Compressive Sensing of Cuff-less Biosensor for Energy-Efficient Blood Pressure Monitoring

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***Abstract*— Compressive Sensing (CS) is an emerging technique in Internet of Medical Things (IoMT) application especially for smart wearable devices to prolong the sensor lifetime, and enable a continuous healthcare monitoring system. This paper describes the performance of CS on our wrist-based cuff-less biosensor for estimating blood pressure (BP) continuously. The proposed biosensor offers a novel BP estimation method by only using the biosignal from subject wrist. A CS technique is implemented to encrypt and reduce the data transmission load of the dual biosignal, which include impedance plethysmography (IPG) and photo plethysmography (PPG). Therefore, multiple compression ratio (*CR*) were tested to the original signal. We further compare the CS-based extracted features called pulse transit times (PTTs). Based on our experiments, CS-based PTT value that calculated from the IPG peak point to the PPG max_2 point (F2), achieved the best correlation coefficient (R) of -0.85 and -0.43 to the systolic BP and diastolic BP, respectively. These results suggest that the implementation of CS on our proposed wrist biosensor is suitable for non-intrusive, yet long-term continuous BP monitoring.**

I. Introduction

The Internet of Medical Things (IoMT) brings the reliable remote patient monitoring of people with chronic and long-term disease conditions. Recent technologies, including wearable devices and mobile health (mHealth), are equipped with the wireless communication protocol that allow the machine-to-machine-communication which is the basis of IoMT. It will significantly improve the quality of care of the telemedicine, and simplify the caregiver and medical expert job to remotely monitor their patient's health condition. The challenges for researcher in this field is always related to provide the reliable, robust system while still offering a non-intrusive and ultra-low power consumption system.

The reliable and robust wearable system is an emerging research topic since most of the people are unaware with their health condition and lifestyle. Here we focused on developing a wearable system for blood pressure (BP) monitoring. High BP or hypertension is a well-known diseases to silently killed people. Therefore, monitoring BP value regularly is a very important task for both patients and healthy subjects. Further, the continuous monitoring of BP may provide the critical recommendation and suggestion information to the user according to their recent food consumption behavior, lifestyle, mental statement, and physical activity so that they may prevent the diseases.

Furthermore, the more challenging task is to offer a non-intrusive and ultra-low-power wearable system. In BP monitoring, one of the method to realize a non-intrusive system is by utilizing a non-cuffed sensor. Conventionally, cuffed sensor and sphygmomanometer are used to detect BP. However it required experts and only for intermittent measurement. Here we proposed a wrist-based cuff less biosensor to estimate BP continuously. The proposed configuration offers a simplified measurement system, which require a single measurement site that is subject's wrist, while most of the previous method require a multiple sensor placement such as on subject's chest, foot, and finger [1].

To realize an ultra-low-power wearable system [2, 3], one may utilized an ultra-low-power microcontroller (MCU), an ultra-low-power analog-to-digital converter (ADC), an ultra-low-power analog front end (AFE), and not to mention an ultra-low-power wireless radio chipset. The energy harvesting and a passive sensor or electrodes also can be a considered to extend the sensor lifetime. In this paper, we devise an ultra-low-power solution applicable for long-term continuous BP monitoring system based on the Compressive Sensing (CS) technique. A higher sampling rate is usually required for clinical biosignal monitoring system such as electrocardiogram (ECG), photo plethysmography (PPG), and impedance plethysmography (IPG), however it cost with the high energy consumption also, which mean shortening the overall system lifetime. The proposed technique is known to realize an energy efficient system, by encrypting and reducing the data transmission load.

In this paper, we investigated the effect of CS on the received biosignal collected from our novel wrist biosensor. Moreover, we analyzed a reconstructed signal after CS to find its possibility to estimate BP value continuously. The main goal of this research is to find the possibilities for CS-based cuff less BP monitoring in a long-term continuous BP monitoring system.

II. Methods

A. Wrist-based Biosensor Design

Fig.1 describes our proposed multimodal biosensor design. Each sensor attached to the wristband strap and has a direct contact to the subject's skin. The proposed PPG sensor measured arterial blood volume pulsation at the area of interosseous artery located at the outer part of the wrist. The proposed PPG sensor utilized LED that transmit light on the near infrared optical spectra of 940 nm. Moreover, IPG sensor

*This work was supported by new technology creation laboratory program through a BISTEP grant in 2019.

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978-1-5386-1311-5/19/$31.00 ©2019 IEEE

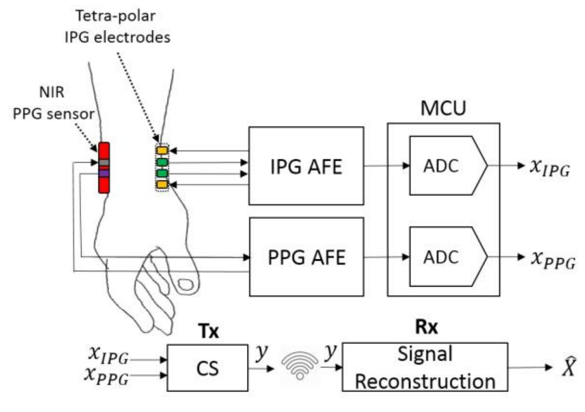

Figure 1. Measurement Setup with proposed biosensor attached on the subject wrist.

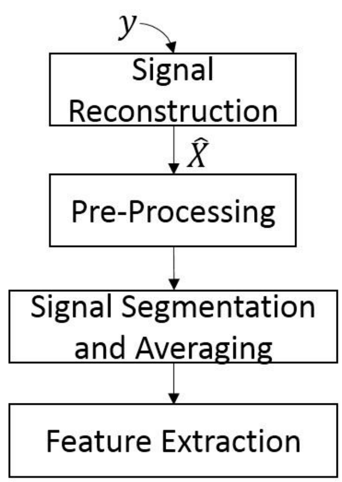

Figure 2. The proposed digital signal processing on the receiver side after CS.

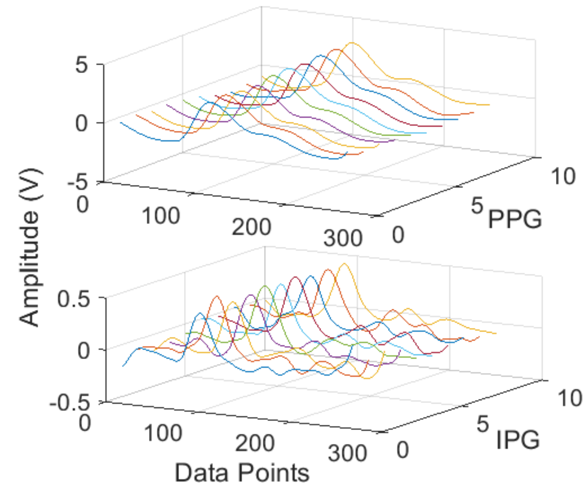

Figure 3. Segmented PPG and IPG Signal for further signal averaging.

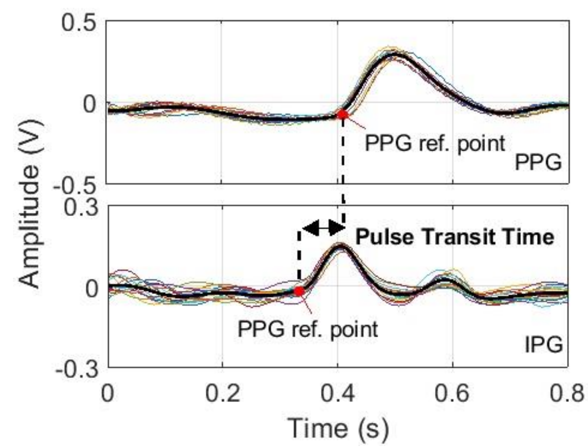

Figure 4. PTT Feature Extraction.

equipped with tetra-polar electrodes configuration and measured the radial impedance of the radial artery. The detail of the proposed wrist biosensor design was described in our prior report [4].

B. Compressed Sensing

CS is a data compression technique, in which the original signal of length N, denoted by $x \in \mathbb{R}^{Nx1}$, is compressed by a randomly generated sensing matrix. Mamaghanian et al. [5] proposed a CS technique based on the sparse binary sensing matrix, they mentioned that the sparse binary sensing matrix may reduce the energy consumption drastically compared to the wavelet-based data compression algorithm. Thus, it lead us here to utilize a sparse binary matrix as our proposed system sensing matrix. The sparse binary matrix contain of zeros and several d nonzero entries in each column, here it denoted by $\Phi \in \mathbb{R}^{MxN}$ with $M \ll N$, the overall signal model expressed as follow:

$$y = \Phi \mathrm{x} \tag{1}$$

Where y is the compressed signal. In wearable and IoMT application, the value of sensing matrix Φ is also known by the receiver for data x reconstruction.

C. Signal Reconstruction

Our system uses block sparse signal model as it seems to improve the signal reconstruction performance [6]. The proposed block sparse signal of x has the following structure:

$$x = \left[x_1, \dots, x_{k_1}, \dots, x_{k_{r-1}+1}, \dots x_{k_s}\right]^T \tag{2}$$

Which means x has s blocks, and a few blocks of it are nonzero. Moreover, here we used the block size of $k_1 = \dots = k_s = 25$. For the signal reconstruction, block sparse Bayesian learning (BSBL) framework was used for high performance non-sparse signal reconstruction [7]. This algorithm exploit the block structure and intra-block correlation by modelling them as a parameterized multivariate distribution. In specific, we are using one of the derived algorithm of BSBL, called Bound Optimization-based BSBL algorithm (BSBL-BO) [6, 7].

D. Feature Extraction

The original raw data was sampled by ADC with the *Fs* = 256 Hz, for easier calculation here we chose the *Fs* equal to the sensing matrix column N, so that each signal compression and reconstruction from the 1 s signal. To limit the energy

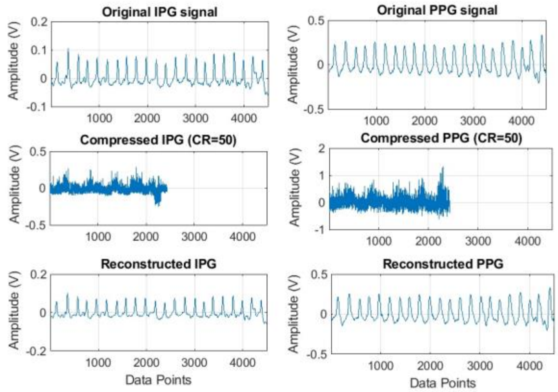

Figure 5. Compressed sensing on dataset from proposed biosensor system (CR = 50).

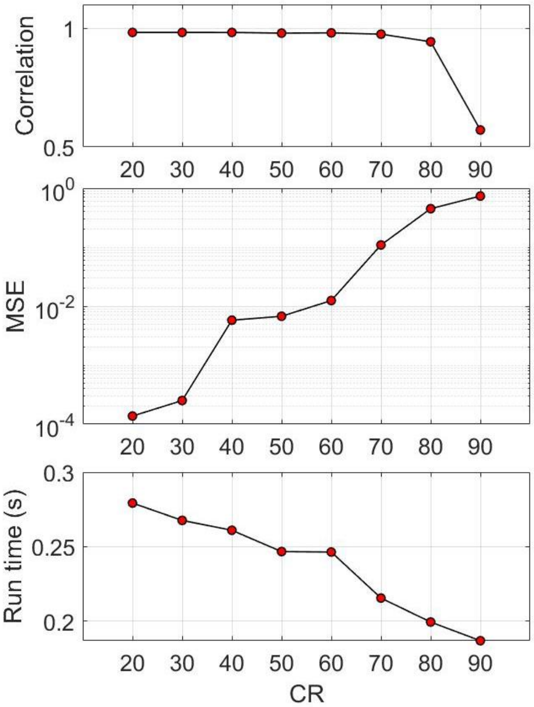

Figure 6. Performance of CS on different compression ratio (CR) percentage.

consumption on-sensor, here we directly compress raw IPG and PPG signal. Therefore, in the receiver side we then compute some digital signal processing for noise reduction and feature extraction. The discrete wavelet transform (DWT) is used to remove baseline wander noises in signal pre-processing step. Moreover, for feature extraction, each IPG and PPG signal cycle were segmented based on its peak detected using local maxima algorithm. The segmented signal further averaged by using ensemble algorithm. The overall block diagram of the proposed digital signal processing is shown in Fig. 2.

In total, four features are extracted called pulse transit times (PTTs). Two points are extracted from IPG signal which are IPG B-point, detected from the location of zero crossing prior to the maximum of its first derivative, and IPG Peak, detected from the peak value of the IPG signal. Furthermore, another two reference points are extracted from PPG signal, called PPG peak, detected from the peak value of the PPG signal and PPG max_2, detected from the peak value of its second derivative. The overall segmented signal and feature extraction example is shown in Fig. 3 and Fig. 4, respectively.

TABLE I.

CORRELATION OF FEATURES BEFORE AND AFTER CS ON DIFFERENT COMPRESSION RATIO (CR).

Feature	Reference points (proximal)	Reference points (distal)	Correlation (R)	
			CR = 50	CR = 60
F1	Peak (IPG)	Peak (PPG)	0.94	0.93
F2	Peak (IPG)	Max_2(PPG)	0.77	0.57
F3	B-point (IPG)	Peak (PPG)	0.92	0.90
F4	B-point (IPG)	Max_2(PPG)	0.03	0.25

TABLE II.

CORRELATION OF PTT (AFTER CS WITH CR = 50) TO BP VALUE.

Feature	Correlation (R)	
	SBP	DBP
F1	0.48	-0.11
F2	-0.85	-0.43
F3	-0.06	-0.44
F4	0.6	0.05

III. EXPERIMENTAL RESULTS

Multiple experiment have been conducted to test the performance of CS on the received biosignal collected from the proposed wrist-based cuff-less biosensor. The first experiment is related to the correlation value R of the CS-based reconstructed signal $\hat{x}$ to the original signal x. As mentioned, we collected IPG and PPG signal from subject wrist, the representative results of the reconstructed IPG and PPG signal is shown in Fig. 5. As seen from the figure, the data transmission size is half of the original signal, with compression ratio (CR = 50). To produce the figure, here we took the example of the gathered 5000 data points of both IPG and PPG signal, thus only 2500 data points were wirelessly transmitted to the receiver side using BLE communication protocol. Here the compression ratio (CR) is defined as follows:

$$CR = \frac{N - M}{M} x100 \quad (3)$$

For all of our experiments presented in this paper, we fixed the parameter of N = 256 and number of nonzero value of the Φ, d = 2. Moreover, we first conducted the sparse binary sensing matrices with M = {26, 52, 77, 102, 128, 154, 179, 205} for CR = {90, 80, 70, 60, 50, 40, 30, 20}, respectively. The overall performance of CS in different CR percentage on the gathered IPG and PPG signal is shown in Fig. 6.

Fig. 6 shows that the correlation between the reconstructed wrist biosignal to its original signal is relatively high until CR = 80, however the acceptable MSE of the reconstructed signal is only until CR = 60 where it reduced from $1.4\ x\ 10^{-4}$ to the $1.2\ x\ 10^{-2}$ for CR = 20 and CR = 60, respectively. Furthermore, we also calculate the required run time for each CR percentage, and as expected, the higher the CR percentage, the less processing times are needed.

The second experiment is related to the feature extraction after CS. Here for the first and second experiment, we used the same sensing matrix for the similar CR percentage, thus the energy consumption of each results was the same. For example, to produce Fig. 5, Table 1 (CR = 50), and Table 2 here we use the same binary sensing matrix. Moreover, as seen from the Table 1, the reconstructed signal-based PTTs are correlated well with the original PTTs in case of F1, F2, and F3, respectively. This is highly related to the previous results that shows the reconstructed signal correlation value R is high to the original signal with R = 0.9 until CR = 80. However, the results from F4 is interesting, where it shows a poor correlation value R. Here we calculated F4 from the B-point of IPG signal and the max2 of the PPG signal. Different to the other feature, F4 utilize the extracted reference data points from both the baseline of the signal lower frequency of the signal, where most of the noise are on, including baseline wander [8]. Thus, we assume that this noises reasoned the poor correlation R performance. Moreover, previous study also mentioned that the B-point was not always clearly identifiable [9]. Also, the F1 which extracted from the higher frequency of the signal (IPG and PPG peak) shows the best correlation value R of 0.94 and 0.93, for CR = 50 and CR = 60, respectively.

Finally, Table 2 shows the results of correlation value R of CS-based PTTs F1 – F4 (with CR = 50) to the SBP and DBP value collected from Oscar 2™ (SunTech Medical, USA). Here the Oscar 2™ was utilized to get the BP reference data. Typically, PTT is inversely correlated to the BP value [1, 10], and as seen from the table we also achieved a relatively high to medium negative-correlation value R of F2 to the SBP and DBP, respectively. However, for other PTTs of F1, F3, and F4, the correlation value R are relatively medium to low. Our results also similar with those previous studies that indicated the "foot"-based reference points were superior to the "peak"-based reference points for PTTs calculation [10]. The proposed study shows that, even after CS, the extracted PTTs especially F2 still have an adequate performance and correlation to the reference SBP and DBP data values. Thus it is reasonably to implement CS on the cuff-less BP system. The implementation of CS will highly improve the overall system power consumption, thus a long-term continuous monitoring may be achieved.

IV. Conclusion

This paper describes the effect of CS on the cuff-less BP monitoring system. We implement CS to encrypt and reduce the data transmission load of the IPG and PPG signal. Here we investigate the correlation between the reconstructed bio signals collected from our novel wrist biosensor to the original biosignal. Moreover, we digitally processed the achieved reconstructed signals to extract its feature for SBP and DBP estimation. Four PTT features were extracted and compared to its original signal-based feature. We found out that the CS-based PTTs especially F2 shows an adequate performance with correlation value R of -0.85 and -0.43 to the SBP and DBP, respectively. In this paper, we proved that the CS-based PTT is feasible to estimate subject BP value cufflessly. Thus, in the future, we would like to expand our experiment to measure the efficiency of the CS in term of its power consumption, thus we may further estimate the sensor lifetime.

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