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An ECG Compressed Sensing Method of Low Power Body Area Network

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Abstract

Aimed at low power problem in body area network, an ECG compressed sensing method of low power body area network based on the compressed sensing theory was proposed. Random binary matrices were used as the sensing matrix to measure ECG signals on the sensor nodes. After measured value is transmitted to remote monitoring center, ECG signal sparse representation under the discrete cosine transform and block sparse Bayesian learning reconstruction algorithm is used to reconstruct the ECG signals. The simulation results show that the 30% of overall signal can get reconstruction signal which's SNR is more than 60dB, each numbers in each rank of sensing matrix can be controlled below 5, which reduces the power of sensor node sampling, calculation and transmission. The method has the advantages of low power, high accuracy of signal reconstruction and easy to hardware implementation.

Keywords: *Low power, Body Area Network, ECG, Compressed Sensing*

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1. Introduction

Cardiovascular disease is one of the major diseases which threaten human health and life seriously; the world's population average prevalence rate was 10%-30% and keeping increase year by year [1]. Because cardiovascular disease is occasional and unexpected, therefore, how to carry out real-time dynamic ECG (electrocardiogram) monitoring in the daily lives is major problem of early detection and prevention. Body Area Network (BSN) is a good solution to the problem [2, 3]. But real-time ECG monitoring which use BSN need to collect a large number of ECG data, commonly the sensor nodes which collect data usually powered by battery, therefore, how to reduce the power consumption of sensor node's collection, calculation and transmission is a key problem for prolonging the service life of the battery. The compressed sensing theory can solve this problem. Compressed sensing can reconstruct signal with high probability by undersampling technique which less than the Nyquist sampling rate [4-6], it solve the problem of BSN's low power consumption by reducing data sampling.

At present, aimed at compressed sensing method of low power BSN, Mamaghanian [7] compare ECG compress performance based on discrete wavelet transform with performance based on compressed sensing by using Shimmer wireless body area network hardware platform, found that although the compress performance based on compressed sensing is slightly poor, but its power consumption is much smaller, more suitable for higher real-time body area network. Its shortcoming is the use of the basis pursuit denoising reconstruction algorithm, not well using the structural characteristics of the ECG signal itself. Dixon [8] proposed a kind of 1 bit Bernoulli measurement matrix of dynamic threshold method for ECG signals, and the simulation results which use common compressed sensing reconstruction algorithm show that when SNR is above 60dB, the compression ratio can reach 16 times. It reduces transmission power consumption of body area network sensor node by improving the compression ratio, but the sensor node's computing power consumption is large and not easy to hardware implementation. Using the signal correlation in the block in compressed sensing theory framework, Zhang [9] proposed a reconstruction algorithm based Sparse Bayesian learning, the reconstruction precision of this algorithm is better than other compressed sensing reconstruction algorithm, and this characteristic suit for the body area network remote monitoring center data analysis and diagnosis, but it aimed at fetus ECG. Khaled [10] design a compressed sensing

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analog-to-information conversion hardware circuit based spread spectrum random modulator pre-integrator, which is a new design and implementation of a CS-based A2I read-out system that uses spread spectrum techniques prior to random modulation in order to produce the low rate set of digital samples. But it reduces the reconstruction precision of ECG signal because of using basis pursuit denoising reconstruction algorithm. DING [11] proposed a cardiac arrhythmia detection via compressed measurements of body area network, the Bayesian compressed sensing method was used on the sensor node using for classification of ECG signals, when the heart rate is normal, it transmit only the value of heart rate, if the heart rate is abnormal, it transmit ECG signals to the remote monitoring center. This method reduces the body area network transmission power, however, because the classification is carried out on the sensor node, it is bound to increase the complexity of the sensor node hardware and bring higher calculation power consumption.

In view of the above question, considering the BSN low power problems with reconstruction precision of ECG signal and easy to hardware implementation, this paper proposes an ECG compressed sensing method of low power BSN. Random binary matrices were used as the sensing matrix to measure ECG signals on the sensor nodes. After measured value is transmitted to remote monitoring center, ECG signal sparse representation under the discrete cosine transform and block sparse Bayesian learning reconstruction algorithm is used to reconstruct the ECG signals. The effectiveness of the proposed method is validated by ECG data without noise and noisy from the MIT-BIH arrhythmia database.

2. ECG Body Area Network

Body Area Network (BSN) is a wireless sensor network which is formed by the human body physiological parameters sampling sensors or biosensors transplanted in the human body [3]. As shown in Figure 1, the BSN acquires important physiological signals such as body temperature, blood oxygen, blood pressure and ECG signal and so on, human activity or action signal and body environment information through the wearable or implantable sensor nodes, then these signals are transmitted to the local base station by intelligent mobile phone or PDA, ultimately to the remote medical service center through the internet. The purpose of BSN is to provide ubiquitous computing platform of an integrated hardware, software and wireless communication technology, and provide necessary conditions for the development of health monitoring system.

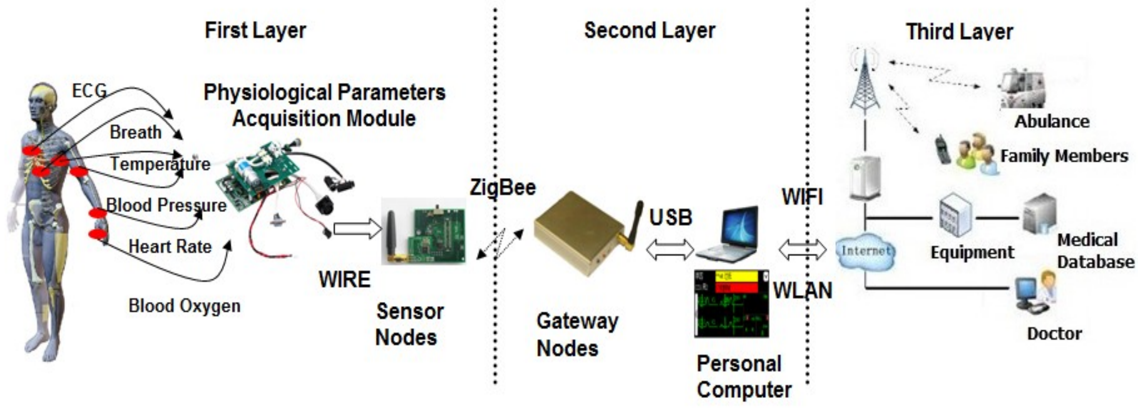


Figure 1. BSN System architecture

Cardiovascular disease has become "the first killer" to human health, in order to timely detect and prevent the disease, the research of ECG signal in BSN is very important. The ECG signal is typical biological electrical signal with characteristics of frequency, phase, amplitude and time difference, at the same time with a certain periodicity and regularity. Each ECG of heartbeat cycle can be divided into different wave and interval. The P wave, QRS wave and T wave are the main characteristic waves, PR interval, QT interval, ST segment of ECG signal is the feature information which reflects heart conduction system and heart lesions in many ways. ECG body area network can realize the real-time ECG dynamic monitoring, but a long time ECG record will inevitably lead to a large amount of data, which also bring body area network many technical issues.

BSN system is currently facing challenges which include network architecture, sensor nodes and gateway, wireless communication technology and low power network design etc. The low power design of BSN is one of the most important issues. In order to avoid patients 'active constrained problem owing to the wired way commonly used, BSN adopts the wireless communication, because all the sensor nodes can only carry a limited battery energy, and long time of the acquisition, processing and transmission of ECG signal will consume a large amount of energy, energy restriction became the bottle of ECG BSN development. At present, the research on low power BSN mainly focused on low power hardware design, low power network communication design and low power signal processing of the sensor node. This paper realizes low power ECG BSN by signal processing method with compressed sensing theory.

3. Compressed Sensing Basic Theory

Compressed sensing theory pointed out that if the measured signal $X : N \times 1$ is sparse or the transformation coefficient Θ of transform domain Ψ is sparse, an observation matrix $\Phi : M \times N(M \ll N)$ which irrelevant to the transform basis Ψ can be used linear projection to the sparse coefficient vector Θ for acquiring observation vector $Y : M \times 1$,and then we can reconstruct the original signal X with precise or high probability from the observation vector Y by using the optimization method . The observation model as shown in (1).

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

Compressed sensing achieve a reduction dimension projection to signal from dimension N to dimension M , thereby realize data compression. The most important two conditions are sparsity and incoherence. Sparsity refers to the most value of the measured signal itself or the coefficients in a transform domain is equal to or close to 0, only a few characteristic value which represent signal is not 0. When the signal itself is sparse, Ψ is the unit matrix; if the signal itself is not sparse, then Ψ can be Fast Fourier Transform (FFT), Discrete Cosine Transform (DCT), Discrete Wavelet Transform (DWT) transform matrix etc. Incoherence is in order to reconstruct the original signal X with precise or high probability from the observation vector Y , the observation matrix Φ must satisfies Restricted Isometric Property(RIP)[12]. For any signals x with r sparse degree, if there are isometric constant $\delta_r \in [0,1)$ to make (2) true, then matrix Φ satisfies the r RIP properties. The observation matrix $\hat{\Phi}$ satisfies the RIP conditions with greater probability When it is Gauss random matrix, consistent ball measurement matrix, binary random matrix, local Fourier matrix, local Hadamard matrix and Toeplitz matrix etc.

$$(1-\delta_r) \| x \|_2^2 \leq \| \Phi x \|_2^2 \leq (1+\delta_r) \| x \|_2^2 \tag{2}$$

In the theory of compressed sensing, for the observation number M is much less than the length N of the signal, therefore we had to solve the problem of the underdetermined equations $Y = \Phi X$ .Because the signal X is sparse or compressible, and at the same time the observation matrix with RIP properties, all of these provide a theoretical guarantee for accurate recovery signal from observations. On the premise of signal is sparse or compressible, solving the underdetermined equations is transformed into the problem of norm problem. However, it is required to list all the non-zero position with C_N^K possible linear combination in X can get the optimal solution. Therefore, solving (3) is numerical calculation instability and is an NP hard problem. Donoho pointed out that it can produce the same solution to solving (4) with simpler l_1

norm problems. So it turned into a convex optimization problem. It can conveniently use linear programming to deal with, Basis Pursuit (BP) algorithm is typical method.

$$\min \| X \|_0 \quad s.t. \quad \Phi X = Y \tag{3}$$

$$\min \| X \|_1 \quad s.t. \quad \Phi X = Y \tag{4}$$

The commonly reconstruction algorithms of compressed sensing are greedy tracking algorithm, convex relaxation method, nonconvex method and combination algorithm etc. Because the ECG signals with sparse characteristics, to effectively improve the accuracy of reconstruction signal, a reconstruction algorithm based on Sparse Bayesian Learning (SBL) was adopted in this paper.

4. ECG Compressed Sensing Method of Low Power Body Area Network

Compressed sensing theory breaks through the traditional Nyquist sampling theorem that the sampling frequency must be at least 2 times greater than the maximum frequency of the signal to completely recover the original signal. Compressed sensing theory adopt direct sampling information rather than signal, which reduce the sampling data, and then reduce the data of BSN sensor node processing, transmission and routing calculation, provide favorable conditions for BSN low power working requirements. ECG body area network compressed sensing principle as shown in Figure 2, sparse representation, design of measurement matrix and reconstruction algorithm of ECG low-power body area network are researched in this paper.

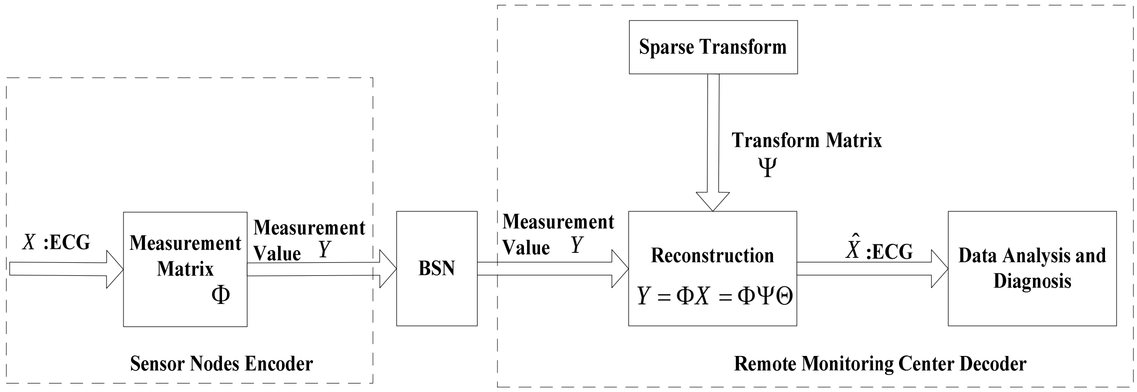


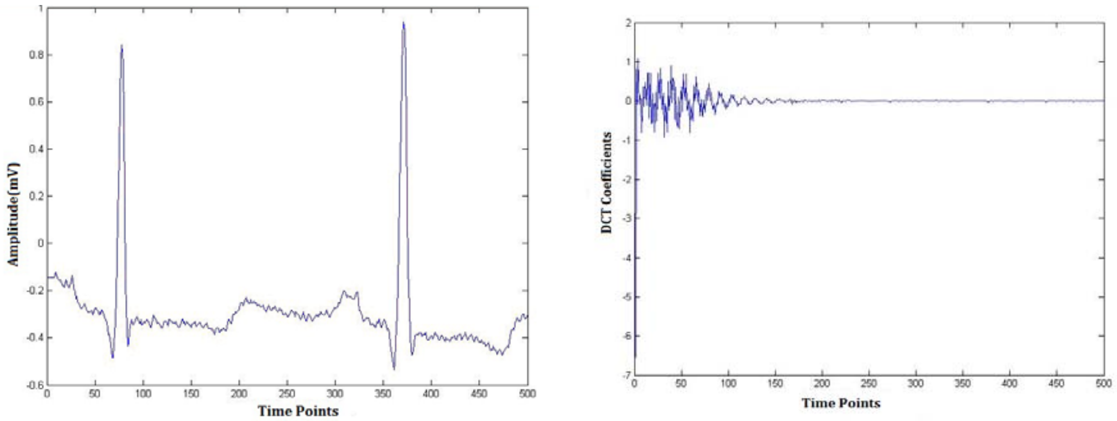
Figure 2. ECG BSN compressed sensing principle block diagram

4.1. Sparse Representation

ECG signal especially noisy ECG signal is not sparse in time domain, but is sparse in a transform domain or overcomplete dictionary. At present the transform domain commonly used include: fast Fourier transform, discrete cosine transform and discrete wavelet transform etc. Because of the discrete cosine transform coefficient are concentrated in the vicinity of 0, the dynamic range is very small, with fewer quantization bits can represent the DCT coefficient, and at the same time it has the advantages of fast calculation speed, belongs to the orthogonal transformation, so it can better satisfy the ECG signal sparse representation requirements based on compressed sensing. Combined with the characteristics of real-time requirements of body area network, this paper adopts discrete cosine transform as ECG sparse representation method. Figure 3 are the first 500 sampling points of ECG original signal in the MIT-BIH arrhythmia database and the sparse coefficient of DCT domain, it can be seen in the figure that the ECG signal is sparse in the DCT domain.

4.2. Observation Matrix

Because DCT basis is orthogonal basis, any random observation matrix can meet the RIP requirements. The commonly used Random observation matrix are Gauss random matrix, consistent ball measurement matrix and binary random matrix. The sparse binary random measurement matrix [7] is used in this paper.



(a) ECG Signal (b) DCT coefficients of ECG

Figure 3. Sparse representation of ECG

As (5) shows, the number of 1 in each column of the matrix is the same and far less than the matrix rows, its positions are random and other value is 0. When in the actual measurement, observation value can be considered as the result of matrix multiplication algorithm by matrix and ECG discrete value. Because the observation matrix contains only 1 and 0 elements, 0 elements does not participate in the operation, the 1 elements of the operation is equivalent to add operation of the ECG discrete value, so the product operation of two matrices is changed into add operation. But if use observation matrix such as Gauss random matrix , the matrix elements have non integer item, therefore needs to deal with multiplication, so using sparse binary random measurement matrices as observation matrix can effectively reduce CPU operation power consumption of sensor node. On the other hand , it can also reduce the power consumption of sensor node through reducing the number of 1 in the observation matrix . In addition, because the value of matrix elements is 1 or 0, similar to electronic switch on or off, its hardware circuit is also easy to implement.

$$\begin{pmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_M \end{pmatrix} = \begin{pmatrix} 1 & 0 & 1 & 0 & \cdots & 1 \\ 0 & 1 & 1 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \cdots & \vdots \\ 1 & 0 & 0 & 1 & \cdots & 0 \end{pmatrix} \begin{pmatrix} X_1 \\ X_2 \\ X_3 \\ \vdots \\ \vdots \\ X_N \end{pmatrix} \tag{5}$$

4.3. Signal Reconstruction

ECG signal reconstruction is implemented in body area network remote monitoring center, because the reconstruction ECG signal need to perform the various follow-up data analysis and medical diagnosis, so the reconstruction signal must have high reconstruction accuracy or even completely recover the original ECG signal. Reconstruction algorithm based on BSBL (Block Sparse Bayesian Learning) framework [13] which exploits the amplitude correlation of inner-block element of solution vectors is adopted in this paper. Comparing with the compressed sensing reconstruction algorithms such as OMP, BP, CoSaMP, SL0, Block-

OMP and so on, it is found that the reconstruction accuracy of BSBL algorithm is higher, and it meet the BSN application requirements. The basic mathematical model based on BSBL algorithm framework can be described:

$$y=Ax+v \tag{6}$$

where $x \in \mathbb{R}^{N\times 1}$ is the original signal to compress with length N, $A \in \mathbb{R}^{M\times N} (M \ll N)$ is a measurement matrix which linearly compress x, any M columns of A are linearly independent, and v is an unknown noise vector. The task is to estimate the source vector x in Model (6), it has some structure, the most common is the block structure.

$$x = [\underbrace{x_1, \quad \cdots, \quad x_{d_1}}_{x_1^T}, \cdots, \underbrace{x_{d_{g-1}+1}, \quad \cdots, \quad x_{d_g}}_{x_g^T}]^T \tag{7}$$

The compressed sensing model Based on the formula (6) (7) called block sparse model. In this model, the source vector x can be divided into g blocks (number of elements in each block structure are not necessarily the same), and the non zero elements of x are concentrated in a few blocks. In BSBL, assuming that each block x_i satisfies a multivariate Gauss distribution:

$$p(x_i; \gamma_i, B_i) \sim N(0, \gamma_i B_i) \tag{8}$$

where B_i is a an unknown positive definite matrix capturing the correlation structure of the i-th block. γ_i is a nonnegative parameter controlling the block sparse of x, when $\gamma_i = 0$, x_i become a zero block, during the learning process, most γ_i close to zero which contributed block sparsity of solution. Similarly, assuming that the noise satisfy multivariate Gaussian distribution, namely $p(v; \lambda) \sim N(0, \lambda I)$, where λ is a positive scalar and I is the identify matrix, so we can the get the posterior distribution of x by Bayesian rule, then Type-II maximum likelihood estimation is used to estimate the parameters, finally obtaining the maximum posteriori estimate of x.

Combined the sparse representation method with the design of the observation matrix and reconstruction algorithm of ECG signals above, the low power BSN compressed sensing method can be described as the following steps:

Step 1: Draw two kinds of ECG data which are clean and noise from MIT-BIH ECG database.

Step 2: Generating $M \times N$ dimensional sparse binary random measurement matrix Φ, using $Y = \Phi X$ to project N dimensional ECG data X then obtain M dimensional observation value Y.

Step 3: Obtaining sparse representation of the initial ECG data $\Theta = \Psi^T X$ by using the DCT transform basis Ψ.

Step 4: Using the observation value Y, the observation matrix Φ and DCT transform basis Ψ to get reconstruction sparse coefficients $\hat{\Theta}$ by BSBL reconstruction algorithm.

Step 5: Using reconstruction sparse coefficient $\hat{\Theta}$ to get reconstruction ECG signal $\hat{X}$ by $\hat{X} = \Psi^{-1}\hat{\Theta}$.

Step 6: Comparing signal to noise ratio (SNR), Compress Rate (CR) and observation power consumption of reconstruction signal $\hat{X}$ with the original signal X.

Step 7: Adjusting M value and the number of 1 in each column of sparse binary random measurement matrix, then repeating steps 3, 4, 5, 6 to get SNR, CR and observation power optimal combination value, finally obtaining the observation matrix.

5. Simulation and Analysis

MIT-BIH arrhythmia database is adopted in the experiments. To validate the method, we selected the no noise and noise of ECG data from the MIT-BIH database. No noise data is record number 100 ECG data, since the data contains the MLII and V5 two leads data, this paper we adopt the MLII lead data which sampling frequency is 360Hz and the number of sampling points is 650000, the former 500 sampling points are adopted. The gain of the signal is 200ADC units/mV, ADC value of zero is 1024. Noise ECG data is tested by record number 118e12, because the data includes the MLII and the V1 two leads data, this experiment adopts the MLII lead data. The former 5 minutes of the noisy signal is excluding noise signal, after that, every 2 minutes alternately contain SNR=12dB high frequency noise, therefore this experiment we utilize the 500 sampling points which start at the sixth minutes. In order to make the simulation ECG normalization. We carried out the gain and zero value processing in the experiment.

SNR of (9) is used to measure reconstruction error of ECG, SNR is larger, the reconstruction error is smaller. X is the original ECG signal, $\hat{X}$ is reconstruction ECG signal. CR of the (10) is used to measure the ECG signals' compressed rate. N stands for the length of original ECG signal, M is the length of compression ECG signal by the observation matrix. Pearson correlation coefficient of (11) is adopted to measure the similarity of the original ECG signal and the reconstruction ECG signal, R is larger, then the similarity of two signal is higher. where X_i , Y_i respectively denotes the i components of the original signal and the reconstruction signal, $\bar{X}$, $\bar{Y}$ respectively denotes mean value of the original signal and the reconstruction signal.

$$SNR = 20\log_{10}\frac{\| X \|_2^2}{\| X - \hat{X} \|_2^2} \tag{9}$$

$$CR = \frac{N-M}{N} \times 100\% \tag{10}$$

$$R = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \bar{X})^2}\sqrt{\sum_{i=1}^{n}(Y_i - \bar{Y})^2}} \tag{11}$$

The following we deal with the simulation and analysis of ECG signal reconstruction error and the BSN low power.

5.1. Simulation and Analysis of ECG Signal's Reconstruction Error

Because the reconstruction ECG signal need to perform the various follow-up data analysis and medical diagnosis, so the reconstruction signal must have high reconstruction accuracy. The commonly used reconstruction algorithm based on compressed sensing include OMP [14], Basic Pursuit [15], SL0 [16], Elastic-Net [17], Boltzman-Machine [18], Struct-OMP [19], Block-OMP [20] and so on. In this paper, algorithm is divided into exploiting block structure or not exploiting block structure according to whether the use of block structure characteristic of signal, and then compare their reconstruction error. Among them the reconstruction algorithm of optimal boundary frame (BSBL-BO) based on BSBL has the characteristics with exploiting block structure of signals. Reconstruction error SNR of this algorithm is compared with other algorithms as following.

Two kinds of ECG signal which contain record number 100 without noise and record number 118e12 with high frequency noise are adopted in the simulation experiment. In order to effectively compare the reconstruction error, the reconstruction algorithm is divided into two groups, one group exploit block structure of signals, the other not. Because PhysioNet provides conversion tool PhysioBank ATM, and the ECG data can be directly extracted from the database, then automatically changed to the. Mat format files. The first 500 sampling points of the ECG signal were compressed by using 250 × 500 sparse binary random measurement matrix, the number of 1 of every column of the observation matrix is 30, when reconstruction algorithm based on block structure of signals is used, the block length of the signal is 25, finally ECG signal sparse representation under the discrete cosine transform and the reconstruction algorithm above is used to reconstructed the ECG signals. The reconstruction error was compared by 8 kinds of reconstruction algorithms, including 4 kinds exploiting using the block structure of signals, the other 4 not.

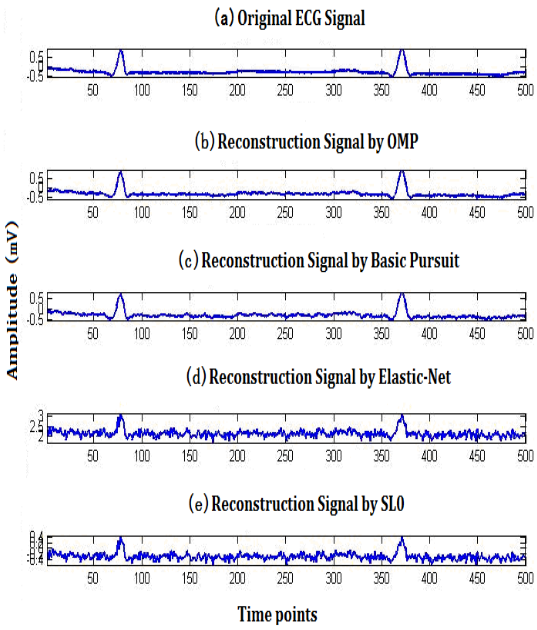


Figure 4. No noise ECG reconstruction not exploiting the block structure

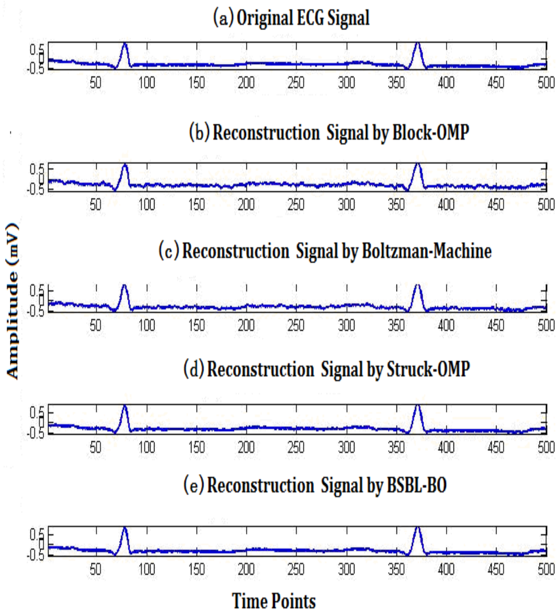


Figure 5. No noise ECG reconstruction exploiting the block structure

Figure 4 and figure 5 respectively is the reconstruction signal waveform of record number 100 ECG exploiting the block structure of signals or not. The reconstruction error of OMP and Basic Pursuit algorithm to is small in figure 4, but the reconstruction error of SL0 and Elastic-Net algorithm is large. The reconstruction error of Boltzman-Machine, Struct-OMP, Block-OMP and BSBL-BO algorithm is small in Figure 5, it also indicates that ECG signal has the characteristics of periodic and block structure. For further quantize reconstruction error, SNR and reconstruction time of 8 algorithms are listed in Table 1, it can be seen from the table, SNR value of the BSBL-BO algorithm is 108.0505, which has the minimum reconstruction error. The reconstruction time is 1.0375s, it is shorter than Boltzman-Machine, Struct-OMP and Elastic-Net algorithm. Because the reconstruction ECG signal of BSN based on compressed sensing is carried out in remote monitoring center which has powerful hardware computing ability, so the reconstruction time of BSBL-BO algorithm can be accepted.

Figure 6 and Figure 7 respectively is the reconstruction signal waveform of record number 118e12 with noise ECG exploiting the block structure of signals or not, the reconstruction error is similar to record number 100 above. Seen from Table 2, SNR value of

BSBL-BO algorithm is 80.5223, the reconstruction error is minimum, but is larger than the record number 100 with no noise. The reconstruction time is 1.5256s which is similar to record number 100, longer than number 100 with no noise .SNR of BSBL-BO algorithm is best, the reconstruction time is in the medium level by comparing the performance with reconstruction algorithm of two different types of ECG signal. Considering the high reconstruction precision of the ECG signal requirements for ECG BSN, the reconstruction time can also meet the system requirements, the algorithm in this paper is suitable completely.

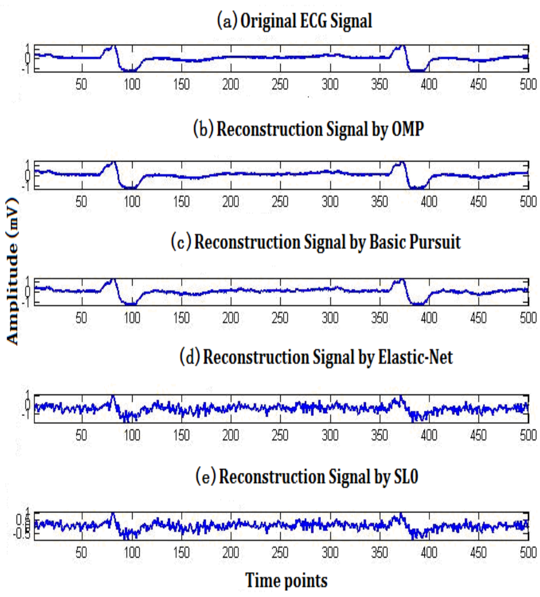


Figure 6. Noisy ECG reconstruction not exploiting the block structure

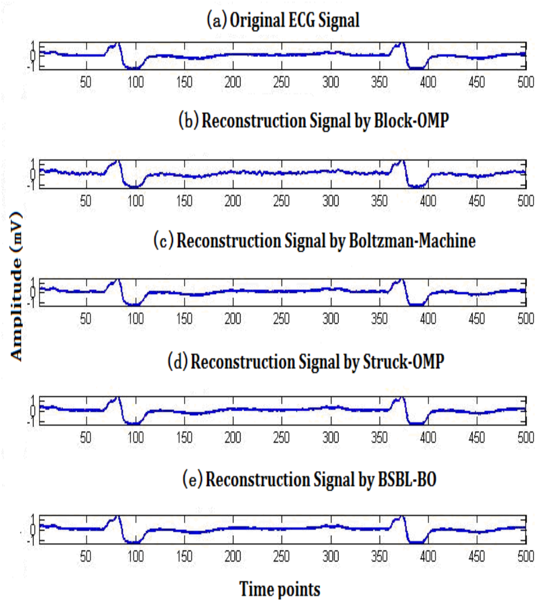


Figure 7. Noisy ECG reconstruction exploiting the block structure

Table 1. No noise ECG reconstruction performance comparison

Algorithm Name	SNR	Reconstruction Time（S）
BSBL_BO	108.0505	1.0375
OMP	88.8534	0.069643
BP	80.5489	0.33238
SL0	62.489	0.16772
E-Net	-9.8492	2.7111
BM	86.1521	121.0114
S-OMP	101.2526	18.923
B-OMP	81.7555	0.032121

Table 2. Noisy ECG reconstruction performance comparison

Algorithm Name	SNR	Reconstruction Time（S）
BSBL_B0	80.5223	1.5256
OMP	61.9405	0.083992
BP	47.4251	0.3707
SL0	20.2549	0.6147
E-Net	-9.3642	2.6851
BM	67.3139	125.5411
S-OMP	75.3883	18.3177
B-OMP	51.8472	0.034092

5.2. Power Performance Simulation and Analysis of BSN

Power consumption of sensor node of ECG BSN based on compressed sensing is mainly related with the ECG compression rate and the design of observation matrix. Compression rate is larger, power consumption is lower, and the compression ratio is relevant to observation row M of observation matrix, M is smaller, the compression rate is larger, the number of sensor node sampling is fewer, therefore sampling power is lower, transmission power consumption is also lower. At the same time, the value G namely the number of 1 in each column of observation matrix is less, the number of calculation of the sensor node is reduced, thereby the calculation power is reduced, however, we must consider that the reconstruction ECG signal should has high reconstruction accuracy when reducing power consumption.

Therefore, aimed at the BSBL-BO algorithm, we carried out power consumption simulate and analyze of BSN from the signal compression ratio, the value G namely the number of 1 in each column of observation matrix, the signal reconstruction error SNR and the Pearson correlation coefficient R based compressed sensing.

Figure 8 and Figure 9 show the relationship between CR and SNR of ECG signal without noise and noisy when G is 1,5,15, and 30. In the figure, the SNR of ECG signal without noise is higher than that of ECG signal with noisy when CR is same. However, for the same signal, SNR of other G values are very close except that G is 1, therefore we didn't do the experiment when each column element of the observation matrix is 1 is. It can be seen in figure, when CR of ECG signals without noisy is less than 85% and CR of ECG signals with noisy is less than 70%, SNR is greater than 60dB. Therefore, for different signal, according to CR formula definition, if CR=70%, then M=0.3, that is sampling 30% of the signal can get high accuracy reconstruction signal which SNR is 60dB. This method can reduce sampling and transmission power consumption of the sensor node by reducing the sampling data and compressing the transmission data.

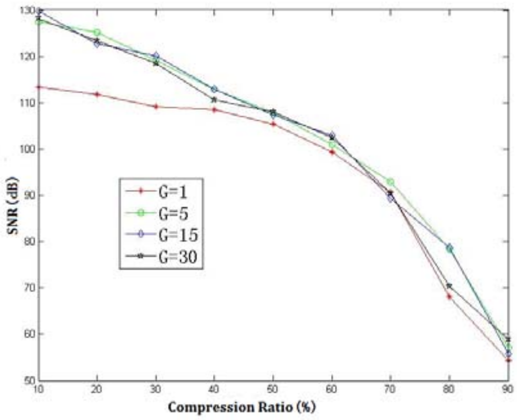


Figure 8. SNR and CR of no noise ECG in different G

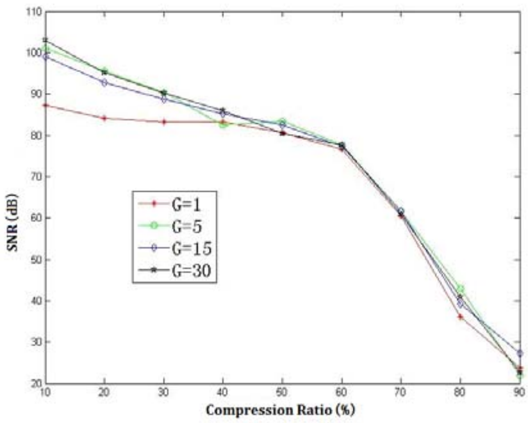


Figure 9. SNR and CR of noisy ECG in different G

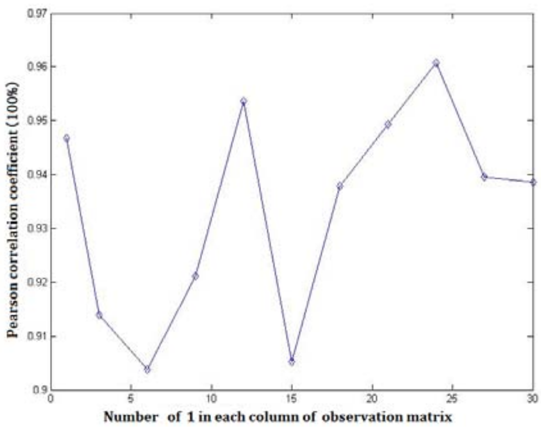


Figure 10. R of no noise ECG in different G

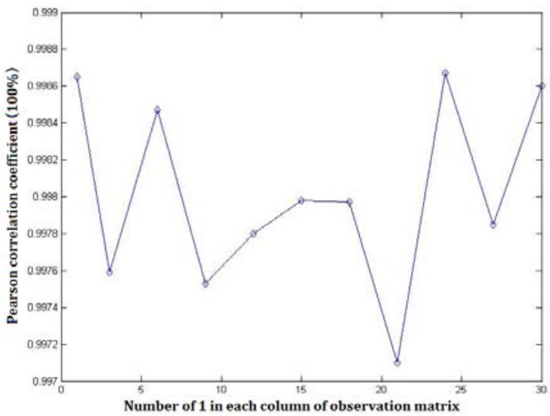


Figure 11. R of noisy ECG in different G

Figure 10 and Figure 11 respectively shows Pearson correlation coefficient R of two kinds of reconstruction ECG signal when G is not the same. Because the observation matrix Φ is the random matrix, the position of 1 in the observation matrix may be different when G is same, which will lead that R of the final reconstructed signal and the original signal are different, therefore, in this paper, we let G = 1, 3, 6, 9, 12, 15, 18, 21, 24, 27, 30 and respectively do 20 experiments, then get the mean value of R and make it as the final value R. Figure 10 is relation diagram about G and R of signal without noisy when CR is 80%. when G=6, the minimum value of R is 0.90375, G =24, a maximum of R is 0.96074, a difference of 0.05699. Figure 11 is relation diagram about G and R of signal without noisy when CR is 70%. when G=21, the minimum value of R is 0.9971, G=24 ,a maximum of R is 0.99867, only difference of 0.00157. Therefore, we can conclusion that different G has very small effect on R, and the mean value of R was more than 0.9, G can get the smaller value below 5 When we design observation matrix Φ so as to reduce the observation sensor node's computing power consumption.

6. Conclusion

In this paper, we proposed an ECG compressed sensing method of low power body area network based on the compressed sensing theory. Different from the traditional Nyquist sampling theorem, it can reduce power consumption of the sensor node sampling, calculation and transmission by undersampling or less sampling ECG signal based on the theoretical framework of compressed sensing, and the MIT-BIH arrhythmia database was used to validate the effectiveness of the method. The simulation results show that the method has the advantages of low power, high accuracy of signal reconstruction and easy to hardware implementation. At the same time, the realization and correlative analysis of the method provides support for the related research of body area network about EEG and EMG signals. Owing to the result is obtained under conditions of simulation experiment based database currently, the ECG body area network hardware platform based on compressed sensing will be established to validate the effectiveness of method in the future.

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