ECG Signal Compression for Low-power Sensor Nodes Using Sparse Frequency Spectrum Features

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***Abstract*—Biosignals often require high data transmission in real-time monitoring and visualization. Low-power techniques are always desirable for designing sustainable wireless sensor nodes. Signal compression techniques provide a promising solution in developing low-power wireless sensor nodes as it can significantly reduce the amount of data transmitted via power-demanding wireless transmission and thus greatly lower the energy consumption of sensor nodes. In this study, we develop a new approach for ECG signal compression on low-power ECG sensor nodes by leveraging sparse features of ECG signals in frequency domain. The experimental results show that our method has better compression performance which achieves the average compression ratio (CR) of 65.91 with the comparable RMSE of no more than 5% than the state-of-the-art that can achieve the CR of around 40 with the same level error rate. The promising compression performance of the proposed method provides a feasible solution to achieve ultra-low power consumption for wireless ECG sensor node design.**

Keywords—Signal compression; ECG sensor node; variational mode decomposition; wireless communication.

I. INTRODUCTION

With the emerging technology of continuous daily healthcare monitoring via Wireless Body Area Network (WBAN), techniques of reducing energy consumption of wireless sensor nodes are highly desirable due to the limited battery life [1]. ECG signal compression techniques provide a promising solution for reducing energy consumption, boosting the battery life, and enabling the continuous daily monitoring of low-power wireless sensor nodes [2]. Typically, ECG compression methods utilize the intrinsic features of ECG signals for eliminating the redundancies and thus compress the signals for wireless transmission. The intrinsic features can be obtained via analyzing the waveform features, transforming to other domains such as discrete cosine transform (DCT) [3] and discrete wavelet transform (DWT) [4], and extracting dominant features such as Compressed Sensing (CS) [5] and neural networks [6]. Generally, the ECG compression methods used for low-power ECG sensor nodes aim to increase the compression ratio (CR), which minimizes the required data size for wireless transmission and thus reduces power consumption. On the other hand, the compression methods should achieve an acceptable quality for recovering the compressed ECG signals and also be efficient in computation energy consumption and algorithm complexity.

In this study, we propose a new approach for ECG signal compression for low-power ECG sensor nodes by leveraging sparse features of ECG signals in frequency domain. Unlike other compression methods such as CS that use a sensing matrix for sparse feature sampling and thus compressing the ECG signals, our method directly extracts the sparse features of ECG signals in frequency domain and further compresses the ECG signals with these pre-extracted sparse features. Since the number of sparse features is limited, the compression performance of this method can be significantly improved. In addition, the lightweight preprocessing and compressing process of our study enables a relatively low computation complexity and thus improves the energy efficiency. The performance is thoroughly evaluated and compared with the state-of-the-art.

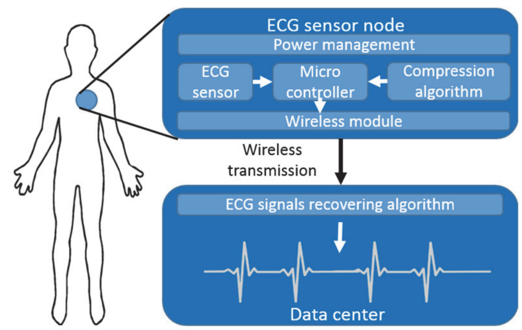


Fig. 1 A typical scheme for ECG compression on sensor nodes.

II. PROPOSED ECG COMPRESSION METHOD

A. Framework

The proposed ECG compression method is based on the scenario as shown in Fig. 1 that the ECG signals are collected with an ECG sensor node that compresses the monitoring signals within the node and further transmits the compressed data wirelessly to the data center where the ECG signals are reconstructed. The driving concept of our method is that the ECG signals can be represented by the linear combination of its dominant features. Therefore, the key point for compression is to find minimum number of dominant features of ECG signals while preserve most of the ECG information. In our method, since the ECG signals are quasi-periodic between adjacent beats, specific segment of ECG signal is extracted as the input ECG segment which is the segment between two subsequent R peaks. The extraction can be performed by identifying the position of R peak through a lightweight QRS detection algorithm. The sparse features of this segment are obtained from frequency domain via Variational Mode Decomposition (VMD) [8] in the

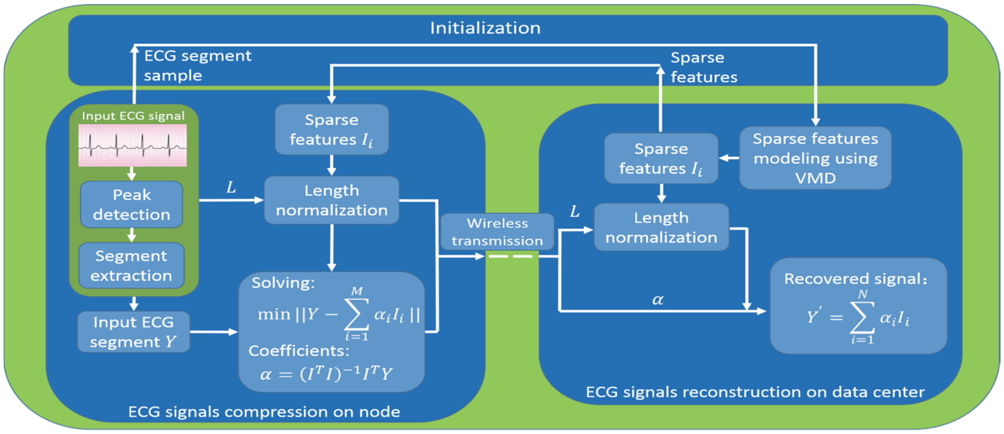


Fig. 2 Proposed ECG compression method

initialization of the method and further stored in the sensor node.

For the compression process, ECG signals are divided into segments by the subsequent R peaks. As the length of each segment is different, the length of the sparse features are normalized to the length of each input segment. The input ECG segments are further represented by the linear combination of the sparse features. Finding the optimal coefficients of the sparse features is exactly the compressing process in which the input ECG segments are compressed to the coefficients. For example, suppose the input ECG segment is with length of 300 samples and the number of sparse features is five, the input ECG segment will be compressed to the five coefficients, which achieves excellent compression performance. For the reconstruction process, the coefficients are transmitted wirelessly from the ECG sensor node to data center for reconstruction with the pre-computed sparse features. The detailed procedures of the proposed ECG compression method as shown in Fig. 2 are explained in the following sections.

B. Initialization and Sparse Feature Modeling

As discussed above, the sparse features of the ECG segment are the bases for compression. In order to find these sparse features, a sample ECG segment is extracted and transmitted to data center for analyzing and creating the sparse features in the initialization part. Figure 3 shows a sample ECG segment and its frequency spectrum from an ECG signal. From the figure, the dominant frequency components of the ECG segment are within the frequnecy range of 0-40 Hz. Since ECG signals are quasi-periodic, each ECG segments will have

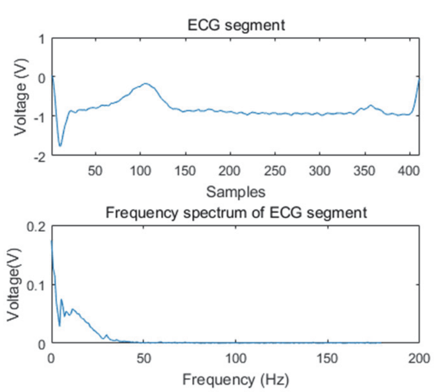


Fig. 3 A sample ECG segment and its frequency spectrum

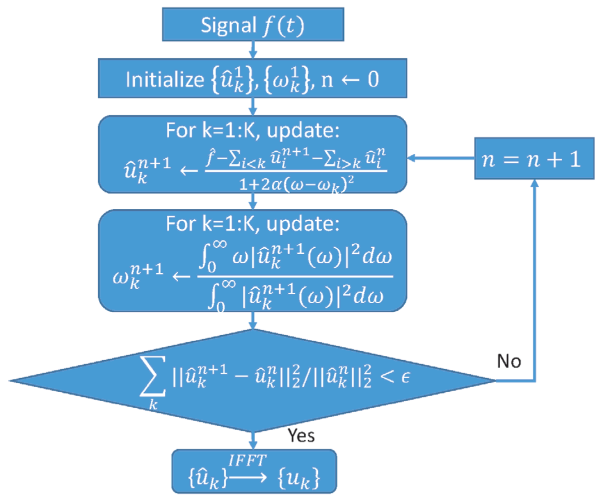


Fig. 4 Algorithm of VMD [8]. $\hat{u}_k$ is the kth frequency component and ω_k is its center frequency. The algorithm outputs K number of sparse frequency components $\hat{u}_k$ with their time domain signals u_k .

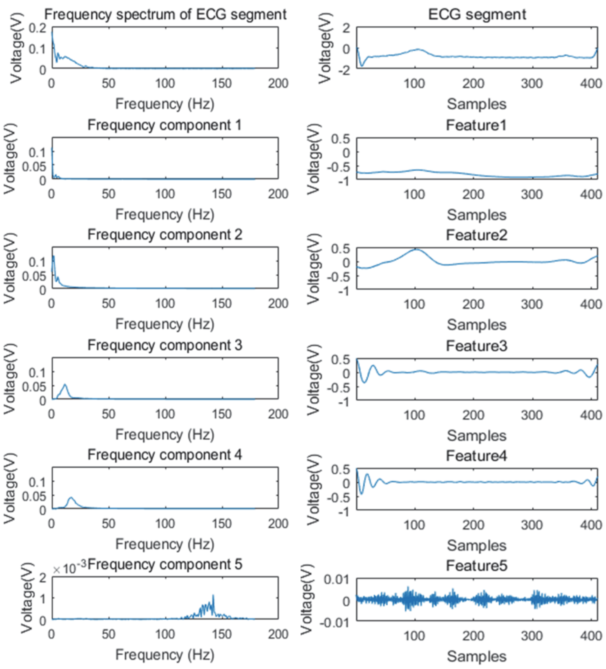
the similar dominant frequency components. Therefore, the frequency feature modeling of one sample ECG segment is possible to be applied for all the ECG segments of the ECG signal.

In order to model these dominant frequency features, we propose to use VMD to construct the sparse frequency components of ECG signals and create the sparse features in time domain. VMD is able to flexibly extract specific number of frequency components from the frequency spectrum of the ECG segment. The extracted frequency components are mostly compact around a center frequency, which ensures the sparsity of the components.

The fundamental of VMD is solving the constrained variational problem as Eq. (1) [8]:

$$\min_{u_k, \omega_k} \{ \sum_k \| \partial_t [(\delta(t) + \frac{j}{\pi t}) * u_k(t)] e^{-j\omega_k t} \|_2^2 \} \quad s.t. \quad \sum_k u_k = f \tag{1}$$

where u_k is the kth component and ω_k is its center frequency, f is the original signal, that is, the ECG segment in this case. The solving process is performed as shown in Fig. 4 in frequency domain. Since ω_k is sparse, the original ECG segment f can be represented with a simple summation of all the sparse



(a) (b)

Fig. 5 Sparse feature modeling. (a) Extraction of sparse frequency features. (b) The corresponding time domain waveforms of the features.

components, $f(t) = \alpha_1 u_1 + \alpha_2 u_2 + ... + \alpha_K u_K$, where each u_k, $k = 1, 2, ...K$, has its center frequency ω_k. Each u_k is initialized as long as the sumation of all the u_k is equal to the original signal f and each ω_k is initialized randomly within the frequency spectrum of ECG signals. For updating each u_k, the residual obtained by subtracting other components from f is filtered iteratively with a Wiener filter centered at ω_k which is updated by the center gravity of the power spectrum of u_k as Eq. (2):

$$\omega_k^{n+1} = \frac{\int_0^\infty \omega \,|\hat{u}_k^{n+1}(\omega)|^2 \, d\omega}{\int_0^\infty |\hat{u}_k^{n+1}(\omega)|^2 \, d\omega} \tag{2}$$

With the equality constraint of Eq. (1), the algorithm iteratively updates u_k and ω_k until the converging requirements are met. Upon convergence, the frequency spectrum of the optimal u_k is compact with the central frequency ω_k. For the ECG segments, since the frequency spectrum of ECG segments are analogous, based on the ability of extracting sparse frequency components in frequency domain, the proposed VMD algorithm is utilized to construct the sparse features in frequency domain for ECG compression. As shown in Fig. 5(a), several frequency components can be extracted from the sample ECG segment and each component, u_k, is compact with a central frequency, ω_k, which indicates the sparsity of the frequency components. For ECG signals, the correponding time domain waveforms of these frequency components are considered as the sparse features, I_i, for compressing. The sparsity of the features is a trade-off between the CR and the recovering fidelity. In order to minimize the number of features for increasing CR with acceptable error rate, according to our experiment, the number of the features can be selected empirically and five features are used in our method. These features are further transmitted to the sensor node and stored in the memory. Since the number of the features is small, the required memory size is limited and the features can be stored in the on-board memory of the microcontroller.

C. ECG Compression on Wireless Sensor Node

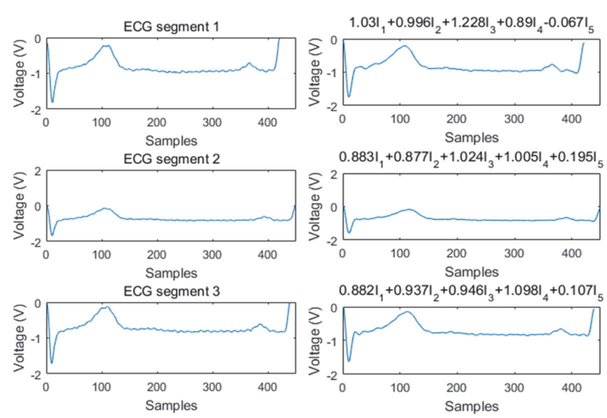
In the compression part, the ECG signals are preprocessed with lightweight functions for extracting the input ECG segments which are further compressed to the coefficients α_i of the features I_i obtained from the initialization.

1) *Preprocessing.* As shown in Fig. 2, in the sensor node, the ECG sensor produces the input ECG signals which are processed with a lightweight peak detector [9] to locate the position of R peaks. Then the segments between subsequent peaks are extracted to obtain each input ECG segment, Y, for compressing. In order to represent an input ECG segment Y with the linear combination of features I_i, the length of the features I_i and that of the input ECG segment Y must be equal. Therefore, the length of each segment, L, is also obtained for normalizing the length of features as L. The length normalization can be easily performed with a computationally inexpensive linear interpolation technique.

2) *ECG Segments Compression.* As discussed in Section II-B, since the features extracted have a linear relationship with the sample ECG segments, it is reasonable to obtain an optimal linear combination of the features for representing the input ECG segments. For an input ECG segment as shown in Fig. 3, the optimal approximation with linear combination of the features for representing the input ECG segment can be obtained by solving Eq. (3):

$$\min_{\alpha} \| Y - \sum_{i=1}^{M} \alpha_i I_i \| \tag{3}$$

where α_i is the coefficient of the features I_i; M is the total number of features. As the number of features M is much smaller than the length of Y, Eq. (3) is a typical underdetermined system. In order to minimizing the computation cost, the least square method is selected.



(a) (b)

Fig. 6 The reconstruction of ECG segments (a) The input ECG segments with different length (b) The corresponding recovered input ECG segments with different coefficients of the same features.

Therefore, the optimal coefficients are obtained with the least square solution equation as Eq. (4):

$$\alpha = (I^T I)^{-1} I^T Y \tag{4}$$

where $I = \{I_1, I_2, ..., I_M\}$, $\alpha = \{\alpha_1, \alpha_2, ..., \alpha_M\}$. Since M is small, the computation of Eq. (4) can be well controlled, and computation complexity is extensively reduced compared to other optimal searching methods. With these optimal coefficients, the input ECG segment can be reconstructed with the features stored in the data center. The compression results, which need to be transmitted wirelessly, only include the bit stream of the coefficients and the length of the input ECG segment, which are only $M+1$ numbers.

D. ECG Reconstruction in Data Center

After receiving the data from the sensor node, the ECG segments can be reconstructed by the linear combinations of the features I_i in the data center as Eq. (5):

$$Y' = \sum_{i=1}^{M} \alpha_i I_i \tag{5}$$

where Y' is the reconstructed input ECG segment. Figure 6 shows the different ECG segments recovered by the same features. With the reconstruction of the subsequent input ECG segments, the input ECG signals can be recovered by connecting all the reconstructed input ECG segments. Part of the input ECG signals recovered with the features are shown in Fig. 7.

III. Experiment and Results

For the purpose of comparing the performance with the state-of-the-art, the proposed method is simulated and validated using the ECG signals from MIT-BIH arrhythmia database [7] which is widely used for compression performance evaluation and comparison in literature. The compression performance of the compression method depends on the compression ratio, $CR = N_o/N_c$, where N_o and N_c are the number of original signal bits and compressed signal bits, and the recovering fidelity which can be measured by the root-mean-square error (RMSE) [2].

In the validation, the ECG signal recordings selected in our simulations include Record 101, 102, 103, 111, 112, 113, and 117. Table 1 is the performance comparison between our method and other ECG compression methods for sensor nodes as well as our previous study [11]. With Record 117, our proposed method achieves the highest CR of 84.78 with the RMSE of 2.96%. The average CR is 65.91, which shows a much better compression performance than the state of the art and our previous study with the comparable RMSE of no more than 5%.

IV. Conclusion

In this study, we propose a new approach for ECG signal compression for low-power wireless ECG sensor nodes by leveraging sparse features of ECG signals in frequency domain. The simulation results show that our method has much better compression performance which shows the high feasibility for ultra-low power wireless sensor node design.

Acknowledgement

This study is partially supported by National Science Foundation (Award No. 1710862).

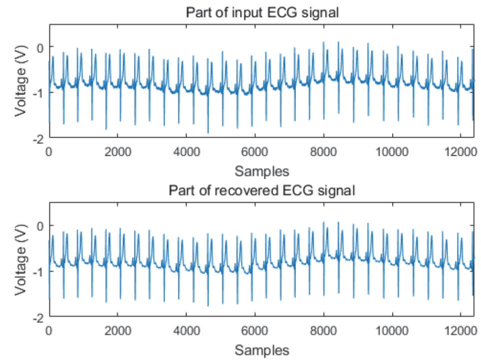


Fig. 7 Sample result of reconstructed input ECG signal.

TABLE I Comparison of ECG compression performance

Methods	ECG record No.	CR	RMSE
Proposed	#101	69.44	3.77%
Proposed	#102	59.44	6.90%
Proposed	#103	62.25	3.94%
Proposed	#111	61.69	6.15%
Proposed	#112	51.12	2.38%
Proposed	#113	72.63	6.66%
Proposed	#117	84.78	2.96%
Proposed	**Average**	**65.91**	**4.68%**
[2]	Average	27.50	5.00%
[10]	Average	13.79	4.20%
[11]	Average	42.8	4.82%

Reference

[1] S. M. Jalaleddine, C. G. Hutchens, R. D. Strattan, and W. A. Coberly, “ECG data compression techniques-a unified approach,” *IEEE Trans. Biomed. Eng.*, vol. 37, no. 4, pp. 329–343, 1990.

[2] M. Hooshmand, D. Zordan, D. Del Testa, E. Grisan, and M. Rossi, “Boosting the battery life of wearables for health monitoring through the compression of biosignals,” *IEEE Internet of Things J.*, vol. 4, no. 5, pp. 1647–1662, 2017.

[3] H. Lee and K. M. Buckley, “ECG data compression using cut and align beats approach and 2-d transforms,” *IEEE Trans. Biomed. Eng.*, vol. 46, no. 5, pp. 556–564, 1999.

[4] B. A. Rajoub, “An efficient coding algorithm for the compression of ECG signals using the wavelet transform,” *IEEE Trans. Biomed. Eng.*, vol. 49, no. 4, pp. 355–362, 2002.

[5] Z. Zhang, T.-P. Jung, S. Makeig, and B. D. Rao, “Compressed sensing for energy-efficient wireless telemonitoring of noninvasive fetal ECG via block sparse bayesian learning,” *IEEE Tran. Biomed. Eng.*, vol. 60, no. 2, pp. 300–309, 2013.

[6] D. Del-Testa and M. Rossi, “Lightweight lossy compression of biometric patterns via denoising autoencoders,” *IEEE Signal Process. Letters*, vol. 22, no. 12, pp. 2304–2308, Dec. 2015.

[7] M. Saeed, M. Villarroel, and R. G. Mark, “Multiparameter intelligent monitoring in intensive care ii (mimic-ii): a publicaccess intensive care unit database,” *Critical Care Medicine*, vol. 39, no. 5, pp. 952, 2011.

[8] K. Dragomiretskiy and D. Zosso, “Variational Mode Decomposition,” *IEEE Trans. Signal Processing*, vol. 62, no. 3, pp. 531 – 544, Feb. 2014.

[9] J. Pan and W. J. Tompkins, “A real-time QRS detection algorithm,” *IEEE Trans. Biomed. Eng.*, no. 3, pp. 230–236, 1985.

[10] S. Lee, J. Luan, and P. Chou, “A new approach to compressing ECG signals with trained overcomplete dictionary,” in *MobiHealthcare*, pp. 83–86, 2014.

[11] H. Huang, S. Hu, and Y. Sun, “Energy-efficient ECG compression in wearable body sensor network by leveraging empirical mode decomposition,” *IEEE-BHI*, 2018, pp. 149–152.