i = 0, 1, 2, \ldots$ denote time series data, for example, blood pressure variability (BPV) and heart rate variability (HRV), respectively, sampled with a sampling period $\Delta t = 0.5$s. They are filtered through a band-pass digital filter with a bandwidth between 0.08Hz and 0.12Hz to limit their frequency components to the Mayer wave band. At a certain time point $t = i \cdot \Delta t$[s], a Hamming window with the interval between $t - 60$[s] and $t + 60$[s] is applied to $u(i)$ and $v(i)$. A cross-correlation coefficient $\rho_{uv}(\tau)$ for a lag of $\tau = j \cdot \Delta t$[s]; $j = \ldots, -1, 0, 1, \ldots$ is calculated as follows:

$$\rho_{uv}(\tau) = \frac{\phi_{uv}(\tau)}{\sqrt{\phi_{uu}(0) \cdot \phi_{vv}(0)}} \tag{1}$$

where, $\phi_{uv}(\tau)$ is a cross-correlation function between $u(i)$ and $v(i)$, and $\phi_{uu}(\tau)$ and $\phi_{vv}(\tau)$ are auto-correlation functions of $u(i)$ and $v(i)$, respectively. The maximum cross-correlation coefficient $\rho_{\max}$ and the lag from BPV to HRV $\tau_{\max}$ are defined as

$$\rho_{\max} = \max_{0\mathrm{s} \le \tau \le 10\mathrm{s}} \rho_{uv}(\tau) \tag{2}$$

$$\tau_{\max} = \arg \max_{0\mathrm{s} \le \tau \le 10\mathrm{s}} \rho_{uv}(\tau). \tag{3}$$

In the present study, $\rho_{\max}$ is successively calculated every one second between $t = 60$[s] and $t = T - 60$[s], where T[s] is the end time of the data obtained from an experiment.

B. Independent component analysis (ICA)

The ICA used in our method is described as follows:

1) Let $x_1(k), x_2(k), \ldots, x_m(k)$ be m feature variables extracted from the PPG signal at the k-th beat. Define a feature vector $\boldsymbol{x}(k)$ as $\boldsymbol{x}(k) = [x_1(k), x_2(k), \ldots, x_m(k)]^{\mathrm{T}}$.
2) Let $s_1(k), s_2(k), \ldots, s_n(k)$ be n unknown physiological parameters that are independent of one another at the k-th beat. Define a parameter vector $\boldsymbol{s}(k)$ as $\boldsymbol{s}(k) = [s_1(k), s_2(k), \ldots, s_n(k)]^{\mathrm{T}}$.
3) Assume that the feature vector $\boldsymbol{x}(k)$ is given by a linear combination of $s_1(k), s_2(k), \ldots, s_n(k)$ as follows:

$$\boldsymbol{x}(k) = \boldsymbol{A}\boldsymbol{s}(k) \tag{4}$$

where, an $m \times n$ matrix $\boldsymbol{A}$ represents an unknown constant mixing matrix consisting of coefficients of the liner combination. Let K be the number of beats observed in an experiment. Define an $m \times K$ matrix $\boldsymbol{X}$ and an $n \times K$ matrix $\boldsymbol{S}$ as $\boldsymbol{X} = [\boldsymbol{x}(1), \boldsymbol{x}(2), \dots, \boldsymbol{x}(K)]$ and $\boldsymbol{S} = [\boldsymbol{s}(1), \boldsymbol{s}(2), \dots, \boldsymbol{s}(K)]$, respectively. Thus, the matrix $\boldsymbol{X}$ is assumed to be given by $\boldsymbol{S}$ as follows:

$$\boldsymbol{X} = \boldsymbol{A}\boldsymbol{S} \tag{5}$$

4) The ICA is applied to estimate the mixing matrix $\boldsymbol{A}$ from the matrix $\boldsymbol{X}$. The independent component $\boldsymbol{S}$ can be obtained by

$$\boldsymbol{S} = \boldsymbol{A}^{+}\boldsymbol{X} \tag{6}$$

where $\boldsymbol{A}^{+}$ is the pseudoinverse matrix of $\boldsymbol{A}$.

In this study, the fast fixed point algorithm (fast-ICA) presented by Hyvärinen and Oja was used to linearly separate $\boldsymbol{S}$ from $\boldsymbol{X}$ [4], [5]. Principal component analysis was used as a preprocessing of the ICA. Furthermore, the number of feature variables, m, was empirically set to 7 on the basis of the variables related to BP.

Figure 1 shows an example of the PPG signal. In this figure, 7 feature variables used in the present study are illustrated. These are defined every beat as follows:

1) FFI: the foot-to-foot interval of PPG
2) t_{d}: the interval from the time maximizing the PPG to the time minimizing PPG
3) t_{maxslope}: the time maximizing the slope of PPG
4) PW_{bias}: the minimum value of PPG
5) PW_{max}: the maximum value of PPG
6) DPW_{max}: the value of PPG at t_{maxslope}
7) $NPWA$: the area of PPG normalized by FFI

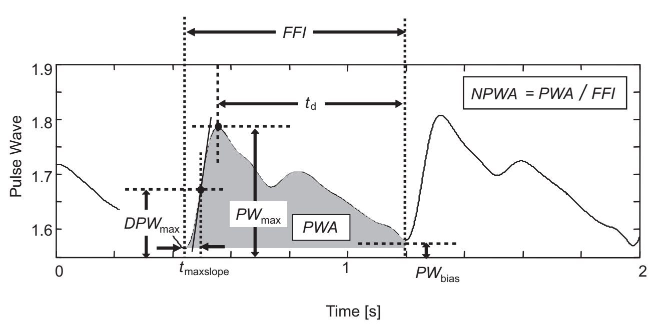

Fig. 1. Definition of feature variables.

These parameters include information on hemodynamic state such as blood pressure, blood volume, and vascular compliance. For example, the parameter $NPWA$ shows the mean value of the pulsatile component of arterial blood volume and is a candidate of substitutes of BPV.

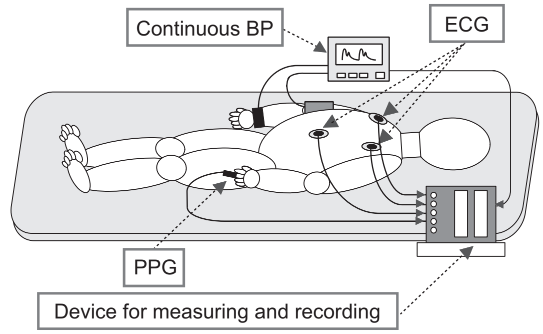

Fig. 2. Setup of experiment with supine posture

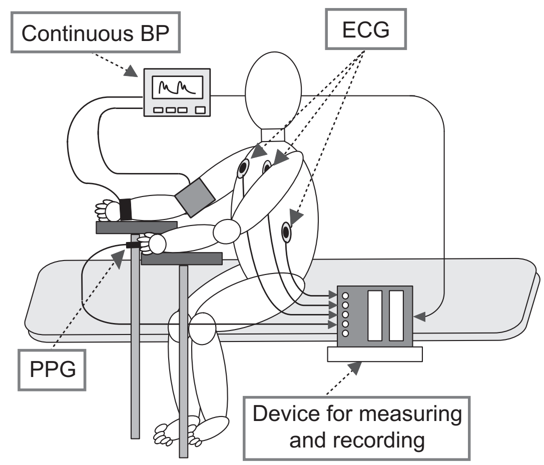

Fig. 3. Setup of experiment with sitting posture

C. Experiment

To evaluate the proposed method, the experiment in which subjects kept the supine posture for 5 minutes and then the sitting posture for 5 minutes under the resting condition, was carried out. The postural change from the supine posture to the sitting posture brings a decrease of blood pressure. Therefore, heart rate is increased by the response of the baroreflex system. We confirmed whether BPV-related information could be obtained from the PPG signal by using the ICA and whether $\rho_{\max}$ calculated from this information could indicate the response caused by the postural change. Healthy 18 subjects (aged 24.2 $\pm$ 3.6) participated in the experiment. Figures 2 and 3 show the setup of the experiment. The subject's ECG, continuous blood pressure, and finger PPG were measured during the experiment.

D. Analyses

On the basis of the observed matrix $\boldsymbol{X}$ obtained from the experiment, the mixing matrix $\boldsymbol{A}$ and the independent component matrix $\boldsymbol{S}$ were calculated with the ICA for each subject. Define n independent component time series IC_l; $l = 1, 2, \dots, n$ as $IC_l = \{s_l(1), s_l(2), \dots, s_l(K)\}$ with the data size of K corresponding to the length of the experiment.

Let time series $\rho_{\max}(BP)$ and $\rho_{\max}(IC_l)$ denote $\rho_{\max}$

between HRV and BPV, and $\rho_{\max}$ between HRV and an independent component IC_l, respectively.

Let l_{BP} denote the optimal number of l that minimizes the sum of the root mean square error (RMSE) between $\rho_{\max}(BP)$ and $\rho_{\max}(IC_l)$ and of the RMSE between $\tau_{\max}(BP)$ and $\tau_{\max}(IC_l)$ as follows:

$$l_{BP} = \arg\min_{l=1,\ldots,n} \left[\sqrt{E[\{\rho_{max}(BP) - \rho_{max}(IC_l)\}^2]} + \lambda \cdot \sqrt{E[\{\tau_{max}(BP) - \tau_{max}(IC_l)\}^2]} \right] \quad (7)$$

where λ represents a weighting factor of the term related to $\tau_{\max}$ and is chosen to be 0.1. Because $\rho_{\max}$ changes from 0 to 1, while $\tau_{\max}$ does from 0 to 10. In addition, the number of independent components, n, was empirically set to 4.

III. RESULTS AND DISCUSSION

Seventeen subjects' data out of 18 could successfully be analyzed in the experiment with the supine posture. Figure 4 shows an example of $\rho_{\max}(BP)$ and $\rho_{\max}(IC_{l_{BP}})$ obtained from a certain subject during the supine posture. Each $\rho_{\max}$ is the averaged value every 30s. BPV-related information of this subject could be estimated. An independent component of this subject consists of BPV-related components.

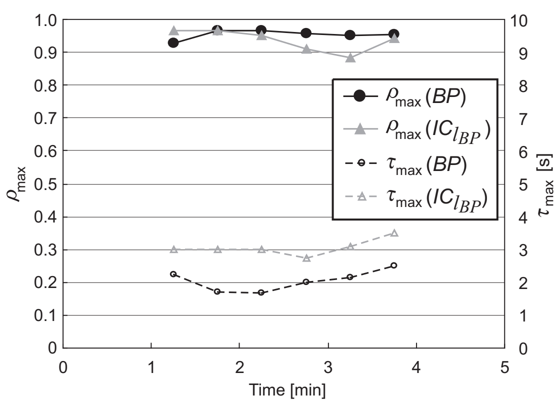

Fig. 4. Example of $\rho_{\max}(BP)$ and $\rho_{\max}(IC_{l_{BP}})$ obtained from certain subject.

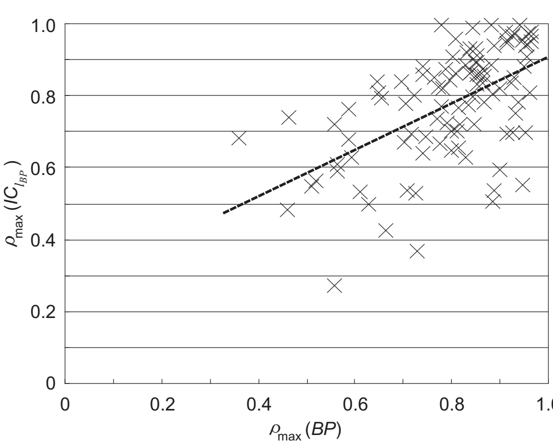

Fig. 5. Comparison between $\rho_{\max}(BP)$ and $\rho_{\max}(IC_{l_{BP}})$ in experiment with supine posture. $r = 0.55$ $(p < 0.01)$

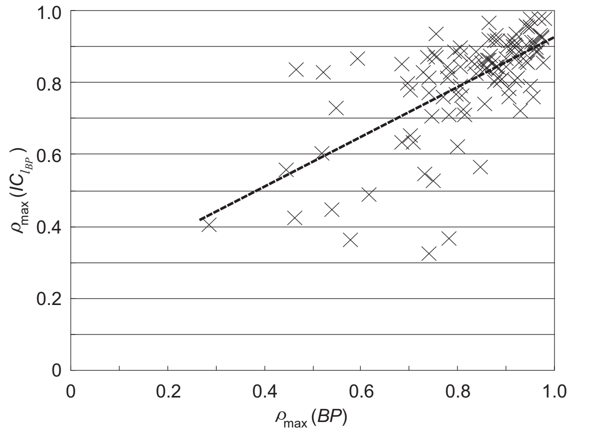

Fig. 6. Comparison between $\rho_{\max}(BP)$ and $\rho_{\max}(IC_{l_{BP}})$ in experiment with sitting posture. $r = 0.65$ $(p < 0.01)$

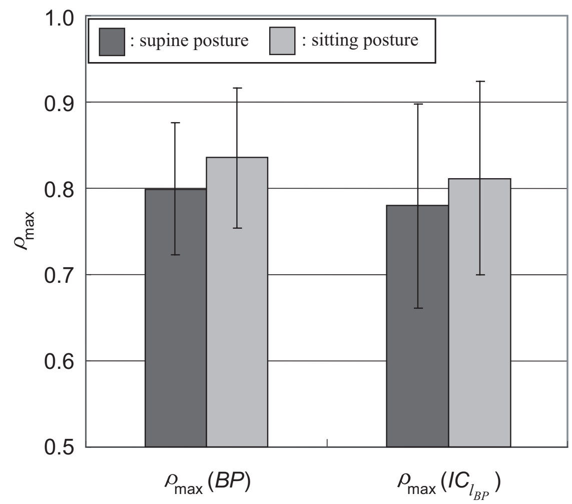

Fig. 7. Comparison between $\rho_{\max}$s of supine posture and of sitting posture.

Figure 5 shows the comparison between $\rho_{\max}(BP)$ and $\rho_{\max}(IC_{l_{BP}})$ during the supine posture. This result indicates that $\rho_{\max}(IC_{l_{BP}})$ correlated significantly with $\rho_{\max}(BP)$ over 17 subjects.

On the other hand, all subjects' data could successfully be analyzed in the experiment with the sitting posture. Figure 6 shows the comparison between $\rho_{\max}(BP)$ and $\rho_{\max}(IC_{l_{BP}})$ during the sitting posture. This result indicates that $\rho_{\max}(IC_{l_{BP}})$ correlated significantly with $\rho_{\max}(BP)$ over 18 subjects.

These results show that the BPV-related parameter could be detected from the PPG feature variables by using the ICA in the experiment of both postures. Thus, it was suggested that the postural change caused little difference in estimation accuracy of BPV.

Figure 7 shows the comparison in $\rho_{\max}$ between the supine posture and the sitting posture. There is no significant difference between $\rho_{\max}$s of two postures. This figure shows that the value of $\rho_{\max}$ of the sitting posture is higher than that of the supine posture. This fact suggests that the postural change caused the response of the baroreflex system, i.e., the manipulation of heart rate was activated further by the baroreflex system to regulate blood pressure level against the deviation of blood perfusion caused by gravity.

IV. CONCLUSION

To estimate blood pressure variability, in this study, we have proposed a new method for extracting a blood pressure-related parameter from finger photoplethysmography by using the independent component analysis. From the experimental results, it was ascertained that the proposed method could extract the independent component related to BPV from the PPG signal to yield the maximum cross-correlation coefficient $\rho_{\max}$ between heart rate used for evaluating the state of the autonomic nervous system.

However, we still need blood pressure information to select the index number for the optimal independent component although the mixing matrix will be able to be applied to yield the blood pressure-related parameter based only on the PPG as long as the subject's posture does not change. In the future, we should develop a method for deciding the mixing matrix with photoplethysmography only using other mathematical theory or calculation algorithm for the ICA. In addition, it is important to clarify the characteristics of the baroreflex function of each subject by using the proposed method.

V. ACKNOWLEDGMENTS

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