Compressed Sensing for Wireless Pulse Wave Signal Acquisition

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***Abstract*—Wireless-enable pulse wave (PW) biosensor is generally used for pervasive and non-invasive health care monitoring. However, the energy efficiency of the present devices still needs to be improved due to the high energy consumption during wireless communication. In this paper, a compressed sensing (CS) scheme for wireless PW signal acquisition is proposed. With the CS-based scheme, airtime over energy-hungry wireless links can be reduced and energy efficiency of the wireless biosensor can be improved. PW signal is sparse under the discrete cosine transform (DCT) basis. Therefore, the CS-based scheme can efficiently compress and recover the signal by the 1-bit sparse quasi-Toeplitz measurement matrix and the basis pursuit de-noising (BPDN) model. The efficiency improvement of node was evidenced by the practical experiments on a MICAz node. By using the proposed scheme, the average percentage root-mean-square difference (PRD) of 4.23%, energy saving of 35.15% and node prolonging of 54.20% can be achieved.**

Keywords—compressed sensing (CS), Pulse wave(PW) signal, health care, wireless biosensor, low-power.

I. INTRODUCTION

Traditional PW signal acquisition devices are wired and bulkiness. They are unsuitable for the pervasive and non-invasive health care monitoring. With the development of the body sensor networks (BSNs), the wireless-enabled biosensor has received significant industrial and academic attention. Up to now, some wireless PW measurement systems have been developed [3, 4]. However, few of these studies consider the issues of energy efficiency. Without energy optimization, the nodes die quickly due to great airtime over the energy-hungry wireless link. The energy efficiency of the present wireless PW biosensors must be improved for long-term working.

The wireless communication consumes over 65% energy of the wireless-enable bio-signal node [5]. This motivates systematic researches to reduce the energy consumption of wireless data transmission to prolong the service life of the bio-sensors. Different studies for energy-efficient data transmission have been investigated in various aspects, including low-power hardware [6] communication protocol [7], coding technology [8] and data compression methods [9, 10]. The previous works [4-8] have shown that achievement of truly low power wireless bio-sensor application is not only required in terms of ultra-low-power devices and advanced communication protocol, but also associated with the proper data compression technology. Using data compression cannot only reduce the amount of the transmitted data, but also decrease the airtime over energy-hungry wireless links, thus prolong the node's life.

In this study, a compressed sensing (CS) scheme for wireless PW signal acquisition is proposed. The proposed scheme is a new low computational complexity data compression method to save the energy of wireless transmission while retaining the signal information. PW signal is sparse under the discrete cosine transform (DCT) basis. In the proposed scheme, a 1-bit sparse quasi-Toeplitz is used to sense and compress the signal, and then the compressed data is sent to the base station (BS), where a L1 normal solver is used to recover the signal by the basis pursuit de-noising (BPDN) model. To the best of our knowledge, CS has been applied to data compression in the wireless ECG biosensors [7, 8], but it has never been considered for PW data compression. This is the first time to discuss the CS-based scheme for PW signal acquisition in the resource- and computation-constrained wireless node. To evaluate the performance of the proposed method, the practical PW signal compression and transmission experiments have been conducted on a MICAz node.

The rest of work is organized as follows: In the next section, a brief theory of CS is introduced. Section III introduces the proposed CS-based scheme for wireless PW signal acquisition. Section VI presents experiment and results, and Section VII concludes the paper.

II. THEORETICAL BACKGROUND

The well-known Nyquist–Shannon sampling theorem states the sampling frequency must be at least twice the maximum frequency of the signal we want to capture and analyze. The redundant samples produced by the Nyquist-rate sampling are costly to wirelessly transmit, and short the lifetime of the sensor nodes. Recently, the compressed sensing theory proposed, it has broken the traditional sampling rule and drawn a lot of attentions from scientists and engineers. The basic idea underlying the CS theory is that the sparse signals can be reconstructed from generally incoherent non-adaptive random measurements [9-11]. The formal definition of CS is as following.

$$Y = \Phi X \tag{1}$$

where X is the N-dimensional input signal, Φ is $M \times N$ measurement matrix ($M \ll N$), which represents a dimensionally reduction, and Y is the collected M-length compressed vector. Using CS can reduce the wirelessly transmitted data during the signal acquisition. Assume signal X can expand in N-dimensional basis Ψ as follows:

$$X = \Psi\alpha \tag{2}$$

where α is N-length vector, if many coefficients of α are zero or can be zeroed without much signal quality loss, and the number of nonzero entries is K ($K \ll N$), then α is called *K-sparse*. And Ψ is sparse basis. We can rewrite the Eq. (1) as

$$Y = \Phi\Psi\alpha \tag{3}$$

Signal recovery is inverse solve Eq. (3). Since $\Phi\Psi$ is non-square, there are many possible solutions. However, the sparsity of α greatly reduces the set of possibilities, making it possible to solve the inverse problem of Eq. (3) by a convex optimization problem [9]:

$$Min\|\hat{\alpha}\|_1 \quad subject\ to \quad Y = \Phi\Psi\hat{\alpha} \tag{4}$$

the solution ($\hat{\alpha}$) in Eq. (4) is exact when the measurement matrix and the sparsity of the signal satisfy the RIP [12, 13]. Then, the recovered signal is $\hat{X} = \Psi\hat{\alpha}$.

To the "nearby" sparsity or noised signal, the practical signal model Y is:

$$Y = \Phi\Psi\alpha + w \tag{5}$$

where w represents measurement noise. The basis pursuit de-noising (BPDN) model [15] is commonly used to find the solution that would simultaneously minimize the error level and the sparsity:

$$Min\left\{\|Y - \Phi\Psi\alpha\|_2^2 + \lambda\|\alpha\|_1\right\} \tag{6}$$

where the regularization parameter λ(>0) balances the sparsity of α and approximation error.

III. CS-BASED WIRELESS PW ACQUISITION SCHEME

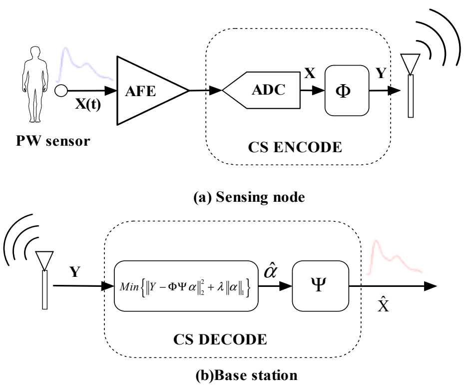


Fig. 1. Block diagram of CS-scheme for Wireless PW signal acquisition

A. Implementation framework

The Block diagram of proposed CS-based scheme is shown in Fig. 1, the ENCODER and DECODER are implemented on the sensing node and the base station, respectively. The former is in charge of sensing and compressing the signal, and the latter is responsible for recovering the signal. As Figure 1(a) shown, after the analog-front-end (AFE) circuits processing, the PW signal X is compressed to Y by the measurement matrix. Subsequently, the M-length Y is wirelessly transmitted to the base station. In the base station, as Figure 1(b) shown, after receiving the transmitted data, an optimization solver is used to recover the PW signal $\hat{X}$.

The randomly measurement is the key of the compression algorithm. Here, the convolution and random down-sampling operations are used to realize the measurement. The base station's decoding algorithm consists of convex optimization problem solver and line-projection. Considering the PW signals contain noise in most cases, the BPDN model of Eq. (6) is adopted to describe the signal recovery problem. Then, the CVX package [14] is used in this work for solving convex programs problem. The final recovered PW signal can be calculated according to Eq. (2).

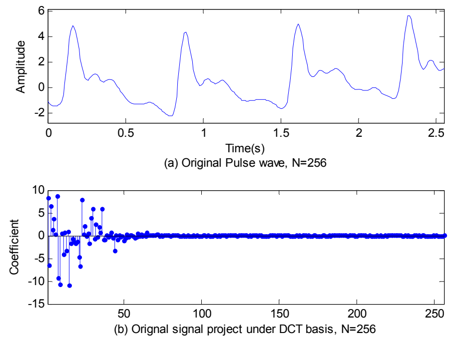


Fig. 2 Typical PW signal and its DCT representation

B. Sparsity of PW signal

Since PW signal is "nearby" sparse under some sparse bases, such as the Daubechies (db10) wavelets basis, discrete cosine transform (DCT) basis and Fourier transform (FT) basis, CS scheme can be used to compress the signal. As Fig. 2 shown, a typical PW signal can be represented as a "nearby" sparsity vector α under the DCT basis and most coefficients of α can be zeroed by a small threshold. From figure 2(b), it is observed that the K is obviously far less than the signal length N after thresholding.

Thresholding leads the signal components loss. To quantify the loss and convince for the following discussion, two metrics are employed here, which are named *Sparsity* and *percentage root-mean-square difference (PRD)*. The *Sparsity* is defined as:

$$Sparsity(\%) = 100 \times (N - K) / N \tag{7}$$

Here, *Sparsity* represents the compressible of signal. The *PRD* quantifies the percent error between the original signal X and recovered signal $\hat{X}$

$$PRD = \frac{\|X - \hat{X}\|_2}{\|X\|_2} \times 100 \tag{8}$$

To guarantee non-distortion diagnosis, *PRD* must not be greater than 9% [16].

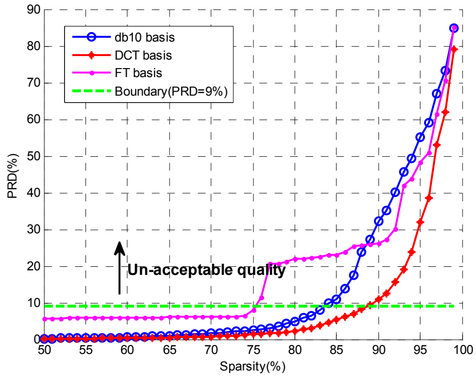


Fig. 3. Comparison of PRD and sparsity, N=256

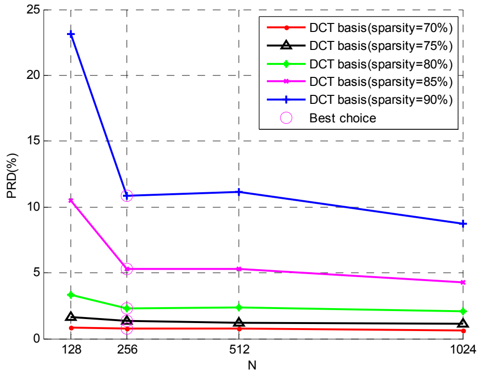


Fig. 4. Comparison of PRD and N under DCT basis

The sparsity of PW signal under different types of bases is various. We fixed the signal length *N*, and analyzed the impact of changing the sparsity level and the type of sparse basis on the PRD. As Fig. 3 shown, the curve of DCT is lowest, which means recovered PW signal under the DCT basis has less quality loss than others with the same sparsity; the acceptable signal recovery quality (*PRD*=9%) is achieved when sparsity is 88.3% under the DCT basis. Therefore, DCT basis is chosen in the proposed scheme.

The parameters of CS-based scheme, such as *N* and *M*, are associated with the sparsity of PW signal. We fixed the sparse basis (DCT basis), and analyzed the impact of changing the sparsity level and the signal length on the PRD. As Fig. 4 shown, *Sparsity* is inversely varied with *PRD* when the *N* is fixed. Greater *sparsity* will cause more signal components loss and high PRD. In the same *sparsity* level, *PRD* is approximately constant when signal length *N* is greater than 256. The experimental results indicate N=256 is a good choice for PW signal compression. With the relationship between the PRD and sparsity shown in Fig. 3, it is can be found *K=30* while *PRD*=9%. Thus, we chose *M*=128 according to the following four-to-one rule.

$$M \geq 4K \tag{9}$$

C. 1-bit sparse quasi-Toeplitz measurement matrix

Measurement matrix directly affects the compression efficiency and the quality of recovered signal. The parameters of a measurement matrix include the bit precision of coefficients, the type of random distribution, structure of the matrix, etc. Commonly used measurement matrix includes Gaussian distribution matrix, Bernoulli distribution matrix and uniform distribution matrix [9-11]. Previous work shows that at least 6-bit coefficients of the measurement matrix are needed for Gaussian and Uniform form distributions to compress the ECG signal [17]. However, the Gaussian, Bernoulli or uniform distribution matrices are costly. They are difficult to generate and store in resource constraint nodes; moreover, their random distribution and high bit precision bring more computation and higher energy consumption, thus they are unsuitable for PW signal compression. Herein, a simple structure measurement matrix is studied in our work.

The proposed measurement matrix is named 1-bit sparse quasi-Toeplitz measurement matrix, its formal definition is as the following.

$$\Phi = D_{random}(T) \tag{10}$$

where $D_{random}(\cdot)$ is a pseudo-randomly selection operator, which means randomly choose M row from the matrix *T*. *T* is a banded sparse N×N quasi-Toeplitz matrix.

$$T_{N\times N} = Toeplitz(F) \tag{11}$$

where *F* is a N-length vector, whose first d entries are 1 and the other is zero; $Toeplitz(\cdot)$ is a Toeplitz square matrix generated operator. The measurement matrix is determined by the parameters of d and M.

In order to figure out the optimal *d* and *M*, we fixed *N*=256, and analyzed the impact of changing M and d on the successful recovery rate. 1000 experiments have done repeatedly. The successful recovery count adds one if the PRD of the recovered signal is less than 9%. The results are shown in Fig. 5. The performance of the proposed measurement matrix is better than the Gaussian distribution matrix; the best robust recovery is achieved when d=9, and the PW signals are 100% successfully recovered while M≥128.

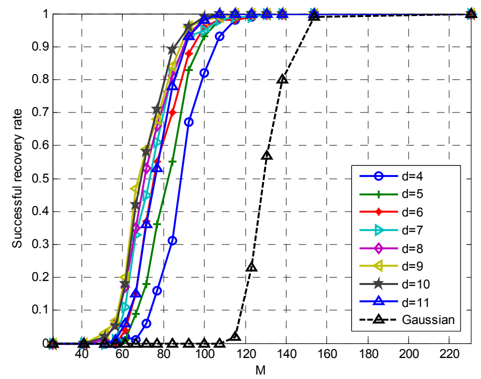


Fig. 5. The relationship between the successful recovery rate and the parameters of measurement matrix

IV. EXPERIMENTAL RESULTS

A. Experimental setup

To evaluate the proposed CS-based scheme in terms of efficacy at compactly representing the PW signal and energy saving, we carried out some experiments. The schematic diagram of the experimental testbed is shown in Fig. 6, the hardware devices include a MICAz node, one mib520 sink node, a National Instrument USB6009 data acquisition (DAQ) card and a laptop (Intel i7 2670qm, 8G RAM) with Matlab and LabVIEW environments. The distance between the sensing node and base station is 1 meter; the sink node and DAQ card are connected to the laptop by the USB cables. The supply power voltage is constant, i.e. 3.3 V, and A 10 Ohm high precision resistor is used to measure the energy consumption of the sensing node.

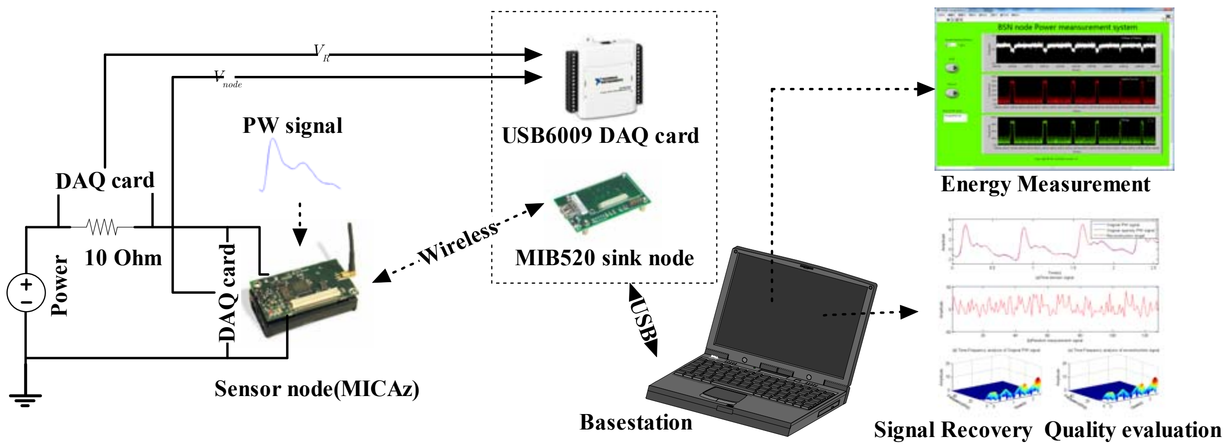


Fig. 6. Schematic diagram of the experimental testbed

The parameters settings of the CS scheme are listed as follows: the sparse basis is DCT basis; the length of each signal frame is 256, and measurement matrix is produced by d=9, M=128; CVX toolbox is used to solve the problem of Eq. (6), and regularization parameter λ is set to 0.01 based on experience.

Since our aim is to evaluate the performance of the proposed scheme on the resource-constraint nodes, we did not perform real PW acquisition, but alternatively used the MICAz to read in a database records at 100 Hz. The database contains 16 healthy volunteers' (10 males and 6 female, 24±3 years old) 16-bit PW signal records. The length of each record is over 40s. In sensing node, the data packet is wirelessly transmitted to base station when the 48-byte long packet with 8 bytes of MAC overhead and 8 bytes of customer defined overhead is filled. The laptop simultaneously records the energy consumption of the node. As shown in the Fig. 6, a 10 Ohm resistor is placed in the power path of the MICAz. The power-supply voltage V_{node}, and resistor voltage V_R are respectively measured by the DAQ card. Subsequently, the power and energy consumption can be calculated. In the base station, the recovered signal quality is assessed by the PRD.

B. Evaluation results

All 16 records evaluation results are shown in Fig. 7 and summarized in TABLE I. The average PRD is 4.23% and the standard deviation is 1.46, which is lower than the 9% unacceptable boundary. Two visual inspection results are shown in Fig. 8, from the figures, it is observed the proposed scheme achieves stable and good performance in both static (No.6 testing) and ambulatory (No.13 testing) PW acquisition scenarios. All experimental results indicate the recovered signals achieve small distortion by using the proposed CS-based scheme when 50% transmitted data is reduced; DCT basis is a qualified sparse basis; the optimal parameters and the BPDN model make the scheme have strong robustness and adaptability. It can conclude the CS-based scheme is suitable for the wireless PW signal acquisition.

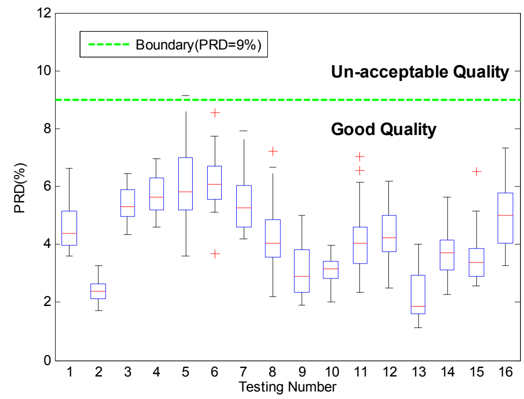
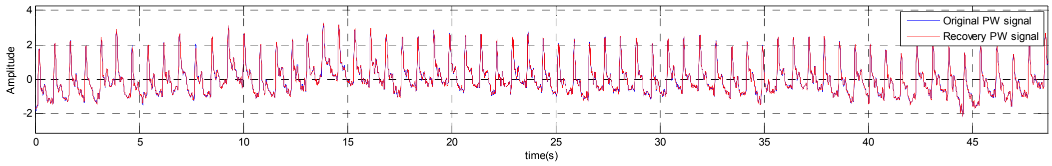


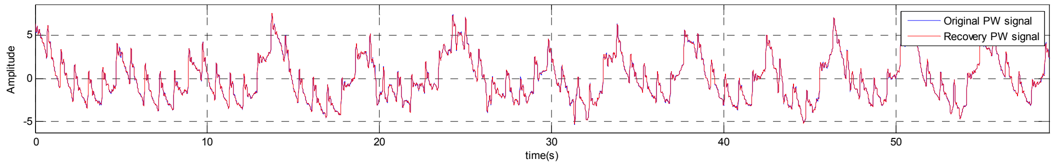
Fig. 7. The recovered signal quality evaluation results

TABLE I. EVALUATION RESULTS OF PROPOSED CS-SCHEME VERSUS DIRECT TRANSMISSION

		CS-based scheme	*Direct transmission*
PRD (%)	mean	4.23	-
	Std.	1.46	-
Recovery time(s)	mean	0.530	-
	max	1.190	-
	Std.	0.493	-
Resource consumption	ROM(Byte)	13649	13554
	RAM(Byte)	952	948
Execution time(ms/frame)	mean	0.9	-
	Std.	0.01	
Energy consumption(mJ)	mean	14.37	22.16
	Std.	1.15	0.81
Lifetime(h)(1000mAh@3.3v)		229.65	148.92

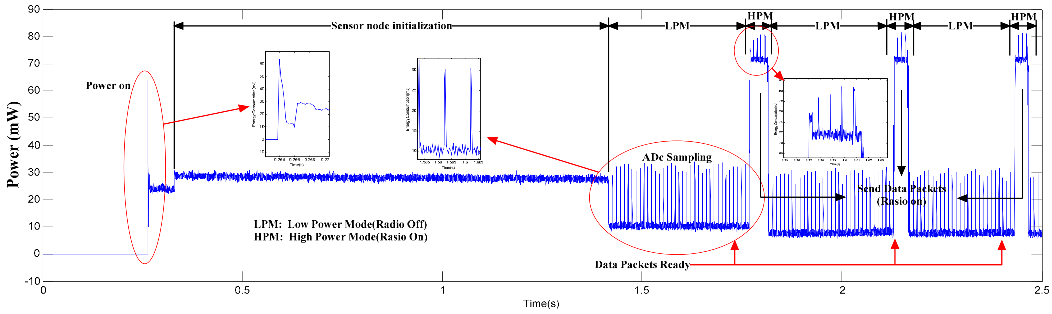


(a) No. 6 testing result

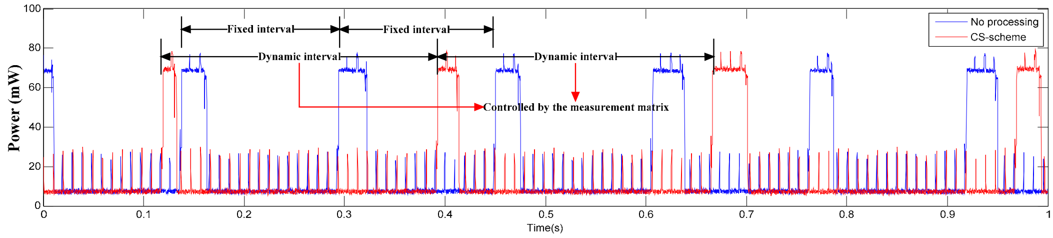


(b) No. 13 testing result

Fig. 8. Visual inspection results



(a) Power consumption of sensing node in different modes



(b) Power consumption comparison of two acquisition methods

Fig. 9. Power traces of MICAz during the wireless PW signal acquisition

The resource consumption and code execution time of CS-based scheme in node's algorithm are listed in the TABLE I. The usage of RAM and ROM increase from 948 Bytes and 13554 bytes to 952 bytes and 13649 bytes, respectively; the code for PW compression only needs 4 byte RAM and 92 bytes ROM. Since the sparse structure and 1-bit character of the measurement matrix, Storage and memory space used by the code is small; the proposed scheme is less resource consumption. The algorithm execution time is 0.9ms/frame. Since the coefficients of the matrix are 1-bit; the convolution operation is simplified as addition operation, the computational complexity of the algorithm is low. These compassion results indicate the proposed scheme is more suitable for the resource constraint nodes. Furthermore, in the base station, the PW signal recovery time of 256 pints per frame is less than 1.19s. It evidences the recovered signal can timely and sustainable present to the doctor or the user. All these attractive results confirm the proposed scheme is less resource consumption, low computational complexity and high time responded.

Fig. 9 (a) shows the power trace of the sensing node running a simple PW data wireless transmission application, in which when the data packet buffer is filled, the raw data is forward to send out without any onboard processing. There are four distinguished phases in Fig. 9 (a): power on, initialization, low power mode (LPM) and high power mode (HPM). After power on and initialization, the sensing node enters the LPM. During the LPM, the radio of the node is off. The sampled data periodically fill in the data buffer. The node immediately enters HPM when the data packet buffer is ready. During the HPM, the node's radio is on, and the data packets are wirelessly transmitted to the sink node. Fig. 9 (a) depicts the transmission of three data packets. After each transmission, the node is seen to automatically go to the LPM until the next data packet is ready.

The power consumption comparison between CS-based scheme method and direct transmission is shown in Fig. 9 (b). Since CS-based scheme reduces the amount of transmitted data, the power consumption of CS-based scheme method is less than the direct transmission in the same time interval. Reducing airtime over energy-hungry wireless links improves the energy efficiency and prolongs the lifetime of the node. The comparisons of the energy consumption and node lifetime between CS-based scheme method and direct transmission are reported in Fig. 10 and TABLE I. As shown in Fig. 10, half of transmitted data is reduced when M=128 and N=256, and node's energy consumption reduces 35.15% and lifetime prolongs 54.20%. With 1000mAh@3.3V battery, the sensing node can continually work over ten days. All those inspiring results evidence the high energy efficiency is achieved by the proposed CS-based scheme.

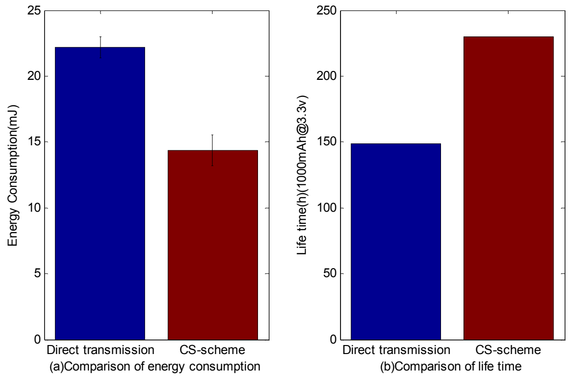


Fig. 10. Comparisons of node energy consumption and lifetime

V. CONCLUSION

In this paper, a CS scheme for wireless PW signal acquisition is proposed. It is the first time to discuss the CS-based scheme for PW signal acquisition in the resource- and computation-constrained sensing node. Using the CS compression scheme can reduce airtime over energy-hungry wireless links and improve the energy efficiency of the wireless PW biosensor. Some practical experiments have done on the MICAz node to verify the efficiency of the proposed method. The CS-based scheme achieves the average PRD, energy saving and lifetime of node prolonging of 4.23%, 35.15% and 54.20%, respectively; And the RAM, ROM and execution time of the CS algorithm code are 4 bytes, 92 bytes and 0.9ms/frame, respectively. The experimental results indicate the proposed scheme is high energy efficiency, high recovery signal quality and low resource consumption.

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