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Research Article

Compressed Sensing Based on the Characteristic Correlation of ECG in Hybrid Wireless Sensor Network

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Hybrid wireless sensor network made up of wireless body area networks (WBANs) and cellular network provides support for telemedicine. In order to facilitate early diagnosis and treatment, WBANs collect and transmit crucial biomedical data to provide a continuous health monitoring by using various biomedical wireless sensors attached on or implanted in the human body. And then, collected signals are sent to a remote data center via cellular network. One of the features of WBAN is that its power consumption and sampling rate should be restricted to a minimum. Compressed sensing (CS) is an emerging signal acquisition/compression methodology which offers a prominent alternative to traditional signal acquisition. It has been proved that the successful recovery rate of multiple measurement vectors (MMV) model is higher than the single measurement vector (SMV) case. In this paper, we propose a simple algorithm of transforming the SMV model into MMV model based on the correlation of electrocardiogram (ECG), such that the MMV model can be used for general ECG signals rather than only several special signals. Experimental results show that its recovery quality is better than some existing CS-based ECG compression algorithms and sufficient for practical use.

1. Introduction

Remote medical monitoring system helps doctors to remotely monitor the patient's medical data and feedback in time. The whole system of hybrid wireless sensor network model composed of a WBAN [1] and cellular network is shown in Figure 1. For providing real-time health monitoring, devices must integrate seamlessly into the patient's life and do not interfere with daily activities. In order to offer continuously sensing, processing, and early detection, an ECG sensor is used to collect and compress ECG signals. And then real-time ECG data are sent to a personal terminal (e.g., smartphone or iPad). Wi-Fi, CDMA, 3G, or other cellular networks can be utilized for transmitting the ECG data to a remote data center. In the terminal, the original ECG signals are recovered by computers for further diagnosis. By utilizing continuous remote heart monitoring, it can enhance ability of prevention and early diagnosis, elevate the personalized service quality, and improve patient autonomy, mobility, and security.

Most of the power in an ECG sensor is consumed when the RF power amplifier transmits data to the personal terminal. A large amount of real-time ECG data is collected, stored, and transmitted. Thus, it is desirable to decrease the amount of data to be transmitted to reduce energy consumption. The WBAN-enabled ECG monitors have three important design constraints [2]. The most important one is energy constrain [3]. As far as possible, it should reduce the energy consumption because of the limited battery life. Due to the low communication capacity of ultralow power short-haul radio devices, another constraint is that transmitted ECG data should be compressed to a large extent. The third constraint is hardware costs. Low hardware costs are easier to make a wireless remote medical monitoring system economically viable and accepted by individual customers. This means that data compression (on sensors) should have low complexity.

Although conventional data compression methodologies [4, 5] are effective in data compression, one still needs to acquire a large amount of data at the Nyquist rate that is compressed later. It consumes significant energy and cannot reduce device cost. As an emerging data acquisition/compression methodology, compressed sensing is a promising program to meet these constraints. Some scholars have applied CS algorithm to ECG compression and have

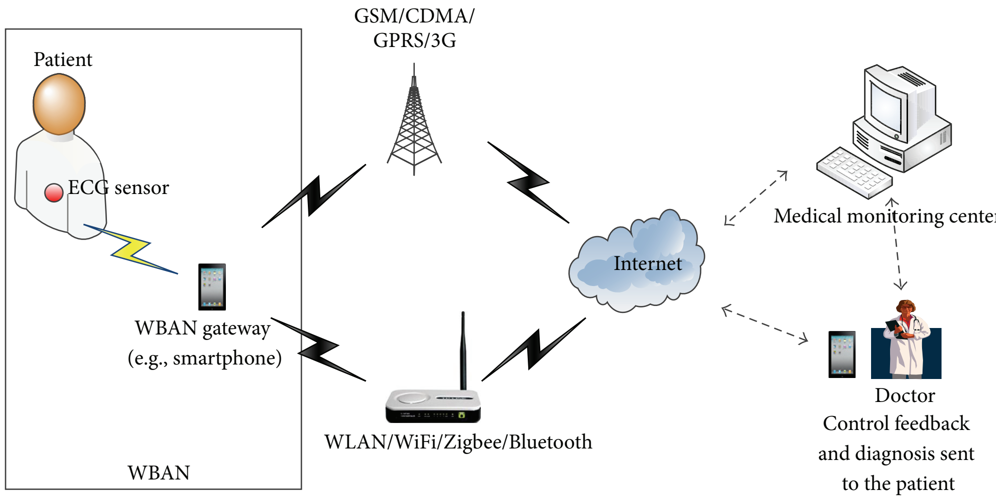


Figure 1: The whole system of hybrid wireless sensor network model.

achieved good effect [6–9]. The application of CS before the transmission of typical ECG signals achieves compression of the data with a proportionate saving in energy. In [6], Mamaghanian et al. proposed a novel approach based on the CS framework to deal with the challenge of ultralow power embedded compression of ECG signals. In [7], several design considerations of CS acquisition systems for ECG and EMG biosignals are presented by Dixon et al. In [8], a dynamic compression (DC) scheme is proposed to tackle the challenge of ultralow power and real-time wireless ECG application. And, in [9], Ravelomanantsoa et al. proposed a simple and efficient CS encoder device used to measure signals within sensor nodes of a WBAN. Nevertheless, a discrete-time ECG signal exhibits a high degree of correlation between its successive samples. Such a signal can be better recovered by using an algorithm that encourages temporal correlation. Recently, so called block sparse Bayesian learning bound-optimization (BSBL-BO) algorithm has been effectively applied for the reconstruction of ECG signals [10]. Inspired by these applications in ECG processing, this paper proposes a novel CS algorithm based on the temporal correlation of ECG, which can transform the SMV model into MMV model for enhancing the quality of the reconstructed signal.

Higher quality of reconstructed ECG signals can better help the doctor to understand the patient's heart function. An ECG signal shows a high degree of correlation between its continuous samples. In this paper, ECG signal is firstly divided into several segments by the presented segmentation algorithm. And then, one-dimension discrete wavelet transform (DWT) is employed to decompose the segmental ECG signals into sparse data. Secondly, the sparse signals are integrated into the solution matrix. In this way, the SMV case is transformed into MMV model. It has been proved that the successful recovery rate of MMV model is higher than the SMV case. The proposed transforming method is relatively simple and of low complexity in encoder (sensor nodes) and consistent with low power consumption of actual system requirements.

The rest of this paper is organized as follows. First, Section 2 introduces the CS theory. And Section 3 describes the characteristics of ECG signals and presents the segmentation algorithm. The framework of transforming SMV model into MMV model is shown in Section 4. Analytical and simulation results based on the MIT-BIH arrhythmia database are shown in Section 5. Finally, Section 6 concludes the paper.

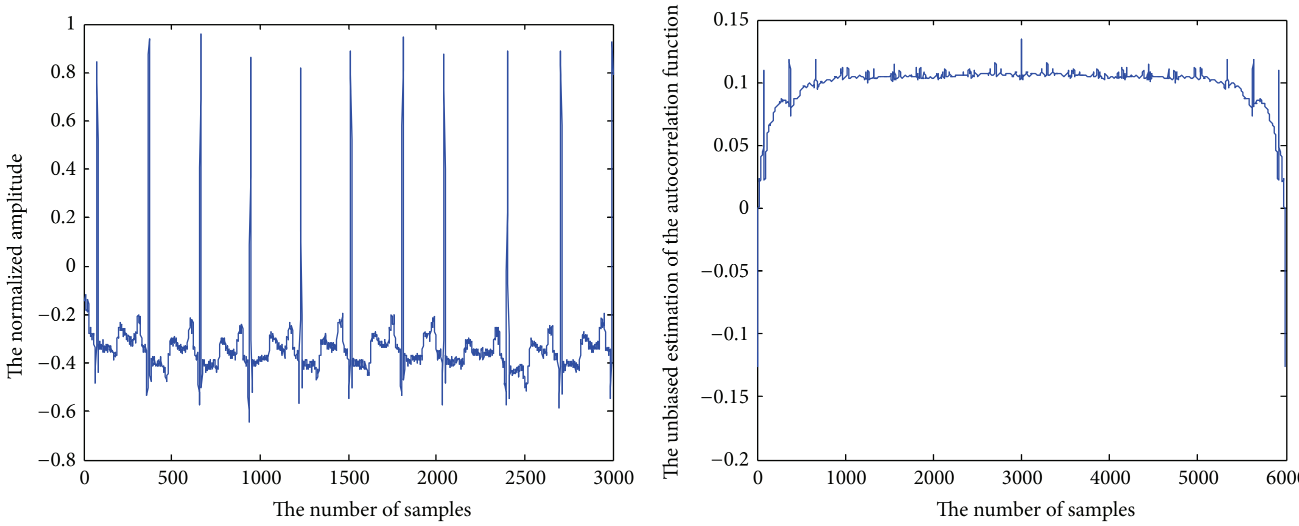
2. Compressed Sensing Background

Compressed sensing [11–13] solves the reconstruction of a sparse signal which contains a few nonzero elements, from its linear measurements, less than the number of unknowns. Many of algorithms have been developed to resolve this underdetermined inverse problem with sparsity prior on the solution. Suppose $\boldsymbol{\omega} \in R^{N\times 1}$ is an unknown source vector with only a few nonzero entries. One wishes to determine $\boldsymbol{\omega}$ via the noisy measurements given by

$$\mathbf{t} = \boldsymbol{\Phi}\boldsymbol{\omega} + \mathbf{v}, \tag{1}$$

where $\mathbf{t} \in R^{M\times 1}$ is an available measurement vector, $\boldsymbol{\Phi} \in R^{M\times N}$ $(M \ll N)$ is a known measurement matrix, and any M columns of $\boldsymbol{\Phi}$ are linearly independent (i.e., satisfies the restricted isometry property (RIP) condition [14]), and $\mathbf{v} \in R^{M\times 1}$ is an unknown noise vector. Furthermore, if signal $\mathbf{x}$ is not sparse itself, it may be represented as a sparse signal in some orthonormal basis $\boldsymbol{\Psi}$; that is, $\boldsymbol{\omega} = \boldsymbol{\Psi}^T\mathbf{x}$ is a sparse signal.

Estimating the sparsest solution vector in accordance with the SMV model (1) is generally an NP-hard problem [14]. For resolving the problem of sparse signal recovery with SMV, a number of efficient algorithms have been proposed. Typical algorithms include basis pursuit (BP) or l_1-minimization approach [15], orthogonal matching pursuit (OMP) [16], lasso [17], FOCUSS [18], iterative reweighted algorithms [19, 20], and Bayesian algorithm [21, 22].



(a) ECG of record 100

(b) Unbiased estimate of autocorrelation function

Figure 2: ECG of record 100 in MIH-BIH arrhythmia database and its unbiased estimate of autocorrelation function.

In some special applications, such as magnetoencephalography (MEG)/electroencephalography (EEG) source location [23, 24], multivariate regression [25], and direction-of-arrival (DOA) estimation [26], where a sequence of measurement vectors has an identical sparsity pattern, the SMV model (1) has been extended to the multiple measurement vector (MMV) model in [27], given by

$$\mathbf{T} = \mathbf{\Phi}\mathbf{W} + \mathbf{V}, \tag{2}$$

where $\mathbf{T} = [\mathbf{t}_{\cdot 1}, \ldots, \mathbf{t}_{\cdot L}] \in R^{M\times L}$, $\mathbf{W} = [\boldsymbol{\omega}_{\cdot 1}, \ldots, \boldsymbol{\omega}_{\cdot L}] \in R^{N\times L}$, and $\mathbf{V} \in R^{M\times L}$ is an unknown noise matrix. Actually, model (2) can be recognized as an inverse problem either with SMV model when $L = 1$ or with MMV model when $L > 1$. A key assumption in the MMV model is that the indexes of nonzero entries of every column in solution matrix $\mathbf{W}$ are common. Many algorithms have been developed to address the new challenges in this scenario. Thanks to a great deal of solutions for the SMV model, one class of algorithms for solving the MMV problem can be obtained by straightforward extension of the basic SMV approaches. And these algorithms can be roughly divided into greedy algorithms [28, 29], algorithms based on mixed norm optimization [30–32], iteratively reweighted algorithms [27, 33], and Bayesian algorithms [34, 35]. Bayesian methods have obtained lots of concerns since they usually achieve the best recovery performance among the MMV algorithms [36]. The sparse Bayesian learning (SBL) algorithm is firstly introduced to sparse signal recovery for the SMV model by Wipf and Rao [22] and later is extended to the MMV model, deriving the MSBL approach [34]. In this paper, we choose the MSBL algorithm as the recovery approach. Although the successful recovery rate of MMV model is higher than the SMV case, the MMV model is suitable for only several special signals. In this paper, we proposed a transformed method to make the general single ECG signals usable in MMV model.

3. The Correlation Characteristics of ECG Signals and Segmentation Algorithm

In this section, we illustrate the correlation characteristics of ECG signals and give the segmentation algorithm. Wavelet transform as the sparse decomposition has been widely used in CS theory. In this paper, the one-dimension DWT is chosen as the sparsifying basis.

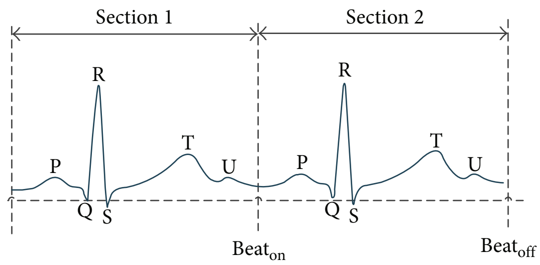
3.1. The Correlation of ECG. The correlation of ECG signal is mainly manifested in the sampling spots and cardiac cycle.

3.1.1. The Correlation between Sampling Points. ECG signal is generated by myocardial continuous motion; thus it has a strong correlation between sample points. As shown in Figure 2(a), we select ECG of record 100 in MIH-BIH arrhythmia database as an example and calculate its unbiased estimate of autocorrelation function:

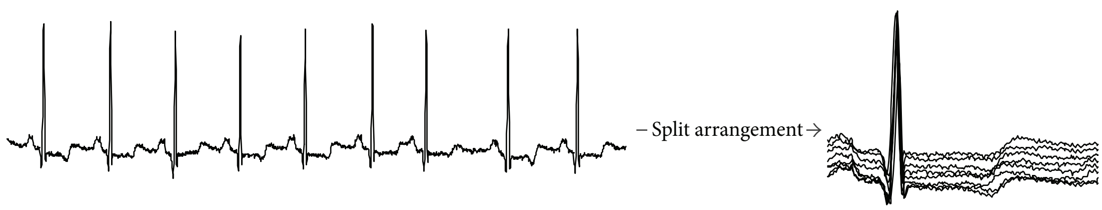
$$R_{xx,\,\mathrm{unbiased}}(m) = \frac{1}{N-|m|} R_{xx}(m), \tag{3}$$

where $N = 3000$ is the number of samples. As can be seen from Figure 2(b), the ECG signal has high correlation between sampling points, and cyclical peak of the autocorrelation function precisely illustrates the pseudo-periodicity of ECG signal; that is, ECG waveform of each cardiac cycle is similar. This conclusion can be more intuitive as seen from Figure 2(a).

3.1.2. The Correlation between the Cardiac Cycles. Typically, long-term monitoring of ECG signals can present more obvious periodicity after pretreatment, such as removal of baseline drift, power frequency interference, and high frequency noise. It can be seen from Figure 2(a) that the shape, location, and duration of P wave, QRS complex wave, and T wave are similar within the cardiac cycle.



(a) Beat segmentation



(b) The specific segmentation process

FIGURE 3: The specific segmentation process of ECG signal.

3.2. Segmentation Algorithm. Since the ECG is a one-dimensional signal, it is firstly transformed into two-dimensional data form in order to implement multiple measurements. The most notable feature of a cardiac cycle is the QRS complex. So we detect the entire QRS complex firstly and then segment the ECG signal on the premise of alignment QRS complex to make each section represent a cardiac cycle. It is important to note that each cardiac cycle length is not strictly equal; therefore, we find out the longest heartbeat cycle firstly, and other sections are complemented by average value according to longest length. The segmentation algorithm divides the ECG signal into beats (complexes). The specific process is shown in Figure 3.

We select ECG of record 100 as a test example. The number of samples $N = 1200$, and then the ECG signal is divided into four sections. Every section is decomposed by 5-scale one-dimensional DWT. Figure 4 shows the wavelet coefficients $\mathbf{c}_1$, $\mathbf{c}_2$, $\mathbf{c}_3$, and $\mathbf{c}_4$. As can be seen from the figure, the variation of the wavelet coefficients is very similar (almost identical). This feature is very important for transforming the SMV model into MMV model. A key assumption in the MMV model is that the indexes of nonzero entries in every column of solution matrix are identical. Inspired by this nature, the wavelet coefficients can generate the matrix $\mathbf{W}$ which meets the requirements of MMV model.

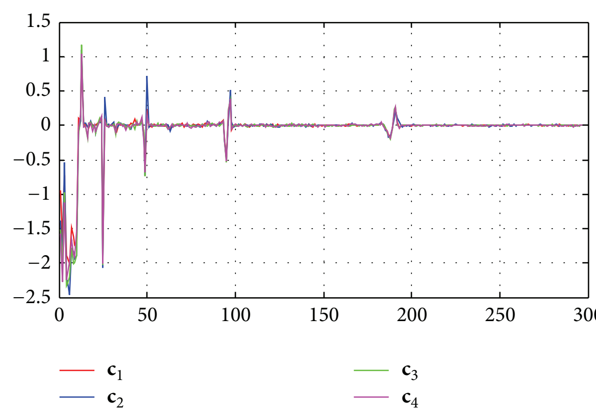


FIGURE 4: The wavelet coefficients $\mathbf{c}_1$, $\mathbf{c}_2$, $\mathbf{c}_3$, and $\mathbf{c}_4$.

4. The Proposed Framework of Transforming SMV Model into MMV Model

In this section, we give the approach of transforming SMV model into MMV model. The proposed framework is shown in Figure 5. Our modeling instructions are summarized as follows.

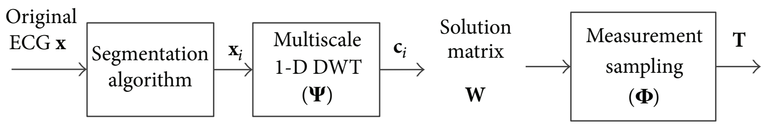
(i) ECG Segmentations. The ECG signal $\mathbf{x}$ is divided into L sections $\mathbf{x}_i$ ($i = 1, 2, \ldots, L$) with the length of n by the proposed algorithm as shown in Section 3.

(ii) DWT. The segmentation $\mathbf{x}_i$ is sparsely represented using multiscale one-dimension DWT, and the wavelet coefficient $\mathbf{c}_i$ is sparse.

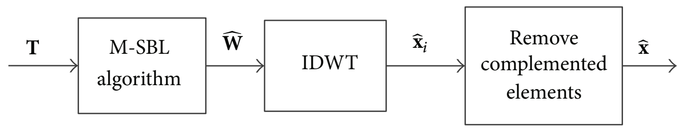
(iii) Transform SMV Model into MMV Model. The wavelet coefficients $\mathbf{c}_i$ are integrated into a solution matrix $\mathbf{W}$. That is,

$$\mathbf{W} = \begin{bmatrix} \mathbf{c}_1 & \mathbf{c}_2 & \cdots & \mathbf{c}_L \end{bmatrix} = \begin{bmatrix} c_1^1 & c_2^1 & \cdots & c_L^1 \\ c_1^2 & c_2^2 & \cdots & c_L^2 \\ \vdots & \vdots & \cdots & \vdots \\ c_1^n & c_2^n & \cdots & c_L^n \end{bmatrix}_{n \times L}. \tag{4}$$

(iv) Measurement. The random Gaussian matrix $M \times n$ ($M \ll n$) $\mathbf{\Phi}$ is employed in measurement sampling of the solution matrix $\mathbf{W}$ to yield a sampled matrix $\mathbf{T} = \mathbf{\Phi}\mathbf{W} + \mathbf{V}$.



(a) Encoder



(b) Decoder

Figure 5: The proposed framework of transforming SMV model into MMV model.

Table 1: PRD and reconstructions signal quality class.

PRD	Reconstructed signal quality
0~2%	"Very good" quality
2~9%	"Good" quality
≥9%	Impossible to determine the quality

(v) Recovery. The decoder firstly recovers the solution matrix $\widehat{\mathbf{W}}$ by the MMV algorithms, for example, M-SBL. We can use the inverse DWT to recover the original segmentations $\hat{\mathbf{x}}_i$. Removing the previously complemented elements in each of the sections $\hat{\mathbf{x}}_i$, finally, we can obtain the reconstructed ECG $\hat{\mathbf{x}}$.

5. Simulations and Analyses

The performance of the proposed transforming algorithm has been evaluated by simulations. We employ two most widely used performance metrics that are compression ratio (CR) and percentage root-mean-square difference (PRD) [37]. CR is defined as

$$\mathrm{CR} = \frac{b_{\mathrm{orig}} - b_{\mathrm{comp}}}{b_{\mathrm{orig}}} \times 100, \tag{5}$$

where b_{orig} and b_{comp} represent the number of bits required for the original and compressed signals, respectively. Here CR is the compressibility of the ECG data, and it also indicates the ratio of radio energy consumption saving [38]. The PRD, as well as associated SNR, quantifies the percent error between the original signal vector $\mathbf{x}$ and the reconstructed signal vector $\hat{\mathbf{x}}$:

$$\mathrm{PRD} = \frac{\|\mathbf{x} - \hat{\mathbf{x}}\|_2}{\|\mathbf{x}\|_2} \times 100, \tag{6}$$

$$\mathrm{SNR} = -20\log_{10}(0.01 \times \mathrm{PRD}). \tag{7}$$

A relationship between PRD and the diagnostic distortion is established in [39]. Table 1 lists the resulting classes of very good quality, good quality, uncertain quality, and the corresponding PRDs.

In this paper, the MIT-BIH arrhythmia database [40] is used to validate the compression performance of the proposed scheme. MIT-BIH arrhythmia database is most commonly used for study of ECG signal compression algorithms, and it consists of two-lead ambulatory ECG recordings from 47 people. Because lead II is most commonly used in ambulatory ECG application, all results in this paper are based on the ECG signals of lead II.

5.1. Performance Analysis of Proposed MMV Model. Two types of heartbeats of 6 s ($N = 2161$) ECG raw signals are tested in this paper. Normal beat records 100, 103, 114, and 234 and left bundle branch block beat records 207 and 214 are processed by the proposed algorithm as shown in Section 4. We choose the 5-scale DWT as the sparsifying basis $\boldsymbol{\Psi}$ for each section and select the common symmetric wavelet function "sym1" as the wavelet basis. When the absolute value of wavelet coefficient is less than a very small value ε ($\varepsilon > 0$), we consider that it is close to zero. In this paper, we set $\varepsilon = 10^{-2}$. The Gaussian random matrix $\boldsymbol{\Phi}$ is employed in measurement sampling of the sparse coefficients. The CR and PRD are calculated by (5) and (6). The recovered ECG signals of using M-SBL algorithm are shown in Figure 6. It is observed that the PRDs of all records are less than 9% and that the proposed method can achieve good quality ECG signal recovery and guarantee nondistortion diagnosis.

5.2. Performance Comparison with Other Methods. This paper numerically simulated the ECG compression with the $\mathrm{CS_{BP}}$ [6], BSBL-BO [10], and DC [8] schemes for comparison of performance with the proposed approach. We choose the first 512 points of MIT-BIH arrhythmia database record 100 as the test signal. The resulting relationships of the signal distortion and compression efficiency are shown in Figure 7. The recovered quality of proposed algorithm achieves lower PRD and higher SNR than compared algorithms at the same CR. What is more, with the increase of CR, the increased rate of PRD is much lower than the compared methods. It indicates that the proposed method has more stable performance for bigger CR conditions.

Meanwhile, the comparisons of time consumption are shown in Table 2. Unfortunately, the time consumption of proposed algorithm is higher than the compared algorithms. However, the time consumption of encoder (on sensors) is not great. This is precisely in accordance with the requirements of sensor networks.

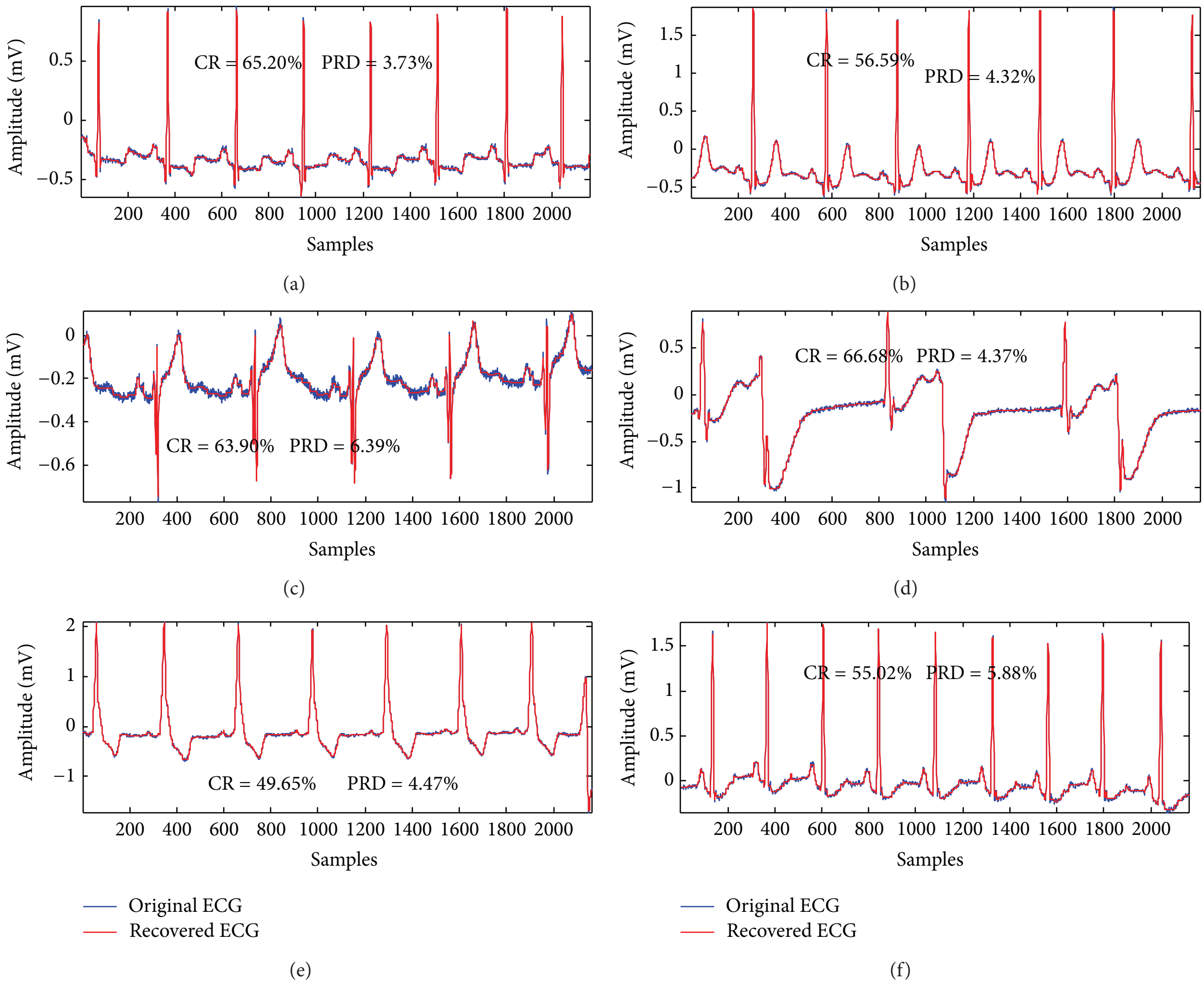
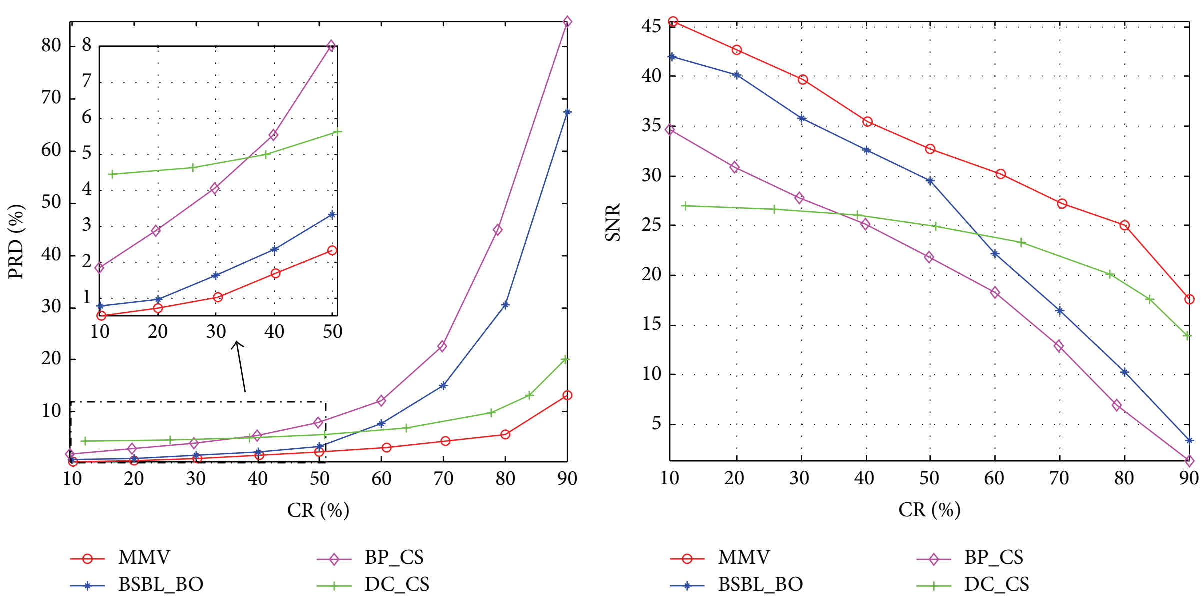


Figure 6: Results of visual inspection of (a) record 100, (b) record 103, (c) record 114, (d) record 207, (e) record 214, and (f) record 234.



(a) Comparison of the output PRD

(b) Comparison of the output SNR

Figure 7: Comparison of the output (a) PRD and (b) SNR versus CR of the MATLAB.

Table 2: The comparisons of time consumption.

Time consumption (ms)	Different algorithms			
	MMV	DC_CS [8]	BP_CS [6]	BSBL_BO [10]
Encoder	12	2	9	4
Decoder	230	12	70	26
Total	242	14	79	30

6. Conclusion

In this paper, we addressed a simple algorithm of transforming the SMV model into the MMV model by exploiting the correlation of ECG signal, such that the MMV model can be used for general ECG signals instead of only several special signals. Based on this framework, the proposed algorithm leads to higher reconstructed quality compared with some existing CS algorithms. Although the time consumption of proposed algorithm is higher, the time consumption of encoder is not great. Extensive experiments have shown that the proposed algorithms have superior performance for general ECG signals.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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References

[1] H. Cao, V. Leung, C. Chow, and H. Chan, "Enabling technologies for wireless body area networks: a survey and outlook," *IEEE Communications Magazine*, vol. 47, no. 12, pp. 84–93, 2009.

[2] Z. L. Zhang, T.-P. Jung, S. Makeig, and B. D. Rao, "Compressed sensing of EEG for wireless telemonitoring with low energy consumption and inexpensive hardware," *IEEE Transactions on Biomedical Engineering*, vol. 60, no. 1, pp. 221–224, 2012.

[3] A. Milenković, C. Otto, and E. Jovanov, "Wireless sensor networks for personal health monitoring: issues and an implementation," *Computer Communications*, vol. 29, no. 13-14, pp. 2521–2533, 2006.

[4] M. S. Manikandan and S. Dandapat, "Quality controlled wavelet compression of ECG signals by WEDD," in *Proceedings of the International Conference on Computational Intelligence and Multimedia Applications (ICCIMA '07)*, pp. 581–586, Tamil Nadu, Indian, December 2007.

[5] Z. Lu, D. Y. Kim, and W. A. Pearlman, "Wavelet compression of ECG signals by the set partitioning in hierarchical trees algorithm," *IEEE Transactions on Biomedical Engineering*, vol. 47, no. 7, pp. 849–856, 2000.

[6] H. Mamaghanian, N. Khaled, D. Atienza, and P. Vandergheynst, "Compressed sensing for real-time energy-efficient ECG compression on wireless body sensor nodes," *IEEE Transactions on Biomedical Engineering*, vol. 58, no. 9, pp. 2456–2466, 2011.

[7] A. M. R. Dixon, E. G. Allstot, D. Gangopadhyay, and D. J. Allstot, "Compressed sensing system considerations for ECG and EMG wireless biosensors," *IEEE Transactions on Biomedical Circuits and Systems*, vol. 6, no. 2, pp. 156–166, 2012.

[8] K. Luo, J. Q. Li, and J. F. Wu, "A dynamic compression scheme for energy-efficient real-time wireless electrocardiogram biosensors," *IEEE Transactions on Instrumentation and Measurement*, vol. 63, no. 9, pp. 2160–2169, 2014.

[9] A. Ravelomanantsoa, H. Rabah, and A. Rouane, "Simple and efficient compressed sensing encoder for wireless body area network," *IEEE Transactions on Instrumentation and Measurement*, vol. 63, no. 12, pp. 2973–2982, 2014.

[10] B. Liu, Z. L. Zhang, and G. Xu, "Energy efficient telemonitoring of physiological signals via compressed sensing: a fast algorithm and power consumption evaluation," *Biomedical Signal Processing and Control*, vol. 11, pp. 80–88, 2014.

[11] D. L. Donoho, "Compressed sensing," *IEEE Transactions on Information Theory*, vol. 52, no. 4, pp. 1289–1306, 2006.

[12] Y. Tsaig and D. L. Donoho, "Extensions of compressed sensing," *Signal Processing*, vol. 86, no. 3, pp. 549–571, 2006.

[13] E. J. Candès, J. Romberg, and T. Tao, "Robust uncertainty principles: exact signal reconstruction from highly incomplete frequency information," *IEEE Transactions on Information Theory*, vol. 52, no. 2, pp. 489–509, 2006.

[14] E. J. Candès, "The restricted isometry property and its implications for compressed sensing," *Comptes Rendus Mathematique*, vol. 346, no. 9-10, pp. 589–592, 2008.

[15] S. S. Chen, D. L. Donoho, and M. A. Saunders, "Atomic decomposition by basis pursuit," *SIAM Journal on Scientific Computing*, vol. 20, no. 1, pp. 33–61, 1998.

[16] Y. C. Pati, R. Rezaiifar, and P. S. Krishnaprasad, "Orthogonal matching pursuit: recursive function approximation with applications to wavelet decomposition," in *Proceedings of the 27th Asilomar Conference on Signals, Systems & Computers*, vol. 1, pp. 40–44, IEEE, Pacific Grove, Calif, USA, November 1993.

[17] R. Tibshirani, "Regression shrinkage and selection via the lasso," *Journal of the Royal Statistical Society. Series B. Methodological*, vol. 58, no. 1, pp. 267–288, 1996.

[18] I. F. Gorodnitsky and B. D. Rao, "Sparse signal reconstruction from limited data using FOCUSS: a re-weighted minimum norm algorithm," *IEEE Transactions on Signal Processing*, vol. 45, no. 3, pp. 600–616, 1997.

[19] E. J. Candes, M. B. Wakin, and S. P. Boyd, "Enhancing sparsity by reweighted l_1 minimization," *The Journal of Fourier Analysis and Applications*, vol. 14, no. 5-6, pp. 877–905, 2008.

[20] R. Chartrand and W. Yin, "Iteratively reweighted algorithms for compressive sensing," in *Proceedings of the IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP '08)*, pp. 3869–3872, Las Vegas, Nev, USA, April 2008.

[21] M. E. Tipping, "Sparse Bayesian learning and the relevance vector machine," *The Journal of Machine Learning Research*, vol. 1, no. 3, pp. 211–244, 2001.

[22] D. P. Wipf and B. D. Rao, "Sparse Bayesian learning for basis selection," *IEEE Transactions on Signal Processing*, vol. 52, no. 8, pp. 2153–2164, 2004.

[23] D. Wipf and S. Nagarajan, "A unified Bayesian framework for MEG/EEG source imaging," *NeuroImage*, vol. 44, no. 3, pp. 947–966, 2009.

[24] R. Zdunek and A. Cichocki, "Improved M-FOCUSS algorithm with overlapping blocks for locally smooth sparse signals," *IEEE Transactions on Signal Processing*, vol. 56, no. 10, pp. 4752–4761, 2008.

[25] G. Obozinski, M. J. Wainwright, and M. I. Jordan, "Support union recovery in high-dimensional multivariate regression," *The Annals of Statistics*, vol. 39, no. 1, pp. 1–47, 2011.

[26] G. Tang and A. Nehorai, "Performance analysis for sparse support recovery," *IEEE Transactions on Information Theory*, vol. 56, no. 3, pp. 1383–1399, 2010.

[27] S. F. Cotter, B. D. Rao, K. Engan, and K. Kreutz-Delgado, "Sparse solutions to linear inverse problems with multiple measurement vectors," *IEEE Transactions on Signal Processing*, vol. 53, no. 7, pp. 2477–2488, 2005.

[28] J. A. Tropp, A. C. Gilbert, and M. J. Strauss, "Algorithms for simultaneous sparse approximation. Part I: greedy pursuit," *Signal Processing*, vol. 86, no. 3, pp. 572–588, 2006.

[29] K. Lee and Y. Bresler, "Subspace-augmented MUSIC for joint sparse recovery with any rank," in *Proceedings of the IEEE Sensor Array and Multichannel Signal Processing Workshop*, pp. 205–208, Jerusalem, Israel, October 2010.

[30] S. Negahban and M. J. Wainwright, "Simultaneous support recovery in high dimensions: benefits and perils of block l_1/l_8-regularization," *IEEE Transactions on Information Technology*, vol. 57, no. 6, pp. 3841–3863, 2011.

[31] J. A. Tropp, "Algorithms for simultaneous sparse approximation. Part II. Convex relaxation," *Signal Processing*, vol. 86, no. 3, pp. 589–602, 2006.

[32] F. R. Bach, "Consistency of the group lasso and multiple kernel learning," *Journal of Machine Learning Research*, vol. 9, pp. 1179–1225, 2008.

[33] D. Wipf and S. Nagarajan, "Iterative reweighted $\ell_1$and ℓ_2 methods for finding sparse solutions," *IEEE Journal on Selected Topics in Signal Processing*, vol. 4, no. 2, pp. 317–329, 2010.

[34] D. P. Wipf and B. D. Rao, "An empirical Bayesian strategy for solving the simultaneous sparse approximation problem," *IEEE Transactions on Signal Processing*, vol. 55, no. 7, part 2, pp. 3704–3716, 2007.

[35] D. P. Wipf, B. D. Rao, and S. Nagarajan, "Latent variable Bayesian models for promoting sparsity," *IEEE Transactions on Information Theory*, vol. 57, no. 9, pp. 6236–6255, 2011.

[36] Z. L. Zhang and B. D. Rao, "Sparse signal recovery with temporally correlated source vectors using sparse bayesian learning," *IEEE Journal on Selected Topics in Signal Processing*, vol. 5, no. 5, pp. 912–926, 2011.

[37] S. M. S. Jalaleddine, C. G. Hutchens, R. D. Strattan, and W. A. Coberly, "ECG data compression techniques—a unified approach," *IEEE Transactions on Biomedical Engineering*, vol. 37, no. 4, pp. 329–343, 1990.

[38] T. Yang, L. Barolli, M. Ikeda, A. Durresi, and F. Xhafa, "Network energy consumption in ad-hoc networks under different radio models," in *Proceedings of the 13th International Conference on Parallel and Distributed Systems (ICPADS '07)*, pp. 1–8, December 2007.

[39] Y. Zigel, A. Cohen, and A. Katz, "The weighted diagnostic distortion (WDD) measure for ECG signal compression," *IEEE Transactions on Biomedical Engineering*, vol. 47, no. 11, pp. 1422–1430, 2000.

[40] MIT-BIH arrhythmia database, 2005, http://www.physionet.org/physiobank/database/mitdb/.