Compressed Domain ECG Biometric with Two-Lead Features

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ABSTRACT

This study presents a new method to combine ECG biometrics with data compression within a common JPEG2000 framework. We target the two-lead ECG configuration that is routinely used in long-term heart monitoring. Incorporation of compressed-domain biometric techniques enables faster person identification as it by-passes the full decompression. Experiments on public ECG databases demonstrate the validity of the proposed method for biometric identification with high accuracies on both healthy and diseased subjects.

Keywords: ECG Biometric; Data Compression; JPEG2000 Image Coding Standard

1. INTRODUCTION

Electrocardiogram (ECG) signal is a recording of heart activity, which is individual-specific in the sense of amplitudes and time durations of recorded cardiac complexes. ECG biometric is particularly effective in health care applications, as the signal can be used for diagnosis of cardiac diseases and also used to identify subjects before granting them medical services. Prior works on ECG biometric[1–4] can be categorized based on the number of ECG channels used, the method for feature extraction, and type of classifier adopted. Most existing algorithms made use of single-lead features and ignored the other leads that may contain additional information.[1,2] On the other hand, some ECG-based biometric research was based on the conventional 12-lead configuration,[3] which is impractical in conditions where convenience and portability are important. This work is aimed at the two-lead configuration that is routinely used in long-term continuous heart monitoring with portable devices. ECG signals from the two leads are essentially two observations of the same physiological activity from two different perspectives. These leads are typically placed such that their orientations are orthogonal to each other, which suggests that the two leads may offer complementary information.[4] It is also important to test the feasibility of ECG biometrics with diseased patients in irregular cardiac conditions. Previous works have shown that ECG biometric problem for healthy persons can be satisfyingly solved with high recognition accuracies, but a much lower accuracy may be achieved for cardiovascular disease patients. Recently, Chiu et al.[2] proposed a DWT-based algorithm and reported overall accuracies of 100% and 81% on 35 normal subjects and 10 arrhythmia patients, respectively.

In wireless telecardiology scenarios, ECG signals are often represented in compressed format for efficient transmission and storage purposes. Most ECG compression methods adopt one-dimensional (1-D) representation for ECG signals. To better exploit both intra-beat and inter-beat correlations, 2-D compression algorithms have been proposed by converting ECG signals into images and then applying the JPEG2000 image coding standard.[5] Irrespective of the underlying method used for data compression, compressed ECG imposes a new challenge for person identification as most existing algorithms have implicitly considered that biometric features are extracted from raw ECG signals.[1–4] Full decompression is then required to convert compressed data into ECG signals prior to feature extraction. This step is undesirable in health care systems, as the hospital may have thousands of enrolled patients and decompression of all their ECG packets is an enormous amount of work. Thus, there has been a new focus on biometric techniques which directly read the compressed ECG to obtain unique features with good discrimination power. Apart from its advantage of by-passing the full decompression, reduced template size also enables faster biometric matching compared to the non-compressed domain approaches. Sufi and Khalil[6] proposed a compressed-domain ECG biometric technique, which starts with the detection of cardiac abnormality and only the normal compressed ECG data are used for person identification. As the discrete wavelet transform (DWT) is an embedded part of the JPEG2000, and DWT itself is one of the best features for ECG biometrics,[2] working in DWT domain remains to be the most promising area for compressed ECG based biometric.

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2. 2-D ECG DATA COMPRESSION

Real Holter records were taken from three public ECG databases, namely, MIT-BIH Normal Sinus Rhythm Database (NSRDB), MIT-BIH Arrhythmias Database (MITDB) and MIT-BIH Supraventricular Arrhythmias Database (SVDB), in order to evaluate the proposed method on normal ECG signals as well as ECG signals with arrhythmias. All databases are freely available on Physionet[7] and they adopted the two-lead configuration, which is widely accepted as the setting for long-term continuous heart monitoring. In most records, channel one ECG1 is a modified limb lead II, and channel two ECG2 is usually a modified chest lead V1 (sometimes V2, V4, or V5, depending on the subject). The NSRDB includes 18 two-lead ECG recordings, each between 20 and 24 hours in length, from subjects without diagnosed cardiac abnormalities. The MITDB consists of 48 two-lead recordings of approximately half-hour and sampled at 360 Hz. The SVDB contains 78 excerpts of two-lead ECG recordings, each 30-min long, selected to supplement the examples of supraventricular arrhythmias in the MITDB. For a fair comparison, only the first half-hour segments of NSRDB samples are used. Also, ECG records of MITDB are resampled to the sampling frequency 128 kHz of the NSRDB and SVDB.

ECG itself is 1-D in the time-domain, but can be viewed as a 2-D signal in terms of its implicit periodicity. Typical ECG waveform of a heartbeat consists of a P wave, a QRS complex, and a T wave. The QRS complex is the most characteristic wave in an ECG waveform and hence, its peak can be used to identify each heartbeat. Thus, by dividing ECG signals into segments with lengths equal to the heartbeats, there should be a large correlation between individual segments. To begin, ECG signals are band-pass filtered to remove various noises and the Pan-Tompkins algorithm[8] is used to detect the R peak of each QRS complex. Accordingly, ECG signals are divided into heartbeat segments and each segment is stored as one row of a 2-D data array. Since the heartbeat segments may have different lengths, each row of the data array is period normalized to a fixed length of $N_p = 100$ samples via cubic spline interpolation. Note that the original heartbeat lengths were represented with 9 bits and transmitted as side information. Finally, we proceed to construct ECG images by gathering together 25 rows of the data array and normalizing the amplitude of each component to an integer ranging from 0 to 255. Proceeding in this way, each ECG image is a matrix of dimension 25×100 when one lead is used and a matrix of dimension 50×100 when two leads are used. The constructed ECG images are then ready to be further compressed by the JPEG2000 coding standard. The JPEG2000 encoding process consists of several operations: preprocessing, 2-D DWT, quantization, entropy coding and bit-stream organization. It begins with a preprocessor which divides the source image into disjoint rectangular regions called tiles. For each tile, the DC level of image samples is shifted to zero and color space transform is performed to de-correlate the color information. The 2-D DWT is then applied to generate an approximation subband and three detail subbands oriented horizontally, vertically and diagonally. With J-level wavelet decomposition, the image will have a total of $3J + 1$ subbands. Let $S_j = \{s_j(m, n), 1 \leq m \leq M_j, 1 \leq n \leq N_j\}$ represent the coefficients of j-th subband whose row and column dimensions are denoted by M_j and N_j with $j \in \{1, 2, \ldots, 3J + 1\}$. Finally, these coefficients are quantized and compressed by two tier encoders for entropy coding.

3. COMPRESSED DOMAIN ECG BIOMETRIC

Person identification is essentially a pattern recognition problem consisted of two stages: feature extraction and classification. Under the JPEG2000 framework, the person identification problem is analogous to a content-based image retrieval (CBIR) problem. The JPEG2000 code-stream is subject to partial decoding and then features relating to ECG morphology are computed directly from the dequantized wavelet coefficients. In the classification stage, the query ECG of an unknown subject will be compared with the enrollment database to find a match. The block diagram of the proposed ECG biometric system is shown in Figure 1. Feature extraction is the first step in applying ECG biometrics to person identification. For large image databases, color, shape and texture features are considered the most important content descriptors in CBIR problems. Due to the grayscale nature of ECG images, we only focus on the texture features that characterize smooth, coarseness and regularity of the specific image. One effective tool for texture analysis is the DWT as it provides good time and frequency localization ability. Furthermore, DWT coefficients can be obtained without involving a full decompression of the JPEG2000 code-stream. This is a favorable property as the inverse DWT and subsequent decoding processes could impose intensive computational burden. Different texture features such as energy, significance map, and modelling of wavelet coefficients at the output of wavelet filter-banks have been successfully applied to CBIR.[9] In

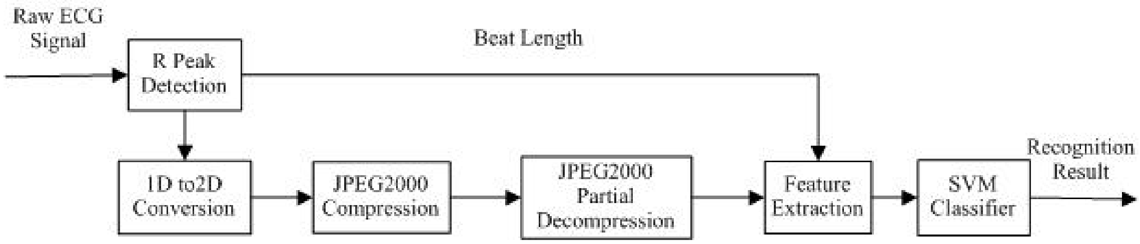

Figure 1. The proposed ECG biometric system.

this work, two different feature sets derived from the compressed ECG, denoted by FS1 and FS2, are presented and investigated.

We began by using the subband energies as a first step towards an efficient characterization of texture in ECG images. It has been suggested[9] that the texture content of images can be represented by the distribution of energy along the frequency axis over scale and orientation. For each subband j, the dequantized wavelet coefficients $\hat{s}_j(m,n)$ are used to compute the subband energy

$$E_j = \frac{1}{M_j N_j} \sum_{m=1}^{M_j} \sum_{n=1}^{N_j} \hat{s}_j^2(m,n). \tag{1}$$

In addition, the average time elapse between two successive R peaks, referred to as the RR_{av}, is used to characterize the dynamics information around the heartbeats. The biometric identification vector (BIV) used for the FS1 will be denoted as $\mathbf{b}^{(1)} = \{E_1, E_2, \dots, E_{3J+1}, RR_{av}\}$. The second feature set FS2 is obtained by applying principal component analysis (PCA)[10] on wavelet coefficients from the lowpass subbands S_1 and S_2. This is because that lowpass subbands represent the basic figure of an image, which features a high similarity among the ECGs of the same person. In order to achieve dimension reduction, PCA finds projection vectors in the directions of highest variability such that the projected samples retain the most information about the original data samples. Let $\mathbf{p}_i$ denote the principal component vector of wavelet coefficients from the lowpass subband $S_i, i = 1, 2$. Together with subband energies and the RR-interval, the BIV for the FS2 is denoted as $\mathbf{b}^{(2)} = \{\mathbf{b}^{(1)}, \mathbf{p}_1, \mathbf{p}_2, RR_{av}\}$.

Enrollment and recognition are two important stages of the ECG biometric system. In the first stage, BIVs of each subject are taken as representations of the subject and enrolled into a database. In the recognition stage, the query BIV of an unknown subject is compared with the enrollment database to find the best match. The classifier considered here is the support vector machine (SVM) which has shown effective in many pattern recognition problems.[11] Since person identification involves the simultaneous discrimination of several subjects, we considered the one-against-one method for solving multiclass SVM problems.[11] For a K-class problem, the method constructs $K(K-1)/2$ binary SVM classifiers where each one is trained on the training data from two classes. Training the binary SVM consists of finding a separating hyperplane with maximum margin and can be posed as the quadratic optimization problem. For the t-th ECG image, suppose that the pair $(\mathbf{x}_t, y_t)$ contains the feature vector $\mathbf{x}_t \in \{\mathbf{b}^{(1)}, \mathbf{b}^{(2)}\}$ and its corresponding class label $y_t \in \{1, 2, \dots, K\}$. Given a set of T training data pairs $\{(\mathbf{x}_t, y_t), t = 1, 2, \dots, T\}$ from classes i and j, SVM algorithm can be formulated as the following primal quadratic optimization problem

$$\begin{aligned} \min_{\mathbf{w}^{ij}, b^{ij}, \xi_t^{ij}} \; & \frac{1}{2}||\mathbf{w}^{ij}||^2 + C \sum_{t=1}^{T} \xi_t^{ij}, \\ \text{subject to: } & (\mathbf{w}^{ij})^{\mathrm{T}} \mathbf{x}_t + b^{ij} \geq 1 - \xi_t^{ij}, \quad \text{if } y_t = i, \\ & (\mathbf{w}^{ij})^{\mathrm{T}} \mathbf{x}_t + b^{ij} \leq -1 + \xi_t^{ij}, \text{ if } y_t = j, \\ & \xi_t^{ij} \geq 0, \end{aligned} \tag{2}$$

where C is a regularization parameter, $\mathbf{w}^{ij}$, b^{ij} and ξ_t^{ij} are the weight vector, bias and slack variable, respectively. After obtaining the optimum values of weight vector $\mathbf{w}^{ij}$, we compute the decision function $f_{ij}(\mathbf{x}_t)$ as follows:

$$f_{ij}(\mathbf{x}_t) = (\mathbf{w}^{ij})^{\mathrm{T}}\mathbf{x}_t + b^{ij}. \tag{3}$$

Finally, the class label y for a new query $\mathbf{x}$ is determined based on the max-wins voting strategy, i.e.,

$$y = \arg\max_{i} \sum_{j\neq i, j=1}^{K} \mathrm{sign}[f_{ij}(\mathbf{x})]. \tag{4}$$

4. EXPERIMENTAL RESULTS

Computer simulations were conducted to evaluate the performances of the proposed ECG biometric system for both healthy and diseased subjects. ECG records from the public databases NSRDB, MITDB, and SVDB were chosen to represent a wide variety of QRS morphologies. The JPEG2000 simulation was run on the open-source software JasPer version 1.900.0.[12] Each ECG image is regarded as a single tile and the dimension of the code-block is 64×64. ECG images were compressed in lossy mode using Daubechies 9/7 filter with 4-level wavelet decomposition. Besides, the targeted coding rate ρ was empirically determined to be 0.15 in order to achieve the compression ratio in the region of 10. A preliminary experiment was first conducted to evaluate the performances of SVM classifiers for the situation where subjects were identified solely by means of one-lead features. ECG1 is most commonly used, since it highlights various segments within the heartbeat, besides displaying P, QRS and T waves. For each subject, 80% of compressed ECG images were used for training in the enrollment stage, and the other 20% were used for testing in the recognition stage. The results are shown in Table 1. Compared with the subband energy-based FS1, the improved performances of FS2 indicate that morphological features of ECG signals are better to be exploited in the DWT domain. The results also show that the recognition performances are affected by ECG variations caused by cardiovascular diseases. For example the SVM obtained from a learning process with features FS2 is able to classify correctly 98.73% of NSRDB, 97.17% of MITDB and 91.37% of SVDB. The fact that the SVDB has lower classification performances is justified by the fact that some records of the SVDB include ECG1 of very low information value, and in some records the morphology of this lead features a high similarity among subjects. Good examples for such a confusing set can be seen in Figure 2 for record 828, 829, 876 and 877. Table 2 shows a confusion matrix using features FS2 for a reduced problem on this confusing set. The rows of the confusion matrix correspond to the subject actually being recorded and the columns indicate the subject identified. The average recognition rate of 77.88% indicates that one-lead information alone cannot provide sufficient cues for discriminating among these four subjects.

Table 1. Recognition rate for each database with one-lead and two-lead features.

Database	ECG 1		ECG 1 & 2	
	FS1	**FS2**	**FS1**	**FS2**
NSRDB	93.53	98.73	93.88	99.40
MITDB	81.71	97.17	83.74	98.17
SVDB	77.07	91.37	80.24	96.26

Table 2. Confusion matrix for the confusing set with one-lead and two-lead features.

Record	ECG 1				ECG 1 & 2			
	828	**829**	**876**	**877**	**828**	**829**	**876**	**877**
828	982	55	16	47	1021	12	18	49
829	20	870	52	158	14	935	4	147
876	20	80	907	93	29	46	955	70
877	91	231	110	668	92	178	66	764

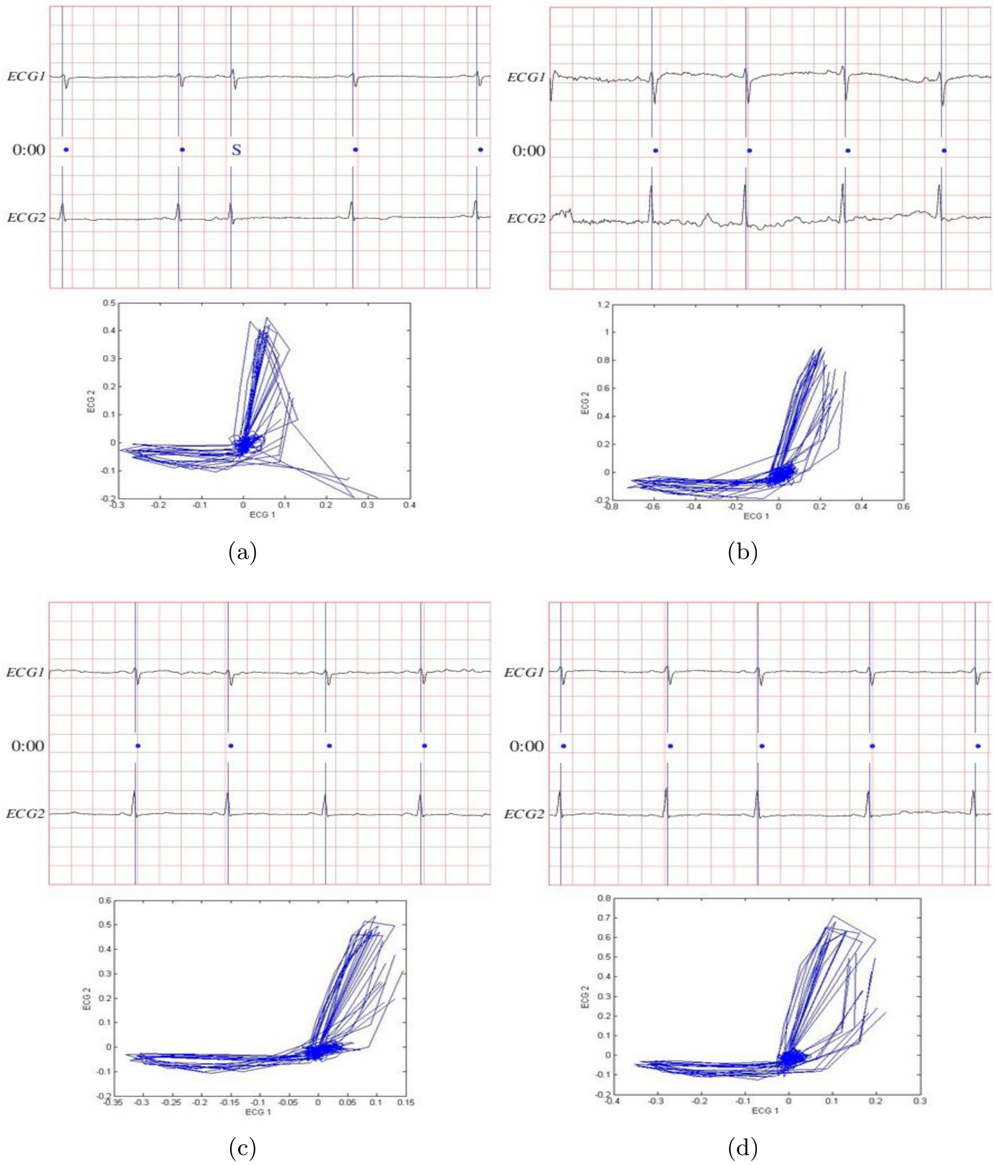

Figure 2. ECG waveforms and VCG contour for record (a)828, (b)829, (c)876, (d)877.

The next step is to examine the performance dependence of ECG biometric on the number of leads employed in constructing an ECG image. According to Goldberger et al.,[7] heartbeat classification categorized as supraventricular ectopic beats (SVEB) and ventricular ectopic beats (VEB) can be favored by information from chest leads of type V1, V2 or V4. Because of this, it is believed that the features extracted by ECG2 may provide many benefits as a secondary source of subject-discriminating information. To illustrate this, we show in Figure 2 the vectorcardiogram (VCG) contours[13] by plotting ECG1 signal on the x-axis against ECG2 signal on the y-axis giving the projection in the vertical plane. It is clearly seen that each subject has his/her characteristic VCG contour differing from all other subjects' contours. The performances of SVM classifiers with two-lead features FS2 for the confusing set are summarized in Table 1. The results clearly demonstrate that the combined use of two leads is more invariant to ECG irregularities induced by cardiovascular diseases. To eloborate further, Table 2 compares the recognition results for each database with one-lead and two-lead features. It can be seen that simultaneous analysis of two ECG channels yields better accuracy compared to using a single channel: the improvement is 0.67% for NSRDB, 1% for MITDB and 4.89% for SVDB. In order to justify the efficiency of the proposed method, we also analyze the run-time complexity of JPEG2000 decoder for ECG data. According to the JPEG2000 coding standard, its full decompression process can be highlighted as: entropy decoding, dequantization to obtain the DWT coefficients, and inverse DWT to reconstruct blocks of pixels. By studying the code execution profiles, we can see that the decoder spends most of its time on the inverse DWT (typically 61.5% or more). By contrast, the amount of time consumed by entropy decoding and de-quantization is about 30.8%. This observation is in accord with the results for natural and synthetic imagery produced by the Jasper software implementation, reported earlier.[12] The complexity analysis results demonstrate that the proposed method has the advantage of by-passing the inverse DWT operation.

5. CONCLUSIONS

This paper proposed a robust method for biometric identification using two-lead features extracted from the JPEG2000 compressed ECG. Under the JPEG2000 framework, the person identification problem is analogous to a content-based image retrieval problem. Morphological features of ECG signals are derived directly from the DWT coefficients without involving full decompression of JPEG2000 bit-stream. Experiments on three ECG databases indicate that the proposed system appears to not only offer good discrimination among subjects, but also robust to the presence of cardiac arrhythmias.

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