Cuff-less blood pressure measurement using pulse arrival time and Kalman filter

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Abstract. The present study designs an algorithm to increase accuracy of continuous blood pressure (BP) estimation. Pulse arrival time (PAT) has been widely used for continuous BP estimation. However, because of motion artifact and physiological activities, PAT-based methods are often troubled with low BP estimation accuracy. This paper used a signal quality modified Kalman filter to track blood pressure changes. Kalman filter guarantees that BP estimation value is optimal in the sense of minimizing the mean square error. We propose a joint signal quality indice (JSQI) to adjust the measurement noise covariance, pushing the Kalman filter to more heavily weight on measurements from cleaner data. Twenty 2-hour physiological data segments selected from the MIMIC II database were used to evaluate the performance. Compared with straightforward use of the PAT-based linear regression model, the proposed model achieved higher measurement accuracy.

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Keywords: Cuff-less blood pressure estimation, pulse arrival time, signal quality index, Kalman filter

1. Introduction

Hypertension has been on the way of the major public health hazard due to lack of awareness and low treatment rate. Continuous blood pressure (BP) estimation is thus on the horizon, which is expected to help improve early hypertension prevention, detection and treatment. However, the most commonly used blood pressure sensors are based on oscillation of blood vessels with the aid of cuff, which brings some inherent limitations caused by the alternate inflation and deflation. Therefore, they are unsuitable for continuous and wearable application. Ideally, continuous BP measurement devices are feasible for daily use.

Pulse transit time (PTT) has captured great interest of researchers for its linear relationship with BP. PTT is defined as the time delay for the BP wave to travel from proximal to distal arterial sites. Though precious PTT is measured through central arteries and via the foot-to-foot time delay between the proximal and distal pressure waveforms, most studies in the literature do not measure such waveforms. For convenience, researchers often use electrocardiogram (ECG) to represent the proximal arterial waveform and photoplethysmogram (PPG) at the finger as a surrogate of the distal waveform, in which case PTT is known as pulse arrival time (PAT). To date, a great number of studies concentrate on PAT-based BP estimation and some achieved promising estimation accuracy, compared with the actual BP (Ye *et al* 2010, Mas *et al* 2011, Gesche *et al* 2011, Choi *et al* 2013, Mccarthy *et al* 2013, Ma 2014, Wibmer *et al* 2014).

While progress on PAT-based approach for BP estimation is obvious, straightforward use of PAT-BP relationship can often be disturbed by noise and artifact. To increase accuracy of continuous blood pressure estimation, this research proposed a signal quality modified Kalman filter based on PAT-BP relationship. A joint signal quality index (JSQI) was calculated by fusing SQI of ECG and PPG. Through JSQI, this algorithm adjusted measurement noise covariance, providing an automatic artifact detection and rejection mechanism.

In this paper, we describe the background of PAT-based BP estimation, design a joint signal quality assessment method, and apply JSQI to modify Kalman filter to mitigate artifact inference on BP estimation. We move forward by comparing performance of the PAT-BP linear regression model and the JSQI modified KF model on the MIMIC II database. We end by suggesting potential application of the proposed algorithm.

2. Background

Blood Pressure, also known as arterial blood pressure, is the force of circulating blood pushing against the walls of blood vessels. Systolic blood pressure (SBP) is defined when the heart is pumping blood, and diastolic blood pressure (DBP) is defined when the heart is at rest (Shriram *et al* 2010). In an ambulatory way, potentially the most convenient indirect parameter for achieving continuous noninvasive BP estimation is the pulse wave velocity (PWV) or the inverse, PTT. The theoretical framework is known as the Moens-Korteweg equation, which defines PWV as a function of vessel and fluid characteristics, thus outlining the relationship between PTT and BP (Marcinkevics *et al* 2009, Cattivelli and Garudadri 2009):

$$c = \frac{L}{PTT} = \sqrt{\frac{E \cdot h}{2\rho R}} \tag{1}$$

where c is the wave velocity, L is the vessel length, PTT is the time that a pressure pulse takes to travel through that length, ρ is the blood density, R is the inner radius

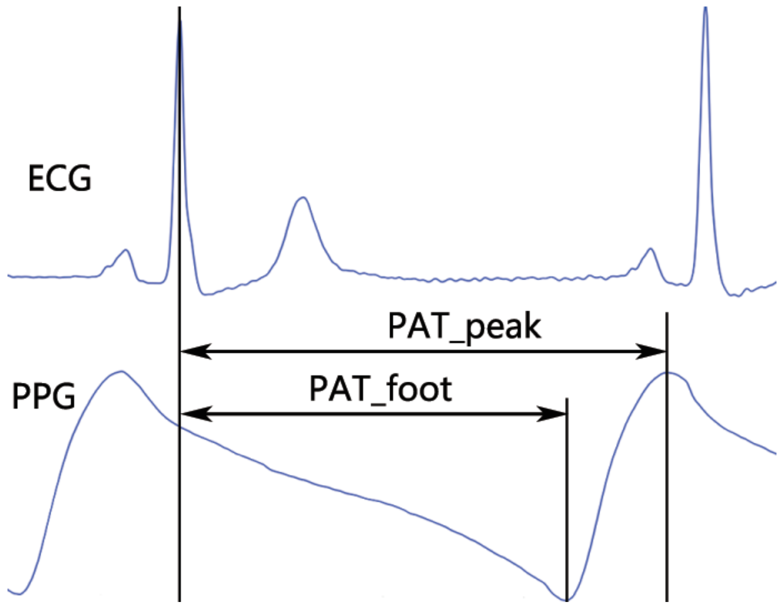

Figure 1. Two common PAT calculation methods: PAT_foot is the time interval between R peak of ECG waves and foot of PPG pulses, PAT_peak is the time interval between R peak of ECG waves and peak of PPG pulses

of the vessel, E is the elastic modulus of vascular wall (Youngs modulus), and h is the vessel wall thickness. For an elastic vessel, there exists an empirical exponential relation between E and the blood pressure P (Hughes *et al* 1978, Chen *et al* 2000), namely

$$E = E_0 \cdot \exp(\kappa \cdot (P - P_0)) \tag{2}$$

where α is a constant, E_0 and P_0 are nominal values of Youngs modulus and pressure, respectively. From (1) and (2) we have a logarithmic dependency between BP and PTT assuming all other parameters are constant, such as:

$$BP = \alpha \cdot \ln PTT + \beta \tag{3}$$

In this work, we followed the common practice of using ECG to represent the proximal arterial waveform and PPG at finger to represent the distal arterial waveform, as in figure 1. Because the PPG foot was minimally impacted by wave reflection, it was chosen as the preferred feature, and we calculated the R-peak-to-foot time delay between two waveforms in a cardiac cycle. In this way, PTT is often referred as PAT.

3. Materials and Methods

3.1. Data Acquisition and Processing

To have a wide representation of PPG and correspondent beat-to-beat BP values, we used the Multiparameter Intelligent Monitoring in Intensive Care II (MIMIC II) database. Each record includes various types of physiological signals, which are all sampled at 125 Hz. ECG waveforms include I, II, III, V, AVF and so on. Continuous blood pressure waveforms include arterial blood pressure (ABP) signal that is invasive from one of the radial arteries. PPG is raw output of the fingertip plethysmograph. Among MIMIC II database, we selected records that all three types of waveforms (ECG, ABP, PPG) were available. Records with missing data even in a short period were dropped. To obtain a clean data subset for the study, waveforms with excessive motion artifacts were also excluded from the study data set.

During preprocessing procedure, ECG, ABP and PPG signals were filtered by the FIR band-pass filter with cut-off frequency [0.5, 40 Hz], [0.5, 20 Hz] and [0.5, 10 Hz], respectively (Mukkamala *et al* 2015). After filtering, we detected R peaks in ECG using the 'eplimited' (Pan and Tompkins, 1985, Hamilton and Tompkins, 1986) based upon an energy threshold approach and foot points in pulsatile waveforms (ABP and PPG) using length transform (Zong *et al* 2003). PTT was calculated by the time delay between R waves and corresponding beat feet of PPG. Beat-to-beat SBP and DBP were extracted from ABP signal, which are viewed as the actual BP values.

3.2. Joint Signal Quality Indice

Given that the PPG and ECG signals are typical of noninvasive measurements, their waveforms are highly susceptible to noise and artifact. Handling artifact in the waveforms is crucial in practice, yet often not mentioned in previous studies. In this paper, we propose a joint signal quality index (JSQI) to modify the Kalman filter for continuous BP estimation. The reliability of detected beat is examined by the JSQI, as in

$$JSQI_n = \begin{cases} 0 & \text{if } ECGSQI_n < 0.5, \\ 0 & \text{if } PPGSQI_n < 0.5, \\ ECGSQI_n \cdot PPGSQI_n, & \text{otherwise.} \end{cases} \tag{4}$$

$ECGSQI$ is based on agreement of two QRS detectors: 'wqrs' and 'eplimited' (Li *et al* 2008, Johnson *et al* 2015), $PPGSQI$ is based on correlation with a beat template formed by averaging previous beats detected from PPG with an open-source script (Clifford *et al* 2015). PTT calculated from high-quality beats was used for BP estimation, which guarantees reliability of new BP estimation.

3.3. JSQI-Modified Kalman Filter

Kalman filter is an optimal state estimator for stochastic states in the sense of the least mean squares given the system observation. Considering the following process equation and measurement equation:

$$\begin{cases} x_{n+1} = F \cdot x_n + B \cdot u_n + w_n \\ y_n = H \cdot x_n + v_n \end{cases} \tag{5}$$

where x_n and u_n are the state variables and input signal, respectively, at time instant n. F is the transition matrix taking the state x_n from time n to time $n+1$. y_n is the observable variables and H is the measurement matrix. Process noise w_n and measurement noise v_n are assumed to be addictive, white, and Gaussian, with zero mean, covariance Q and R, respectively. Moreover, process noise w_n is unrelated with measurement noise v_n.

The problem at hand is to estimate the unknown state x_{n+1} of the system using the noisy observations y_n in an online fashion. First of all, we use the last state to predict the current state of the system as

$$\hat{x}_{n+1|n} = F \cdot \hat{x}_{n|n} + B \cdot u_n \tag{6}$$

where $\hat{x}_{n|n}$ is the optimally estimated value with the associated covariance matrix $P_{n|n}$ at time instant n, and $\hat{x}_{n+1|n}$ denotes the prior estimation of x_{n+1} with associated covariance matrix as $P_{n+1|n}$ such that

$$P_{n+1|n} = F \cdot P_{n|n} \cdot F^{\mathrm{T}} + Q \tag{7}$$

where F^{T} is the transposed matrix of F. Until now this system has been updated. Then we collect the new measured output of this system and correct the estimated state.

$$G_{n+1} = P_{n+1|n} \cdot H^{\mathrm{T}} \cdot (H \cdot P_{n+1|n} \cdot H^{\mathrm{T}} + R)^{-1} \tag{8}$$

$$\hat{x}_{n+1|n+1} = \hat{x}_{n+1|n} + G_{n+1} \cdot (y_{n+1} - H \cdot \hat{x}_{n+1|n}) \tag{9}$$

$$P_{n+1|n+1} = (\mathrm{I} - G_{n+1} \cdot H) \cdot P_{n+1|n} \tag{10}$$

where G_{n+1} represents the Kalman gain. Combining the measured values and prior estimation of states, we can obtain the optimally estimated value of x_{n+1}, i.e., $\hat{x}_{n+1|n+1}$.

PAT and BP hold an approximately linearly reverse relation. In this literature, we view BP as the state and PAT as the observation of the linear system. System can be depicted as

$$\begin{cases} BP_{n+1} = BP_n + w_n \\ PAT_n - \beta = \alpha \cdot \ln BP_n + v_n \end{cases} \tag{11}$$

where α and β are parameters obtained by the least mean squares fitting.

In order to rely more heavily on cleaner data, a modification is made by applying the JSQI to adjust the measurement noise covariance R:

$$R_n = R_0 \cdot \exp(JSQI_n^{-2} - 1) \tag{12}$$

where R_0 was chosen to be unity. The $JSQI_n$ adjusts the measurement noise covariance of Kalman filter, which further affects the Kalman filter gain. At high $JSQI_n$, the exponential factor tends to be unity, pushing Kalman filter to trust the current measurement. As $JSQI_n$ tends low, R_n tends to be infinity (but in practice R_n is limited to a large value), forcing Kalman filter to lower Kalman gain and trust previous value more. In addition, if $JSQI_n$ is below a certain threshold, corresponding PTT is reckoned as not trustworthy and the Kalman filter will not get updated.

4. Results

We selected 20 2-hour data segments from 20 records. The performance of the proposed BP estimation model were evaluated with reference to the invasive BP values obtained from ABP signals. The Association for the Advancement of Medical Instrumentation requires that the mean of the estimation error has to be lower than 5 mmHg in absolute value, and that the standard deviation of the error has to be below 8 mmHg, both for SBP and DBP. Since what we are trying to observe is how close our estimation is to the actual BP, we are applying mean absolute error (MAE) and standard deviation (SD) with respect to AAMI requirements.

Table 1 shows MAE and SD of SBP and DBP estimation, on all 20 records. The linear regression algorithm is denoted by "LR" and the signal quality modified Kalman filter algorithm is denoted by "KF". It is obvious that the "KF" has smaller MAE and SD than the "LR" for both SBP and DBP, which means the estimated BP has smaller bias and error variance. For most records, DBP estimation with "KF" has higher accuracy than that of SBP, though "KF" on some records do not reach requirements of AAMI.

For a specific record 3110856, figure 2 displays the boxplots of estimation error by "LR" and "KF", for SBP and DBP, respectively. In a boxplot, the red line near the middle of the rectangle indicates the median value, the top of the rectangle indicates the third quartile, and the bottom of the rectangle indicated the first quartile. "Whiskers" above and below the rectangle show locations of the maximum and minimum residuals. Any data not included between the whiskers are plotted as an outlier with a dot. As shown in figure 1, for both SBP and DBP, "LR" and "KF" both achieved median error near 0, but "KF" has smaller absolute values of quartiles and extreme values. In other words, the "KF" is better than the "LR" in both mean and variance of the errors.

Since "KF" achieved higher accuracy than "LR" in BP estimation, following two graphs display performance of "KF" in more details. Still with the record 3110856, figure 3 shows the Bland-Altman plot of the SBP and DBP estimation of the proposed methods versus the invasive method, which examines the agreement between estimated and actual BP on average. For a typical Bland-Altman plot, the x-axis defines the average of estimated and actual BP and represents the estimation bias, while the y-axis defines the difference between these two BP values and represents the random fluctuations around this mean. We can see that the majority of points locate within the limits of agreement, for both SBP and DBP, but DBP estimation has smaller fluctuation.

To further illustrate the consistence between the proposed algorithm and the clinical data, figure 4 shows the estimated and actual blood pressure values for the record 3110856, using and "KF". It can be seen that estimation by "KF" tracks closely the treads of the actual values.

Table 1. Mean absolute error (MAE) and standard deviation (SD) for different records

Record	SBP		DBP	
	KF(MAE±SD mmHg)	LR(MAE±SD mmHg)	KF(MAE±SD mmHg)	LF(MAE±SD mmHg)
3910093	7.44 ± 9.50	11.41± 13.69	4.23 ± 6.33	9.54 ± 12.70
3909185	5.98 ± 7.72	15.71± 20.07	2.97 ± 3.87	10.80± 13.79
3908522	8.51 ± 13.12	14.56± 23.78	4.24 ± 5.58	6.39 ± 9.68
3908470	4.69 ± 6.98	6.10 ± 10.01	4.29 ± 5.71	7.31 ± 10.10
3907353	10.79± 14.47	13.74± 18.40	3.94 ± 5.42	4.92 ± 6.73
3906175	10.02± 13.17	17.72± 26.30	5.95 ± 7.60	10.85± 15.94
3902994	7.41 ± 9.55	10.34± 13.60	5.65 ± 7.52	9.01 ± 11.82
3901926	6.62 ± 9.26	9.82 ± 12.86	2.75 ± 4.00	4.15 ± 5.67
3901160	8.18 ± 9.65	8.79 ± 10.77	4.75 ± 5.66	5.44 ± 6.84
3128520	7.95 ± 10.22	11.30± 15.68	4.34 ± 5.21	10.05± 14.21
3128317	7.78 ± 10.04	14.77± 17.33	4.05 ± 5.58	11.44± 15.75
3128243	8.37 ± 11.05	14.20± 17.75	3.84 ± 4.95	7.04 ± 9.21
3125881	7.19 ± 9.53	8.52 ± 11.53	3.72 ± 4.86	4.73 ± 6.35
3124132	5.43 ± 7.08	9.31 ± 12.51	2.39 ± 3.39	4.54 ± 6.05
3118326	8.38 ± 10.76	16.75± 21.94	7.31 ± 11.70	13.83± 15.86
3112538	5.50 ± 7.08	10.06± 13.19	4.67 ± 5.79	8.69 ± 11.30
3111185	8.84 ± 11.06	11.47± 14.76	5.43 ± 6.80	8.88 ± 10.37
3110856	5.42 ± 6.72	8.21 ± 10.79	3.43 ± 4.43	4.85 ± 6.41
3109737	6.64 ± 8.36	11.90± 15.59	5.88 ± 6.64	10.50± 13.59
3109069	7.89 ± 10.59	9.73 ± 10.84	4.48 ± 6.00	5.74 ± 7.59

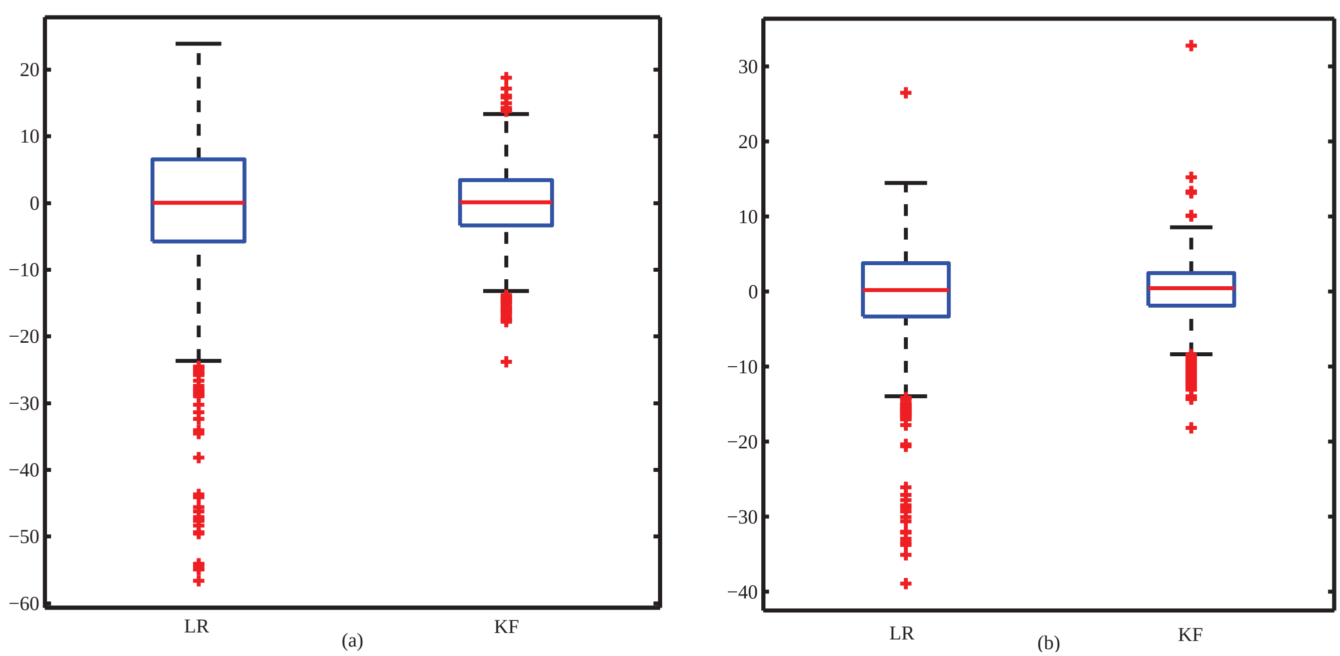

Figure 2. Boxplots of the estimation error for the SBP (a) and DBP (b) by LR and KF methods for the record 3110856.

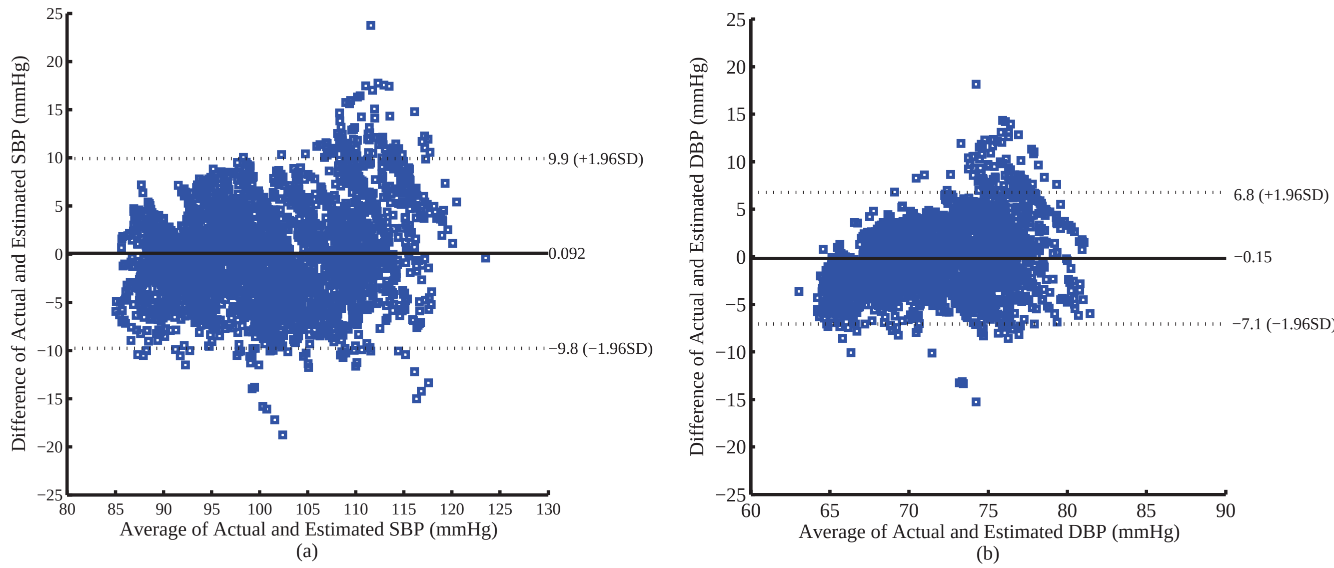

Figure 3. Bland-Altman plot for the estimated and the actual SBP (a) and DBP (b) by the signal quality modified Kalman filter method for the record 3110856.

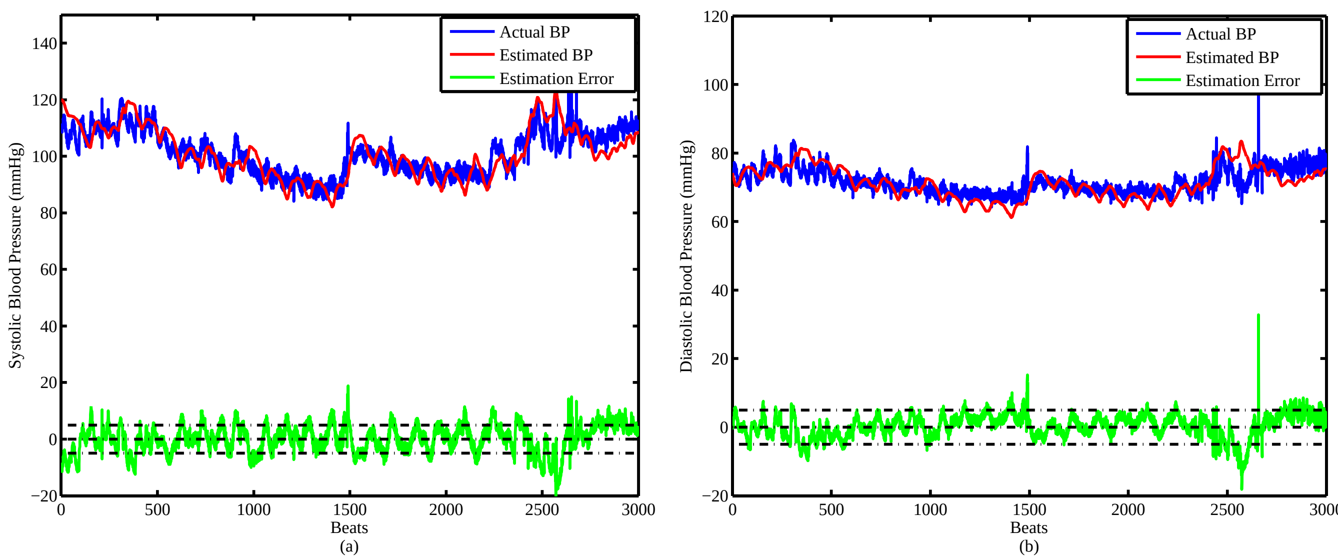

Figure 4. The estimated SBP (a) and DBP (b) by the signal quality modified Kalman filter method for the record 3110856.

5. Discussion and Conclusions

Continuous blood pressure monitoring is in profound need to help improve hypertension detection and control. We proposed a signal quality modified Kalman filter algorithm to track SBP and DBP changes continuously. The method aims to address the problem of large estimation error in the case of low signal quality of ECG and PPG signal. Compared with the linear regression, the proposed method achieved higher estimation accuracy in terms of mean absolute error and standard deviation, for both SBP and DBP.

Records from MIMIC II have a wide representation of PPG and correspondent BP values. Some records in figure 1 did not display acceptable BP estimation accuracy. Partly because these records come from patients whose cardiovascular systems are often disordered. For example, R peaks of premature beats come earlier than normal beats, thus PAT is larger than normal and BP estimation through the normal PAT-BP relationship becomes smaller. Another issue that should be considered is drugs for BP-related diseases. Some antihypertensive drugs may influence natural blood state. Further research should investigate the effect of cardiac diseases, like premature beats, and medical drugs on the PAT-BP relationship.

We took PAT as a surrogate of PTT, but In fact, PAT includes two components: the pre-ejection period (PEP) and PTT. PEP is the isovolumetric contraction time of the heart, which is the time it takes for the myocardium to raise enough pressure to open the aortic valve and start pushing blood out of the ventricle. Although good correlations between BP and PAT have been consistently observed in the literature, only PTT is related to BP through relation (1). More feasible methods are in need to realize PTT measurement.

Recently, it have been widely researched to monitor physiological parameters in portable devices. Due to low computation complexity, the proposed algorithm can be easily transplanted into wearable sensor devices. This algorithm strengthens capacity of the PAT-based approach to continuous BP estimation in wearable application.

References

Cattivelli F S and Garudadri H 2009 Noninvasive Cuffless Estimation of Blood Pressure from Pulse Arrival Time and Heart Rate with Adaptive Calibration *Sixth Int. Workshop on Wearable and Implantable Body Sensor Networks* pp 114-9 IEEE Computer Society

Chen M W, Kobayashi T, Ichikawa S, Takeuchi Y and Togawa T 2000 Continuous estimation of systolic blood pressure using the pulse arrival time and intermittent calibration *Med. Biol. Eng. Comput.* **38** 569-74

Choi Y, Zhang Q and Ko S 2013 Noninvasive cuffless blood pressure estimation using pulse transit time and hilbertChuang transform *Comput. Electr. Eng.* **39** 103-11

Chua C P and Heneghan C 2006 Continuous blood pressure monitoring using ECG and finger photoplethysmogram. *In Engineering in Medicine and Biology Society, 2006. EMBS'06. 28th Annual International Conference of the IEEE* pp 5117-20

Clifford G D, Silva I, Moody B, Li Q, Kella D, Shahin A, Kooistra T, Perry D and Mark R G 2015 Reducing false arrhythmia alarms in the ICU: The physionet/computing in cardiology challenge *Comput. Cardiol.* **42** 273-6

Gesche H, Grosskurth D, Kchler G and Patzak A 2011 Continuous blood pressure measurement by using the pulse transit time: comparison to a cuff-based method Eur. J. Appl. Physiol. **112** 309-15

Hamilton P S and Tompkins W J 1986 Quantitative investigation of qrs detection rules using the mit/bih arrhythmia database *IEEE Trans. Biomed. Eng.* **33** 1157-65

Hughes D J, Geddes L A, Babbs C F and Bourland J D 1978 Measurements of Young's Modulus of the Canine Aorta In-Vivo with 10 MHz Ultrasound *In 1978 Ultrasonics Symposium, IEEE* p 326

Johnson A E, Behar J, Andreotti F, Clifford G D and Oster J 2015 Multimodal heart beat detection using signal quality indices *Physiol. Meas.* **36** 1665-77

Li Q, Mark R G and Clifford G D 2008 Robust heart rate estimation from multiple asynchronous noisy sources using signal quality indices and a kalman filter *Physiol. Meas.* **29** 15

Ma H T 2014 A blood pressure monitoring method for stroke management *Biomed Res. Int.* **2014** 309-22

Marcinkevics Z, Greve M, Aivars J I, Erts R and Zehtabi A H 2009 Relationship between arterial pressure and pulse wave velocity using photoplethysmography during the post-exercise recovery period *Acta Univesitatis Latviensis: Biology* **753** 59-68

Mas M, Mattei W, Cucino R, Faes L and Nollo G 2011 Feasibility of cuff-free measurement of systolic and diastolic arterial blood pressure *J. Electrocardiol.* **44** 201-7

Mccarthy B M, Vaughan C J, O'Flynn B, Mathewson A and Mathna C 2013 An examination of calibration intervals required for accurately tracking blood pressure using pulse transit time algorithms *J. Hum. Hypertens.* **27** 744-50

Mukkamala R, Hahn J O, Inan O T, Mestha L K, Kim C S, Toreyin H and Kyal S 2015 Toward ubiquitous blood pressure monitoring via pulse transit time: theory and practice *IEEE Trans. Biomed. Eng.* **62** 1879-901

Pan J and Tompkins W J 1985 A real-time QRS detection algorithm *IEEE Trans. Biomed. Eng.* **32** 230-6

Payne R A, Symeonides C N, Webb D J and Maxwell S R J 2006 Pulse transit time measured from the ECG: an unreliable marker of beat-to-beat blood pressure*J. Appl. Physiol.* **100** 136-41

Shriram R, Wakankar A, Daimiwal N and Ramdasi D 2010 Continuous cuffless blood pressure monitoring based on PTT *Int. Conf. on Bioinformatics and Biomedical Technology* pp 51-5

Teng X F and Zhang Y T 2006 An evaluation of a PTT-based method for noninvasive and cuffless estimation of arterial blood pressure *In Engineering in Medicine and Biology Society, 2006. EMBS'06. 28th Annual International Conference of the IEEE* pp 6049-52

Wibmer T, Doering K, Kropfsanchen C, Rdiger S, Blanta I, Stoiber K M, Rottbauer W and Schumann C 2014 Pulse transit time and blood pressure during cardiopulmonary exercise tests *Physiol. Res.* **63** 287-96

Ye S Y, Kim G R, Jung D K, Baik S W and Jeon G R 2010 Estimation of Systolic and Diastolic Pressure using the Pulse Transit Time *World Academy of Science Engineering & Technology* **67** 726

Yoon Y, Cho J H and Yoon G 2009 Non-constrained blood pressure monitoring using ECG and PPG for personal healthcare *J. Med. Syst.* **33** 261-6

Zhang G, Gao M, Xu D, Olivier N B and Mukkamala R 2011 Pulse arrival time is not an adequate surrogate for pulse transit time as a marker of blood pressure *J. Appl. Physiol.* **111** 1681-6

Zong W, Heldt T, Moody G and Mark R 2003 An open-source algorithm to detect onset of arterial blood pressure pulses *Proc. Computers in Cardiology (21-24 September 2003)* pp 259-62