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A Pilot Study on Low Power Pulse Rate Detection Based on Compressive Sampling

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Abstract—**Low power consumption is one of the key design challenges for various pervasive healthcare systems. Compressive Sampling (CS) is an emerging technique for reconstructing signals from data sampled under the Nyquist rate. CS has great potentials for low power pulse rate detection based on photoplethysmograph (PPG) signals, since by reducing the PPG data sampling rate the LEDs could be turned off for a prolonged period of time. Obviously the higher CS rate, the lower power consumption and lower pulse rate measurement accuracies. In this paper, a feasibility study of using CS for low power pulse rate detection was conducted. A miniature PPG measurement device based on our body sensor networks platform was employed for signal acquisition. Experiments for evaluation the pulse rate estimation and the power consumption were completed. Results suggested that the Gradient Projection for Sparse Reconstruction (GPSR) algorithm is a highly efficient for retrieving pulse rate from PPG signals. It was suggested that the CS rate should be approximate 3 for low power pulse rate detections with averaging estimation mean-square error being less than 5.**

I. Introduction

THERE are several off-the-shelf WSN products developed by different suppliers that could satisfy typical wireless applications such as environmental sensing and personal area networking. However, these WSN platforms proved to be not suitable for body-proximal applications because of relative large form factors and power consumptions, and being lack of connectivity with various biosensors [1]. The essential goal of a body sensor network (BSN) is to establish a pervasive healthcare system that is capable of monitoring human body's dynamic health conditions and transmitting the sensing data in a secure and real-time manner [2].In this sense, researchers in Biomedical Engineering have to look for a dedicated BSN platform. Researcher in the MIT Media Lab [3], the Harvard University [4], Imperial College London [1] have developed custom-designed BSN platforms for certain applications.

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The photoplethysmograph (PPG) signal contains cardiac function, blood flow in the cardiovascular system and other important physiological information. The blood volume pulse is mainly in the peripheral arterioles, capillaries and other micro-vessels, the PPG signal also contains abundant physiological and pathological information of microcirculation. Pulse rate (PR) is one of the most significant physiological parameters. PR is relevant to oxygen uptake and energy consumption [5-7]. In order to design a pervasive monitor system to collect physiological signals, we have developed a high-integrated and low-power BSN platform that is tailored for the strong requirements of overall system optimizations.

A PPG device typically consumes power of 20-60mW. Considering that the LEDs (both read and infrared) account for most of the power consumptions, Rhee et al designed a power efficient 'finger-ring' PPG sensor, in which the light duty cycle of LED was reduced, and its power consumption is only 1.5mW [8]. However, it uses uniform sampling at Nyquist rate.

The Compressive Sampling (CS) is an emerging technology, known as a novel sensing paradigm that goes against the common wisdom in data acquisition. It asserts that one can recover certain signals or images from far fewer samples or measurements than traditional methods [9]. If the CS could be applied in the PPG system, it would help for saving more power by reducing the power consumptions of the LEDs. In this paper we evaluate the feasibility of using CS for PPG signal processing and the effect of PR estimation after reconstruction.

II. System Design and Compressive Sampling

A. BSN Platform

The BSN development platform we have developed consists of five components: four BSN nodes, a Base-Station board with an antenna that connects with a PC or a PDA, a PPG sensor electronics board that interfaces with a generic PPG sensor, a respiratory inductive plethysmograph (RIP) sensor electronics board, and a battery board with a charger IC that provides power supply for node and sensor boards. Fig. 1 illustrates the complete BSN hardware development platform.

The BSN node was designed with the TI low-power processor, 915MHz radio transceiver, 64M-bit memory, 3-D accelerometer and regulator on the main board with other customizable components on stackable daughter boards. And also an expansion port allows the sensor electronics board(s) and other board to be stacked with the BSN node board. The basic structure of the BSN node and photo of the node board were depicted in Fig. 2. Table I shows the average power consumption of a BSN node under different transmission modes. The supply voltage is 3.3V. The node works at 915MHz, 0dBm and10kbps.

TABLE I
AVERAGE POWER CONSUMPTION AT DIFFERENT MODES

Mode	Average Power Consumption
Sleep	860μW
Standby	1.3mW
Active @ TX	7.8mW
Active @ RX	8.2mW

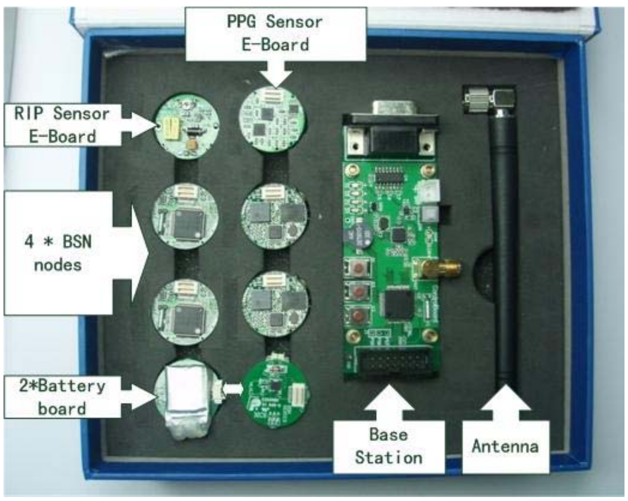

Fig. 1.BSN hardware development platform

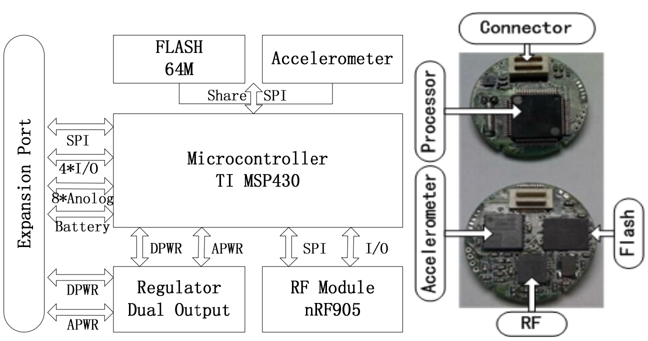

Fig. 2. (a) Structure of the BSN node (b) BSN node board

B. *PPG Board*

The PPG sensor electronics board was used to provide the switched driving currents for the LEDs DLED-660/905, and to condition the weak current signals from the photodiode BPW34S. Low power and high accuracy instrumentation amplifier INA118 was employed for differential trans-impedance amplification. OPA2277 high precision OpAmp was used to amplify and band-pass filter the PPG signal. A switched capacitor voltage converter LM2664 was applied to convert the positive voltage 3.3V to corresponding negative voltage -3.3V. The gain and the bandwidth of the analogue signal conditioning channels were designed to be programmable. Fig.3 shows the head-worn PPG device we have developed.

C. *COMPRESSIVE SAMPLING*

Compressive Sampling, also known as Compressed Sensing, is a simple and efficient signal acquisition protocol

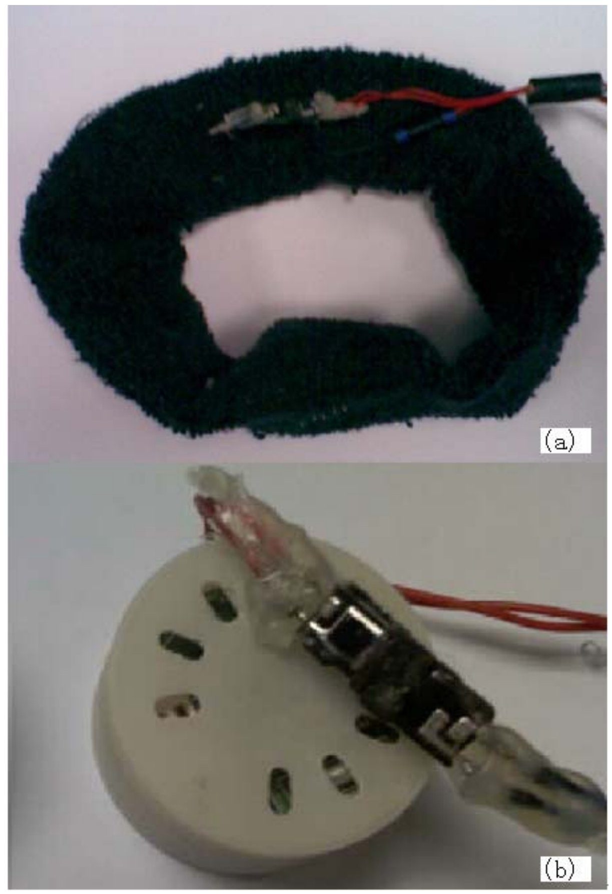

Fig. 3 (a) Headworn PPG system (b) PPG Sensor and PPG Node

which samples - in a signal independent fashion - at a low rate and uses computational power for reconstruction from what appears to be an imcomplete set of measurement [9]. CS relies on the two basic principles: sparsity and incoherence. Sparsity expresses the idea that the information rate of a continuous time signal maybe much smaller than suggested by its bandwidth, or that a discrete time signal depends on a number of degrees of freedom which is comparably much smaller than its (finite) length. Incoherence extends the duality between time and frequency and expresses the idea that objects have a sparse representation must be spread out in the domain in which they are acquired.

Suppose x is an unknown N×1 vector, and it has a sparse representation in some orthonormal basis $\psi N\times N$. So the transform of x in such a basis is given by $x=\psi\alpha$, where α represents the transform coefficients of x, and ψ is the matrix representation of the observation. If a number of frequency samples randomly if its number meets some conditions , then solving (subject to Φψα=Φx=y) will recover x exactly. Here, Φ is random measurement matrix[10]. CS remains quite effective even when the samples are noisy. Its recovery procedure can be case as a linear program. The l1_ls and Gradient projection for sparse reconstruction (GPSR) are different algorithms to solve CS recovery problems. The l1_ls is an interiro-point method, and its each search step is computed using preconditioned conjugate gradients and requires products involving Φ and ΦT. The GPSR is a gradient projection algorithm for the bound-constrained quadratic programming formulation.The code of l1_ls [11] and GPRS [12] algorithms can be freely available for download from www.lx.it .pt/~mtf/GPSR/, and the GPSR has GPSR-BB and GPSR-Basic realization.

III. RESULTS

In the BSN-based PPG system, the LED consumed most of the electrical power. To evaluate the effects of applying CS on our BSN-based PPG system, in-situ experiments were conducted.

In the experiments, the in vivo PPG signal was sampled at 100Sps and five 8-second episodes were recorded. The CS rate varied from 2 to 10. The results were illustrated in Fig. 4. A computer, which has 3.4GHz CPU and 512 MB memory, was used for the calculations of pulse rate recovery.

From Fig. 4, it could be concluded that the higher the CS rate, the less calculation time involved. It also indicated that

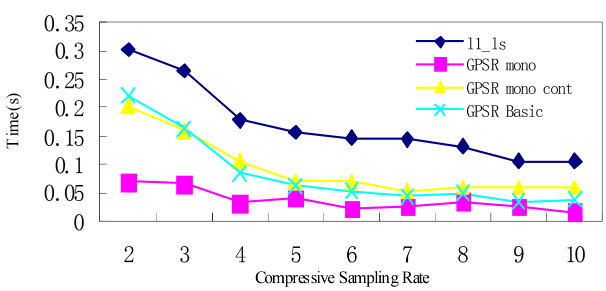

Fig. 4. CS rate versus to time. The l1_ls, GPSR monomono cont and Basic are differenr approaches reported in [12].

l1_ls approach consumes more time than the other three GPSR-based approaches during reconstruction. Clearly the GPSR-mono consumed less calculation time (equivalent to less computation power) than the GPSR_Basic and GPSR_cont did whilst CS rate was 2-4.

To evaluate the quality of recovery signals, a Mean Square Error (MSE) value was calculated to compare recovery signals with original signals. The instantaneous pulse rate (IPR) was acquired by the peak-peak distance between the middle of each arising edge. The MSE was relative to the difference of IPR between the reconstructed and the original. In the experiment, three PPG segments (with averaged PR or 97, 85 and 85) were selected. Fig. 5 visualized the original signals. Fig. 6 showed the MSE of the IPR of reconstructed PPG relative to the original. From the Fig. 6, it indicated that

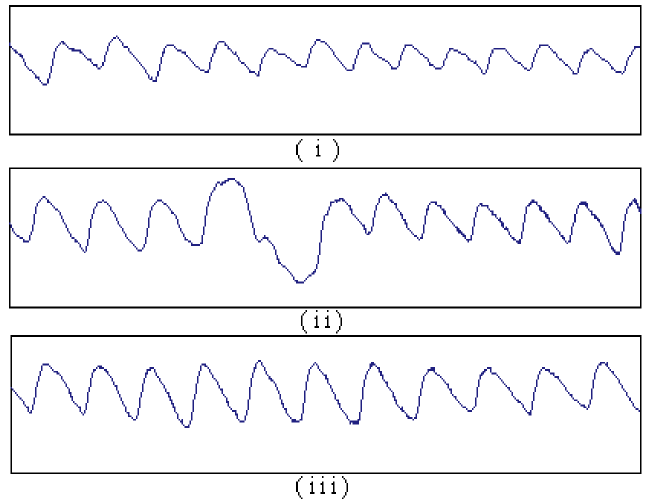

Fig. 5. Different PPG waveform with averaged pulse rate or 97, 85, 85

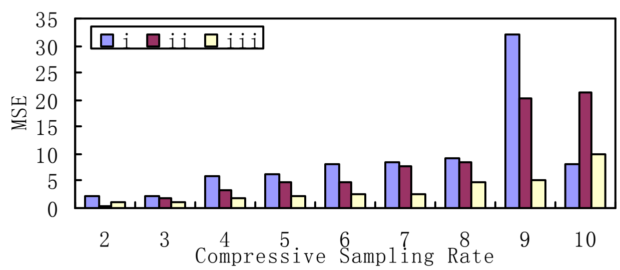

Fig. 6. MSE of the PR of reconstructed PPG relative to the original

the MSE of IPRs was acceptable (les than 5 beat per minute), if the CS rate was set to be 2 or 3, which means the power consumption of the LED was reduced to be approximate 1/2 or 1/3, respectively.

IV. CONCLUSION

The GPSR is a high efficient CS recovery algorithm, which is suitable for the reconstruction of pulse rate from under sampled PPG signals. Considering to the time consumption and the reconstruction efficiency, the CS rate should be set to be less than 3 for our BSN-based PPG detection device. The work is preliminary but it indicates the feasibility of applying CS for a greater range of low power biomedical signal processing applications..

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