Development of a Continuous Blood Pressure Monitoring System based on Pulse Transit Time and Hemodynamic Covariates

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Abstract: There were many studies showing the relation between pulse transit time (PTT) and blood pressure (BP). Besides, hemodynamic covariates may also contribute to BP values. Our previous study has proposed a BP model based on PTT, HR, stiffness index (SIx) and descent time (DT), which has been validated on the Multi-parameter Intelligent Monitoring for Intensive Care (MIMIC) database. In this article, we present a prototype cuff-less monitoring device for non-invasive estimation of BP, which can obtain both electrocardiogram (ECG) and finger plethysmograph (PPG) signals synchronously. The model proposed above has been validated by using ECG and PPG records from 22 healthy subjects with no cardiovascular disease and hypertension, and the error of BP estimation was 0.002 ± 8.544 mmHg for SBP, 0.005 ± 6.690 mmHg for DBP. The reliability of this method in long-term BP monitoring was further verified by studying the data of one individual for 28 days, while the error was 5.204 ± 5.462 mmHg for SBP, 2.714 ± 4.756 mmHg for DBP without calibration. The results show that the model could estimate the BP value within the acceptable error range based on this study, which is extremely close to AAMI's standard (5±8mmHg) and consistent with the cuff-method. The proposed ultra-low power, wearable, time-synchronized prototype monitoring device with an embedded hemodynamic covariate model, can measure SBP and DBP values accurately, which is expected to estimate continuous blood pressure better.

1 INTRODUCTION

Blood pressure (BP) is the lateral pressure on the vessel wall during blood flow. BP varies continuously due to different factors such as emotion variation, physical activities, medication, and disease. Many studies have shown a significant correlation between BP variability and cardiovascular mortality (Kikuya et al., 2000). Continuous measurement of blood pressure (BP) can dynamically monitor blood pressure fluctuation, which has very important practical significance and clinical value.

Although continuous BP can be accurately measured by invasive methods (e.g. insertion of an intra-arterial catheter), it could introduce risks to the patient and workload for physicians (Fung, Dumont, Ries, Mott, & Ansermino, 2005). Therefore, there is an urgent requirement for non-invasive BP measurement. Auscultation and oscillometry are the two most widely used cuff-based ways to measure BP noninvasively (Mukkamala et al., 2015). However, they can provide only intermittent BP readings with periodic cuff inflation and deflation. In particular, cuffs are cumbersome, occlusive and time-consuming to use, disruptive during ambulatory monitoring (Josep et al., 2013; Peter, Noury, & Cerny, 2014). Volume clamping and tonometry provide continuous beat-to-beat BP monitoring. While they both require relatively complex mechanical structures and are highly sensitive to the sensor's position and precision (Imholz, Wieling, van Montfrans, & Wesseling, 1998; Sato, Nishinaga, Kawamoto, Ozawa, & Takatsuji, 1993).

According to the limitations, the estimation of BP in successive cardiac cycles via pulse wave velocity (PWV) or pulse transit time (PTT) has been extensively proposed(Ding, Zhang, Liu, Dai, & Tsang, 2016; Jernstedt & Newcomer, 1974; Mase, Mattei, Cucino, Faes, & Nollo, 2011; Obrist et al., 1978). The PTT is defined as the period spent by the arterial pulse propagating from the heart to a peripheral circulation and is indeed expected to be in inverse relation with BP (Huynh, Jafari, & Chung, 2019; Josep et al., 2013; Mase et al., 2011).

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Furthermore, many methods with additional covariates (e.g. heart rate, pulse wave characteristic parameters) have been recommended to improve the precision of predicted BP (Cattivelli & Garudadri, 2009; Jadooei, Zaderykhin, & Shulgin, 2013; Lin et al., 2015).

In our previous study, we proposed a BP model based on PTT and other hemodynamic covariates (Feng, Huang, Zhou, & Ye, 2018). We derived the relationship between BP and PTT and presented an improved method utilizing PTT, HR, stiffness index (SIx) and descent time (DT) to prompt a better BP estimation based on MIMIC database. The results demonstrated that this method had the potential to continuously track BP with higher accuracy and less calibration frequency. While the limitation is that model-based data mainly focus on the patient in the intensive care unit, lacked the verification of healthy individuals in the normal living and working conditions.

In this paper, we introduced a reliable hardware system to validate the blood pressure estimation algorithms and models proposed in previous studies from multiple data sets of healthy individuals. The system was intended to detect both ECG and PPG signals synchronously, which enabled continuous cuff-less blood pressure evaluation. We established a common model and studied the universal applicability, expected to achieve a general estimation of population blood pressure by only changing the individual parameters of the model. In particular, we investigated the accuracy and reliability of long-term BP monitoring without calibration by collecting data of a specific individual for 28 days. Subsequently, we validated our approach according to the AAMI standard.

2 MATERIALS AND METHODS

2.1 System Overview

Figure 1 depicts a schematic view of the system developed, including a wireless signal detection system, a cuff blood pressure reference instrument and a host computer (PC).

The signal detection system acts as a slave device to synchronously collect ECG and PPG signals and transmit data via Bluetooth; the PC acts as a host for receiving data, performing signal processing and BP calculations. To evaluate and calibrate our results, the Omron-8713 electronic sphygmomanometer was used to measure cuff blood pressure as a reference. The developed device is about 4 cm long and 3.5 cm wide, which was smaller than a typical prototype (Austad et al., 2016; Kim et al., 2013).

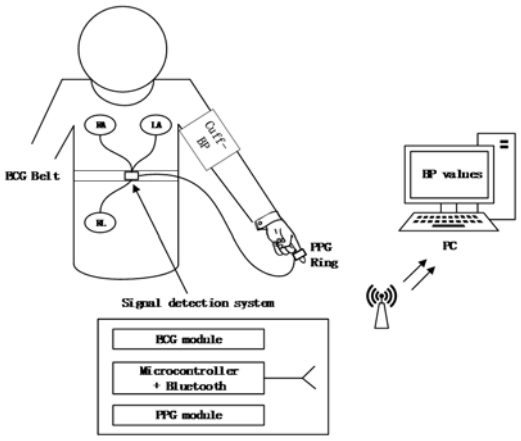


Figure 1: System overview.

Figure 2 describes the block diagram of the signal detection system, which involves an ECG module (AD8232), a PPG module (MAX30102), a microcontroller with Bluetooth combined (NRF52832) and power management unit. The controller collects the ECG data of the AD8232 at a sampling frequency of 200 Hz and reads the PPG data of the IIC interface at the same rate to guarantee time synchronization.

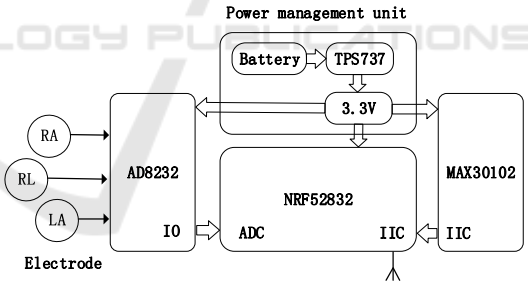


Figure 2: The block diagram of signal detection system.

The ECG module obtains the lead I configuration ECG signal from the three electrodes (RA, LA, and RL), and the electrode feeds the original signal into the ECG analog acquisition front end through the lead wire. A reflective optoelectronic sensor with embedded red and infrared emitters and phototransistors is used to acquire the PPG signal at the fingertips. The microcontroller pre-processes and transmits the two signals, and then the PC performs filtering, feature extraction, and calculation of SBP and DBP. In this study, PTT was calculated from the peak of each R-wave in the ECG to the maximum value of the PPG.

In our previous research, we found that discrete systems bring some uncontrollable delays(Espina, Falck, Muehlsteff, & Aubert, 2006). Since PTT is a time-sensitive parameter, the delay will cause a deviation in the blood pressure estimation. We use the same one microcontroller to pick up ECG and PPG signals (with Bluetooth device integrated inside the microcontroller), which ensured synchronization.

2.2 BP Model Description

Our previous study has attempted to derive the relationship between BP and PTT. This method has been verified to perform better on the MIMIC database than the two representative studies (Chen, Kobayashi, Ichikawa, Takeuchi, & Togawa, 2000; Poon & Zhang, 2005).

In addition to pulse wave transit time (PTT), the BP model proposed in our previous studies introduces some other hemodynamic parameters. Among them, the heart rate (HR) is affected by the regulation of baroreflex, the latter can adjust the short-term regulation of BP and prevent wide fluctuations; the stiffness index (SIx) exhibits the time interval from the main wave peak to a later diastolic peak, indicates the arterial stiffness; the descent time (DT) is interpreted as the duration from the onset of the dicrotic notch to the end of the diastole，which is associated to the ventricular diastolic phase.

Figure 3: The BP modelling process.

The basic process of blood pressure modelling is shown in Figure 3. We perform correlation analysis on the standardized characteristic parameters and select features according to the degree of relevance. Afterward, features with high partial correlation were selected for multiple linear regression to obtain the BP model. Then, we established a regression equation (Eqs.1 and Eqs.2) for SBP and DBP (Feng et al., 2018).

$$\text{SBP} = a_1 + b_1 \times \frac{1}{PTT^2} + c_1 \times HR + d_1 \times SIx \quad (1)$$

$$\text{DBP} = a_2 + b_2 \times \frac{1}{PTT^2} + c_2 \times HR + d_2 \times DT \quad (2)$$

where a, b, c, and d are coefficients.

2.3 Experimental Protocols

A total of 22 healthy subjects (15 males and 7 females) were recruited for a 4-week experiment, and data were collected 1 to 3 times per day for each subject. The subjects all aged between 22 and 50, with an average age of 24. Participants were requested not to drink alcoholic and caffeinated drinks for at least 4 hours before the test. Measurements were carried out under certain temperature (24 ℃ ~27 ℃) and humidity conditions (50%~60%) compensated by air condition.

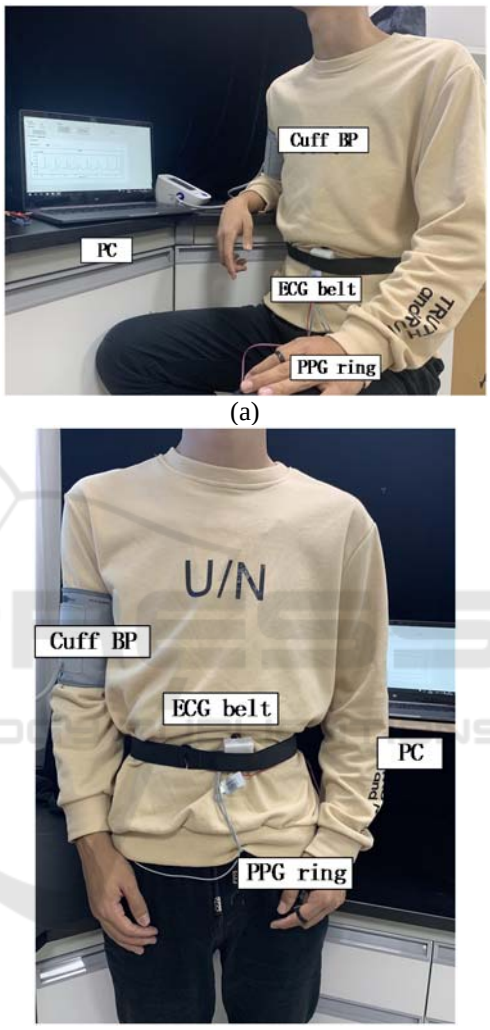


Figure 4: experimental set-up: sit position (a), stand position (b).

The protocol involved tests in two postures: sitting and standing; each data acquisition session took 5 minutes. Specific steps of the protocol are shown in Figure 4. Before starting the test, the subjects were requested to rest for 5 minutes, and the initial SBP1, DBP1, and HR1 were measured with an Omron sphygmomanometer. Then, the ECG and PPG signals were collected simultaneously for 2 minutes using the developed monitoring system, and then SBP2, DBP2, and HR2 were measured. The average

of the two indications measured by Omron was taken as the average blood pressure reference value within 2 minutes. After five minutes of rest, the above steps were repeated in a standing position to obtain a 2 minute ECG, PPG signal and reference SBP, DBP, HR. When measuring BP with Omron sphygmomanometer, we ensure that the cuff is always at the same level as the heart. If the current two blood pressure values differ by >5 mmHg, the blood pressure values are repeatedly measured after 2 minutes and the average of three measurements is taken. Figure 5 shows the process.

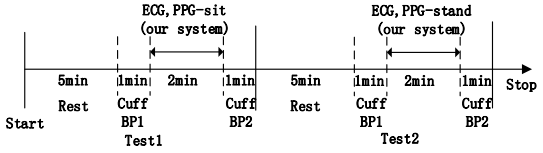


Figure 5: experimental protocols.

2.4 Data Analysis

2.4.1 Preprocessing

To enhance processing efficiency, we separated the raw signal into 30s segments. Since the original signal has been preprocessed by the hardware system, we used the wavelet transform to eliminate the residual baseline drift and artifact on PC. It has been pointed out that discrete wavelet decomposition provides better phase response and computational efficiency(Kachuee, Kiani, Mohammadzade, & Shabany, 2017). The ECG and PPG segments were decomposed into eight levels by the Daubechies db5 wavelet function, the fifth-order contour component was removed from the ECG signal, while the seventh-order contour component was removed from the PPG signal, thereby selecting a suitable approximation layer to reconstruct the signal.

2.4.2 Feature Extraction

Based on our previous research, we extracted the parameters required for blood pressure modelling and validated the proposed model. For the ECG signal, we extract the R-peak of each cardiac cycle through the sliding window and the dynamic adaptive threshold and then calculated the HR from the adjacent R–R interval.

The maximum value of the PPG waveform was extracted as the pulse onset point in the same cardiac cycle. Hence, PTT can be obtained by calculating the time interval between the R peak of the ECG signal and the corresponding feature point of the PPG signal. Furthermore, we also extracted several morphological parameters mentioned above and normalized all features.

3 RESULTS

Based on the relationship among BP, PTT and hemodynamic covariates obtained in our previous studies, we have established systolic and diastolic blood pressure models, respectively. We verified the accuracy of the proposed BP model by comparing the mean error and root-mean-square error between the estimated BP value and the reference value of the Omron sphygmomanometer. Ultimately, we assessed the consistency of the two methods by Bland-Altman analysis.

According to our experimental protocol, the population universal model and the individual long-term model were studied separately.

3.1 Universal BP Model

Data were collected for each individual for 1~3 times, a total of 248 segments of data. During the experiment, a total of 20 valid subjects and 180 data segments were analyzed, while the signals of two subjects were screened out for the low signal to noise ratio in the PPG signals for a good estimation of PTT. Table 1 summarized the basic information about the subject.

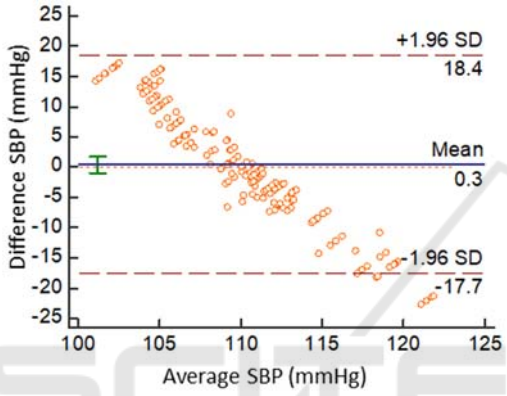
Table 1: Subject statistics.

Subjects details	
Number	22
Data sets	180 segments
Sex(m/f)	15/7
Age	Range: 22-50 mean+SD: 27.96+7.12
DBP	mean+SD: 74.42+9.87
SBP	mean+SD: 112.49+12.23

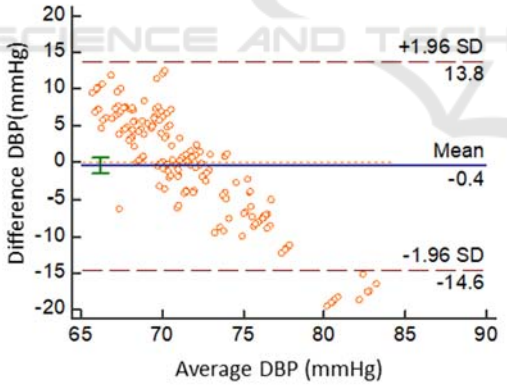
All valid data sets were divided into 10 parts by using the method of 10-fold cross-validation, nine of which were taken in turn as training data to establish a BP model, and one was used as test data to estimate the BP value. Then compared the value with reference values measured by the Omron sphygmomanometer to calculate errors. Table 2 shows the mean error and root-mean-square of the results of the 10-fold cross-validation. The average error was 0.002±8.544 mmHg for SBP, 0.005±6.690 mmHg for DBP, which extremely approached the standard of AAMI (5±8 mmHg).

Table 2: The results of 10-fold cross-validation.

	SBP (mmHg)		DBP (mmHg)	
	mean	std	mean	std
1	0.0397	8.6899	0.0184	6.8063
2	-0.0133	8.5496	0.0366	6.6011
3	-0.0124	8.4692	-0.0054	6.6397
4	0.0216	8.7775	-0.0118	6.8001
5	-0.0252	8.3874	-0.0110	6.6463
6	-0.0389	8.4475	-0.0215	6.6103
7	0.0223	8.4548	0.0180	6.5604
8	0.0012	8.5908	-0.0095	6.8713
9	-0.0021	8.4272	-0.0008	6.5995
10	0.0274	8.6498	0.0421	6.7686
Mean	0.0020	8.5444	0.0055	6.6904



(a)



(b)

Figure 6: Bland-Altman analysis of SBP(a), DBP(b) estimation for universal BP model.

The Bland-Altman plot of the SBP and DBP estimation for our proposed method versus Omron sphygmomanometer are given in Fig. 6. The x-axis presents the average of the two methods, while the y-axis shows the difference between them.

We observed that a total of 97.8% of the SBP, and 95% of the DBP measurements lie in the limits of agreement (1.96 × SD), indicating that the estimated BP with the proposed method is in close agreement with the Omron sphygmomanometer.

3.2 Individual Long-term BP Model

To investigate the validity of the evaluation of a particular subject's BP model over several consecutive days, further studies were performed on a selected subject. Regression models related to PTT, hemodynamic parameters, and BP values (SBP, DBP) were constructed by collecting data throughout one day at various time intervals during the subject's regular working hours. To demonstrate the accuracy and reliability of the model in long-term continuous monitoring scenarios, we compared the estimated BP values with the Omron sphygmomanometer. Measurements were performed at three different times of the day (10:00 am, 3:00 pm, 7:00 pm) based on fluctuations in blood pressure, and the experiment lasted for one month(29 days).

A total of 683 segments of data were collected for the same individual, excluding invalid data caused by collection failure. The individual BP model was created using 24 data sets on the first day, and the remaining 27 days of data were used to test the model to verify its long-term effectiveness. Similarly, we compared the estimated 28-day blood pressure with the Omron sphygmomanometer, and the mean and RMS of the statistical errors were shown in Table 3. The average error was 5.204±5.462 mmHg for SBP, 2.714 ± 4.756 mmHg for DBP, which extremely approached the standard of AAMI (5±8 mmHg).

Table 3: Individual model error analysis.

SBP (mmHg)		DBP (mmHg)	
mean	std	mean	std
5.2043	5.4624	2.7141	4.7561

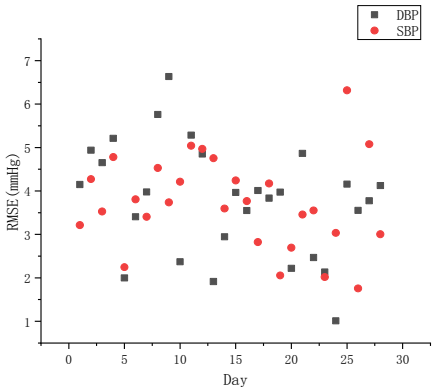
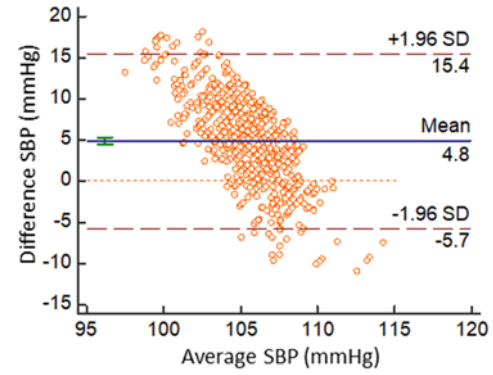
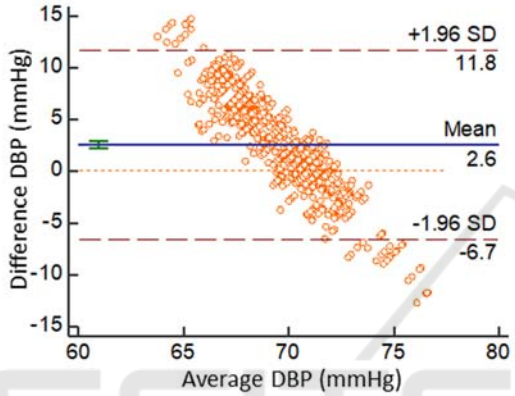


Figure 7: RMSE of BP estimated with the proposed measurement system with the reference system over 28 days for a subject.



(a)



(b)

Figure 8: Bland-Altman analysis of SBP(a), DBP(b) estimation for individual long-term BP model.

Figure 7 illustrates the observed trend of the estimated RMSE of estimated versus reference BP value. The proposed method can track BP values with lower RMSE values in 28 days with an error within an acceptable range. The Bland-Altman plot of the SBP and DBP estimation for the individual long-term model we proposed versus the Omron sphygmomanometer are given in Figure 8, which indicates that the two methods are in close agreement.

4 DISCUSSION

This study introduced a reliable hardware system to verify the proposed models on normal subjects. The system guarantees high quality and strict time synchronization of the original signal, thus eliminating errors caused by noise and uncontrolled delays. Moreover, high-quality signals can improve the accuracy of feature extraction, which in turn contributes to the estimation of blood pressure models.

However, there are some limitations to our study. First, we recruited healthy young and middle-aged people who were at higher risk of cardiovascular disease due to high mental stress and daily work intensity. Despite this, we still need data from older people or patients with cardiovascular disease to support the model. Second, the range of BP fluctuations in the experimental protocol is not obvious enough. Different BP perturbations must be applied to rigorously evaluate the validity of the proposed model, such as exercise test, cold pressor test.

5 CONCLUSIONS

In this paper, we proposed a wearable signal detection system that can simultaneously acquire ECG and PPG signals, ensuring signal integrity and reliability. Subsequently, we built a generic BP model and an individual long-term BP model to calculate SBP and DBP values, then compared the two values with the Omron sphygmomanometer, which showed a good agreement. Further, the errors between Omron and our system of the two models (generic SBP: 0.002 ± 8.544 mmHg, DBP: 0.005 ± 6.690 mmHg; individual SBP: 5.204 ± 5.462 mmHg, DBP: 2.714 ± 4.756 mmHg) are close to the AAMI standard(5 ± 8 mmHg). The results indicate that our system has the potential to continuously track BP for a long time without calibration. Nonetheless, more validation in various subjects and situations should be conducted with the system.

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REFERENCES

Austad, H. O., Vedum, J., Røed, M. H., Dalgard, S., et al. (2016). An Unobtrusive Wearable Device for Ambulatory Monitoring of Pulse Transit Time to Estimate Central Blood Pressure. International Joint Conference on Biomedical Engineering Systems and Technologies, BIOSTEC 2016, 179-186.

Cattivelli, F. S., & Garudadri, H. (2009). Noninvasive Cuffless Estimation of Blood Pressure from Pulse Arrival Time and Heart Rate with Adaptive Calibration. 2009 Sixth International Workshop on Wearable and Implantable Body Sensor Networks, 114-119.

Chen, W., Kobayashi, T., Ichikawa, S., Takeuchi, Y., & Togawa, T. (2000). Continuous estimation of systolic blood pressure using the pulse arrival time and intermittent calibration. Medical & Biological Engineering & Computing, 38(5), 569-574.

Ding, X. R., Zhang, Y. T., Liu, J., Dai, W. X., & Tsang, H. K. (2016). Continuous Cuffless Blood Pressure Estimation Using Pulse Transit Time and Photoplethysmogram Intensity Ratio. IEEE Trans Biomed Eng, 63(5), 964-972.

Espina, J., Falck, T., Muehlsteff, J., & Aubert, X. (2006). Wireless Body Sensor Network for Continuous Cuff-less Blood Pressure Monitoring. IEEE/EMBS International Summer School on Medical Devices & Biosensors.

Feng, J., Huang, Z., Zhou, C., & Ye, X. (2018). Study of continuous blood pressure estimation based on pulse transit time, heart rate and photoplethysmography-derived hemodynamic covariates. Australas Phys Eng Sci Med, 41(2), 403-413.

Fung, P., Dumont, G., Ries, C., Mott, C., & Ansermino, M. (2005). Continuous noninvasive blood pressure measurement by pulse transit time. International Conference of the IEEE Engineering in Medicine & Biology Society.

Huynh, T. H., Jafari, R., & Chung, W. Y. (2019). Noninvasive Cuffless Blood Pressure Estimation Using Pulse Transit Time and Impedance Plethysmography. IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING, 66(4), 967-976.

Imholz, B. P., Wieling, W., van Montfrans, G. A., & Wesseling, K. H. (1998). Fifteen years experience with finger arterial pressure monitoring: assessment of the technology. Cardiovasc Res, 38(3), 605-616.

Jadooei, A., Zaderykhin, O., & Shulgin, V. I. (2013). Adaptive algorithm for continuous monitoring of blood pressure using a pulse transit time. Electronics & Nanotechnology.

Jernstedt, G. C., & Newcomer, J. P. (1974). Blood-Pressure and Pulse-Wave Velocity-Measurement for Operant-Conditioning of Autonomic Responding. Behavior Research Methods & Instrumentation, 6(4), 393-397.

Josep, S., Martin, P. A., Damien, F., Jacques-André, P., et al. (2013). Noninvasive and Nonocclusive Blood Pressure Estimation Via a Chest Sensor. 60(12), 3505-3513.

Kachuee, M., Kiani, M. M., Mohammadzade, H., & Shabany, M. (2017). Cuffless Blood Pressure Estimation Algorithms for Continuous Health-Care Monitoring. IEEE Trans Biomed Eng, 64(4), 859-869.

Kikuya, M., Hozawa, A., Ohokubo, T., Tsuji, I., et al. (2000). Prognostic significance of blood pressure and heart rate variabilities: the Ohasama study. Hypertension, 36(5), 901-906.

Kim, H., Lee, H., Baek, H., Lee, W., et al. (2013). A preliminary study of non-intrusive blood pressure monitoring using portable device. International Conference on Biomedical Electronics and Devices, BIODEVICES 2013, 163-167.

Lin, H., Xu, W. Y., Guan, N., Ji, D., et al. (2015). Noninvasive and Continuous Blood Pressure Monitoring Using Wearable Body Sensor Networks. IEEE Intelligent Systems, 30(6), 38-48.

Mase, M., Mattei, W., Cucino, R., Faes, L., & Nollo, G. (2011). Feasibility of cuff-free measurement of systolic and diastolic arterial blood pressure. J Electrocardiol, 44(2), 201-207.

Mukkamala, R., Hahn, J. O., Inan, O., Mestha, L., et al. (2015). Towards Ubiquitous Blood Pressure Monitoring via Pulse Transit Time: Theory and Practice. 62(8), 1879-1901.

Obrist, P. A., Light, K. C., Mccubbin, J. A., Hutcheson, J. S., et al. (1978). Pulse transit time: Relationship to blood pressure. 10(5), 623-626.

Peter, L., Noury, N., & Cerny, M. (2014). A review of methods for non-invasive and continuous blood pressure monitoring: Pulse transit time method is promising? IRBM, 35(5), 271-282.

Poon, C. C., & Zhang, Y. T. (2005). Cuff-less and noninvasive measurements of arterial blood pressure by pulse transit time. Conf Proc IEEE Eng Med Biol Soc, 6, 5877-5880.

Sato, T., Nishinaga, M., Kawamoto, A., Ozawa, T., & Takatsuji, H. (1993). Accuracy of a continuous blood pressure monitor based on arterial tonometry. Hypertension, 21(6 Pt 1), 866-874.