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A digital signal processor (DSP)-based system for embedded continuous-time cuffless blood pressure monitoring using single-channel PPG signal

Qirui ZHANG[†], Qingsong XIE[†], Kefeng DUAN, Bo LIANG, Min WANG & Guoxing WANG[*]

Department of Micro-Nano Electronics, Shanghai Jiao Tong University, Shanghai 200240*, China*

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Dear editor,
According to a 2015 World Health Organization (WHO) report, cardiovascular diseases accounted for the death of approximately 17 million people worldwide each year, i.e., 37% of the annual global deaths [1]. Therefore, the prevention and prediction of cardiovascular diseases are urgent global need to ease future diagnosis and treatment. Blood pressure (BP) is an important indicator for cardiovascular conditions. Continuous ambulatory BP is a powerful indicator of immanent cardiovascular events than clinic or office BP measurements [2]. Additionally, at-home BP monitoring prevents white-coat hypertension and is superior to clinic BP measurement in predicting important end points like mortality and geriatric functional decline [3]. Although conventional cuff-based BP monitoring provides accurate measurements, the method cannot be used for continuous-time BP monitoring and can cause discomfort and inconvenience to the user. Therefore, new methods are needed for user-friendly, continuous, and cuffless at-home BP monitoring.

This study proposes a user-friendly digital signal processing (DSP) system for embedded continuous-time cuffless blood pressure (BP) monitoring. The device utilizes only a single-channel photoplethysmograph (PPG) signal. Figure 1(a) illustrates the overall architecture of the system. First, the analog PPG signal from the sensor module is quantized by an analog-to-digital converter (ADC) in the DSP system. Further, to improve signal quality, a morphological filter (MF) and a low-pass filter (LPF) are applied to the PPG signal. After preprocessing, just two features are extracted and normalized from the PPG signal. These features are then fed into the inference function of a least squares support vector machine (LSSVM) [4] to calculate the BP estimation results. The LSSVM model parameters are stored in the read-only memory (ROM) of the DSP system and are loaded into the DSP system from a personal computer (PC) using a universal serial bus (USB) when the DSP system is initialized.

The estimated systolic BP (SBP) and diastolic BP (DBP) values and heart rate (HR) together with preprocessed PPG signal are then transmitted to the PC via a universal asynchronous receiver and transmitter (UART) interface. The PPG signal, HR, and BP values are then displayed using a graphical user interface (GUI) to allow real-time monitoring.

Activities such as respiration or slight movements of the system user can cause baseline wan-

* Corresponding author (email: guoxing@sjtu.edu.cn)
† Zhang Q R and Xie Q S have equal contribution to this work.

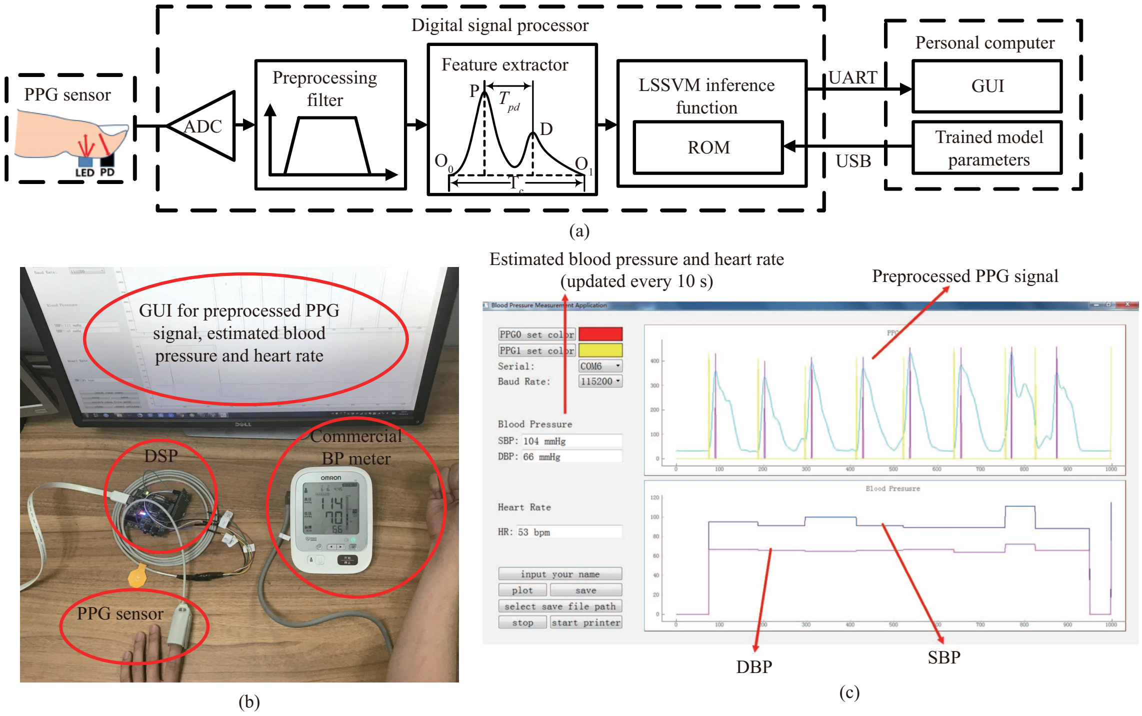

Figure 1 (Color online) (a) Overall system architecture; (b) prototype for the proposed system; (c) GUI of the proposed system.

dering (BW) interference, which in turn causes severe distortion in the original PPG signal. To mitigate BW interference, the MF from [5] is applied to the PPG signal. The BW is calculated from the MF and subtracted from the PPG signal. Further, a finite impulse response (FIR) LPF with 5 Hz cut-off frequency is applied to eliminate high-frequency noise.

When implementing a machine learning-based estimation model in embedded systems, using extravagant features might lead to an impractical computational burden. To balance the trade-off between computational complexity and model accuracy, only two features are extracted from the PPG signal in our proposed system shown in Figure 1(a). The first feature $f_1 = 1/T_c$ is the instantaneous HR, which is the inverse of PPG period T_c. The second feature f_2 is T_{pd}, which is the time delay between the percussion and dicrotic peaks in the PPG signal. HR is related to BP, and T_{pd} is correlated to transit time of blood-pressure waves, which is also a strong indicator of BP value [6].

To normalize the extracted features and suppress outliers, the feature sets are sorted offline to find the first and third quartiles Q_1 and Q_3, and the second quartile Q_2 is taken as the median. Then the features are normalized in the DSP system using (1), with lower and upper bounds (LB and UB) of the training set for a certain feature f set to $Q_1 - 2(Q_3 - Q_1)$ and $Q_3 + 2(Q_3 - Q_1)$, respectively.

$$f_{\text{scaled}} = \frac{f - \text{LB}(f)}{\text{UB}(f) - \text{LB}(f)}, \tag{1}$$

$$f(x) = \sum_{k=1}^{N} \alpha_k K(x, x_k) + b, \tag{2}$$

$$K(x, x_k) = \exp\left(-\frac{\|x - x_k\|^2}{2\sigma^2}\right). \tag{3}$$

The regression version of the LSSVM algorithm [4] is applied in the proposed system to estimate the BP value from these extracted features. The inference function of LSSVM is displayed in (2), where $f(x)$ is the estimation result for a given feature-input vector x. α_k is the Lagrange multiplier or weight coefficient, and x_k is the support vector, which also serves as the feature-input vector for corresponding training samples. K is the kernel function and b is a bias. Here, the popular Gaussian kernel shown in (3) is used, where σ is the training parameter. N is the number of support vectors, which is typically also the total number of training samples used in the LSSVM algorithm.

Training and testing samples of the LSSVM model are taken from the University of Queensland Vital Signs data set [7]. The ranges of SBP and DBP labels are 70–150 mmHg and 40–110 mmHg, respectively. 1962 samples were used for testing the model, which was implemented in MATLAB. The mean absolute errors (MAE) and standard deviations (SD) (in the form of MAE ± SD) of SBP and DBP estimation results are 7.41 ± 9.93 mmHg and 6.10 ± 8.37 mmHg, respectively.

The proposed BP estimation method was implemented using C programming language on the TMS320C5535 eZdsp$^{\mathrm{TM}}$ platform from Spectrum Digital, Inc., which features a low-power fixed-point DSP chip (TMS320C5535 from Texas Instruments) designed for biomedical and wearable applications. To record the PPG signal, we used a customized high-sensitivity sensor chip with a wide dynamic range [8]. The analog PPG signal from the sensor chip is sampled by a 10-bit ADC on the DSP platform at 100 Hz. The 16-bit fixed-point arithmetic routine in DSP is used to calculate the LSSVM decision function in (2).

A photo of the DSP-based cuffless BP monitoring system prototype is displayed in Figure 1(b). For comparison, the commercial cuff-based BP meter from OMRON was used to record the ground-truth BP values. Figure 1(c) shows the GUI used with the proposed system. The BP and HR estimation results are averaged for a 10 s window and are updated every 10 s. Also, the preprocessed PPG signal and BP curves are continuously displayed.

An experiment comprising 20 subjects (20–60 years of age) was conducted to test the performance of the proposed system in realistic applications. All measurements were conducted at room temperature. The subject's finger was placed directly above the PPG sensor. Subjects were seated on a chair with back support, feet positioned flat on the floor and forearms supported at the height of the heart. Three BP estimation results and corresponding ground-truth values were recorded for every subject. Then the recorded values were averaged to give the final BP estimation and corresponding ground-truth result for each subject. Absolute error of the BP estimation was calculated as the absolute difference between the averaged BP estimation and the averaged ground-truth value. The MAEs between the 20 estimated BP results and BP ground-truth values are 5.5 and 4.8 mmHg for SBP and DBP, respectively. The mean errors and their SDs are 1.3 ± 6.1 mmHg and −0.1 ± 5.6 mmHg for SBP and DBP, respectively, which satisfies the medical device standards of the Association for the Advancement of Medical Instrumentation (AAMI) [9].

Though the estimation accuracy needs to be improved further, the proposed system requires only a single-channel PPG signal and two classifying features. This simplicity reduces the hardware complexity and cost of the system. The user experience is also improved as users only need to wear one PPG sensor on a finger. Furthermore, LSSVM is a non-parametric model, so frequent calibration is not needed, which increases user convenience of BP monitoring.

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References

1 Mozaffarian D, Benjamin E J, Go A S, et al. Executive summary: heart disease and stroke statistics–2016 update: a report from the american heart association. Circulation, 2016, 133: 447–454
2 Hoshide S, Cheng H M, Huang Q, et al. Role of ambulatory blood pressure monitoring for the management of hypertension in Asian populations. J Clin Hypertens, 2017, 19: 1240–1245
3 Sheikh S, Sinha A D, Agarwal R. Home blood pressure monitoring: how good a predictor of long-term risk? Curr Hypertens Rep, 2011, 13: 192–199
4 Suykens J A K, Vandewalle J. Least squares support vector machine classifiers. Neural Process Lett, 1999, 9: 293–300
5 Sun P, Wu Q H, Weindling A M, et al. An improved morphological approach to background normalization of ECG signals. IEEE Trans Biomed Eng, 2003, 50: 117–121
6 Cattivelli F S, Garudadri H. Noinvasive cuffless estimation of blood pressure from pulse arrival time and heart rate with adaptive calibration. In: Proceedings of the International Workshop on Wearable and Implantable Body Sensor Networks, Berkeley, 2009. 114–119
7 Liu D, Görges M, Jenkins S A. University of Queensland vital signs dataset: development of an accessible repository of anesthesia patient monitoring data for research. Anesthesia Analgesia, 2012, 114: 584–589
8 Atef M, Wang M, Wang G X. A fully integrated high-sensitivity wide dynamic range PPG sensor with an integrated photodiode and an automatic dimming control LED driver. IEEE Senss J, 2018, 18: 652–659
9 White W B, Berson A S, Robbins C, et al. National standard for measurement of resting and ambulatory blood pressures with automated sphygmomanometers.. Hypertension, 1993, 21: 504–509