Continuous Blood Pressure Monitoring Algorithm Using Pulse Transit Time and Modified Kalman Filter

QiangZhang[1,2],Xianxiang Chen[1], Zhen Fang[1], and ShanhongXia[1*]
[1]Institute of Electronics, Chinese Academy of Sciences, China
[2]University of Chinese Academy of Sciences, China
E-mail: shxia@mail.ie.ac.an

Cardiovascular diseases have been a major hazard for human health. Continuous blood pressure monitoring is in great need to improve hypertension detection and treatment. However, the most commonly used blood pressure (BP) sensors are based on oscillation of blood vessels with the aid of cuff, due to the alternate inflation and deflation and significant inconvenience and uncomfortableness, they are not suitable for continuous and wearable monitoring. Previous literature reported that pulse transit time (PTT) is a potential candidate of BP indicator, but this method faces the problem of large error in the case of low signal quality of electrocardiogram (ECG) and photoplethysmogram (PPG) signal.

To increase accuracy of continuous blood pressure monitoring, this research designs a novel algorithm based on PTT derived from ECG and PPG wavefrom, and Kalman filter, as shown in figure 1.Through signal quality index (SQI) assessment, this algorithm provides an automatic artifact detection and rejection mechanism, hence permits determination of BP more accurately. A joint signal quality index (JSQI) is proposed to modify Kalman filter, in order to increase reliability of BP estimation. Furthermore, this algorithm can be easily transplanted to wearable sensors due to its low computation complexity.

PTT is conventionally defined as time interval from the characteristic points of synchronously recorded ECG and PPG. As shown in Figure 2, PTT-peak and PTT-foot are time difference from the R point in ECG to the peak and foot of PPG respectively, with the latter used in this algorithm. PTTs and BPs hold a linearly reverse relation and the potential model to fit this relation is shown in formula (1).

$$P = \alpha \cdot \ln T + \beta \qquad (1)$$

where coefficients α and β can be obtained by least mean square error (LMSE) fitting.

The characteristic points of beat detected from ECG and PPG directly influences PTT calculation and thus plays an important role in BP estimation.The reliability evaluation of detected beat is performed by the JSQI:

$$JSQI = ECGSQI \cdot PPGSQI \qquad (2)$$

ECGSQI represents the SQI of ECG, which is based on agreement of two QRS detectors: wqrs and eplimiteds[1], PPGSQI means the SQI of PPG, which is based on correlation with a beat template formed by averaging previous beats detected from PPG with an open-source script[2]. Only PTT calculated from high-quality beats is used for BP estimation.

Kalman filter is an optimal state estimation method for stochastic signals[3]. It is employed to track the systolic blood pressure (SBP) changes and overcome noise disturbance. In order to rely more heavily on clean data, a modification is made by using the JSQI to adjust the measurement noise covariance, R:

$$R \to R \cdot \exp\left(JSQI^{-2} - 1\right), \;\; JSQI > 0 \qquad (3)$$

At high JSQI, the exponential factor tends to be unity, pushing Kalman filter to trust the current measurement. As JSQI tends low, R tends to be infinity (but in practice R is limited to a large value), forcing Kalman filter to lower Kalman gain and trust previous value more. In addition, if current JSQI is below a certain threshold, i.e. $JSQI_{th}$, then corresponding PTT is reckoned as not trustworthy and Kalman filter will not get updated.

The effectiveness of this algorithm is tested with the MIMIC database where there are 58 records, over 2000 hours of simultaneous ECG, PPG and arterial blood pressure (ABP) data. ABP is viewed as a *gold standard* and used to derive true SBP values. Figure 3 depicts the estimation accuracy of one record, which is based on the root mean squared error (rMSE) of difference between each estimated SBP and the true SBP. As shown in figure 3, compared with the linear regression, this new algorithm could track overall SBP changes better and the estimated SBP values are more close to true values. With JSQI-modified Kalman filter, the mean error and standard deviation decreased from 7.27 mmHg to 4.86 mmHg and from 10.35 mmHg to 6.54 mmHg respectively, satisfying the Association for the Advancement of Medical Instrumentation (AAMI) limits of 5 mmHg bias and 8 mmHg precision.

REFERENCE

[1]Li Qiao, and G. Clifford. "Signal quality indices and data fusion for determining acceptability of electrocardiograms collected in noisy ambulatory environments." Computing in Cardiology 38 (2011).

[2]Li, Q., and G. D. Clifford. "Dynamic time warping and machine learning for signal quality assessment of pulsatile signals." Physiological measurement 33.9 (2012): 1491.

[3]Brown, Robert Grover. "Introduction to random signal analysis and Kalman filtering". John Wiley &Sons, 1983.

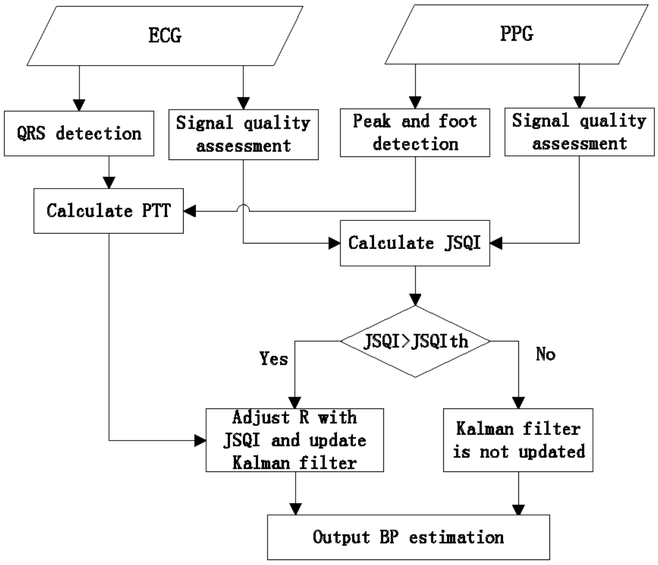

Figure 1. General method for estimating SBP from ECG and PPG

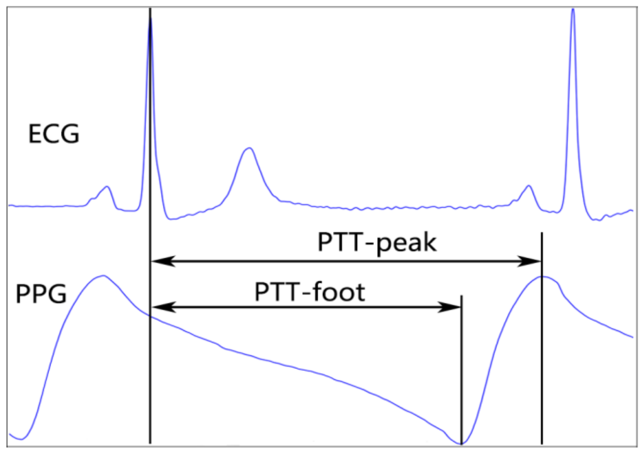

Figure 2. PTT-peak and PTT-foot determined by ECG and PPG

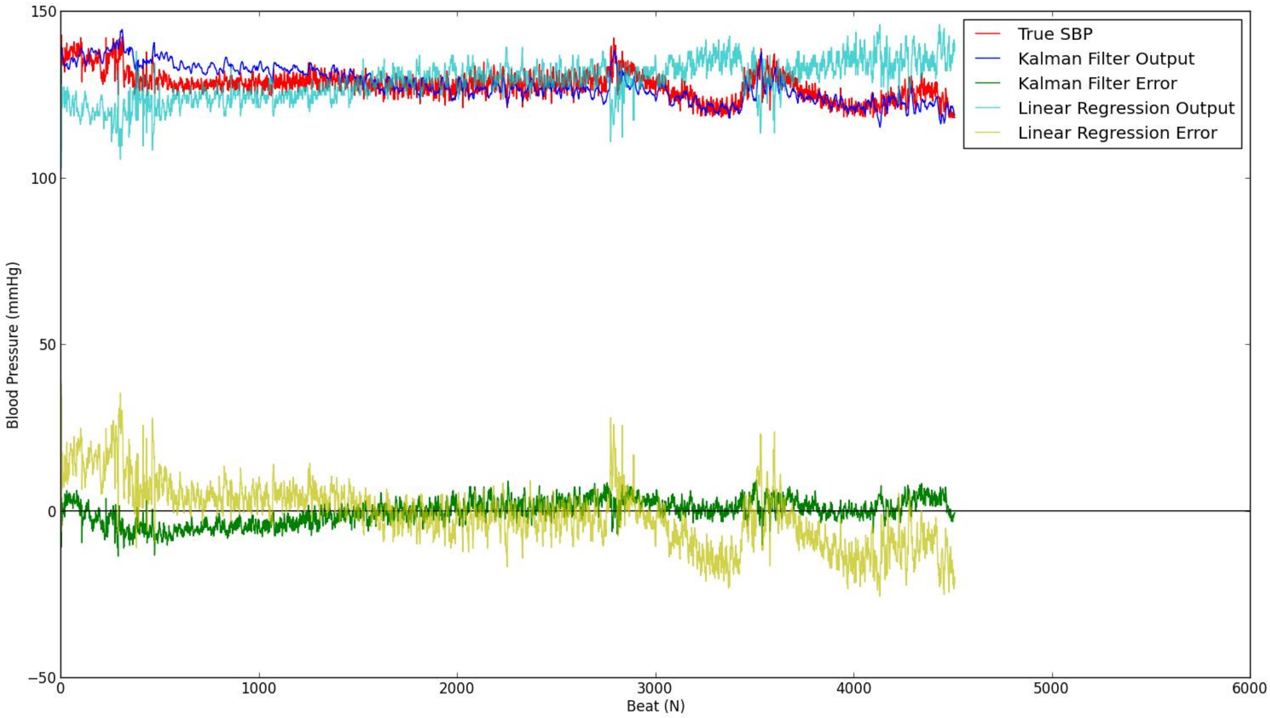

Figure 3. Comparison of estimated SBP and true SBP values