

Energy-Efficient ECG Signal Compression for User Data Input in Cyber-Physical Systems by Leveraging Empirical Mode Decomposition

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Human physiological data are naturalistic and objective user data inputs for a great number of cyber-physical systems (CPS). Electrocardiogram (ECG) as a widely used physiological golden indicator for certain human state and disease diagnosis is often used as user data input for various CPS such as medical CPS and human-machine interaction. Wireless transmission and wearable technology enable long-term continuous ECG data acquisition for human-CPS interaction; however, these emerging technologies bring challenges of storing and wireless transmitting huge amounts of ECG data, leading to energy efficiency issue of wearable sensors. ECG signal compression technique provides a promising solution for these challenges by decreasing ECG data size. In this study, we develop the first scheme of leveraging empirical mode decomposition (EMD) on ECG signals for sparse feature modeling and compression and further propose a new ECG signal compression framework based on EMD constructed feature dictionary. The proposed method features in compressing ECG signals using a very limited number of feature bases with low computation cost, which significantly improves the compression performance and energy efficiency. Our method is validated with the ECG data from MIT-BIH arrhythmia database and compared with existing methods. The results show that our method achieves the compression ratio (CR) of up to 164 with the root mean square error (RMSE) of 3.48% and the average CR of 88.08 with the RMSE of 5.66%, which is more than twice of the average CR of the state-of-the-art methods with similar recovering error rate of around 5%. For diagnostic distortion perspective, our method achieves high QRS detection performance with the sensitivity (SE) of 99.8% and the specificity (SP) of 99.6%, which shows that our ECG compression method can preserve almost all the QRS features and have no impact on the diagnosis process. In addition, the energy consumption of our method is only 30% of that of other methods when compared under the same recovering error rate.

CCS Concepts: • **Information systems** → **Data compression**; • **Applied computing** → **Health care information systems**; • **Hardware** → **Digital signal processing**; • **Computer systems organization** → *Sensor networks*;

Additional Key Words and Phrases: Signal compression, energy efficiency, empirical mode decomposition

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1 INTRODUCTION

Human interaction is ubiquitous in a variety of cyber-physical systems (CPS), in which user inputs need to be well considered in the design and application of these CPS. Among various human interfaces, physiological signals provide a naturalistic and objective user data input for a great number of CPS, such as medical CPS (Haque et al. 2014; Méndez and Ren 2012; Zhang et al. 2013b) and assistive robotics (Schirner et al. 2013). Electrocardiogram (ECG) is one of the most widely used physiological signals as user data input in human-CPS interaction not only for healthcare monitoring (Natarajan et al. 2016; Prittopaul et al. 2015; Yang et al. 2016) but also for human-machine interaction (Méndez and Ren 2012; Zhang et al. 2013b), which necessitates innovative techniques of continuous data acquisition and analytics. With the increasing advancement of enabling technologies for out-of-hospital, patient-centric healthcare, the continuous ECG data acquisition as user data input can be performed by Internet-of-Things (IoT) enabled wearable sensors (Amendola et al. 2014; Pantelopoulos and Bourbakis 2010), which greatly reduces the healthcare costs due to in-hospital care and also improves prevention and diagnosis of cardiovascular diseases and patients' life quality. As a result, two challenges are generally involved with these wearable sensors for continuous ECG monitoring. One is the vast amounts of recorded ECG data, which result in tough requirements of storage and transmission (Jalaaliddine et al. 1990; Lee and Buckley 1999). However, wireless enabled wearable sensors impose a stringent constraint on energy consumption due to the vast amounts of data from continuously sampling and their power-demanding wireless transmission (Cao et al. 2009; Ma et al. 2012; Ryckaert et al. 2005). Therefore, it is desirable to develop an effective ECG compression technique that can not only achieve excellent compression efficiency for reducing the amount of data with no impact on ECG monitoring and diagnosis but also improve the energy efficiency for saving energy in wearable ECG sensors.

ECG signal compression techniques have gained popularity for several decades. Actually, signal compression for biosignals has been investigated for storage and remote transmission previously (Jalaaliddine et al. 1990; Lee and Buckley 1999; Moses and Deisy 2014). However, most of the high-efficiency compression methods require high computation costs, which are not feasible for implementation on resource-limited wearable sensors. As the emerging of IoT enabled wearable ECG sensors, new ECG compression techniques with low computation complexity are needed. It has become an emerging technique for low-power ECG compression to boost battery life of wearable devices. A number of signal compression algorithms for ECG compression have been proposed and recently reviewed in 2017 (Hooshmand et al. 2017). Generally, ECG compression schemes can be classified into three categories. The first is the direct methods, including amplitude zone time epoch coding (AZTEC) (Cox et al. 1968), coordinate reduction time encoding system (CORTES) (Abenstein and Tompkins 1982), and lightweight temporal compression (LTC) (Schoellhammer et al. 2004), which generally compress signals by discarding unnecessary samples directly and reconstruct signals using linear approximation. This type of methods is easy to be implemented and requires less computation. However, if the compression ratio (CR) increases, then the reconstruction becomes a big challenge. The second is the transform methods that transform the original signal into other domains and select a part of transforming parameters to reconstruct, in which Fourier transform (Reddy and Murthy 1986), discrete cosine transform (DCT) (Lee and Buckley 1999), and discrete wavelet transform (DWT) (Rajoub 2002) are popularly used. For these predefined analytical transform bases, the signal features may not be represented well and thus impact the CR. Third, parameter extraction methods are based on the rationale that the dominant features can be extracted from signals and used for modeling the signal morphology. Recently numerous new compression techniques have been proposed with some new perspectives such as neural networks (Maglaveras et al. 1998), compressed sensing (Lin et al. 2015; Mamaghanian et al. 2011; Zhang et al. 2013a), and online learning dictionary (Hooshmand et al. 2017). With a promising

capability of signal compression, the parameter extraction methods are attracting more and more investigation.

In this work, we propose a novel ECG compression scheme with high compression efficiency and energy efficiency based on Empirical Mode Decomposition (EMD) constructed feature dictionary. The proposed method compresses ECG signals with sparse waveform features and thus achieves much higher CR and lower energy consumption than the state of the art with comparable recovering error rates and diagnostic distortion. The main contributions of this article are summarized as follows:

- We developed the first scheme of leveraging EMD on ECG signals for sparse feature modeling and compression and further proposed a new ECG signal compression framework with high compression efficiency and energy efficiency.
- We proposed and verified that downsampling operation on feature dictionary significantly reduces the computation costs for ECG compression as well as the memory size for feature dictionary storage in the compressing stage with negligible recovering error rate increasing.
- We proposed to use combined compressing, which is able to compress multiple ECG frames concurrently, and significantly increase the CR with negligible recovering error rate increasing.
- Our experimental results demonstrate that our method achieves excellent performance for ECG signal compression from both mathematical distortion perspective and diagnostic distortion perspective. For the mathematical distortion, the CR of our method is up to 164 with the RMSE of around 3.48% and the average CR is 88.08 with the RMSE of 5.66%. Compared with the state of the art, which is around 40 of CR and 5.5% of RMSE, our method achieves more than twice of the CR of other existing methods with similar recovering error rate of around 5%. For the diagnostic distortion, our method achieves high QRS detection performance with the SE of 99.8% and the SP of 99.6%. In addition, the total energy consumption including both computation and wireless transmission energy consumption of our method is only 30% of that achieved by other methods with the same RMSE of 7.5%.

This article is organized as follows: Section 2 introduces the proposed method of ECG compression. Section 3 discusses the performance optimization for the ECG compression method. In Section 4, the simulation of the ECG compression is presented, and the results are compared with existing studies in Section 5. A summary of the work is given in Section 6.

2 PROPOSED ECG COMPRESSION FRAMEWORK

In this study, we propose to perform sparse feature modelling on ECG signals to produce a very limited number of waveform features for developing ECG compression technique of high CR and alleviate the high recovering error rate issue by transforming the compression process to an optimization problem with low computation costs. The proposed framework for ECG signal compression is based on signal decomposition using EMD. As the ECG signal is quasi-periodic, redundancies exist between adjacent beats (Zigel et al. 2000). The EMD algorithm is adopted for the decomposition of one-beat ECG to extract the sparse waveform features for reducing the redundancies between adjacent beats. Unlike other decomposition methods such as Fourier, wavelet, and polynomial that use predefined analytical bases, EMD explores the self-similarities and leverages the inherent property of signals for decomposition. The results of the decomposition show the nonlinearity of the original signal, which is a reasonable choice for modeling the ECG signal waveform features and constructing a feature dictionary. These features are stored in an online dictionary for ECG compressing and recovering. ECG signals are then compressed to the coefficients of these features that are then further transmitted via wireless communication. Thus, the proposed

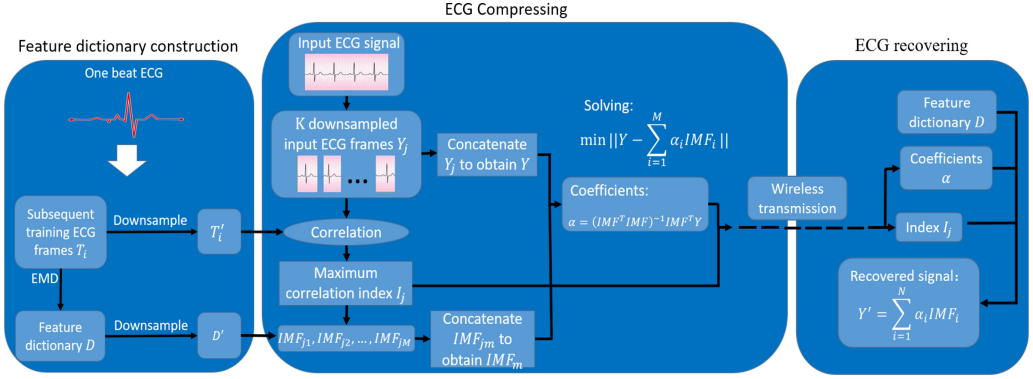


Fig. 1. System architecture of the proposed ECG signal compression framework.

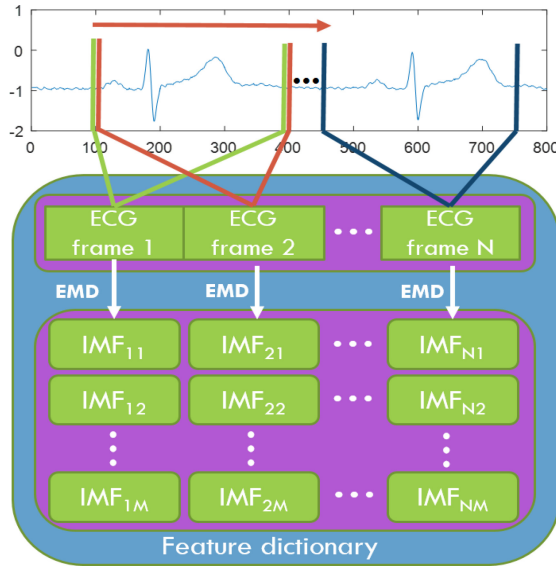


Fig. 2. The architecture of ECG frame feature dictionary.

ECG signal compression framework includes three phases, feature dictionary construction, ECG compressing, and ECG recovering after wireless transmission, as shown in Figure 1.

2.1 Feature Dictionary Construction

In ECG compression techniques, as the redundancies exist between adjacent beats in ECG signals, the traditional ECG compression process generally extracts the quasi-periodic segments for ECG compression, which are typically between two peaks in ECG signals. During this process, the peak identification and searching is first performed. In addition, as the recurrent heartbeat periods are unnecessarily the same length, additional process such as length normalization is further needed (Hooshmand et al. 2017). These preprocessing procedures for ECG compression require extra computation costs. In our study, a training ECG signal, which is typically the initial part of the ECG signal, is scanned and extracted sample by sample with a fixed length of window as shown in Figure 2. The length of the scan window is less than the average length between two peaks and

greater than the length of QRS complex. The resulting equal-sized subsequent ECG frames are the training ECG frames that contain the complete features of a typical one-beat ECG signal. Therefore, the input ECG signals can be segmented with fixed length for compression and no pre-processings such as peak detection and length normalization are needed for incoming signals, which reduces the computation costs and energy consumption during online processing. The features of the one-beat ECG are further extracted using EMD and stored in the feature dictionary. Although the incoming signal is composed of quasi-periodic one-beat ECG, which means the intervals between two peaks may vary with time, any ECG segment can be matched with a similar training ECG frame in the feature dictionary. That is, for any equal-sized frame of the input ECG signal, there is a similar ECG frame in the feature dictionary. The features of this matched frame can be used to represent the input ECG frame, though differences between the input ECG frame and stored training ECG frame exist.

ALGORITHM 1: Decompose Signal $x(t)$ into IMFs (Huang et al. 1998)

- (1) Identify all extrema of $x(t)$;
 - (2) Interpolate the local maxima to form an upper envelop $u(t)$;
 - (3) Interpolate the local minima to form a lower envelop $l(t)$;
 - (4) Calculate the mean envelop $m(t) = (u(t) + l(t))/2$;
 - (5) Extract the mean $m(t)$ from the signal and obtain $h(t) = x(t) - m(t)$;
 - (6) 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 $h(t)$.
-

2.1.1 ECG Decomposition. In various ECG compression methods, the decomposition of ECG signal into different bases is the essential of these ECG compression methods. Typical bases such as sinusoid functions, polynomials, and wavelets are used. However, these predefined analytical bases limit the compression performance, since the recovering of ECG signal often requires numerous bases, which greatly impact the compression rate. In this study, we propose to leverage EMD for the feature extraction of ECG as the bases. Unlike other decomposition methods that use predefined analytical bases, EMD explores the self-similarities and utilize the inherent features of signals for decomposition. In addition, the inherent features are sparse, which greatly reduces numbers of feature bases for signal recovering. The reason for the sparsity of the features is that EMD is able to decompose a signal into a finite number of Intrinsic Mode Functions (IMF) that have the property that the number of extrema and zero-crossings in an IMF differ at most by one (Huang et al. 1998). By decomposing signal into finite number of IMFs, the nonlinearity of signal can be represented by the sparse IMFs. The algorithm for decomposing a signal into IMFs is as Algorithm 1 (Huang et al. 1998). Figure 3 shows the EMD applied on different ECG frames. With these IMFs, one training ECG frame in the dictionary can be recovered by the simple summation of all its IMFs, whereas one input ECG frame that has matching waveform feature with the training ECG frame can be recovered by solving

$$\min_{\alpha} \left\| Y - \sum_{i=1}^M \alpha_i IMF_i \right\| \quad (1)$$

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

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

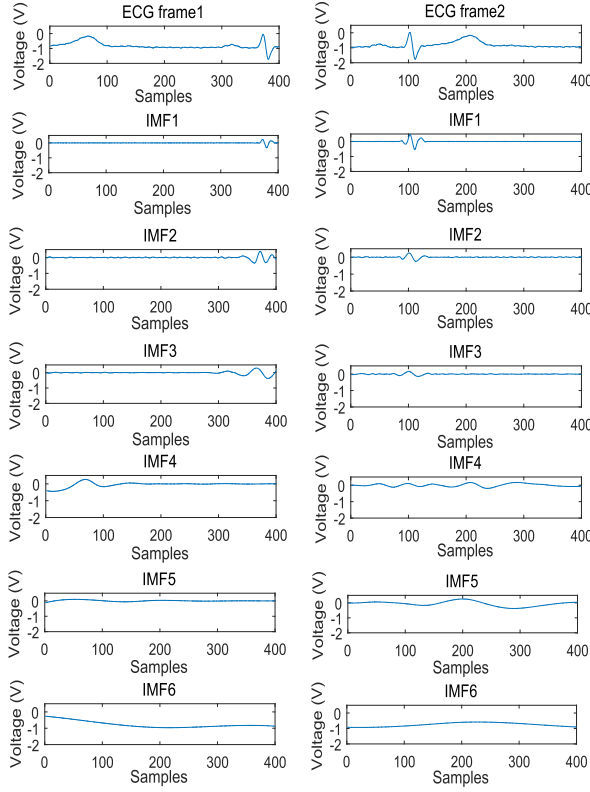


Fig. 3. EMD on different frames of ECG signal.

where R is the residue error of the reconstruction of the input ECG frame. Figure 4(a) displays the reconstruction of typical ECG frames with the training ECG frame that has matching waveform features. The recovering of ECG frames shown in Figure 4(b) verifies the feasibility of IMFs as the sparse waveform features of ECG signal.

2.1.2 Feature Dictionary Construction. The feature dictionary contains two layers as shown in Figure 2. The first layer is the training ECG frames that are a series of subsequent N -sample-length ECG frames extracted from scanning one heartbeat period in the training ECG signal using N -sample-length moving windows. The second layer stores the IMFs decomposed from the training ECG frames in the first layer using EMD. Each column contains the M number of IMFs decomposed from the corresponding training ECG frame. As mentioned previously, the length of the scan moving window should be less than the average length between two peaks and greater than the length of the QRS complex. For example, in Figure 4(a), the length of $N = 360$ samples is selected for the moving window to cover the complete features of one-beat ECG signal. The start point of the scan can be the center between two peaks or the peak of the QRS complex. The moving distance of the moving window is also selected as $N = 360$ samples. Therefore, the feature dictionary is constructed by extracting N (for this case $N = 360$) subsequent ECG frames from the ECG time series for the first layer and further performing EMD on each ECG frame to obtain the IMFs for the second layer. 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

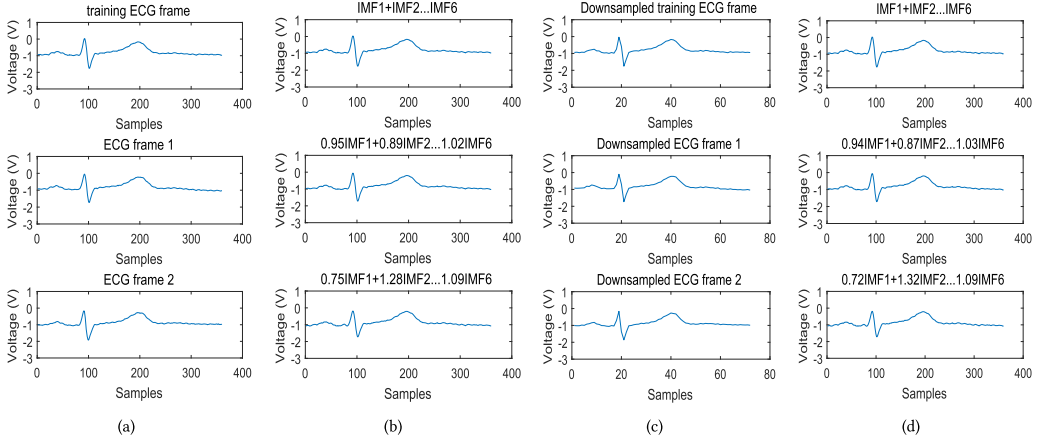


Fig. 4. Recovering ECG frames with IMF features. (a) The training ECG frame and input ECG frame 1 and 2 with similar waveform feature. (b) Recovered input ECG frame 1 and 2 using IMFs from EMD on the training ECG frame. (c) The downsampled training ECG frame and downsampled input ECG frame 1 and 2 with similar waveform feature. (d) Recovered input ECG frames by compressing via downsampled input and feature dictionary and recovering via undownsamped feature dictionary.

will result in less error in the reconstruction and obviously more computation, memory size, and energy consumption for wireless transmission.

2.1.3 Feature Dictionary Downsampling. As shown in Figure 2, the feature dictionary D stores the complete features of the one-beat ECG signal, which requires relatively large memory size for storage. However, in wearable devices, memory size is limited as well as the power supply. To further reduce the size of the feature dictionary, downsampled feature dictionary D' is used in the ECG compressing phase, while the original feature dictionary D is used in the ECG recovering phase to avoid loss of recovering performance. Consider a signal $x[n]$, the downsampling operation on $x[n]$ to obtain the downsampled $x_d[n]$ is as Equation (3):

$$x_d[n] = x[r \cdot n] \quad (3)$$

where r is the downsampling rate. The reason of why the downsampled feature dictionary D' can be used in the compressing process is that the IMF features mainly rely on the waveform features. Signals downsampled with a proper rate will not result in the loss of main waveform features. Figure 4(c) and (d) show the recovered ECG frames using downsampled feature dictionary for compressing.

2.2 ECG Compressing

In the ECG compressing phase, the incoming input ECG signal is first cut out to obtain K input ECG frames that are further downsampled for producing the downsampled input ECG frames, Y_j , $1 \leq j \leq K$, where K is the total number of frames cut out from the input ECG signal, with downsampling rate r used in the feature dictionary downsampling. The downsampled input ECG frame Y_j and feature dictionary D' are used for compressing the j th input ECG frame to coefficients of the IMFs, which represent the compressed ECG signal and will be used for original signal recovering in the third phase. The detailed procedure is described in the following steps.

2.2.1 ECG Frame Matching. With the downsampled input ECG frame Y_j , finding the matching training ECG frame in the first layer of the downsampled feature dictionary D' is the first step.

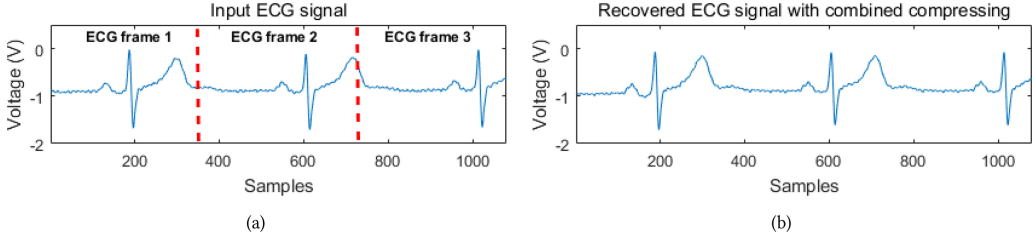


Fig. 5. ECG compressing using combined compressing. (a) The input ECG signal is cut out to three input ECG frames. (b) Recovered ECG signal using combined compressing.

Suppose I_j is the index of the matching training ECG frame, this I_j th training ECG frame will have the most similar waveform with Y_j among all the training ECG frames. The similarity can be represented by the Pearson correlation coefficient, whereby two waveforms with the highest Pearson correlation are considered similar. Therefore, the ECG frame matching process is to calculate the Pearson correlation coefficients between the input ECG frame Y_j and all the training ECG frames in the dictionary and then find the matching frame with index I_j , which has the maximum correlation coefficient with Y_j , so that the corresponding IMF features can be used to represent Y_j .

2.2.2 ECG Compressing. The compressing process is to represent the downsampled input ECG frame Y_j by the IMF features found in the previous process according to Equation (1). By solving Equation (1), the coefficients of IMFs, α , can be determined and Y_j is compressed to those coefficients. Equation (1) is a typical underdetermined system, which can be solved using least squares method. The coefficients α are obtained according to Equation (4):

$$\alpha = (IMF^T IMF)^{-1} IMF^T Y_j \quad (4)$$

where α is the vector of coefficients of each IMF and $\alpha = \{\alpha_1, \alpha_2, \dots, \alpha_M\}$, $IMF = \{IMF_1, IMF_2, \dots, IMF_M\}$. The inverse matrix of $(IMF^T IMF)$ can be the pseudoinverse matrix in case it is non-invertible. With Equation (4), the compressing process can be easily implemented compared with other compression methods that require a more complicated process for signal compression. Also the computation can be well controlled to optimize the overall energy consumption. However, the data to be transmitted only include the coefficients α and the index I_j of the matching training ECG frame. The compressed ECG frame only contains $M + 1$ numbers.

2.2.3 Combined Compressing. According to the compressing process described previously, in one compression cycle only one input ECG frame can be compressed. To increase the compression rate, there are basically two options. One is to decrease the number of IMF features, M ; the other is to increase the length of each input ECG frame, N . However, as the IMF features greatly impact the recovering performance and a lower M brings more errors in the recovering process, decreasing M may not be a good option. Since the length of the training ECG frame in the feature dictionary is equal to that of the input ECG frame (i.e., both have N samples), directly increasing the length of both results in more computation and energy consumption and bigger memory size for the feature dictionary.

In our study, combined compressing is used for increasing the compression rate. The basic idea is to compress J number of input ECG frames in one compression cycle. For example, $J = 3$ input ECG frames are cut out from the input ECG signal as shown in Figure 5 and downsampled to the downsampled input ECG frames Y_1, Y_2, Y_3 . Correspondingly, the indexes I_1, I_2, I_3 of the matching training ECG frames are obtained as well as the three groups of IMF features denoted by IMF_1, IMF_2, IMF_3 . When J single input frames are cut out, J groups of IMF features will be generated, each of which

is denoted as IMF_j , where $IMF_j = \{IMF_{j1}, IMF_{j2}, \dots, IMF_{jM}\}$, $j = 1, 2, \dots, J$. The next step is to concatenate the three input ECG frames Y_1, Y_2, Y_3 to a long ECG frame Y . The three groups of IMF features are also concatenated to a group of long features IMF , in which each feature denoted by IMF_m is created by concatenating $IMF_{1m}, IMF_{2m}, IMF_{3m}$, $m = 1, 2, \dots, M$. Subsequently, the long input ECG frame Y can be represented by the newly created IMF and compressed to the coefficients of IMF_m by solving Equation (1). In total, the compressed signal includes the three index number I_j and the coefficients α_m , the number of which is $M + 3$. However, the length of each input ECG frame is three times longer. Therefore, with combined compressing, the compression rate is increased significantly.

2.3 ECG Reconstruction

In the last phase, the compressed ECG data will be decompressed to obtain the recovered ECG signal. According to the previous discussion, the original feature dictionary D is used for the recovering process. First, the matching ECG frames I_j as well as the corresponding groups of IMFs are identified according to the indexes in the compressed ECG data. These groups of IMF features are concatenated to a group of long features IMF' using the same way in the combined compressing process. Note that the long features IMF' are exactly the concatenated IMF without downsampling. Therefore, the recovered ECG frame Y' is also without downsampling, which can be generated by the linear combination of the elements of IMF' with the respective coefficients α_m as Equation (5):

$$Y' = \sum_m^M \alpha_m IMF'_m \quad (5)$$

where M is the number of decomposed IMFs, IMF'_m is the element in IMF' . Figure 4 shows the recovered ECG with one input ECG frame. Figure 5 is the recovered ECG from three input ECG frames using combined compressing. Consequently, the continuous ECG signal can be compressed and recovered frames by frames with acceptable error.

3 PERFORMANCE OPTIMIZATION

As described in Section 2, the proposed method contains several variable parameters that affect the ECG compression performance, since the waveform features of ECG signals vary with different people, sensing devices, and measuring method. The proposed method is able to flexibly manipulate the waveform features for reducing the redundancy of ECG signals and compression computation cost and thus improve the compression performance. These parameters include ECG frame length N , downsampling rate r , number of selected IMF M , and number of combined ECG frame J . These four parameters can be determined according to specific ECG compression objective with acceptable reconstruction fidelity. The optimization process can be performed in the data receiver or data center as the initialization parts of the ECG compression. Typically, the objectives include minimizing the memory size for dictionary storage, reducing computation costs, minimizing signal recovering error rate, and maximizing the CR. For example, for minimizing the memory size, the involved parameters are the downsampling rate r , frame length N , and number of IMF M . Since the three parameters are independent, the optimization process can be performed on the three parameters separately. For the complicated cases of achieving multiple objectives, the tradeoff can be determined from the tradeoff curves of the above parameters. An example case is presented for the detailed optimization and tradeoff process in the following context.

For the objective of minimizing the computation cost and maximizing the CR with acceptable error rate, we use the ECG record 117 from the MIT-BIH arrhythmia database, which is explained

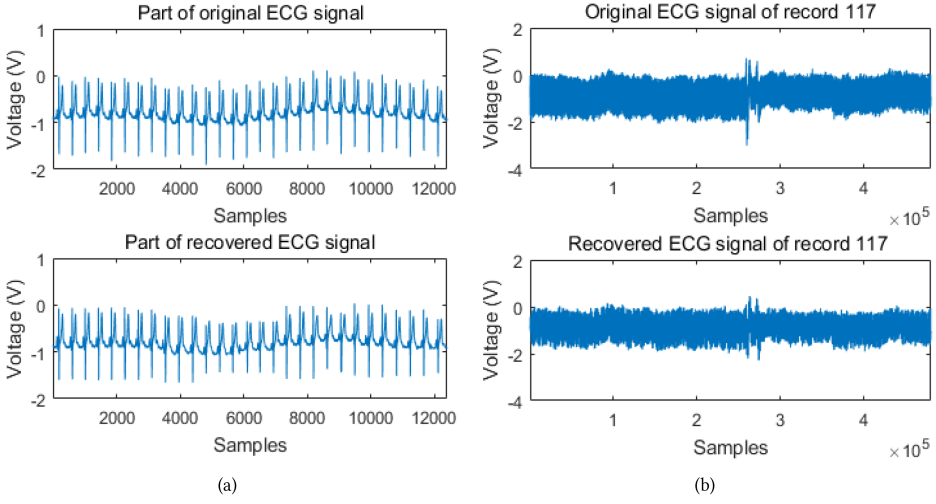


Fig. 6. Original and reconstructed ECG signal of record 117. (a) Part of the original and recovered ECG signal from record 117. The QRS complex of the ECG signal can be recovered well by our method. (b) The complete original and recovered ECG signal of record 117. The complete ECG signal can be recovered with acceptable errors by our method.

in Section 4 as an example to explain the process. For this ECG signal, the parameters of $N = 400$, $r = 5$, $M = 6$, and $J = 3$ are selected. Figure 6 shows the recovered ECG signal, which presents well-recovered waveform features of the ECG signal. In Figure 6(a), in addition to the ECG QRS complexes, the baseline wandering in the signal can also be recovered. For Figure 6(b), the complete ECG signal contains motion artifacts that are recovered as well. To explore how the parameters above impact the performance of the proposed method, each parameter is discussed for evaluating the ECG compression performance in the following sections. Since the computation cost has a simple monotonically increasing relationship with other parameters, the tradeoff curves are obtained by only varying the parameters with the RMSE and CR as shown in Figure 7.

3.1 ECG Frame Length N

The length of the ECG frame N is related to the CR as $CR = N/(M + J)$ when the other parameters are considered as constant. Figure 7(a) shows how the RMSE and CR vary with the frame length N when changing the ECG frame length N from 360 to 460. It shows that the RMSE decreases first and then increases as the ECG frame length N becomes greater. The reason of why the RMSE will decrease first is that a longer frame length N is able to include more waveform features of the one-beat ECG signal. However, if the frame length N is too long, then the adjacent one-beat ECG signal will also contribute to the waveform features, which impacts the waveform feature extraction of one-beat ECG and further increases the errors when recovering the ECG frames. Therefore, number of samples of $N = 400$ is chosen for this case.

3.2 Downsampling Rate r

The downsampling process for the input ECG frames as well as the feature dictionary not only lowers the memory size for storing the feature dictionary on sensor nodes but also significantly reduces the computation complexity for the ECG compression and the computation energy consumption. Figure 7(b) shows the tradeoff curve of the RMSE with variable downsampling rate r . The value of the RMSE ranges from 5.2% to 6.5%, which means that even the input ECG frames

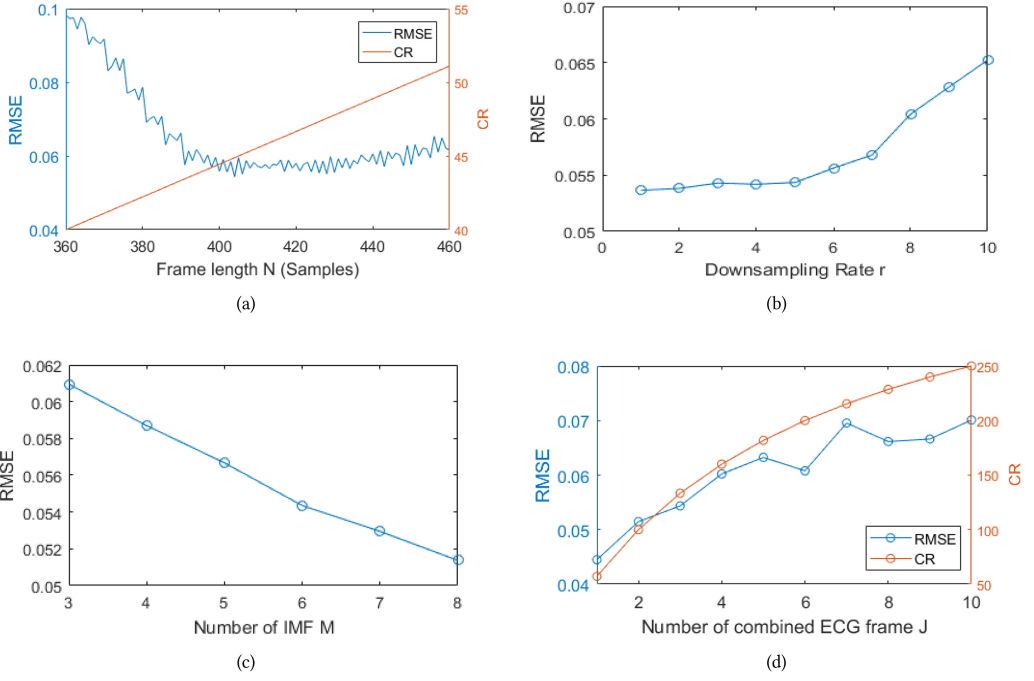


Fig. 7. Tradeoff curves of the four parameters, frame length N , downsampling rate r , number of IMF M , and number of combined ECG frame J . These parameters enable the capability of our method for flexibly adapting to different ECG signal compression objectives. (a) Frame length N versus RMSE and CR with $J = 3$, $M = 6$. (b) Downsampling rate r versus RMSE with $N = 400$, $J = 3$, and $M = 6$. (c) Number of IMF M versus RMSE with $N = 400$, $r = 5$, and $J = 3$. (d) Number of combined ECG frame J versus RMSE and CR with $N = 400$, $r = 5$, and $M = 6$.

and feature dictionary are downsampled with $r = 10$, the RMSE of the ECG recovering only increases by 1%. One might wonder that the loss of data by downsampling can still be recovered. This is because the downsampling process does not lose the waveform features of the one-beat ECG signal significantly. Although the input ECG frames are downsampled, the waveform features represented by the IMFs are also downsampled. The coefficients of the IMFs for representing the input ECG frame will have negligible variation as shown in Figure 4(b) and (d). With the downsampling process, the computation, the memory size as well as the computation energy consumption of the ECG signal compression will be significantly reduced with negligible recovering performance loss. Based on the above discussion, the downsampling rate $r = 5$ is selected in our experiments.

3.3 Number of IMF Features M

The number of IMFs is determined by the EMD algorithm. Typically, the EMD algorithm will decompose the ECG signal to finite number of IMFs, in which the main waveform features of the ECG signal are included within the first several IMFs from the decomposition. As shown in Figure 7(c), increasing the number of IMF features M will result in better recovering performance. However, more IMF features mean more computation for ECG compression, more coefficients of the compressed ECG signal with smaller CR and more memory size for the feature dictionary. To obtain an acceptable RMSE, $M = 6$ is a good choice for the tradeoff in this case.

3.4 Number of Combined ECG Frames J

As illustrated in Section 2, the combined compressing method significantly improves the CR for ECG compression. Figure 7(d) shows how CR changes with increasing J . However, the recovering performance will also be reduced accordingly, as shown in Figure 7(d), since the combined compressing method only concatenates the combined ECG frames and IMF features. And this operation may lose some of the waveform features located at the junctions of the combined ECG frames. Although concatenating the IMF features can include most of the waveform features of the concatenated input ECG frame, some feature loss is inevitable and will be worse if more ECG frames are combined. In our experiment, the number of $J = 3$ is selected to obtain an acceptable RMSE of around 5%.

4 SIMULATION

In this section, we validate our method and optimization using real ECG data simulation. Simulations and performance metrics are described in this section to evaluate the performance of the proposed ECG compression method from three aspects that are mathematical distortion metric, diagnostic distortion metric, and energy saving. The performance is then compared with the state of the art in Section 5.

4.1 Simulation Database

The proposed method is validated using a widely used ECG database, MIT-BIH arrhythmia database (Saeed et al. 2011), which is popularly used by other ECG compression studies (Craven et al. 2017; Hooshmand et al. 2017; Jalaleddine et al. 1990; Lee and Buckley 1999; Lee et al. 2014; Ma et al. 2015; Wang et al. 2016). It contains various arrhythmia ECG records sampled at 360Hz with 11-bit resolution. For example, typical ECG signals, arrhythmia, as well as ECG signals with baseline wander, electrode motion, and muscle artifacts are all provided in this database. Therefore, the above ECG database brings an excellent diversity of realistic ECG signals to evaluate the effectiveness and performance of our proposed method under various scenarios. Further, as the duration of one ECG records in the database is long, for easy comparison and visual examination, the duration of 10–20 minutes of the ECG records is selected from each record.

4.2 Mathematical Distortion Metrics

For the evaluation of compression efficiency and recovering fidelity, we use CR and RMSE to show quantitative results of the proposed method.

4.2.1 Compression Efficiency. The compression efficiency can be quantified by the ratio of the total number of bits that are required for the original signal and the compressed bits required for transmission and recovering as Equation (6),

$$CR = \frac{N_o}{N_c} \quad (6)$$

where N_o is the total number of original signal bits and N_c denotes the number of compressed signal bits. A larger CR means higher compression efficiency.

4.2.2 Recovering Fidelity. Generally, the signal recovering performance is measured by comparing the original signal with the recovered signal. Various mathematical criteria can be used for evaluating the recovering performance. In our work, since the compressing and recovering process are based on the waveform feature extraction, the performance of which may be masked by some standard metric such as percentage root mean square difference (PRD). As pointed out in Blanco-Velasco et al. (2005), to avoid the performance masking issue of PRD, another metrics of RMSE is

selected for measuring the recovering performance and can be calculated using (Hooshmand et al. 2017):

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

where $p2p$ is the average peak-to-peak amplitude of ECG signal, y_i and y'_i are the i th samples in original ECG signal and reconstructed ECG signal, respectively, and L is the length of ECG signal. A higher value of RMSE represents a worse recovering fidelity.

4.3 Diagnostic Distortion Metrics

From the point of view of diagnosis, the mathematical distortion metric may not be directly relevant to the diagnostic fidelity of the reconstructed ECG signal. As the essential task of the ECG diagnosis, the QRS detection from ECG signals plays a vital role in human cardiac health diagnosis (Deepu and Lian 2015; Khamis et al. 2016; Kyrkos et al. 1988; Lin and Chang 1989; Pan and Tompkins 1985). Therefore, the QRS detection performance of ECG signal is selected for evaluating the diagnostic distortion of the proposed ECG compression method.

The QRS detection performance is based on a popularly used QRS detector (Pan and Tompkins 1985), which can evaluate accuracy of QRS complex monitoring and extraction capabilities in ECG detection systems. The QRS detector is performed on both the original ECG signal and the recovered ECG signal from compression to get the number of QRS complexes detected. The diagnostic distortion performance can be evaluated by the following metrics:

$$Sensitivity(SE) : SE = \frac{TP}{TP + FN} \times 100\% \quad (8)$$

$$Specificity(SP) : SP = \frac{TP}{TP + FP} \times 100\% \quad (9)$$

where TP means true positive, which is the number of QRS complexes correctly detected, FN stands for false negative, which is the number of QRS complexes not detected, and FP denotes false positive, which is the number of QRS complexes incorrectly detected. For the meaning of the two metrics, the SE is the percentage of correctly detected QRS complexes in the recovered ECG signal of all the QRS complexes in the original ECG signal, which indicates the ability for detecting QRS complexes correctly. The SP is the percentage of the correctly detected QRS complexes out of all the detected QRS complexes from the recovered ECG signal, which measures the ability for identifying non-QRS complexes.

4.4 Energy Consumption Evaluation

To evaluate the energy consumption performance of the proposed ECG compression method, two kinds of energy consumption are computed. The first is the energy consumption due to the computation of the execution of the algorithm, which can be evaluated by the number of operations performed in microcontrollers. The other is the energy consumption during wireless transmission.

4.4.1 Computation and Energy Consumption. The amount of the computation can be estimated from the number of additions, multiplications, divisions, and comparisons, which are further converted to the corresponding number of clock cycles and the energy consumption per cycle considering ARM Cortex M4 processor (Karakus et al. 2013). The proposed ECG compression framework utilizes an online feature dictionary stored in sensor nodes. Although the computation for constructing the feature dictionary is high, this part of computation is not included within the total computation of ECG compression as the feature dictionary constructing is offline and will be updated according to the health condition of subjects in a certain time period. The on-board

Table 1. Number of Operations for Compressing an ECG Frame from Record 117 with Length of 1,200 Samples and Parameters of $N = 400$, $R = 5$, $M = 6$, and $J = 3$

	ECG frame matching	ECG compressing	Total
Additions	1,440	18,936	20,376
Multiplications	960	18,936	19,896
Comparisons	240	0	240
Shifts	0	1,440	1,440
Readings	9,600	1,400	11,040
Writings	0	9	9
Divisions	9	0	9

computation of ECG compression is to find the matching training ECG frames in the feature dictionary and the corresponding coefficients of the IMF features for recovering the input ECG frames. In the step of ECG frame matching, calculating the Pearson correlation coefficients requires $6N/r$ additions, $4N/r$ multiplications, three divisions as well as $N \cdot N/r$ reading operations. Finding the maximum coefficients requires N/r comparisons. Therefore, the energy consumption can be calculated according to the following equation:

$$E_1 = N \cdot \frac{N}{r} \varepsilon_{rd} + \frac{6N}{r} \varepsilon_{add} + \frac{4N}{r} \varepsilon_{multi} + \frac{N}{r} \varepsilon_{comp} + 3\varepsilon_{div} \quad (10)$$

where ε_{rd} , ε_{add} , ε_{multi} , ε_{div} , and ε_{comp} are the energy consumption for read, addition, multiplication, division, and comparison operations per byte in the processor, respectively. In combined compressing, J number of indexes are obtained for the matching ECG frames and the corresponding energy consumption is $J \cdot E_1$. After concatenating the IMFs from the obtained indexes, the concatenated IMF features are loaded for compressing the combined input ECG frame. In the step of compressing, according to Equation (4), the calculation for α requires $M \cdot J(N/r)$ shifts, $J(N/r) \cdot M^2 + M^3 + J(N/r) \cdot M^2 + M \cdot J(N/r)$ additions and multiplications plus $M \cdot J(N/r)$ reading and M writing operations. Therefore, the energy consumption for compressing is as Equation (11):

$$E_2 = J \frac{N}{r} \cdot M(\varepsilon_{shift} + \varepsilon_{rd}) + \left(2J \frac{N}{r} \cdot M^2 + M^3 + M \cdot J \frac{N}{r} \right) (\varepsilon_{add} + \varepsilon_{multi}) + (M + J) \varepsilon_{wrt} \quad (11)$$

where ε_{shift} and ε_{wrt} are the energy consumption for shifting and writing operation per byte, respectively. Table 1 summarizes the number of operations for the ECG compressing complexity of record 117 with length of 1,200 samples and parameters of $N = 400$, $r = 5$, $M = 6$, and $J = 3$.

4.4.2 Wireless Transmission Energy Consumption. For evaluating the energy consumption during wireless transmission, a popular wireless transmission platform of Texas Instruments CC2540 low-energy Bluetooth system-on-chip is selected. Although the energy consumption by wireless transmission varies with different kinds of factors such as distance, the average energy required for transmitting 1 byte of data can still be estimated (Siekkinen et al. 2012). Therefore, the wireless transmission energy consumption can be evaluated by the transmitted number of bytes, which is denoted by ε_{tran} , and the total transmission energy consumption is $(M + J) \varepsilon_{tran}$.

Table 2. Results of ECG Compressing Performance

Methods	ECG record No.	CR	RMSE
Proposed	#101	86.4	6.62%
	#102	104.5	5.89%
	#103	159.43	4.12%
	#105	98.4	5.72%
	#107	51.33	6.58%
	#113	64.73	5.72%
	#115	80.5	4.71%
	#117	133.3	5.58%
	#201	62.92	4.91%
	#205	104.55	5.16%
	#210	60.3	5.82%
	#212	70.0	4.79%
	#214	68.45	6.94%
	#220	164	3.48%
	#221	45.3	6.40%
	#230	81.3	6.84%
	#234	61.91	6.87%
Proposed	Average	88.08	5.66%
(Hooshmand et al. 2017)	Average	39.50	6.60%
(Lee et al. 2014)	Average	13.79	4.20%
(Lee and Buckley 1999)	Average	12.0	7.00%
(Wang et al. 2016)	Average	23.50	6.80%
(Schoellhammer et al. 2004)	Average	32.0	6.50%
(Ma et al. 2015)	Average	25.64	5.50%

5 RESULTS

In this section, the results are presented from the corresponding three aspects described in Section 4 for the performance evaluation of the proposed method. The first one is the compression efficiency with recovering fidelity by mathematical distortion metrics. The second is the diagnostic distortion with the SE and SP for QRS detection; and the third one is the energy consumption for ECG signal compression with a comparable recovering error rate. Since not all the ECG signals in the MIT-BIH arrhythmia database are useful, because some ECG signals may have long useless periods due to disconnection of the ECG sensor or high motion artifacts, the following ECG records in the database are considered for the experiments: 101, 102, 103, 105, 107, 113, 115, 117, 201, 205, 210, 212, 214, 220, 221, 230, and 234.

5.1 Compression Efficiency and Recovering Fidelity

Table 2 compares the compression performance of the proposed method with other ECG compressing methods. According to Table 2, our proposed method can achieve the CR of up to 164 with the RMSE of 3.48% and the average CR of 88.08 with the RMSE of 5.66%. The average CR is more than twice of the other methods with comparable recovering error rate. Compared to our previous study (Huang et al. 2018), the compressing performance is improved more than 100% with negligible increasing of the recovering error rate. The results show that the compression performance of our method significantly transcends the performance achieved by other ECG compression methods.

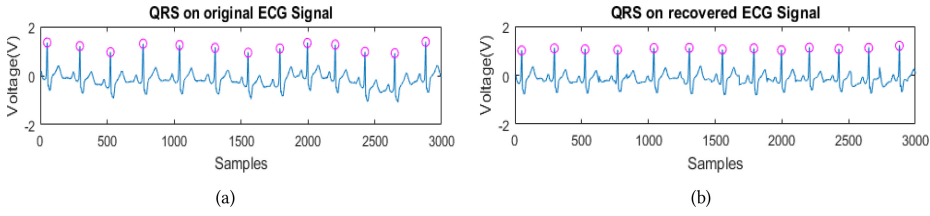


Fig. 8. QRS detection on part of ECG record 212. (a) The detected QRS on the original ECG signal. (b) The detected QRS on corresponding recovered ECG signal. The QRS detected on the recovered ECG signal is exactly the same as on the original ECG signal, which demonstrates the excellent ability for keeping the QRS features in ECG signal of our method.

Table 3. Results of Diagnostic Performance for ECG Compressing

ECG record No.	QRS in original ECG	QRS in recovered ECG	TP	FP	FN	SE (%)	SP (%)
#101	1,008	1,012	1,008	4	0	100	99.6
#102	1,547	1,546	1,546	0	1	99.9	100
#103	1,083	1,083	1,083	0	0	100	100
#105	1,138	1,133	1,133	0	5	99.6	100
#107	905	914	905	9	0	100	99
#113	968	986	968	18	0	100	98.1
#115	956	966	956	10	0	100	99
#117	1,130	1,116	1,116	0	14	98.9	100
#201	807	826	807	19	0	100	97.7
#205	1,558	1,550	1,550	0	8	99.5	100
#210	976	974	974	0	2	99.8	100
#212	1,092	1,094	1,092	2	0	100	99.8
#214	1,051	1,055	1,051	4	0	100	99.6
#220	1,090	1,076	1,076	0	14	98.7	100
#221	689	707	689	8	0	100	98.8
#230	1,077	1,077	1,077	0	0	100	100
#234	1,161	1,162	1,161	1	0	100	99.9
Total	18,236	18,277	18,192	75	44	99.8	99.6

5.2 Diagnostic Performance

For the proposed ECG signal compression method, the performance from the point of view of diagnosis is the ability to keep the QRS features after the ECG compressing and recovering. Figure 8 shows the QRS detection for the original ECG signal and the corresponding recovered ECG signal in part of the ECG record 212 in the database. Table 3 shows the number of QRS complexes detected from the original ECG signal and the corresponding recovered ECG signal. The diagnostic performance of the proposed method is evaluated through the SE and SP for the QRS detection according to Equations (8) and (9). According to Table 2 and Table 3, the proposed method achieves high QRS detection performance with the SE of 99.8% and the SP of 99.6% with the RMSE of 5.66%. With the excellent diagnostic performance, the proposed ECG compression method can preserve almost all the QRS features and have no impact in the diagnosis process.

5.3 Energy Consumption

To compare the energy consumption of the proposed method with other methods, both the computation and the wireless transmission energy consumption are included in the total energy

Table 4. Energy Consumption Values for Operations per Byte Performed in Processor

Operations	Add. ϵ_{add}	Multi. ϵ_{multi}	Comp. ϵ_{comp}	Div. ϵ_{div}	Readings ϵ_{rd}	Writings ϵ_{wrt}	Shifts ϵ_{shift}	Transmission per byte ϵ_{comp}
Energy consumption (nJ)	3.30	9.90	3.30	9.90	0.26	4.30	3.30	672

Table 5. Average Number of Operations and Energy Consumptions for
Compressing a ECG Segment of 1,200 Samples with RMSE of 7.5%
(Proposed Method of $N = 400$, $R = 5$, $M = 6$, and $J = 3$)

	LTC	DCT	DWT	OD	Proposed
Additions	5,035	53,852	31,239	168,822	20,376
Multiplications	0	36,359	27,534	165,636	19,896
Comparisons	4,924	121	30,892	3,948	240
Shifts	0	0	0	0	1,440
Readings	1,200	1,200	1,200	1,200	11,040
Writings	38	100	51	31	9
Divisions	2,536	0	1,292	3760	9
Transmission bytes	38	100	51	31	9
Computation energy (μ J)	1.48	2.96	3.52	23.8	2.72
Transmission energy (μ J)	25.54	67.2	34.27	20.83	6.05
Total energy (μ J)	27.02	70.16	37.79	44.63	8.77

consumption. According to the study in Karakus et al. (2013), the number of computational operations and wireless transmission energy consumption of several existing ECG compression methods are investigated at the RMSE of 7.5%. Although the ECG compression methods are performed on different hardware platforms such as different microprocessors, the amount of computation and compressed ECG signal bits are the same. Therefore, they can be compared with the proposed method, which evaluates the energy consumption in the same way. In our experiments, the computation platform is the ARM Cortex M4 and the wireless transmission is based on Texas Instruments CC2540. The energy consumptions of unit of operation and transmitted byte are shown in Table 4 according to Karakus et al. (2013) and Craven et al. (2017). The results from Hooshmand et al. (2017) are scaled to that of the ECG segment length of 1,200 samples. Table 5 is the comparison of the total energy consumption between the proposed method and other existing methods. From Table 5, the computation energy consumption of the proposed method has no big difference from other ECG compression methods presented here, which is mainly due to the downsampling process and the simple solution for the feature coefficients. In addition, the transmission energy consumption of the proposed method is much lower than the other existing methods, which is only 30% of the lowest energy consumption achieved by the LTC method. This is because of the high CR achieved by using combined compressing. Although combined compressing may increase the ECG recovering error rate to some acceptable extent, the high CR it achieves can significantly reduce the total energy consumption for ECG compression for wearable ECG sensing.

6 CONCLUSION

In this article, we develop the first scheme of leveraging EMD on ECG signals for sparse feature modeling and compression and further propose a new ECG signal compression framework with excellent compression efficiency and energy efficiency based on EMD constructed feature

dictionary. Both the compression performance and energy consumption are evaluated using the popularly used ECG records from MIT-BIH database. The experimental results show that the proposed method can achieve the CR of up to 164 with the RMSE of 3.48% and the average CR of 88.08 with the RMSE of 5.66%. In addition, it achieves high QRS detection performance with the SE of 99.8% and the SP of 99.6%. The energy consumption of the proposed method for compressing ECG signals is only 30% of that achieved by other methods with the same recovering error rate. The proposed method is found to have excellent compression performance and low energy consumption comparing to the state of the art, which shows high feasibility for wearable IoT applications in the long run.

REFERENCES

- John P. Abenstein and Willis J. Tompkins. 1982. A new data-reduction algorithm for real-time ECG analysis. *IEEE Trans. Biomed. Eng.* 29, 1 (1982), 43–48.
- Sara Amendola, Rossella Lodato, Sabina Manzari, Cecilia Occhiuzzi, and Gaetano Marrocco. 2014. RFID technology for IoT-based personal healthcare in smart spaces. *IEEE IoT J.* 1, 2 (2014), 144–152.
- Manuel Blanco-Velasco, Fernando Cruz-Roldán, J. Ignacio Godino-Llorente, Joaquín Blanco-Velasco, Carlos Armien-Aparicio, and Francisco López-Ferreras. 2005. On the use of PRD and CR parameters for ECG compression. *Med. Eng. Phys.* 27, 9 (2005), 798–802.
- Huasong Cao, Victor Leung, Cupid Chow, and Henry Chan. 2009. Enabling technologies for wireless body area networks: A survey and outlook. *IEEE Commun. Mag.* 47, 12 (2009).
- J. R. Cox, F. M. Nolle, H. A. Fozzard, and G. C. Oliver. 1968. AZTEC, a preprocessing program for real-time ECG rhythm analysis. *IEEE Trans. Biomed. Eng.* 15, 2 (1968), 128–129.
- Darren Craven, Brian McGinley, Liam Kilmartin, Martin Glavin, and Edward Jones. 2017. Adaptive dictionary reconstruction for compressed sensing of ECG signals. *IEEE J. Biomed. Health Inf.* 21, 3 (2017), 645–654.
- Chacko John Deepu and Yong Lian. 2015. A joint QRS detection and data compression scheme for wearable sensors. *IEEE Trans. Biomed. Eng.* 62, 1 (2015), 165–175.
- Shah Ahsanul Haque, Syed Mahfuzul Aziz, and Mustafizur Rahman. 2014. Review of cyber-physical system in healthcare. *Int. J. Distrib. Sens. Netw.* 10, 4 (2014), 217415.
- Mohsen Hooshmand, Davide Zordan, Davide Del Testa, Enrico Grisan, and Michele Rossi. 2017. Boosting the battery life of wearables for health monitoring through the compression of biosignals. *IEEE IoT J.* 4, 5 (2017), 1647–1662.
- Hui Huang, Shiyuan Hu, and Ye Sun. 2018. Energy-efficient ECG compression in wearable body sensor network by leveraging empirical mode decomposition. In *Proceedings of 2018 IEEE EMBS International Conference on Biomedical & Health Informatics (BHI'18)*. IEEE, 149–152.
- Norden E. Huang, Zheng Shen, Steven R. Long, Manli C. Wu, Hsing H. Shih, Quanan Zheng, Nai-Chyuan Yen, Chi Chao Tung, and Henry H. Liu. 1998. The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis. In *Proceedings of the Royal Society of London A: Mathematical, Physical and Engineering Sciences*. The Royal Society, 903–995.
- Sateh M. S. Jalaliddine, Chriswell G. Hutchens, Robert D. Strattan, and William A. Coberly. 1990. ECG data compression techniques—a unified approach. *IEEE Trans. Biomed. Eng.* 37, 4 (1990), 329–343.
- Celalettin Karakus, Ali Cafer Gurbuz, and Bulent Tavli. 2013. Analysis of energy efficiency of compressive sensing in wireless sensor networks. *IEEE Sens. J.* 13, 5 (2013), 1999–2008.
- Heba Khamis, Robert Weiss, Yang Xie, Chan-Wei Chang, Nigel H. Lovell, and Stephen J. Redmond. 2016. QRS detection algorithm for telehealth electrocardiogram recordings. *IEEE Trans. Biomed. Eng.* 63, 7 (2016), 1377–1388.
- A. Kyrkos, E. A. Giakoumakis, and G. Carayannis. 1988. QRS detection through time recursive prediction techniques. *Sign. Process.* 15, 4 (1988), 429–436.
- Hanwoo Lee and Kevin M. Buckley. 1999. ECG data compression using cut and align beats approach and 2-D transforms. *IEEE Trans. Biomed. Eng.* 46, 5 (1999), 556–564.
- Seungjae Lee, Jun Luan, and Pai H. Chou. 2014. A new approach to compressing ECG signals with trained overcomplete dictionary. In *Proceedings of the 2014 EAI 4th International Conference on Wireless Mobile Communication and Healthcare (Mobihealth'14)*. IEEE, 83–86.
- Kang-Ping Lin and Walter H Chang. 1989. QRS feature extraction using linear prediction. *IEEE Trans. Biomed. Eng.* 36, 10 (1989), 1050–1055.
- Yu-Min Lin, Yi Chen, Hung-Chi Kuo, and An-Yeu Andy Wu. 2015. Compressive sensing based ECG telemonitoring with personalized dictionary basis. In *Proceedings of the 2015 IEEE Biomedical Circuits and Systems Conference (BioCAS'15)*. IEEE, 1–4.

- JiaLi Ma, TanTan Zhang, and MingChui Dong. 2015. A novel ECG data compression method using adaptive fourier decomposition with security guarantee in e-health applications. *IEEE J. Biomed. Health Inf.* 19, 3 (2015), 986–994.
- Tao Ma, Pradhumna Lal Shrestha, Michael Hempel, Dongming Peng, Hamid Sharif, and Hsiao-Hwa Chen. 2012. Assurance of energy efficiency and data security for ECG transmission in BASNs. *IEEE Trans. Biomed. Eng.* 59, 4 (2012), 1041–1048.
- Nicos Maglaveras, Telemachos Stamkopoulos, Konstantinos Diamantaras, Costas Pappas, and Michael Stryntz. 1998. ECG pattern recognition and classification using non-linear transformations and neural networks: a review. *Int. J. Med. Inf.* 52, 1–3 (1998), 191–208.
- Hossein Mamaghian, Nadia Khaled, David Atienza, and Pierre Vanderghenst. 2011. Compressed sensing for real-time energy-efficient ECG compression on wireless body sensor nodes. *IEEE Trans. Biomed. Eng.* 58, 9 (2011), 2456–2466.
- Eduardo Ojeda Méndez and Shangping Ren. 2012. Design of cyber-physical interface for automated vital signs reading in electronic medical records systems. In *Proceedings of the 2012 IEEE International Conference on Electro/Information Technology (EIT'12)*. IEEE, 1–10.
- Diana Moses and C. Deisy. 2014. A novel lossless ECG compression technique for transmission in GSM networks. In *Proceedings of the 3rd International Conference on Soft Computing for Problem Solving*. Springer, 947–958.
- K. Natarajan, B. Prasath, and P. Kokila. 2016. Smart health care system using internet of things. *J. Netw. Commun. Emerg. Technol.* 6, 3 (2016).
- Jiapu Pan and Willis J. Tompkins. 1985. A real-time QRS detection algorithm. *IEEE Trans. Biomed. Eng.* 32, 3 (1985), 230–236.
- Alexandros Pantelopoulos and Nikolaos G. Bourbakis. 2010. A survey on wearable sensor-based systems for health monitoring and prognosis. *IEEE Trans. Syst. Man Cybernet. C* 40, 1 (2010), 1–12.
- P. Prittopaul, S. Sathya, and K. Jayasree. 2015. Cyber physical system approach for heart attack detection and control using wireless monitoring and actuation system. In *Proceedings of the 2015 IEEE 9th International Conference on Intelligent Systems and Control (ISCO'15)*. IEEE, 1–6.
- Bashar A. Rajoub. 2002. An efficient coding algorithm for the compression of ECG signals using the wavelet transform. *IEEE Trans. Biomed. Eng.* 49, 4 (2002), 355–362.
- B. R. Shankara Reddy and I. S. N. Murthy. 1986. ECG data compression using Fourier descriptors. *IEEE Trans. Biomed. Eng.* 33, 4 (1986), 428–434.
- Julien Ryckaert, Claude Desset, Andrew Fort, Mustafa Badaroglu, Vincent De Heyn, Piet Wambacq, Geert Van der Plas, Stéphane Donnay, Bart Van Poucke, and Bert Gyselinckx. 2005. Ultra-wide-band transmitter for low-power wireless body area networks: Design and evaluation. *IEEE Trans. Circ. Syst. I: Regul. Pap.* 52, 12 (2005), 2515–2525.
- Mohammed Saeed, Mauricio Villarroel, Andrew T. Reisner, Gari Clifford, Li-Wei Lehman, George Moody, Thomas Heldt, Tin H. Kyaw, Benjamin Moody, and Roger G. Mark. 2011. Multiparameter intelligent monitoring in intensive care II (MIMIC-II): A public-access intensive care unit database. *Crit. Care Med.* 39, 5 (2011), 952.
- Gunar Schirmer, Deniz Erdogmus, Kaushik Chowdhury, and Taskin Padir. 2013. The future of human-in-the-loop cyber-physical systems. *Computer* 46, 1 (2013), 36–45.
- Tom Schoellhammer, Eric Osterweil, Deborah Estrin, Ben Greenstein, and Mike Wimbrow. 2004. Lightweight temporal compression of microclimate datasets. In *Proceedings of the 29th Annual IEEE International Conference on Local Computer Networks*. pp. 516–524.
- Matti Siekkinen, Markus Hienkari, Jukka K. Nurminen, and Johanna Nieminen. 2012. How low energy is bluetooth low energy? Comparative measurements with zigbee/802.15. 4. In *Proceedings of the 2012 IEEE Wireless Communications and Networking Conference Workshops (WCNCW'12)*. IEEE, 232–237.
- Xiaoxiao Wang, Zhijian Chen, Jiahui Luo, Jianyi Meng, and Yin Xu. 2016. ECG compression based on combining of EMD and wavelet transform. *Electron. Lett.* 52, 19 (2016), 1588–1590.
- Zhe Yang, Qihao Zhou, Lei Lei, Kan Zheng, and Wei Xiang. 2016. An IoT-cloud based wearable ECG monitoring system for smart healthcare. *J. Med. Syst.* 40, 12 (2016), 286.
- Zhilin Zhang, Tzyy-Ping Jung, Scott Makeig, and Bhaskar D. Rao. 2013a. Compressed sensing for energy-efficient wireless telemonitoring of noninvasive fetal ECG via block sparse Bayesian learning. *IEEE Trans. Biomed. Eng.* 60, 2 (2013), 300–309.
- Zhaoyang Zhang, Honggang Wang, Chonggang Wang, and Hua Fang. 2013b. Interference mitigation for cyber-physical wireless body area network system using social networks. *IEEE Trans. Emerg. Top. Comput.* 1, 1 (2013), 121–132.
- Yaniv Zigel, Arnon Cohen, and Amos Katz. 2000. The weighted diagnostic distortion (WDD) measure for ECG signal compression. *IEEE Trans. Biomed. Eng.* 47, 11 (2000), 1422–1430.

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