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Blood pressure estimation by photoplethysmogram Decomposition into Hyperbolic Secant Waves

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Abstract: We propose a method to estimate blood pressure based on photoplethysmogram decomposition with Hyperbolic Secant function. The decomposition method assumes a model where the photoplethysmogram pulse curve is formed by the sum of three waves: one forward wave and two backward waves. The forward wave is known as a wave due to heart ejection. The backward waves are known as waves due to reflection of the forward wave at renal and iliac arteries branches. These waves have different paths in the circulatory system. The circulatory system is affected by blood pressure. Thus, features of these waves are expected to describe blood pressure. Previous studies have proposed blood pressure estimation based on the decomposition method with Gaussian function. However, it is not known if Gaussian waves are the best pulse decomposition functions for optimal BP estimates. In this study, we show that the Hyperbolic Secant function has higher accuracy to estimate blood pressure than Gaussian function. Continuous blood pressure and the corresponding photoplethysmogram data acquired from ten subjects are used for the analysis. Results imply that Hyperbolic Secant waves decomposition is preferable to Gaussian wave pulse decomposition for blood pressure estimate models.

Keywords: Blood Pressure, Hyperbolic Secant function, Photoplethysmography, Pulse Decomposition Analysis

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1. Introduction

Blood pressure is one of the most important indicators of human health. It reflects the cardiovascular system condition. More specifically, blood pressure is a measure of the pressure in the arteries, which depends on parameters such as cardiac output, blood vessel stiffness, and blood viscosity. Keeping blood pressure high on a daily basis increases the risk of various diseases such as heart failure, myocardial infarction, cerebral infarction, cerebral hemorrhage, and chronic kidney disease [1]. Epidemiological study [2] is showing the importance of blood pressure control. In order to prevent the above diseases, it is important to be able to measure blood pressure easily and continuously.

Currently, there are two main types of blood pressure measurement methods: invasive and non-invasive. The method should be chosen according to the situation and the accuracy required. The invasive method is mainly used for critically ill patients in intensive care units and operating rooms, and is a method of obtaining blood pressure by inserting a thin tube called a catheter and measuring real-time pressure directly through the catheter [3]. This method is the most accurate way to measure blood pressure, although it places a heavy burden on the patient derived from the need to insert the catheter directly

into the patient's blood vessel. However, the invasive method is not suitable for daily use, making it difficult to use for routine monitoring applications. On the other hand, the non-invasive method of measuring blood pressure by wrapping a cuff around the arm is called oscillometric method and is widely used. This method measures blood pressure by pressurizing a cuff worn on the arm and using the vascular sound (Korotkoff sound) that indicates the turbulence of blood flow that occurs when the cuff pressure is above diastolic pressure and below systolic pressure [4,5]. However, this non-invasive oscillometric method cannot measure blood pressure continuously because the tightening of the cuff may cause discomfort to the patient, and it takes time. Therefore, it is desirable to develop an alternative non-invasive cuffless method for continuous blood pressure measurement.

Pulse Decomposition Analysis (PDA) [8,9] is a non-invasive method of measuring pulse wave transit time (PTT) without a cuff, which correlates with blood pressure [6,7]. The pulse wave is defined as the blood pressure and volume changes in the peripheral vasculature associated with the beating of the heart. A heartbeat is a set of contractions and dilations of the heart. With each beat, blood flows from the heart's left ventricle to the aorta, and the resulting blood pressure fluctuations propagate to the peripheral arteries, generating a pulse wave. The pulse wave is usually measured using a device called a photoplethysmograph (PPG). A PPG is usually worn on the finger or earlobe. A PPG is usually worn on the finger or earlobe and irradiates light onto the skin. As the blood absorbs the irradiated light, the volume of the arteries changes with the beating of the heart, causing the amount of light reflected or transmitted to change. By measuring this light, it is possible to measure pulse waves non-invasively.

The PDA considers that the shape of the peripheral pulse consists of the primary wave coming directly from the heartbeat and its reflected wave, which is shown in Figure 1. Reflection occurs when the pulse wave propagates to the lower extremities and is reflected by the bifurcated iliac artery and by the renal artery. The time difference between the propagation of these waves is proportional to the PTT, which varies with the stiffness of the aorta, which in turn correlates with blood pressure. The most accepted PDAs use Gaussian pulse decomposition [8, 9]. However, because Gaussian PDAs generate noise between pulses [14], a potentially large number of heartbeats are required to obtain acceptable signal-to-noise blood pressure estimates [6, 7].

In this study, we investigated the use of secant hyperbolic wave (sech) for PDA of PPG signal for its application in blood pressure measurement. It is believed that the sech wave provides a better PDA because it is a physical solution to the Moens-Korteweg equation describing the pressure pulse in an elastic tube. We experimentally acquire PPG data and simultaneously acquire near real-time continuous blood pressure. The parameters of the PDA using sec waves were multiple regressed against blood pressure and compared with the corresponding values of the PDA using Gaussian pulses.

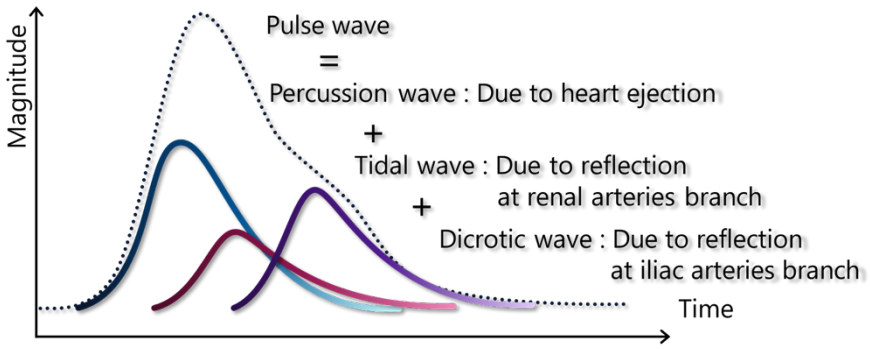

Figure 1. The three constituent waves of pulse wave [14, 17]

2. Method

2.1. Pulse wave model for blood pressure estimation

In this subsection, we first describe the pulse decomposition models used for both the sech and Gaussian PDAs. Then, the characteristics of the PPG PDA used for the regression analysis on the experimental ground-truth blood pressure readings are presented.

2.1.1. The mathematical models of the pulse decomposition analysis

The PDA model assumes that each pulse wave measured by a PPG device is composed of multiple pulse wave reflections, as illustrated in Figure 1. The multiple reflections do not necessarily propagate at the same speed. Here, we use the three waves decomposition, which has been shown to be adequate for blood pressure estimates using Gaussian decomposition [8]. For this study, we use both the Gaussian (Equation. (1)), and our proposed sech PDA (Equation. (2)):

$$f_G = a_G \exp\left[-\frac{(t-\mu_G)^2}{2\sigma_G^2}\right]. \quad (1)$$

$$f_S = a_S \operatorname{sech}\left[\frac{t-\mu_S}{2a_S}\right]. \quad (2)$$

where a_G and a_{Sh} are amplitudes, σ_G and σ_{Sh} are widths, and μ_G and μ_{Sh} are the center positions along time axis of the respective waveforms. Each of the waves in the pulse wave decomposition of Figure 2 can be described by a set of three Gaussian waves, or by three sech waves. The goal of this paper is to verify which decomposition based on either Gaussian function or sech function is more appropriate to describe blood pressure.

2.1.2. Features Extraction from decomposed waves based on pulse wave

First, the PPG pulse waves are fitted with Equation. (1) or Equation. (2). For curve fitting, after data preprocessing, and individual pulse waves separation, we use Matlab's lsqcurvefit to solve the no'linear curve approximation by the least-squares method. The fitting of each pulse wave to three sets of Equations such as Equations (1) or (2), gives 3 sets of parameters. First, the time difference between the peak of the first wave and the peak of the second wave of the three decomposed waves, $\Delta t_{0,1}$, and the time difference between the peak of the first wave and the peak of the third wave, $\Delta t_{0,2}$, are obtained as features corresponding to PTT. Next, the amplitude 'a' of the waves are used as a feature. The pulse wave amplitude is obtained from each of the three decomposition waves. Finally, the half-width at half maximum (FWHM) of the waves is also used as a feature. The reason for using the half-width at half maximum is that it is known that pulse wave strain correlates with blood pressure, and changes in pulse wave strain are thought to affect the half-width [11]. The half-width at half maximum is also obtained from each of the three decomposition waves. In this study, we investigate the possibility of estimating blood pressure using a total of eight features: the time difference $\Delta t_{0,1}$, $\Delta t_{0,2}$ from the three decomposed waveforms, the amplitudes a_0, a_1, and a_2 of the three waveforms, and the full width at half maximums $FWHM_0$, $FWHM_1$, and $FWHM_2$ of the three waveforms.

2.1.3. Multiple regression for relationship between the features and blood pressure

In order to determine the adequacy of the PDA features of PPG for blood pressure estimation, we perform a multiple regression between the features and the ground truth

blood pressure. Up to eight features can be used in this study, and the feature combination depends on the number of features used. Since the number of features is small, we adopt the set of the features which indicates the best performance in all combinations of the features.

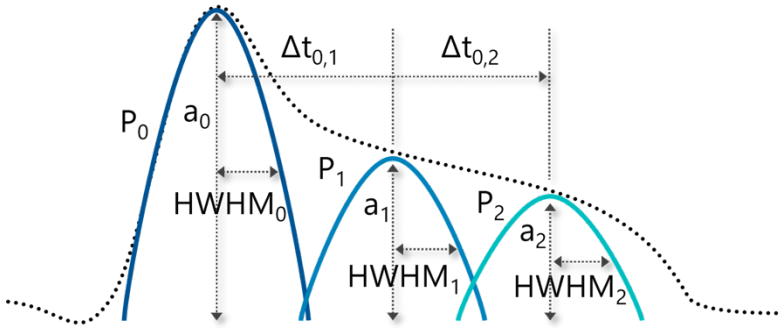

Figure 2. PPG pulse decomposition into three constituent waves and extracted features.

2.2. Dataset construction for the verification of our proposed method

2.2.1. Vital signs acquisition

In this study, we experimentally construct a data set by continuously measuring blood pressure using a continuous sphygmomanometer (Finometer MIDI, Finapres Medical Systems), which measures blood pressure with each beat of pulse and pulse wave with a sampling rate of 200 [Hz]. This continuous sphygmomanometer can measure blood pressure non-invasively by attaching a cuff to the fingertip. In addition, we acquire the pulse wave which is measured using a photoplethysmography (Procomp/BVP fingertip PPG, 2048 samples per second, with output sampling rate of 200 samples per second.). The subjects in this experiment were 10 adult Japanese volunteer students, of mean age 22.4±1.7 years (2 females, 8 males). Each volunteer was explained both orally and in writing about the risks of exercise before consenting to the experiment. Since it is necessary to vary the subject's blood pressure in the experiment, subjects repeatedly relax and holds their breath. Each phase of holding-breath is a maximum of 60 seconds within a comfortable level for them. The phase of relax is placed before and after each phase of holding-breath and is repeated three times.

2.2.2. Data pre-processing

Since the measured pulse wave contains noise, pre-processing is necessary. In particular, if the pressure applied to the finger wearing the PPG changes, a trend will appear in the pulse wave shown in Figure 3. Therefore, it is necessary to remove the trend. First, trend elimination is performed on the measured pulse wave. For trend elimination, the trend elimination method proposed by Tarvainen et al. is used [13]. Next, a band-pass filter is applied to the trend-removed pulse wave to remove mainly high-frequency noise. The transmission frequency of the band-pass filter was set to be 0.5 to 10 Hz. By performing this process, the trend and noise of the pulse wave can be removed, as shown in Figure 4. Next, one-time experimental data with a data length of 480 seconds is divided into 60 segments with a data length of 8 seconds. In each segment, the unit pulse waveform was extracted, the features obtained from each waveform were averaged and used for multiple regression. Each unit pulse waveform was obtained by segmenting the pulse wave based on the position of the detected pulse wave trough. Blood pressure measured with a continuous sphygmomanometer was similarly divided into 60 segments with a data book of 8 seconds from one experimental data with a data length of 480 seconds. In each segment,

the mean value of systolic blood pressure is used for multiple regression analysis. Figure 5 shows the box plot with 60 systolic blood pressure (sbp) of each subject which are averaged in each window of 8 second.

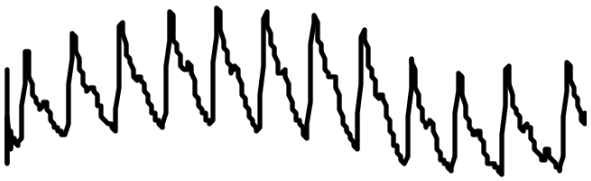

Figure 3. Original pulse wave

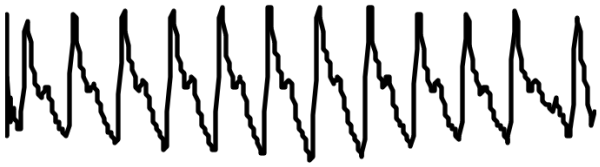

Figure 4. Processed pulse wave

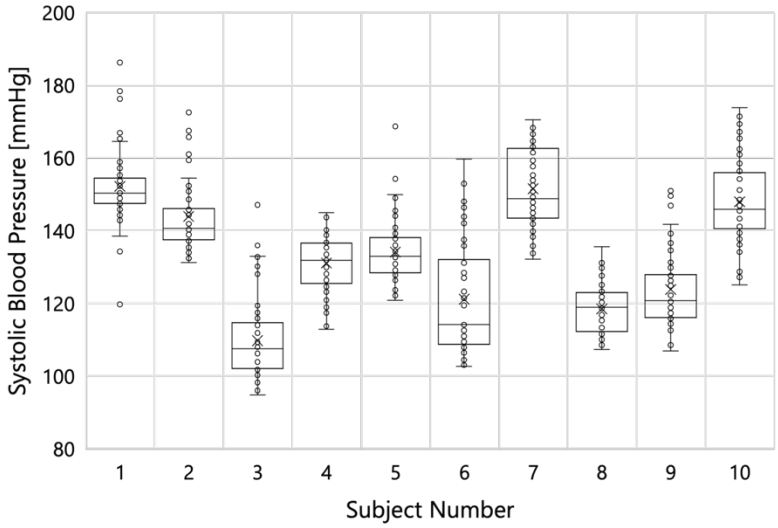

Figure 5. The box plot with 60 systolic blood pressure (sbp) of each subject which are averaged in each window of 8 second

2.3. The verification of our proposed method

In this study, the two estimation methods based on Sech function-based PDA or Gaussian function-based PDA are subjected to two validations: the first is the accuracy of the model for known data, and the second is the accuracy of the model for unknown data. In addition, two analyses are performed for each validation. The first is an analysis using only each subject's data, which does not take into account individual differences. The second is an analysis using all the subjects' data, which is a revision of the wisdom that takes individual differences into account.

First, multiple regression analysis is performed using the subject data set. The goodness of fit of the multiple regression analysis is quantified by calculating the multiple regression coefficients, which determine the extent to which the features achieve a description of blood pressure within the known data. In this validation, two analyses are performed, one for each subject data and the other for all subject data.

Second, to quantify the estimability for the unknown data, Leave One Out method is applied to the dataset and the correlation coefficient between the ground truth and the estimate is calculated. Similarly, in this validation, two analyses are performed, one for each subject data and the other for all subject's data.

Regarding the selected features, for verification on known data, the feature set that provides the best performance is used with multiple correlation coefficients as a criterion. For verification on unknown data, the feature set that provides the best performance is used with correlation coefficients as a criterion. On verification on known data, all features have provided the best performance on all subject data. On verification on unknown data, the features set shown in Table. 1 have provided the best performance.

Table 1. The combination of the features used in the Leave One Out.

	Combination of features	
Subject number	Sech-PDA	Gaussian-PDA
1	Δt01, FWHM2	Δt02, a1, a2, FWHM1, FWHM2, FWHM3
2	a3, FWHM1, FWHM2, FWHM3	Δt02, FWHM1
3	Δt01, a1, a2, FWHM2	Δt01, a2
4	Δt01,a1, a2, FWHM1	Δt01, FWHM1
5	FWHM2, FWHM3	Δt01, FWHM1, FWHM2, FWHM3
6	Δt01, a2, a3, FWHM3	Δt01, Δt02, a1, a2, FWHM1,
7	a1, a3, FWHM2, FWHM3	Δt01, FWHM3
8	Δt01, a3	Δt01, a1, a2, a3, FWHM1, FWHM2, FWHM3
9	Δt01, a2, FWHM1, FWHM2	Δt01, a2, FWHM1, FWHM2
10	Δt01, Δt02, a2, FWHM1, FWHM2	Δt01, a1, a2, FWHM2, FWHM3
all	a2, FWHM1, FWHM2	Δt01, Δt02, a2, FWHM2, FWHM3

3. Result

Multiple regression was performed between PDA (Gaussian and Sech) on the plethysmographic data, and the continuous blood pressure measurement data from the 10 subjects (60 segments of 8 seconds, for each subject), as discussed in the Method section.

Figure 6 shows the comparison of the multiple correlation coefficients when multiple regression analysis was performed for each subject data as the known data and the correlation coefficients for the unknown data when Leave One Out was performed for each subject data. The multiple correlation does not take into account individual differences because we are modeling each subject data individually. The correlation coefficient does take into account individual differences because we are modeling each subject data individually.

Figure 7 shows the two comparisons: the multiple correlation coefficients when multiple regression analysis was performed for all subject data as the known data, and the comparison of the correlation coefficients for the unknown data when Leave One Out was performed for all subject data.

In this case, Leave One Out method means that we estimate blood pressure with one segment data based on the multiple regression model learned with the other segments' data, and we repeat the above process to test all segments data comprehensively. Since we repeat the verification for as many segments as there are, we calculate an evaluation value for as many segments as there are, and average the evaluation values. Leave One Out method is conducted with Scikit-learn, which is a machine learning library for the Python programming language.

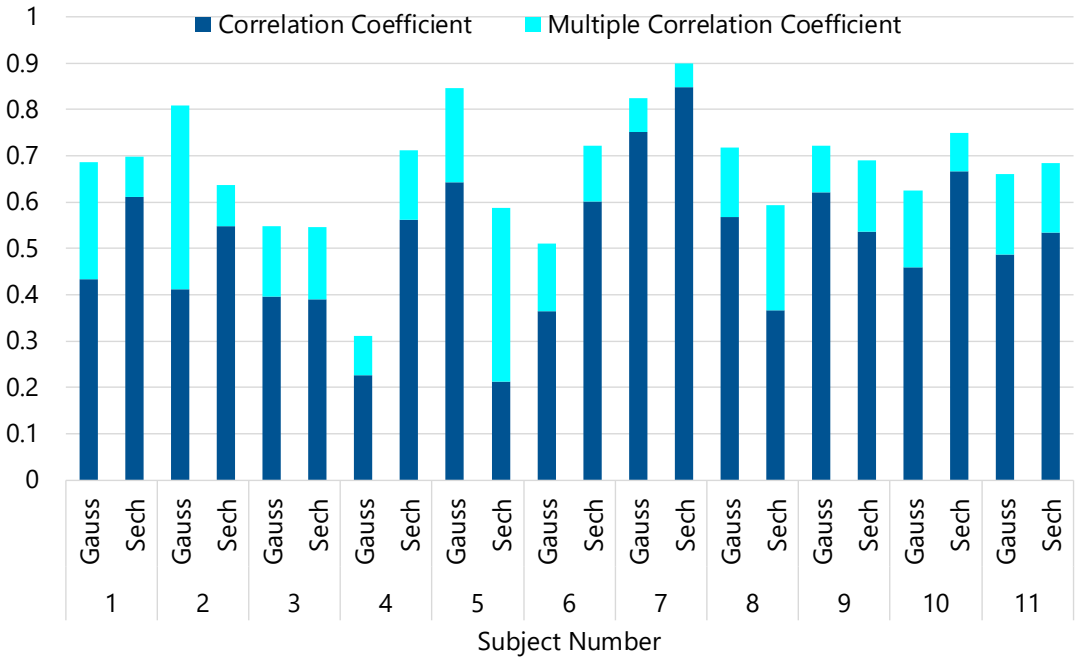

Figure 6. The comparison of the multiple correlation coefficients for each subject data as the known data and the correlation coefficients calculated by Leave One Out for each subject data as the unknown data. To calculate the multiple correlation coefficient, for each subject, multiple regression was performed with 60 simultaneous 8-second segments of continuous systolic blood pressure vs. PPG pulse decomposition features. To calculate the correlation coefficient, as Leave One Out, we estimate systolic blood pressure with an 8-second segment based on the multiple regression model learned with the other segments, and we repeat the process to test all 60 segments data comprehensively. Subject Number 11 is the value which is calculated by averaging the 10 subjects' data. The standard deviation of averaged multiple correlation coefficients based on Gauss-PDA is 0.167. The standard deviation of averaged multiple correlation coefficients based on Sech-PDA is 0.101. The standard deviation of averaged correlation coefficients based on Gauss-PDA is 0.156. The standard deviation of averaged correlation coefficients based on Sech-PDA is 0,176.

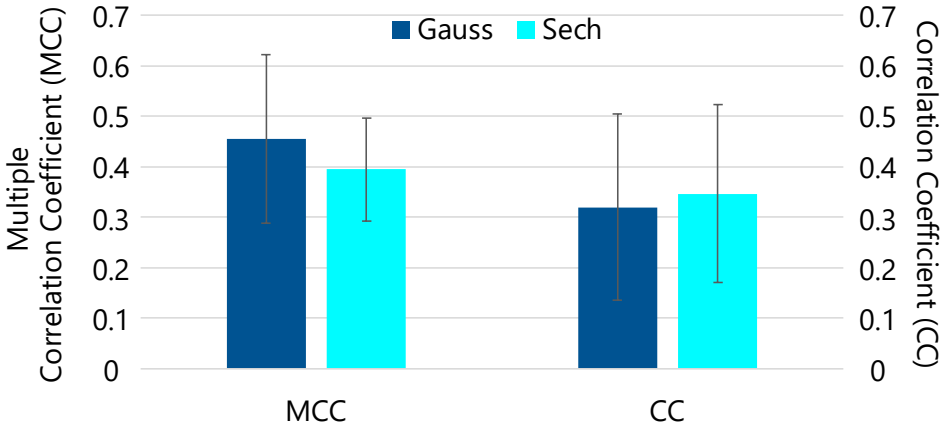

Figure 7. The multiple correlation coefficients for all the subjects and for all the data and the correlation coefficients for all the subjects' data with Leave One Out analysis.

4. Discussion

Here, we discuss the appropriateness of blood pressure description by sech-PDA and by Gaussian-PDA, and their characteristics. Gaussian PDA has shown the best performance in the literature on blood pressure measurement [8]. However, sech-PDA has not been tested in the literature for blood pressure estimates. Our results show that the use of sech-PDA instead of Gaussian-PDA could lead to more accurate and robust blood pressure measurement.

Figure 6 shows that the multiple correlation coefficient for each subject data in the known data is higher for the Sech PDA than for the Gaussian PDA. It also shows that the Sech PDA has a smaller variance in accuracy for each subject data than the Gaussian PDA. Meanwhile, Figure 6 shows that the Sech PDA has a higher correlation coefficient for each subject data in the unknown data than the Gaussian PDA. It also shows that the Sech PDA has a lower variance in accuracy for each subject data than the Gaussian PDA. From these results, two things can be inferred. First, the Sech PDA can describe blood pressure more accurately than the Gaussian PDA. Second, the Sech PDA is more robust to individual differences than the Gaussian PDA.

Figure 7 shows that the multiple correlation coefficient of the Sech PDA is lower than that of the Gaussian PDA for all subjects in the known data. Meanwhile, Figure 7 shows that the Sech PDA has a higher correlation coefficient for all subjects' data in the unknown data than the Gaussian PDA. From these results, it can be inferred that the Gaussian PDA overfits the known data and the Sech PDA has better generalization performance. This can be attributed to the findings in previous studies and the fact that the sech PDA is characterized by less variability between successive pulses compared to the Gaussian PDA [14].

Furthermore, our results show that in a multiple regression between PDA features and blood pressure using all features achieves higher accuracy compared to simply using one feature. We have higher accuracy with all features than the other combination of the features in multiple correlation coefficient. In addition, there is a report which systolic blood pressure has a preferable correlation with a_2/a_1 [3]. We have conducted the multiple regression with a_2/a_1. Specifically, we have conducted multiple regression with each subject data out of all the ten subject data to calculate a multiple correlation coefficient, and average the ten multiple correlation coefficients. As the result, Gaussian PDA has the mean of 0.20, the 0.17 of standard deviation, the minimum value of 0.031, the maximum value of 0.50. Sech PDA have brought the mean of 0.26, the 0.17 of standard deviation, the minimum value of 0.034, the maximum value of 0.59. Compared to the index a_2/a_1, which has been reported to correlate with systolic blood pressure, all features without arithmetic operations such as taking ratios have brought higher multiple correlation coefficient for all subject data. This is thought to be due to the more comprehensive description of the pulse wave contour by using the total feature value.

There are mainly three limitations of this study. The first is a necessity of a window process, which averages the features value or blood pressure in a time range of 8 sec. The window process brings two limitations: to be likely to decrease the estimation accuracy and to be an obstacle to the extension to estimation of continuous blood pressure. In this study, a mean value is adopted as a value representing the values distribution in a window. However, there is possibility not to represent sufficiently the distribution in a window, especially in the case of a large variation of blood pressure in a window. Also, Estimation of continuous blood pressure requires analysis of pulse wave from a narrow range or single point of time.

Finally, we will consider future work. We consider to have three main future work. The first is the introduction of calibration. Blood pressure depends on an individual's weight, height, and body mass index [18]; there is room to consider this information in the description of blood pressure using PDA. The second is an extension to neural networks (NN). There are two main types of the extension. It is a combination type of PDA-NN and an end-to-end type. The PDA-NN combination type expresses the relationship

between PDA features and blood pressure by NN. The end-to-end type estimates blood pressure directly from pulse waves without using a PDA. The PDA-NN combination type has the potential to function more preferably than multiple regression analysis. The reason is that there is sufficient possibility that the relationship between PDA features and blood pressure is non-linear. It is expected that the accuracy will be improved by expressing the non-linearity by NN. Similarly, the end-to-end type has a good possibility of improving the accuracy compared to the proposed method. The reason is non-linearity and directness. Regarding non-linearity, NN overcomes the concern that the relationship between pulse wave and blood pressure is non-linear. Regarding directness, as mentioned above, indirectness via PDA may reduce the estimation accuracy. The end-to-end type eliminates that indirectness. Comparing these two methods, the PDA-NN combination type is considered to be superior in interpretability and learning lightness, and the end-to-end type is considered to be superior in accuracy. This is because the PDA-NN combined type performs feature design halfway manually in the form of a PDA based on the physical characteristics of the pulse wave, while the end-to-end type performs all feature design by learning. The third is the application to imaging Photoplethysmography (iPPG). In recent years, camera-based pulse wave measurement has been actively researched [19]. The adaptation of the proposed method to iPPG is worth considering. This is because iPPG opens up the limitation of contact type sensors. In general, however, there is a concern about the accuracy of pulse wave extraction in iPPG compared to PPG. Therefore, there are issues, such as the possible improvement of the pulse wave extraction accuracy of iPPG and the verification and improvement of the robustness of the pulse wave accuracy of PDA.

5. Conclusion

In this study, we proposed a method for decomposing the pulse wave into three hyperbolic orthogonal waves and estimating blood pressure based on the features obtained from the waves. This method was applied to a dataset constructed by measuring pulse waves while varying blood pressure. The results showed that the proposed method can describe the blood pressure with high accuracy. In the future, we plan to study individual differences in estimated values and differences between systole and diastole. In addition, additional biometric information (weight, height, age, etc.) and individual calibration may be required for blood pressure measurement.

6. Ethics

This study has been approved by the Ethical Committee for Epidemiology of Hiroshima University and conducted in accordance with the Declaration of Helsinki.

Author Contributions: Conceptualization, Ryo Takahashi, Raquel Pantojo de Souza, and George C. Cardoso; Formal analysis, Takumi Nagasawa, Ryo Takahashi, Mari Tsunomura, and Kaito Iuchi; Investigation, Takumi Nagasawa, Ryo Takahashi, and, Kaito Iuchi; Methodology, Takumi Nagasawa, Ryo Takahashi, and Raquel Pantojo de Souza; Software, Takumi Nagasawa, Ryo Takahashi, Raquel Pantojo de Souza, and Kaito Iuchi; Supervision, Norimichi Tsumura and George C. Cardoso; Validation, Keiko Ogawa-Ochiai, Norimichi Tsumura, and George C. Cardoso; Writing – original draft, Kaito Iuchi; Writing – review & editing, George C. Cardoso, Keiko Ogawa-Ochiai, and Norimichi Tsumura.

Institutional Review Board Statement: This study has been approved by the Ethical Committee for Epidemiology of Hiroshima University and conducted in accordance with the Declaration of Helsinki.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Conflicts of Interest: The authors declare no conflict of interest.

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