PAPER

Biometric Identification Using JPEG2000 Compressed ECG Signals*

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SUMMARY In wireless telecardiology applications, electrocardiogram (ECG) signals are often represented in compressed format for efficient transmission and storage purposes. Incorporation of compressed ECG based biometric enables faster person identification as it by-passes the full decompression. This study presents a new method to combine ECG biometrics with data compression within a common JPEG2000 framework. To this end, an ECG signal is considered as an image and the JPEG2000 standard is applied for data compression. Features relating to ECG morphology and heartbeat intervals are computed directly from the compressed ECG. Different classification approaches are used for person identification. Experiments on standard ECG databases demonstrate the validity of the proposed system for biometric identification with high accuracies on both healthy and diseased subjects.

key words: *ECG biometric, person identification, JPEG2000*

1. Introduction

The demand for improved security for person identification has been growing rapidly, and among the potential alternatives is employing innovative biometric traits. Biometric identification is reliant on pattern recognition approaches by extracting physiological or behavioral traits of human body and matching them with an enrollment database. Various biometrics have been proposed for use in person identification, such as voice, face, and fingerprint [1]. However, these biometrics either cannot provide reliable performance or not robust enough against falsification. Recent studies have suggested the possibility of using electrocardiogram (ECG) as a new biometric modality for person identification [2]–[9]. ECG signal is a recording of the electrical activity of the human heart, which is individual-specific in the sense of amplitude and time durations of the fiducial points. Furthermore, ECG signal can deliver the proof of subject's being alive as extra information which other biometrics cannot deliver as easily. It is believed that ECG biometric would be particularly effective in health care applications, as the signal can be used for diagnosis of cardiac diseases and also be used to identify subjects before granting them medical services. Recently, ECG biometric recognition has been successfully commercialized as products in mobile applications such as health care and online payment. For example, Nymi wristband [10] is a wearable biometric authentication device that recognizes unique ECG patterns and interfaces directly with mobile devices as a replacement for passwords. In 2015, Linear Dimensions also announced a family of biometric authentication devices including ECG Biolock and ECG optical wireless mouse [11]. Both devices offer proven security and will authenticate users by learning their unique biometric signature in ECG waveform pattern. Prior works on ECG biometrics can be categorized based on the number of ECG channels used, the method for feature extraction, and type of classifier adopted. Of these, ECG as a biometric based on a single channel is the most studied [3]–[9]. Based on the features that are extracted from ECG signals, we can further classify ECG biometrics as either fiducial points dependent [2]–[5] or independent [6]–[9]. Fiducial-based approaches rely on local features linked to the peak and time durations of the P-QRS-T waves. On the other hand, non-fiducial approaches extract statistical features based on the overall morphology of ECG waveform.

In wireless telecardiology scenarios, compressed ECG packets are often preferred for efficient transmission and storage purposes. Most ECG compression methods adopt one-dimensional (1-D) representation for ECG signals and focus on the utilization of the intra-beat correlation between adjacent samples [12]. To better exploit both intra-beat and inter-beat correlations, 2-D compression algorithms have been proposed by converting ECG signals into data arrays and then applying vector quantization [13] or the JPEG2000 image coding standard [14]. 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 [2]–[9]. 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. In 2011, Sufi and Khalil [15] proposed a clustering method for compressed-

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domain ECG biometric using specially designed compression algorithms. The method starts with the detection of cardiac abnormality and only the normal compressed ECG data are used for person identification. It is expected that considering the ECG as images and then applying the JPEG2000 will lead to better results. 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 [8], [9], working in DWT domain remains to be the most promising area for compressed ECG based biometric.

Another problem which requires further investigation is 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 (CVD) patients. This is mainly because that CVD may cause irrecoverable damage to the heart and incurs different forms of distorted ECG morphologies. Recently, there have been initial studies of ECG biometrics for diseased patients with ECG irregularities. Chiu et al. [9] proposed a DWT-based algorithm and reported overall accuracies of 100% and 81% on 35 normal subjects and 10 arrhythmia patients, respectively. Agrafioti and Hatzinakos [16] obtained 96.42% recognition rate using autocorrelation method when tested on 26 healthy subjects from two databases and 30 patients with atrial premature contraction and premature ventricular contraction. Another recent study [17] indicated that a normalization and interpolation algorithm can achieve 100% and 90.11% in accuracies on 52 healthy subjects and 91 CVD patients, respectively. The main purpose of this study is to extract features in a way that the intra-subject variability is minimized and the inter-subject variability is maximized.

The rest of this paper is organized as follows. Section 2 describes the ECG fundamentals and presents a preprocessor which converts ECG signals to 2-D images. Also included is a short overview of the JPEG2000 encoding algorithm. Details of the algorithms for the proposed ECG biometric system are provided in Sect. 3. Section 4 presents the experimental results on standard ECG databases for both healthy and diseased subjects. Finally, Sect. 5 gives our conclusions.

2. 2-D ECG Data Compression

2-D ECG data compression algorithms are designed to exploit both intra-beat and inter-beat correlations of ECG signals. To begin, we apply a preprocessor which can be viewed as a cascade of two stages. In the first stage, the QRS complex in each heartbeat is firstly detected for segmenting and aligning 1-D ECG signals to 2-D images and in the second stage, the constructed ECG images are compressed by the JPEG2000 [18]. Figure 1 shows the block diagram of the 2-D ECG compression scheme described in [14].

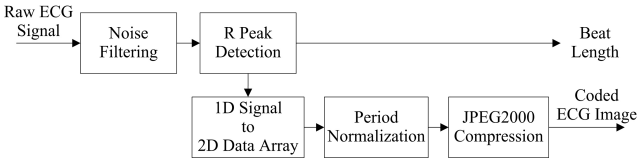

Fig. 1 Block diagram of the 2-D ECG compression scheme [14].

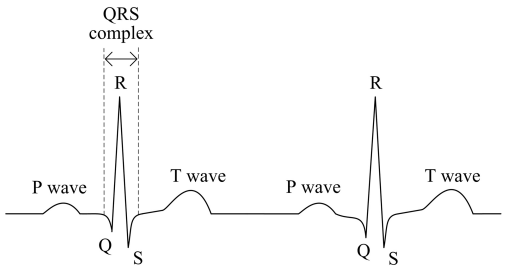

Fig. 2 Typical ECG waveform in time-domain.

2.1 Signal Preprocessing

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 [19]. The P wave corresponds to the depolarization of the right and left atria, whereas the T wave occurs due to ventricular repolarization. The QRS complex is produced when the ventricles depolarize and squeeze the blood from the right ventricle to the aorta. The QRS complex is the most characteristic wave in an ECG waveform and hence, its peak can be used to identify each heartbeat. As shown in Fig. 2, ECG signals tend to exhibit considerable similarity between adjacent heartbeats, along with short-term correlation between adjacent samples. Thus, by dividing ECG signals into segments with lengths equal to the heartbeats, there should be a large correlation between individual segments.

2-D ECG compression algorithms generally starts with a preprocessor which converts 1-D ECG signals into 2-D images. To begin, ECG signals are band-pass filtered to remove various noises such as baseline wander and power-line interference. Afterwards we apply the Biomedical Signal Processing Toolbox [20] 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. Having constructed the data array as such, the intra-beat correlation is in the horizontal direction of the array and the inter-beat correlation is in the vertical direction. Since the heartbeat segments may have different lengths, each row of the data array is period normalized to a fixed length of $N_p = 200$ samples via cubic spline interpolation. This choice was based on the observation that the average heartbeat length is about 0.8 second, which corresponds to 200 samples for a sampling frequency of 250 Hz. Note that the original heartbeat lengths were represented with 9

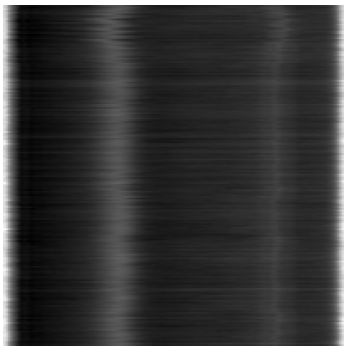

Fig. 3 ECG image for a healthy subject.

bits and transmitted as side information. Finally, we proceed to construct ECG images of dimension $N_c \times 200$ by gathering together N_c rows of the data array and normalizing the amplitude of each component to an integer ranging from 0 to 255. To illustrate this, an example of an ECG image with $N_c = 200$ is shown in Fig. 3. The constructed gray scale ECG images are then ready to be further compressed by the JPEG2000 coding standard.

2.2 JPEG2000 Encoding Algorithm

The JPEG2000 coding standard supports lossy and lossless compression of grayscale and color imagery. Although the standard was originally developed for still image compression [18], its applicability for ECG compression has been proposed in [14]. Apart from its advanced features in scalability and flexibility, the wavelet-based JPEG2000 also supports region of interest coding so that different parts of an image can be coded with different fidelity. As shown in Fig. 4, 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 can be viewed as applying a 1-D DWT decomposition along the lines then the columns to generate an approximation subband and three detail subbands oriented horizontally, vertically and diagonally. With respect to the lifting realization of 1-D DWT [21], prediction and update steps are performed on the input signal to obtain the detail and the approximation signals. A multiresolution representation of the input image over J decomposition levels is obtained by recursively repeating these steps to the resulting approximation coefficients.

With J-level wavelet decomposition, the image will have a total of $3J + 1$ subbands, as shown in Fig. 5. To simplify the notation, the subbands S_j are numbered from 1 to $3J + 1$, with 1 and $3J + 1$ corresponding to the top-left and bottom-right subbands, respectively. Let $S_j = \{s_j(m,n), 1 \le m \le M_j, 1 \le n \le N_j\}$ represent the j-th subband whose row and column dimensions are denoted by M_j and N_j with

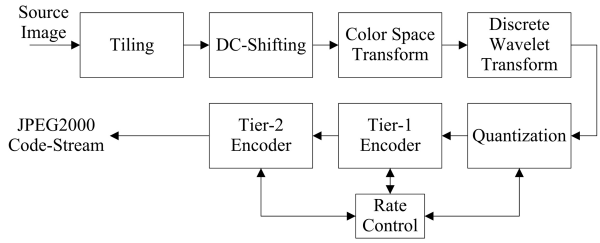

Fig. 4 Fundamental building blocks of JPEG2000 encoder [18].

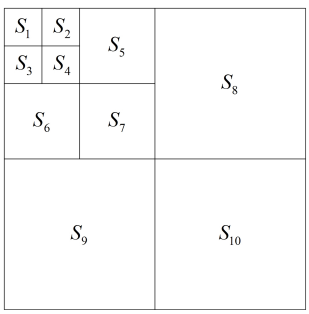

Fig. 5 The subband structure for a 3-level, 2-D wavelet decomposition.

$j \in \{1, 2, \ldots, 3J + 1\}$. For each coefficient $s_j(m,n)$ located at position (m,n), a mid-tread uniform quantizer is applied to obtain an index $v_j(m,n)$ as follows:

$$v_j(m,n) = \text{sign}[s_j(m,n)] \cdot \left\lfloor \frac{|s_j(m,n)|}{\Delta_j} \right\rfloor, \tag{1}$$

where Δ_j denotes the quantizer step size for the j-th subband. A different quantizer is employed for the coefficients of each subband and therefore, a bit allocation among the subbands is carried out in order to meet a targeted coding rate ρ. The last step in JPEG2000 encoding consists in entropy coding of the quantizer indexes with two tier encoders. The tier-1 encoder employs a context modeling to cluster the bits of quantizer indexes into groups with similar statistics in order to improve the efficiency of the arithmetic coder. In the tier-2 encoder, the output of the arithmetic coder is collected into packets and a bit-stream is generated according to a predefined syntax.

3. The Proposed ECG Biometric System

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. Concerning compressed-domain biometric techniques, the JPEG2000 code-stream is subject to partial decoding and then features relating to ECG morphology are computed directly from the de-quantized 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 Fig. 6.

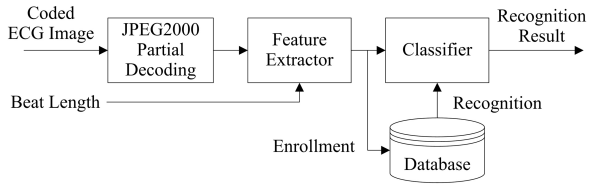

Fig. 6 The proposed ECG biometric system.

3.1 Feature Extraction in DWT Domain

Feature extraction is the first step in applying ECG biometrics to person identification and one that conditions all the subsequent steps of system implementation. 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. Its multi-resolution nature also allows the decomposition of an ECG image into different scales, each of which represents particular coarseness of the signal. 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 [22]–[24]. In general, any measures that provide some degree of class separation should be included in the feature set. However, as more features are added, there is a trade-off between classification performance and computational complexity. In this work, three different feature sets derived from the compressed ECG, denoted by FS1, FS2, and FS3, 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 [22], [23] 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, the de-quantized wavelet coefficients $\hat{s}_j(m,n)$ are computed as follows:

$$\hat{s}_j(m,n) = \{v_j(m,n) + \delta \cdot \mathrm{sign}[v_j(m,n)]\} \cdot \Delta_j, \tag{2}$$

where $\delta \in [0,1)$ is a user defined bias parameter. Although the value of δ is not normatively specified in the standard, it is likely that many decoders will use the value of one half. Then, the energy of subband j is defined as

$$E_j = \frac{1}{M_j N_j} \sum_{m=1}^{M_j} \sum_{n=1}^{N_j} \hat{s}_j^2(m,n). \tag{3}$$

The resulting subband energy-based features are used as a morphological descriptor of ECG signals. Another feature of interest is the average time elapse between two successive R peaks, referred to as the RR_{av}. Certain ectopic heartbeats, such as premature ventricular contraction and atrial premature beats, are related with premature heartbeats that provide shorter RR-intervals than other types of ECG signals. Thus, changes in the RR-interval plays an important role in characterizing the dynamics information around the heartbeats. Notice that the RR_{av} can be calculated from the heartbeat lengths which are transmitted as side information along with the JPEG2000 code-stream. With J-level wavelet decomposition, a total of $(3J+2)$ features are used to form a biometric identification vector (BIV) of the subject. The BIV used for the FS1 will be denoted as $\mathbf{b}^{(1)} = \{E_1, E_2, \ldots, E_{3J+1}, RR_{av}\}$.

The second feature set FS2 is obtained by applying principal component analysis (PCA) [25] on wavelet coefficients from the lowpass subband S_1. The validity of using S_1 is supported by the fact that the lowpass subband represents 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. To begin, consider a training dataset consisting of ECG images of dimension $N_c \times 200$. Let M_1 and N_1 denote the row and column dimensions of the lowpass subband S_1 after the wavelet decomposition, respectively. Before applying the PCA, M_1 rows of the subband S_1 are concatenated to form a wavelet coefficient vector of length $M_1 \times N_1$, i.e., $\mathbf{u} = \{\hat{s}_1(1,1), \hat{s}_1(1,2), \ldots, \hat{s}_1(M_1,N_1)\}$. Then, the mean vector $\bar{\mathbf{u}}$ and the covariance matrix $\Sigma_{\mathbf{u}}$ are computed using the training dataset. Following the eigen-decomposition, we obtain an eigenvalue matrix D and its corresponding eigenvector matrix V with its column vectors sorted in the descending order of eigenvalues. Finally, the wavelet vector $\mathbf{u}$ is projected on the eigenvectors to obtain the principal component vector $\mathbf{p} = V^{\mathrm{T}}(\mathbf{u} - \bar{\mathbf{u}})$. In this work, only the first seven principal components are selected based on containment of 99% of the total variability. Together with the RR-interval, the BIV for the FS2 is composed of eight features and is denoted as $\mathbf{b}^{(2)} = \{p(1), \ldots, p(7), RR_{av}\}$. As for the feature set FS3, it is a combined version of FS1 and FS2 and the corresponding BIV is denoted as $\mathbf{b}^{(3)} = \{\mathbf{b}^{(1)}, \mathbf{b}^{(2)}\}$.

3.2 Enrollment and Recognition

Enrollment and recognition are two important stages of the person identification system. In the enrollment 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 a match. The recognition performance depends on the underlying classifier used for person identification. First, nearest-neighbor (NN) classifiers are exploited for testing various feature sets in discriminating different subjects. The NN classifier tends to search for the most similar class to a given query BIV with similarity de-

fined by the normalized Euclidean distance [23].

Another classification approach considered here is the support vector machine (SVM) which has shown effective in many pattern recognition problems [26], [27]. This is partly due to their good generalization capability derived from the structural risk minimization principle. Since person identification involves the simultaneous discrimination of several subjects, we considered the one-against-one method for solving multiclass SVM problems [27]. 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 $\mathbf{x}_t \in \{\mathbf{b}^{(1)}, \mathbf{b}^{(2)}, \mathbf{b}^{(3)}\}$ and its corresponding class label $y_t \in \{1, 2, \ldots, K\}$. Given a set of T training data pairs $\{(\mathbf{x}_t, y_t), t = 1, 2, \ldots, T\}$ from classes i and j, SVM algorithm can be formulated as the following primal quadratic optimization problem:

$$\begin{aligned} &\min_{\mathbf{w}^{ij}, b^{ij}, \xi_t^{ij}} \frac{1}{2}\|\mathbf{w}^{ij}\|^2 + C\sum_{t=1}^{T}\xi_t^{ij}, \\ &\text{subject to: } (\mathbf{w}^{ij})^{\mathrm{T}}\mathbf{x}_t + b^{ij} \geq 1 - \xi_t^{ij}, \quad \text{if } y_t = i, \\ &\qquad\qquad (\mathbf{w}^{ij})^{\mathrm{T}}\mathbf{x}_t + b^{ij} \leq -1 + \xi_t^{ij}, \text{ if } y_t = j, \\ &\qquad\qquad \xi_t^{ij} \geq 0, \end{aligned} \tag{4}$$

where C is a regularization parameter, $\mathbf{w}^{ij}$, b^{ij} and ξ_t^{ij} are the weight vector, bias and slack variable, respectively. Due to various complexities, a direct solution to minimize the objective function (4) with respect to $\mathbf{w}^{ij}$ is usually avoided. A better approach is to apply the method of Lagrange multipliers to solve the dual problem as follows:

$$\begin{aligned} &\max_{\mathbf{a}^{ij}} \sum_{t=1}^{T} a_t^{ij} - \frac{1}{2}\sum_{t=1}^{T}\sum_{t'=1}^{T} a_t^{ij} a_{t'}^{ij} y_t y_{t'} \mathbf{x}_t^{\mathrm{T}}\mathbf{x}_{t'}, \\ &\text{subject to: } \sum_{t=1}^{T} a_t^{ij} y_t = 0, \\ &\qquad\qquad 0 \leq a_t^{ij} \leq C, \end{aligned} \tag{5}$$

where $\mathbf{a}^{ij} = (a_1^{ij}, a_2^{ij}, \ldots, a_T^{ij})$ is the vector of Lagrange multipliers. In this work, the dual problem to SVM learning is solved using the sequential minimal optimization method [26]. After obtaining the optimum values of Lagrange multipliers $\mathbf{a}^{ij}$, it is then possible to determine the corresponding weight vector $\mathbf{w}^{ij}$ and the decision function $f_{ij}(\mathbf{x}_t)$ as follows:

$$\mathbf{w}^{ij} = \sum_{t=1}^{T} a_t^{ij} y_t \mathbf{x}_t, \tag{6}$$

$$f_{ij}(\mathbf{x}_t) = (\mathbf{w}^{ij})^{\mathrm{T}}\mathbf{x}_t + b^{ij}. \tag{7}$$

Finally, the class label y for a query BIV $\mathbf{x}$ of a new subject is determined based on the max-wins voting strategy [27]. More precisely, each binary SVM casts one vote for its preferred class and the final result is the class with the highest vote, i.e.,

$$y = \arg\max_i \sum_{j \neq i, j=1}^{K} \text{sign}[f_{ij}(\mathbf{x})]. \tag{8}$$

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 PhysioNet QT Database [28] were chosen to represent a wide variety of QRS and ST-T morphologies. First, 10 healthy subjects that are originally from the MIT-BIH Normal Sinus Rhythm Database are used in the experiments and denoted as dataset D1. Subjects that are added to the database to examine the effects of diseased ECG consist of 10 records from the MIT-BIH Arrhythmia Database, 10 records from the MIT-BIH Supraventricular Arrhythmia Database, and 10 records from the Sudden Cardiac Death Holter Database. For convenience, these three groups of diseased subjects are denoted as D2, D3, and D4, respectively. Each of these records is 15 minutes in duration and are sampled at 250 Hz with a resolution of 11 or 12 bits/sample. The JPEG2000 simulation was run on the open-source software JasPer version 1.900.0 [29]. 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 5-level wavelet decomposition. Besides, the targeted coding rate ρ was empirically determined to be 0.15 and 0.08 in order to achieve the compression ratio in the region of 10 and 20, respectively.

A preliminary experiment was first conducted to examine the performance dependence of 2-D compression on the number N_c of heartbeats employed in constructing an ECG image. The system performance is evaluated in terms of the compression ratio (CR) and the percent root mean square difference (PRD). The CR is defined as $\text{CR} = N_{ori}/N_{com}$, where N_{ori} and N_{com} represent the total number of bits used to code the original and compressed ECG data, respectively. The PRD is used to evaluate the reconstruction distortion and is defined by

$$\text{PRD}(\%) = \sqrt{\frac{\sum_{l=1}^{L}[x_{ori}(l) - x_{rec}(l)]^2}{\sum_{l=1}^{L} x_{ori}(l)^2}} \times 100, \tag{9}$$

where L is the total number of original samples in the record and x_{ori} and x_{rec} represent the original and reconstructed ECG signals, respectively. Table 1 presents the average results of CR and PRD for JPEG2000 simulation with coding rate $\rho = 0.15$ and $\rho = 0.08$. As expected, the system yielded better performance with an increase in the heartbeat number N_c. However, the increasing delay may limit its practical applicability as the JPEG2000 must buffer a total of $N_c \times 200$ samples before it can start encoding. Thus, we

Table 1 Average CR and PRD (%) performances for JPEG2000 with coding rate $\rho = 0.15$ and $\rho = 0.08$.

Dataset	N_c	Rate $\rho = 0.15$				Rate $\rho = 0.08$			
		50	100	150	200	50	100	150	200
D1	CR	12.19	13.45	14.04	14.28	21.62	21.90	21.84	21.84
	PRD	3.59	3.19	3.19	3.08	8.72	5.91	5.55	5.55
D2	CR	9.03	9.37	9.49	9.70	16.81	16.92	16.84	16.84
	PRD	4.19	3.48	3.36	3.26	11.36	7.95	7.18	7.18
D3	CR	10.07	10.06	10.06	10.61	18.90	19.19	18.87	18.87
	PRD	4.53	3.56	3.45	3.18	11.86	8.75	7.99	7.94
D4	CR	10.11	10.23	10.42	10.05	19.11	19.13	19.13	19.13
	PRD	4.21	3.32	3.19	3.29	12.35	8.76	7.92	7.92

empirically choose $N_c = 200$ as the best compromise in the sequel. Note that while the 2-D compression method works well for normal ECGs, it may suffer from ECG irregularities due to the false QRS detection in the preprocessor stage. For the case of $\rho = 0.08$ and $N_c = 200$, the PRD performance has dropped from 5.55% in the D1 to 7.92% in the D4.

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 [30]. It was found that the execution time breakdown for the JPEG2000 decoder depends heavily on the particular image and coding scenarios employed. In the case of lossless image compression, tier-1 decoding usually requires the most time (typically more than 50%), followed by the inverse DWT (typically 30–35%), and then tier-2 decoding. For lossy image compression, as in our case, the inverse DWT accounts for the vast majority of the decoder's execution time (typically 60–80%). The complexity analysis results demonstrate that the proposed method has the advantage of by-passing the inverse DWT operation.

The next step is to evaluate the recognition performances of NN classifiers on the feature sets FS1 and FS2. Both feature sets have in common the RR_{av} to provide dynamics feature of ECG signals. Morphological features to be computed for the FS1 are subband energies $\{E_j, 1 \leq j \leq 16\}$, and PCA-based features $\{p(i), 1 \leq i \leq 7\}$ for the FS2. The system performance is evaluated in terms of the recognition rate, which is normally defined as the ratio of the number of correctly identified subjects to the total number of testing subjects. First of all, the proposed systems were individually tested on datasets from D1 to D4. Since ECG records from the QT database may vary in the number of heartbeats, a total of 4 to 8 ECG images of dimension 200×200 would be generated for different individuals. For a fair assessment, 1000 trials of repeated random subsampling were implemented to eliminate possible classification biases. In each trial, four compressed ECG images per subject were randomly selected for feature extraction. Among them, the first two ECG images are used for training in the enrollment stage, and the other two are used for testing in the recognition stage. Table 2 presents the average recognition rates associated with various datasets for JPEG2000 coding with $\rho = 0.15$ and $\rho = 0.08$. 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 the case of FS2 and $\rho = 0.15$, the recognition rate was 100% for normal subjects, 91.82% for arrhythmia subjects, 95.62% for supraventricular arrhythmia subjects, and 91.77% for sudden cardiac death subjects. The possible reasons resulting in a lower recognition rate for diseased subjects could be unstable QRS-complex that appear aperiodically in ECGs. It is important to note that the lower value of $\rho = 0.08$ did not result in a significant performance degradation. This can be attributed to the fact that the JPEG2000 supports a lower coding rate by enlarging the quantizer step sizes within high frequency subbands. This has little effect on the recognition performance, as the frequency content of the QRS complex is most concentrated in low frequency subbands. To elaborate further, we also include in Table 2 the recognition performances for the case where normal and diseased subjects are jointly enrolled and tested. As the table shows, the additional inclusion of 30 diseased subjects has dropped the recognition rate by 4.45%. The results indicate that the combined use of FS2 and NN classifier is still not robust enough to handle the inclusion of diseased patients in the database.

Table 2 Recognition rates (%) of NN classifiers using feature sets FS1 and FS2.

Dataset	JPEG2000 ($\rho = 0.15$)		JPEG2000 ($\rho = 0.08$)	
	FS1	FS2	FS1	FS2
D1	96.16	100	95.29	99.98
D2	86.82	91.82	86.73	91.75
D3	91.61	95.62	91.75	95.50
D4	84.50	91.77	83.52	91.91
D1, D2, D3, D4	88.92	95.55	88.85	95.57

Another problem which requires further investigation is to test the proposed system for the situation where subjects were identified solely by means of DWT-based mor-

Table 3 Recognition rates (%) of NN classifiers using feature sets FS1 and FS2 without RR-interval.

Dataset	JPEG2000 (ρ = 0.15)		JPEG2000 (ρ = 0.08)	
	FS1 (no RR_{av})	FS2 (no RR_{av})	FS 1 (no RR_{av})	FS2 (no RR_{av})
D1	95.77	99.73	94.93	99.65
D2	85.61	88.18	85.93	88.40
D3	91.27	95.34	90.84	95.57
D4	80.98	90.20	77.73	89.69
D1, D2, D3, D4	86.32	94.58	86.46	94.56

phological features. The performances of NN classifiers for FS1 and FS2 without incorporating the RR-interval are summarized in Table 3. A comparison between Table 2 and 3 indicates that the inclusion of RR-interval is likely to help in discriminating between subjects with greater accuracy. However, we should state that the issue of whether it is better to use RR-interval in the ECG biometric does not appear to be settled and may be problem dependent [5]. Prior works on ECG biometric [2]–[4], [15] have suggested the use of the RR-interval as a second source of biometric data to supplement morphological features of ECG signals. However, almost all these works exploited a database containing ECG signals in rest conditions, which represents also a limitation for practical issues of biometric systems. Recent studies [5], [31] have shown that ECG signals acquired in different physiological conditions allow for substantial variability in heart rates, which could significantly impact the performance of the biometric system. Continuing this research, we will address ourselves to the study of robust ECG biometric algorithms utilizing biometric features without the RR-interval.

We next compare the performances of NN and SVM classifiers trained on the combined feature set FS3. With 5-level wavelet decomposition, a total of 24 features are used to form the FS3, including RR_{av}, $\{p(i), 1 \le i \le 7\}$, and $\{E_j, 1 \le j \le 16\}$. Table 4 gives the recognition performances of various datasets using NN and SVM for classification. With respect to the implementation of SVM classifiers, the simulation was run on the open-source software LIBSVM [32], which supports SVM formulations for various classification problems. The results clearly demonstrate the improved performances achievable using the FS3 in comparison to those of FS1 and FS2, even with a simple NN classifier. The main reason for this is that the FS3 features a high similarity among the BIVs of the same person, either healthy or with CVD, but a much lower similarity between two BIVs of different persons. The results also indicate that the SVM classifiers trained on FS3 are very effective with 100% recognition rate in all test datasets. Compared with NN classifier, the SVM shows better generalization ability on the limited training data, which is indeed the case performed in this study. Also included in the table are the performances when 86 ECG records from the QT database are jointly enrolled and tested. The proposed system can achieve 99.50% and 99.48% in accuracies for JPEG2000 compression with ρ = 0.15 and ρ = 0.08, respectively. The results indicate that the combined use of FS3 and SVM classifier is more invariant to ECG irregularities induced by cardiovascular diseases.

Table 4 Recognition rates (%) of the feature set FS3 using NN and SVM classifiers.

Dataset	JPEG2000 (ρ = 0.15)		JPEG2000 (ρ = 0.08)	
	NN	SVM	NN	SVM
D1	100	100	99.99	100
D2	98.99	100	98.93	100
D3	99.85	100	99.99	100
D4	97.37	100	97.44	100
D1, D2, D3, D4	99.09	100	99.15	100
QT database	96.06	99.50	96.15	99.48

Table 5 Recognition rates (%) of the feature sets FS3 with and without quantization.

Dataset	FS3		FS3 (uncompressed)	
	NN	SVM	NN	SVM
D1	100	100	100	100
D2	98.99	100	98.89	100
D3	99.85	100	99.91	100
D4	97.37	100	97.39	100
D1, D2, D3, D4	99.09	100	99.11	100
QT database	96.06	99.50	96.09	99.49

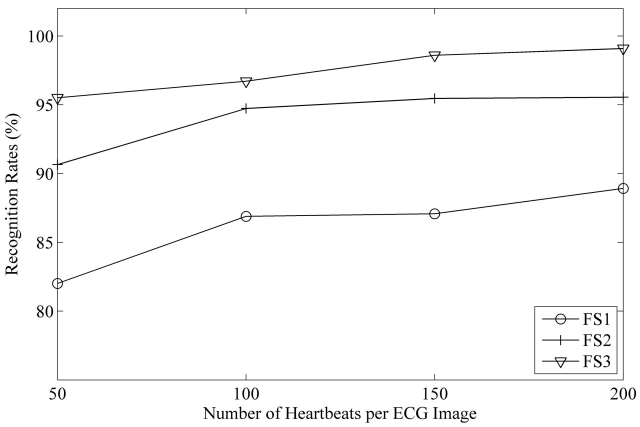

Fig. 7 Recognition rates for different ECG image sizes using JPEG2000 with ρ = 0.15.

In addition to the above-mentioned schemes, we also investigated the situation where the feature set FS3 was extracted using uncompressed data. Toward this end, we repeated the same steps as the proposed system, only this time the DWT coefficients do not go through the quantization but instead they go directly to the feature extractor for classification. Table 5 gives the results that compare the case where morphological features were extracted using quantized DWT coefficients (ρ = 0.15) against the case that was extracted using uncompressed data. As the table shows, the quantization does not degrade the accuracy of the proposed identification system. Finally, we examine how the recognition performance changes as a function of the number of heartbeats used in constructing an ECG image. The results are illustrated in Fig. 7 for various image sizes using an NN classifier and a combined dataset from D1 to D4. Our general conclusion is that better performances can be achieved

with an increase in the heartbeat number N_c, but the performance has a tendency to become flattened for $N_c \geq 100$. This would be beneficial for future works on real-time implementation of the proposed ECG biometric systems.

5. Conclusions

This paper proposed a robust method for biometric identification using wavelet-based 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. Also, dynamic feature such as RR-interval proved to be beneficial for ECG biometric. Combined performance from both healthy persons and diseased patients indicate that the proposed system enables faster biometric identification in compressed domain and at the same time it is more invariant to ECG irregularities induced by cardiovascular diseases.

It should be noted that the results presented in this work, while promising, were obtained from a moderate size of datasets. Also, the experiments were conducted off-line, using ECG signals collected under controlled conditions from public databases. In practical applications, however, a range of issues would require further investigations. First, the ECG biometric system needs to be tested in more realistic environments, varying with respect to the type and quantity of data collected. Second, the effects of varying mental and physiological conditions on the recognition accuracy, as well as the delay induced by JPEG2000 coding also need to be resolved.

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