Energy-Efficient ECG Compression in Wearable Body Sensor Network by Leveraging Empirical Mode Decomposition

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Abstract— **Wearable body sensor network (BSN) is widely used in daily monitoring, well-being management, and rehabilitation. Energy efficiency imposes a stringent constraint in wearable BSN, in which wireless transmission is significantly power-demanding. Compressed sensing (CS) provides a good solution to reduce power consumption for data transmission due to the sparsity of signals which can use limited transmitted data to reconstruct original signals. In this study, we develop a new method for non-sparse ECG signal compression by leveraging empirical mode decomposition (EMD) and online dictionary for wearable devices. Comparing to the state-of-the-art of ECG compression which can achieve the compression ratio (CR) of around 25 with the root mean square error (RMSE) around 5%, our method can achieve the CR up to 60 with the same level of RMSE for wearable ECG. In addition, our method also has low computational complexity, which can achieve lower compression energy. The validation experiments are conducted on both clinical data and wearable ECG detected by our BSN in noisy environment. The proposed method shows high feasibility for real CS on board to achieve ultra-low power consumption.**

Keywords—Compressed sensing; wearable device; empirical mode decomposition; body sensor network

I. INTRODUCTION

Body sensor network emerges increasingly in the recent decades, which enables the pervasive healthcare by performing continuous human wellness monitoring and diagnosis using various wearable sensors. The collected biosignals from these wearable sensors, such as electrocardiogram (ECG), heart or respiratory rates (RESP), and photoplethysmographic (PPG), can be used for disease diagnosis, well-being management, as well as elderly care [1]. To make wearable sensors flexible and minimize the impact on daily life, the collected signals can be transmitted wirelessly. Therefore, low-power consumption becomes a major challenge in continuous biosignal collection with limited battery life. For sensor nodes, most of the energy is consumed on wireless data transmission.

Biosignal compression has been investigated historically and is recently attracting more and more attention on low-power data transmission in wearable devices. A number of compression algorithms for ECG compression have been proposed and recently reviewed in 2017 by [2]. Generally, ECG compression can be classified into three categories, namely, direct method which generally compresses signals by discarding unnecessary samples directly [3], [4], transform method which transforms original signal into other domains and select a part of transforming parameters to transmit such as discrete cosine transform (DCT) [5] and discrete wavelet transform (DWT) [6], and parameter extraction method which extract dominant features that can be used for signal reconstruction such as neural networks [7] and Conmpressed sensing (CS) [13].

In this work, we propose a new method for non-sparse wearable ECG compression by leveraging EMD to construct a new online dictionary composed of Intrinsic Mode Functions (IMF). Unlike other decomposition methods such as Fourier, wavelet, and polynomial that use predefined analytical basis, EMD explores the self-similarities and leverages the inherent property of signals for decomposition, which significantly reduces the necessary transforming parameters for reconstructing ECG and achieves very high CR up to 60 with RMSE around 5%, which is higher than the state-of-the-art of different methods of ECG compression with CR of 25-35 [2]. In addition, no peak identification step is required during ECG compression, and thus the computation complexity is relatively low.

This paper is organized as follows: Section 2 introduces the proposed method of ECG compression. Section 3 presents the experiments and results for both clinical data and wearable ECG in noisy environment. A summary of work is given in Section 4.

II. ECG COMPRESSION BASED ON EMD

A. Proposed ECG Signal Compression Framework

The proposed ECG signal compression framework includes three phases, online dictionary construction, ECG compression, and recovering after wireless transmission, as shown in Fig. 1. In Phase 1, a two-layer dictionary is constructed as shown in Fig. 2. In the dictionary, the first layer is a series of subsequent N samples length ECG frames using N moving windows extracted from one heartbeat period. The second layer stores the IMFs decomposed from the ECG frames in the first layer using EMD, which contains the M IMFs of each ECG frame. These IMFs are self-similarities leveraging the inherent property of ECG signals for decomposition, which is different from existing bases. Subsequently, in Phase 3 the ECG signals received at the gateway node are reconstructed by these IMFs.

Phase 2 is the compression stage. In order to compress and recover an arbitrary N-length input ECG frame, the input ECG framework needs to identify a matching ECG frame in the dictionary with extracted features. That is, the location of QRS complexes in both the input ECG frame and the matching ECG framework needs to be close enough. Subsequently, the input ECG frame is represented by the linear combination of the

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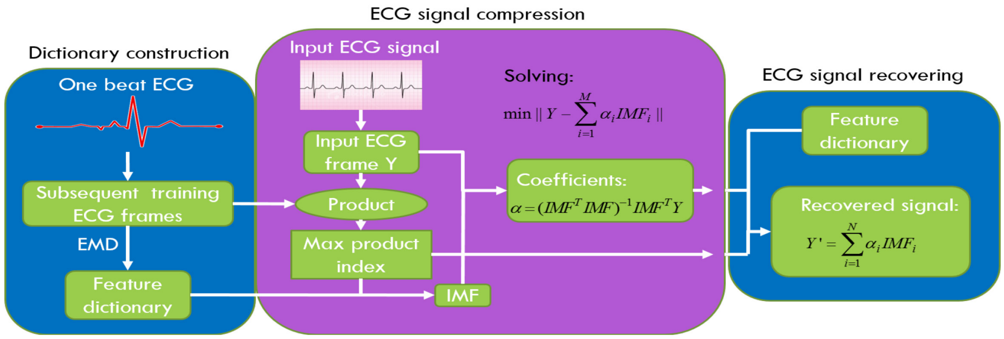


Fig. 1 Proposed ECG compression diagram with IMF constructed dictionary basis based on EMD

IMFs from the matching ECG frame. The coefficients of the M IMFs with the index of the matching ECG frame, which is $M+1$ number of data, will be used for reconstruction. The N samples length input ECG is then compressed to $M+1$ data points for wireless transmission ($M<<N$). The pre-computed IMF bases are pre-stored without computational cost. In addition, according to the health condition of subjects, the IMF bases can be dynamically updated by updating new ECG frames computed in the gateway node after a certain time period and transmitting the IMF bases back to the sensor nodes.

The following of this paper presents the detailed process for the proposed ECG compression framework. The performance for both clinical data from MIT-BIH arrhythmia databases [9] and wearable ECG detected by our BSN [14] are used for validation in Section 3.

B. ECG Decomposition and Dictionary Construction

In ECG compression, the periodicity of ECG signals is often used as features to search compression window, in which peak identification and searching often take place at the beginning. The compression process generally requires normalization of segments between peaks to a fixed size. However, as the recurrent heartbeat period is unnecessarily the same size, additional process such as length normalization is then needed, which induces more computation cost. In our study, the morphology features of each equal-size subsequent frames during heartbeat period are stored in the feature dictionary; then any segment of ECG signals which have arbitrary morphology can be represented using the feature dictionary without considering the segment locations.

We propose to extract the morphology feature of ECG signals using EMD which is able to decompose a signal into a finite number of IMFs. The number of extrema and zero-crossings in an IMF differs at most by one. By decomposing signals into IMFs, the nonlinearity of signal can be represented

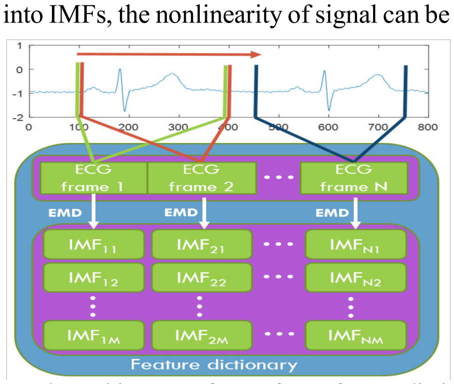


Fig. 2 The architecture of ECG frame feature dictionary

Algorithm 1: Decompose signal into IMFs

a) Identify all extrema of $x(t)$;

b) Interpolate the local maxima to form an upper envelop $u(x)$;

c) Interpolate the local minima to form an upper envelop $l(x)$;

d) Calculate the mean envelope $m(t) = (u(x) + l(x))/2$.

e) Extract the mean from the signal and obtain $h(t) = x(t) - m(t)$.

f) Check whether $h(t)$ satisfies the IMF property. If $h(t)$ is an IMF, iterate all the above steps on the residue $r(t) = x(t) - h(t)$. Otherwise, keep iteration on $h(t)$.

by its own self-similar IMFs. The algorithm is as Algorithm 1 [10]. Figure 3 shows the EMD applied on different frames with size longer than the heartbeat duration. With these IMFs, the training ECG frame in the dictionary can be recovered by simply linear combination of all the IMFs; whereas the input ECG frames which have matching signal morphology with the training frame can be recovered by solving

$$\min \| Y - \sum_{i=1}^{M} \alpha_i IMF_i \| \tag{1}$$

where Y is the input ECG frame, α_i is the coefficient of the ith IMF from the training ECG frame, M is the total number of IMFs. Therefore, the input ECG frame can be represented by

$$Y = \sum_{i=1}^{M} \alpha_i IMF_i + R \tag{2}$$

where R is the error of the reconstruction of ECG frame. Figure 4 displays the reconstruction of typical ECG frames with the training ECG frames which have matching morphology.

As mentioned previously, the training ECG frames in the dictionary should be extracted from one heartbeat period of ECG time series. The reasons are that the size of interval between two peaks is unnecessary equal and multiple peaks in one frame should be avoided. Thus, it requires a proper frame size selection. In our study, a single beat based ECG frame size is selected, which covers one period of ECG in a single heartbeat and avoids two peaks of ECG in one frame. For example, the sampling rate of the selected ECG data is 360 Hz, and one heartbeat ECG typically lasts less than 1 s. Therefore, ECG frame size of 300 samples is selected for covering the features of a single heartbeat. The dictionary is constructed by extracting a series of subsequent N (for this case $N=300$) ECG frames from the one beat ECG time series for the first layer,

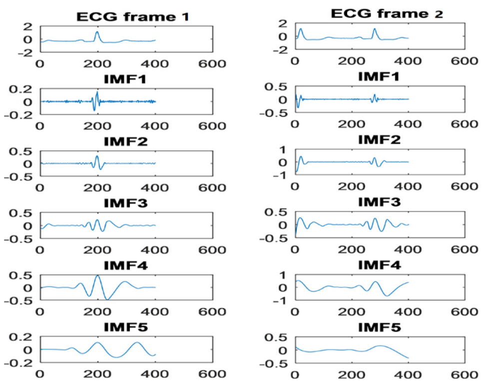
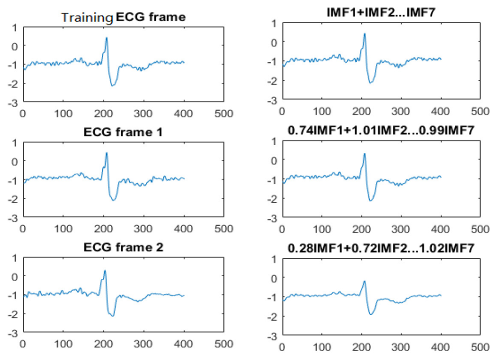


Fig. 3 EMD on different frames of ECG signal.



(a) (b)

Fig. 4 (a) The training ECG frame and input ECG frame 1 and 2 with similar morphology. (b) Recovered input ECG frame 1 and 2 using IMFs from EMD on the training ECG frame.

and then performing EMD on each frame to obtain the IMFs for each ECG frame. The number of IMFs M is empirically selected according to ECG signals, as the EMD results in finite number of IMFs. Typically, more IMFs used for reconstruction will result in less error in the reconstruction and obviously more computation and energy consumption.

C. ECG Frame Matching and Compression

The ECG signal is intercepted with a fixed size, which is the size of the training ECG frame, to form the input ECG frame. The first step for compressing the input ECG frame is called ECG frame matching which refers to finding the similar training ECG frame in the first layer of dictionary which has similar signal morphology with the input ECG frame. For minimizing the computation, finding the maximum dot product of input ECG frame with training ECG frame is used for the ECG frame matching process.

After finding the matched training ECG frame, the index of it is obtained. The corresponding IMFs are used for compressing the input ECG frame which is compressed to the coefficients of IMFs by solving Eq. (1). This equation is a typical underdetermined system, which can be solved using least squares method. The coefficients are obtained by Eq. (3):

$$\alpha = (IMF^T IMF)^{-1} IMF^T Y \tag{3}$$

where $\alpha = \{\alpha_1, \alpha_2, ..., \alpha_M\}$, $IMF = \{IMF_1, IMF_2, ..., IMF_M\}$, Y is the input ECG frame. With Eq. (3), the computation complexity is extensively reduced compared to other compression methods which require more complicated process for signal compression. On the other hand, the data need to be transmitted wirelessly only includes the coefficients and the training ECG frame index which is only $M+1$ numbers.

D. ECG Reconstruction

The ECG reconstruction will be performed on the receiver. First, the matching ECG frame is identified by the received index. Subsequently, the recovered ECG frame Y' is the linear combination of the corresponding IMFs under the matching ECG frame with the respective received coefficients as following:

$$Y' = \sum_{i=1}^{M} \alpha_i IMF_i \tag{4}$$

Finally, the input ECG signal can be reconstructed frame by frame using the above proposed method. Figure 4 shows the recovered ECG. In Fig. 4, the QRS complexes of all three ECG frames locate approximately at the same point in the frame and they can be recovered by the IMFs from training ECG frame with acceptable error.

III. Experiment and Results

The proposed method is validated through clinical data from MIT-BIH arrhythmia database [9] and wearable ECG by our wearable sensor in practical environment [14]. Typical ECG signals as well as baseline wander and motion artifacts are all considered in the ECG recordings for performance evaluation of the proposed ECG compression method.

A. Performance Metric

The performance can be represented by two parameters which are CR and RMSE. The CR parameter refers to the ratio of the original signal bits and the necessarily transmitted compressed signal bits as Eq. (5),

$$CR = \frac{N_o}{N_c} \tag{5}$$

where N_o denotes the number of original signal bits, N_c is the number of compressed signal bits. For the recover fidelity parameter, a typical metrics is the percentage root mean square difference (PRD) as Eq. (6):

$$PRD = \frac{\| Y - Y' \|}{\| Y \|} \times 100 \tag{6}$$

where Y is the input ECG signal, Y' is the reconstructed ECG signal. In our work, the mean value of the original signal impacts the actual performance as the reconstruction is based on the morphology feature extraction, which may be masked by metric of PRD [2]. As pointed in [2], another metric of RMSE can easily gauge the error against the signal's range. The RMSE can be computed as:

$$RMSE = \frac{1}{p2p} \sqrt{\frac{\sum_{i=1}^{L} (y_i - y'_i)^2}{L}} \times 100 \tag{7}$$

where $p2p$ is the average peak-to-peak amplitude of ECG signal, y_i and y'_i are the ith samples in original ECG signal and reconstructed ECG signal, respectively, and L is the length of ECG signal.

B. Clinical Results

For the MIT-BHI ECG data, the fix size of frame is 300,

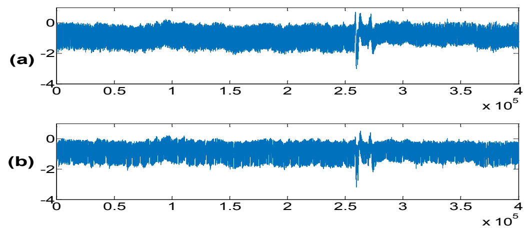


Fig. 5 Clinial ECG of Record 117. (a) Original raw signal; (b) reconstructed signal with CR of 42.8.

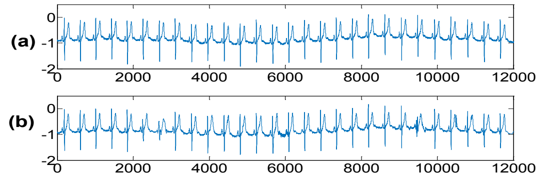


Fig. 6 Clinical ECG. (a) Original ECG signal; (b) reconstructed signal with CR of 42.8.

and length of ECG signal is 1115 seconds. The number of IMF selected can be used to vary the CR. In our experiment, *M=7* IMFs are selected as the feature basis and *N=300* ECG frames are extracted to cover the whole one beat ECG signal. This will require a memory size of 720 kB. The training ECG frames are created from the first ECG QRS complex of the whole ECG signal. Figure 5 shows the complete reconstructed signal and the original signal, from which the motion artifacts are also contained in the recovered signals. For the QRS complex, Figure 6 shows the ECG signal morphology recovering, in which the baseline wander can also be reconstructed.

Table 1 compares the performance with other dictionary based ECG compression method. Our proposed method achieves the CR up to 42.8 while has similar average RMSE of 4.82%. Since the ECG frame size and IMF number are fixed, the CR is also fixed. If the frame size is greater, the CR can also be improved.

C. *Wearable Sensor Results*

The wearable ECG compression is based on our previous wearable ECG sensor [14]. The length of ECG signal is 30 seconds with 300 Hz sampling rate. Since the ECG signal from wearable sensor has less IMFs than the clinic data, only *M=4* IMFs are selected as the feature basis. The fix frame size is 300 and *N=318* ECG frames are extracted to include the one beat ECG feature. Figure 7 shows the reconstructed signal of wearable ECG with the CR of 60 and the RMSE of 5.67%.

TABLE I RESULTS OF ECG COMPRESSIONPERFORMANCE

Methods	**ECG record No.**	**CR**	**RMSE**
Proposed	#101	42.8	4.83%
Proposed	#102	42.8	3.54%
Proposed	#103	42.8	5.33%
Proposed	#111	42.8	4.14%
Proposed	#112	42.8	5.43%
Proposed	#113	42.8	7.60%
Proposed	#117	42.8	2.88%
Proposed	Average	42.8	4.82%
[2]	Average	27.50	5.00%
[11]	Average	25.64	5.50%
[12]	Average	13.79	4.20%

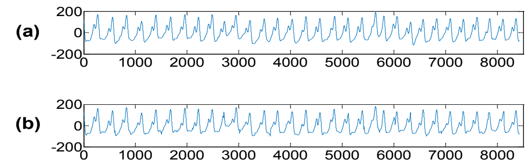


Fig. 7 Wearable heartbeat by our wearable HR sensor. (a) Original heartbeat signal detected by the system; (b) Reconstructed signal with CR of 60.

The CR is increased with fewer IMFs. However, the dictionary size is larger than other methods, which means more memory is required on wearable devices to store the feature dictionary.

IV. CONCLUSION

In this paper, we proposed a new ECG signal compression method based on EMD constructed dictionary bases. The results show that it can achieve the CR of at least 42.8 for clinical ECG and 60 for wearable sensor compared to the state-of-the-art (CR of around 25 with RMSE around 5%). The future work seeks to reduce the size of the dictionary and the reconstruction error.

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