Comparison of Four Recovery Algorithms used in Compressed Sensing for ECG Signal Processing

Zhimin Zhang[1], Shoushui Wei[1], Dingwen Wei[2], Liping Li[3], Feng Liu[4], Chengyu Liu[1]

[1]School of Control Science and Engineering, Shandong University, Jinan, China
[2]School of data science and soft Engineering, Qingdao university, Qingdao, China
[3]School of Science and Technology, Shandong University of Traditional Chinese Medicine, Jinan, China
[4]School of Information Technology and Electrical Engineering, University of Queensland, Queensland, Australia

Abstract

Compressed Sensing (CS) has been used in ECG signal compressing with the rapid development of real-time & dynamic ECG applications. Signal reconstruction process is an essential step in CS-based ECG processing. Many recovery algorithms have been reported in the last decades. However, the comparative study on their reconstructing performances for CS-based ECG signal processing lacks, especially in real-time applications. This study aimed to investigate this issue and provide useful information. Four typical recovery algorithms, i.e., compressed sampling matching pursuit (CoSaMP), orthogonal matching pursuit (OMP), expectation-maximum-based block sparse Bayesian learning (BSBL_EM) and bound-optimization-based block sparse Bayesian learning (BSBL_BO) were compared. Two performance indices, i.e., the percentage of root-mean-square difference (PRD) and the reconstructing time (RT), were tested to observe their changes with the change of compression ratio (CR). The results showed that BSBL_BO and BSBL_EM methods had better performances than OMP and CoSaMP methods. More specifically, BSBL_BO reported the best PRD results while BSBL_EM achieved the best RT index.

1. Introduction

Wireless body sensor network (WBSN) provides large-scale and cost-effective solutions for personalized, real-time and long-term ambulatory ECG monitoring for chronic patients [1]. WBSN requires efficiency compressing algorithms since a mass amount of data from the long-term recording. Recently, compressed sensing (CS) has been successfully applied in the WBSN long-term signal monitoring since it can help to cut down the energy and improve the recording speed in sensing process.

Reconstruction of the original ECG signal from the compressed signal is usually computational costly. Thus the recovery algorithm is an essential key step for the CS-based signal compressing. Typical recovery algorithms used in CS include: orthogonal matching pursuit (OMP), compressed sampling matching pursuit (CoSaMP) and Bayesian learning-based methods. OMP is a classical greedy algorithm and has been designed as OMP-based reconstruction hardware implementation in [2]. However, its performance is dependent heavily on the properties of the measurement matrix [3]. The improved version of CoSaMP offers a theoretical reconstruction guarantee in noise environment by exploiting a backtracking framework and has achieved a widely application image reconstruction [4]. However, CoSaMP relies on the sparsity of signal and its usefulness in processing 1-D signal is open to question . Bayesian learning provides a block sparse Bayesian learning framework and seems like a promising method for performing 1-D CS signals [5]. Expectation-maximum-based block sparse Bayesian learning (BSBL_EM) and bound-optimization-based block sparse Bayesian learning (BSBL_BO) are two common Bayesian learning-based methods [6].

The CS-based long-term ECG signal compressing has shown a huge potential in the past several years. However, there is currently little information available on the comparison of the reconstructing performances between different recovery algorithms. This study aimed to provide this information by detailed comparing the aforementioned four CS recovery algorithms.

2. Methods

2.1. Experimental data

Thirty-six ECG recordings from the MIT-BIH Normal Sinus Rhythm Database labelled from "16265" to "19830" were used in this study. These recordings were collected from 18 subjects (5 male and 13 female; aged from 20 to 50 years). For each recording, the first 10-s ECG episodes were extracted for CS-based compressing and reconstructing. The data basic information is summarized in Table 1.

Table 1. Basic information of the experimental data.

Subjects		ECG signals used	
No.	18	No.	36
Age (years)	34±8	Length (s)	10
Male	5	Sampling frequency (Hz)	128
Female	13	Resolution (bits)	11

2.2. Program description

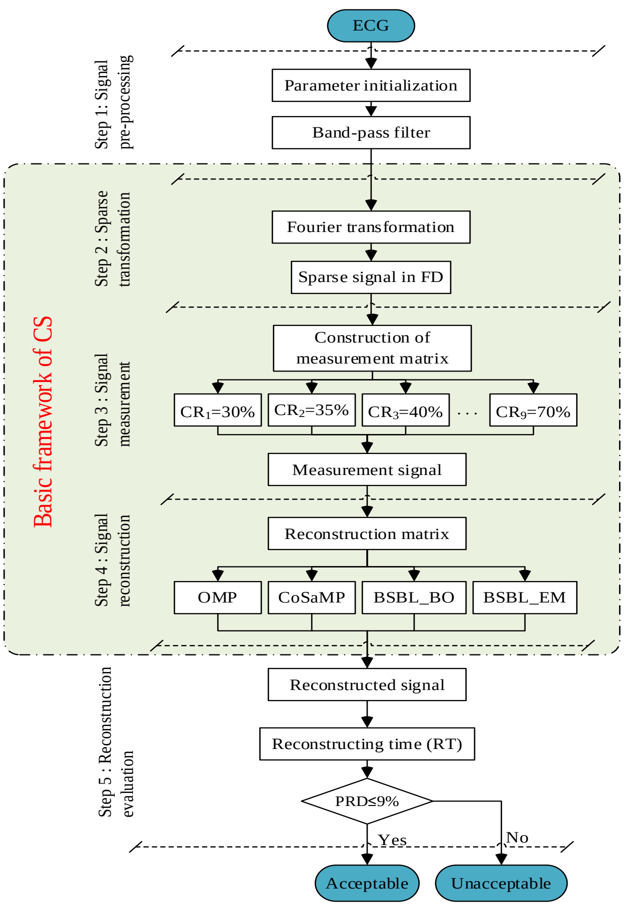

Figure 1. Program flow chart. FD: frequency domain, RT: reconstructing time; CR: compression ratio; PRD: percentage of root-mean-square difference.

Figure 1 shows the program flow chart, which consists of five steps: Step 1, signal pre-processing; Step 2, sparse transformation; Step 3, signal measurement; Step 4, signal reconstruction and Step 5, reconstruction evaluation. Each step consists of several sub-steps.

In Step 1, the data were firstly re-sampled as 360Hz. Then a 5~40 Hz band-pass filter was used for filtering the noises from body movements, electrode contact, EMG and 50 Hz power frequency interference.

As shown in Figure 1, Steps 2-4 are the basic CS framework. The premise of applying CS is that the signal is sparse. In Step 2, we transformed the ECG data into its frequency domain, in which ECG signal has better sparsity than in the time domain.

In Step 3, a Gaussian random matrix (GRM) was constructed and used as measurement matrix in this study. The construction method for GRM refers to reference [7].

In Step 4, the compressed ECG signal was reconstructed by the four comparable recovery algorithms respectively. OMP intended to reconstruct the first K maximum in the frequency domain of ECG signal and to acquire the reconstructed data through inverse Fourier transformation. CoSaMP had similar principles to OMP while it chose more atoms than OMP did during the iteration. For BSBL_BO and BSBL_EM, they both intended to explore and exploit the intra-block correlation in the block sparse model.

In Step 5, the percentage of root-mean-square difference (PRD) between the reconstructed and the original ECG signals was used as the evaluation index for reconstruction quality [8]. PRD was defined as:

$$PRD = \left\|\hat{x} - x\right\|_2 \times 100 \big/ \left\|x\right\|_2 \qquad (1)$$

where $\hat{x}$ denotes the reconstructed signal and x denotes the original signal, $\|\cdot\|_2$ means the 2-norm operation. The smaller PRD was, the better the reconstruction quality would be. The reconstructed signal was regarded as acceptable if PRD $\leq$ 9% [9].

In addition, the reconstructing efficiency was evaluated by the reconstructing time (RT).

The evaluation indices of PRD and RT were influenced by the signal compression ratio (CR), which was defined as:

$$CR = \frac{M}{N} \qquad (2)$$

where $N = 3600 = 10s \times 360Hz$ represents the length of ECG episode and M represents the number of compressed signal.

The smaller CR was, less information reserved, thus inducing a larger PRD value while a smaller RT value. We evaluated the performances of PRD and RT indices under the different CR values, aiming to determine the suitable CR values for different recovery algorithms. Since the measurement matrix was randomly generated, thus the evaluation program run 100 times for each 10-s ECG episode. We reported the mean and standard deviation (SD) values for the evaluation indices for each recovery algorithm.

3. Results

Table 2 showed the total results of PRD and RT indices from all 36 10-s ECG episodes when performing the aforementioned four recovery algorithms. For each recovery algorithm, PRD index increased with the decline of CR values from 30% to 70%, i.e., for OMP method, PRD increased from 7.51% to 81.95%; for CoSaMP, it from 6.07% to 71.09%;, for BSBL_BO, it from 1.75% to 15.33% and for BSBL_EM, it from 1.79% to 38.09%. The corresponding RT decreased respectively from 1.50 s to 1.27 s for OMP, from 8.31 s to 0.19 s for CoSaMP, from 3.06 s to 1.83 s for BSBL_BO and from 2.28 s to 1.04 s for BSBL_EM.

To clearly present the reconstructing performances, Figure 2 plots the corresponding error bar results. Figure 2 (A) showed that compared with OMP and CoSaMP methods, BSBL_BO and BSBL_EM methods had smaller PRD values under the same CR level. A threshold of PRD ≤ 9% was usually used for evaluating the reconstructed ECG signal as acceptable signal for the signal compressing. To achieve this goal, OMP method needed at least a 55% CR, CoSaMP needed even higher a 65% CR. However, for the Bayesian learning-based methods, BSBL_BO only needed a 35% CR and BSBL_EM needed a 40% CR. The yellow dotted line showed the CR threshold for acceptable signal reconstruction. What's more, the smaller SD values in BSBL_BO and BSBL_EM methods also indicated the stability of the Bayesian learning-based methods.

As to RT, Figure (B) showed that OMP, BSBL_BO and BSBL_EM methods had similar slightly decreased trends with the decline of CR values whereas CoSaMP showed a quick decreased trend. CoSaMP method has the longest RT values during the high CR levels while BSBL_BO method had the longest RT results during the small CR levels. Figure 3 gives an example of the reconstructed ECG waveforms under the CR value of 45%. The red lines represent the original 1-s ECG signal, and the blue lines represents the corresponding reconstructed signal using the four recovery algorithms respectively. How much these two lines overlapped demonstrates how good the reconstruction was. It is clear that BSBL_BO and BSBL_EM methods achieved acceptable reconstructed signal while OMP and CoSaMP methods had obvious reconstruction errors.

Table 2. Total results of PRD and RT indices from all 36 10-s ECG episodes when performing the aforementioned four recovery algorithms.

CR	PRD (%)				RT (s)			
	OMP	CoSaMP	BSBL_BO	BSBL_EM	OMP	CoSaMP	BSBL_BO	BSBL_EM
70%	7.51±0.52	6.07±0.30	1.75±0.09	1.79±0.06	1.50±0.01	8.31±0.73	3.06±0.15	2.28±0.14
65%	7.78±0.66	8.33±0.41	2.15±0.12	2.16±0.08	1.54±0.56	6.32±0.70	2.97±0.14	2.09±0.10
60%	8.21±0.69	10.71±3.73	2.63±0.12	2.56±0.10	1.49±0.51	4.63±0.54	2.79±0.36	2.07±0.11
55%	8.90±1.09	15.79±0.78	3.23±0.17	3.03±0.11	1.47±0.44	2.99±0.21	2.54±0.10	1.95±0.22
50%	10.73±3.32	19.83±1.67	4.04±0.20	3.57±0.12	1.38±0.23	2.29±0.15	2.24±0.10	1.58±0.12
45%	23.53±15.10	29.57±3.84	4.96±0.24	4.76±0.22	1.34±0.18	1.36±0.10	2.08±0.11	1.42±0.08
40%	49.01±14.62	49.63±11.11	6.29±0.29	8.63±0.86	1.31±0.22	0.73±0.05	1.79±0.10	1.31±0.07
35%	68.70±9.62	63.08±7.67	8.49±0.57	20.71±2.60	1.28±0.08	0.30±0.04	1.61±0.07	1.15±0.08
30%	81.95±10.51	71.09±7.98	15.33±2.84	38.09±2.81	1.27±0.24	0.19±0.02	1.83±0.59	1.04±0.07

4. Conclusions

In this study, we have compared the performances of four commonly used recovery algorithms. We concluded that BSBL_BO and BSBL_EM method were more stable and efficient for CS-based ECG compressing and had better performances than OMP and CoSaMP methods. These two Bayesian learning-based methods can save more resources and reduce the burden of sampling, storing and transformation process of hardware facilities. Specifically, BSBL_BO had the best PRD performance while BSBL_EM achieved best RT results.

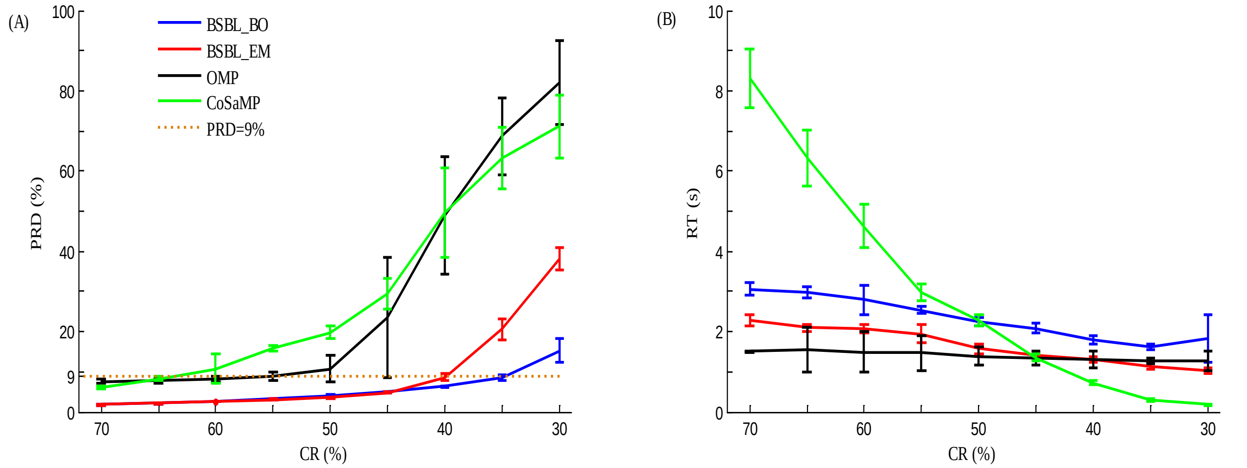

Figure 2. Comparison of reconstruction quality among these four recovery algorithms. (A) Curves of PRD change as CR. (B) Curves of RT change as CR.

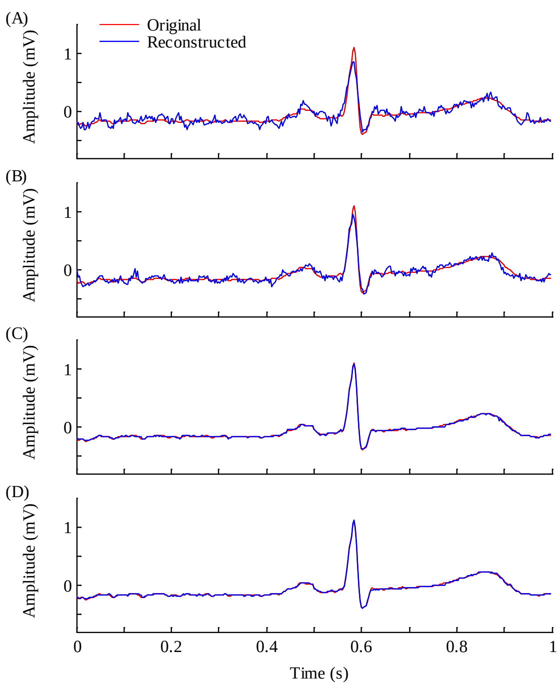

Figure 3. Example of the reconstructed ECG waveforms (1 s) using the four recovery algorithms respectively under the CR value of 45%: (A) CoSaMP method with PRD=29.57%, (B) OMP method with PRD=23.53%, (C) BSBL_BO method with PRD=4.96% and (D) BSBL_EM method with PRD=4.76%.

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Address for correspondence.

Shoushui Wei
School of Control Science and Engineering
Shandong University
17923 Jingshi Road, Jinan, China 250061
E-mail: sswei@sdu.edu.cn