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ECG steganography using curvelet transform

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ABSTRACT

ECG steganography allows secured transmission of patient data that are tagged to the ECG signals. Signal deterioration leading to loss of diagnosis information and inability to retrieve patient data fully are the major challenges with ECG steganography. In this work, an attempt has been made to use curvelet transforms which permit identifying the coefficients that store the crucial information about diagnosis. The novelty of the proposed approach is the usage of curvelet transform for ECG steganography, adaptive selection of watermark location and a new threshold selection algorithm. It is observed that when coefficients around zero are modified to embed the watermark, the signal deterioration is the least. In order to avoid overlap of watermark, an $n \times n$ sequence is used to embed the watermark. The imperceptibility of the watermark is measured using metrics such as Peak Signal to Noise Ratio, Percentage Residual Difference and Kullback-Leibler distance. The ability to extract the patient data is measured by the Bit Error Rate. Performance of the proposed approach is demonstrated on the MIT-BIH database and the results validate that coefficients around zero are ideal for watermarking to minimize deterioration and there is no loss in the data retrieved. For an increased patient data size, the cover signal deteriorates but the Bit Error Rate is zero. Therefore the proposed approach does not affect diagnosability and allows reliable steganography.

1. Introduction

Modern wearable biomedical devices enable ubiquitous healthcare monitoring. The bio-physiological parameters acquired by these devices can be transmitted over the internet. This allows patients to receive care giver's assistance even remotely. During transmission, patient data such as their personal identity is tagged along with the medical information. Patient data protection needs to be ensured in spite of the threat of unauthenticated access [1–3]. One way to achieve this is by employing data hiding techniques [4–6]. Steganography is one such technique where personal data are hidden in biomedical signals [7–12]. Example of personal data include: patient name, age, gender and past treatment details. In medical domain, the bio-medical signal is the cover signal and personal data to be hidden is referred to as watermark. In this work, ECG is the cover signal and patient data is the watermark.

Steganography causes irreversible deterioration to the cover signal. In ECG signals, the characteristic points that help in diagnosis are the QRS complex, P and T waves. Hence, in ECG steganography it is imperative to minimize the deterioration at these characteristic points. This permits preserving the information needed for diagnosis, despite the deterioration. The extent of deterioration is an usual performance measure of a steganography algorithm. Steganography is usually performed in frequency domain. It consists of cover signal decomposition, digital watermark embedding and watermark retrieval. The signal is usually decomposed using a selected transform. Widely used transformation techniques are Discrete Wavelet Transform (DWT) and Fast Discrete Curvelet Transform (FDCT) [7,13–16]. Chen et al. [8] evaluates ECG steganography using DWT, Discrete Fourier Transform (DFT) and Discrete Cosine Transform (DCT). They conclude that ECG steganography in transform domain is efficient and useful.

Watermarking methods such as Least Significant Bit (LSB), coefficient quantization and Singular Value Decomposition (SVD) are used to embed the data into the cover signal [7,8,17]. The challenge lies in selecting coefficients that will lead to minimal changes at the characteristic points. In order to avoid overlapping of watermark allocation and modification of pixel value, Hong et al. [18] separates each watermarked position by at least one pixel. Researchers [10–12] proposed wavelet based watermarking schemes in biomedical images. They demonstrated improvements in robustness, imperceptibility and integrity control capability. Despite promising results, wavelets have limitations in representing curves. Curves are where important phenomenon or

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information such as characteristic points are present. Hence, it is desirable to develop a steganography framework with the following features: (i) identify the coefficients that store the crucial information for diagnosis (ii) minimally deteriorate the cover signal while preserving the diagnosability information and (iii) retrieve patient data without any loss.

In the recent past, Candes et al. [19] introduced a new member in the family of wavelet transforms called the curvelet transforms. They were developed to address the limitations of traditional multiscale representations. They also provide optimal sparse representation of edges. Curvelet coefficients are computed from different scale, orientation and translation analysis of an image. Therefore, curvelets are able to represent curved edges well. Hien et al. [13] evaluated watermarking in curvelet coefficients of an image using thresholding algorithm. A high capacity image steganography using curvelet transform is presented by Al-Ataby et al. [14]. Here, the threshold value is the mean of curvelet coefficients. Curvelet coefficients whose values are less than the threshold value are chosen for watermarking. Feature point based image watermarking using curvelet transform is proposed by Huang et al. [15] to resist the geometric distortion. Leung et al. [16] conducts an extensive study of watermarking methods using curvelet transform. They introduced a blind watermarking scheme which uses secret keys to determine the watermark position. The advantage of blind watermarking scheme is that the cover image is not necessary during watermark extraction. These studies show that curvelet transform can be used in image steganography successfully and we extend the idea to ECG steganography.

In this study, FDCT based ECG steganography is investigated. FDCT allows identifying the coefficients that represent curves. An adaptive thresholding algorithm is proposed to minimize signal deterioration. A signal from MIT-BIH normal sinus rhythm database [20] is used for demonstration purpose. The proposed approach improves the imperceptibility of watermark and reduces error rate in extracted patient data. The performance of steganography algorithm is measured using Peak Signal to Noise Ratio (PSNR) and Bit Error Rate (BER), respectively. Percentage Residual Difference and Kullback-Leibler divergence (KL) which provides the distance between the original and the watermarked signal are also provided. Imperceptibility of watermark is also measured by the watermarking capacity referred to as watermark size. We present the performance of the proposed approach for different watermark sizes as well.

The rest of the paper is organized as follows: In methodology section, the general framework of steganography is presented along with discussions on curvelet and quantization approach. The description of the proposed approach is presented next following which discussions on adaptive watermarking and threshold selection are presented. The performance of the proposed approach is presented in results and discussions.

2. Methodology

The basic architecture of steganography using biomedical signal consists of two major components: watermark embedding and watermark extraction, as shown in Fig. 1. The biomedical signal when subjected to a transformation results in coefficients. The watermark embedding algorithm hides the patient data into these coefficients. The inverse transform is then applied to construct the watermarked signal. This watermarked signal upon transmission is received by the health care provider. Here, the patient data need to be retrieved. The data can be extracted by subjecting the watermarked signal to transformation and using a Key. The Key is an array which contains the positions of patient data in watermarked coefficient matrix.

In this paper, a 1D ECG signal from MIT-BIH normal sinus rhythm database [20] is used as the biomedical signal. The sampling rate of the chosen signal is 128 Hz. The 1D signal is converted into a 2D image. Curvelet transforms are used so as to represent the curved edges well [19,21]. Curvelet obeys parabolic scaling relation, width $\approx$ length^2 and provides optimally sparse representation of an image with edges. Unequally-spaced Fast Fourier Transform (USFFT) is one of the digital implementation methods of Fast Discrete Curvelet Transform (FDCT). The curvelet coefficient (c) of an ECG image can be calculated using USFFT–FDCT as given in the following equation:

$$c\,(j,l,k) = \int \hat{f}\,(S_{\theta l}\omega)\,\tilde{U}_j\,(\omega)\,e^{i\langle b,\omega\rangle}\,\mathrm{d}\omega \qquad (1)$$

where j, l and k are the parameters of scale, orientation and translation, respectively; $\hat{f}$ is the two dimensional (2D) Discrete Fourier Transform (DFT) of an image f; $S_{\theta l}$ and ω are shear grid and frequency variable, respectively; $\tilde{U}_j(\omega)$ is a Cartesian window which isolates the frequencies near the wedge $\{(\omega_1,\omega_2): 2^j \le \omega_1 \le 2^{j+1}, -2^{-j/2} \le \omega_1/\omega_2 \le 2^{-j/2}\}$; Cartesian grid $b=(k_1 2^{-j}, k_2 2^{-j/2})$ where k_1 and k_2 are the translation parameters.

The discrete curvelet coefficients (c^D) of a Cartesian array input $f[t_1,t_2]$ are computed as given in the following equation:

$$c^D(j,l,k)=\sum_{n_1,n_2\in p_j} \hat{f}[n_1,n_2-n_1\tan\theta_l]\tilde{U}_j[n_1,n_2]e^{i2\pi\left(k_1n_1/L_{1,j}+k_2n_2/L_{2,j}\right)} \qquad (2)$$

where $\hat{f}[n_1,n_2]$ is the Discrete Fourier Transform of an image $f[t_1, t_2]$; $\tan\theta_l$ is the slope, length $L_{1,j}$ and width $L_{2,j}$ are the original dimensions of the parallelogram p_j. The readers are referred to Candes et al. [19] for digital implementation methods of FDCT.

The patient data is converted into its equivalent binary form. The binary data is hidden in c^D using quantization approach as presented in the following equation:

$$c^*(i,j) = \alpha\left|c^D(i,j)\right| w \qquad (3)$$

where c^* is the watermarked coefficients; α is an embedding strength ($0<\alpha\le 1$); (i,j) are the coordinates of watermark positions in c^D; w is set to 1 if the watermark bit is 1 and w is set to -1 if the watermark bit is 0. The choices of coefficients to be modified are made based on a threshold algorithm. The threshold corresponds to the size of watermark. When the modified coefficients are subjected to inverse FDCT, the watermarked ECG image is obtained.

Upon transmission, the watermarked ECG image is subjected to FDCT for extracting the patient data. The reference key is used to identify the positions of watermarked coefficients. The reverse of watermark embedding is applied to extract the watermark bits as given in the following equation:

$$w_r = \begin{cases} 1, & \text{if}\ \ \hat{c}(i,j) > 0 \\ 0, & \text{if}\ \ \hat{c}(i,j) < 0 \end{cases} \qquad (4)$$

where $\hat{c}$ is the retrieved coefficient; w_r is the extracted watermark bit; If $\hat{c}$ is greater than zero, the extracted watermark bit is 1; if $\hat{c}$ is less than zero, the extracted watermark is 0.

In this work, we propose an adaptive watermarking scheme which allows for less deterioration of the signal. This results in no compromise on diagnosability and better data extraction. The major components of the proposed method are presented in Fig. 2 which includes:

(1) Preprocessing:
  (a) Conversion of 1D ECG signal to 2D ECG image and calculate curvelet coefficients of the image.
  (b) Obtain binary format of the watermark to embed in the curvelet coefficients.

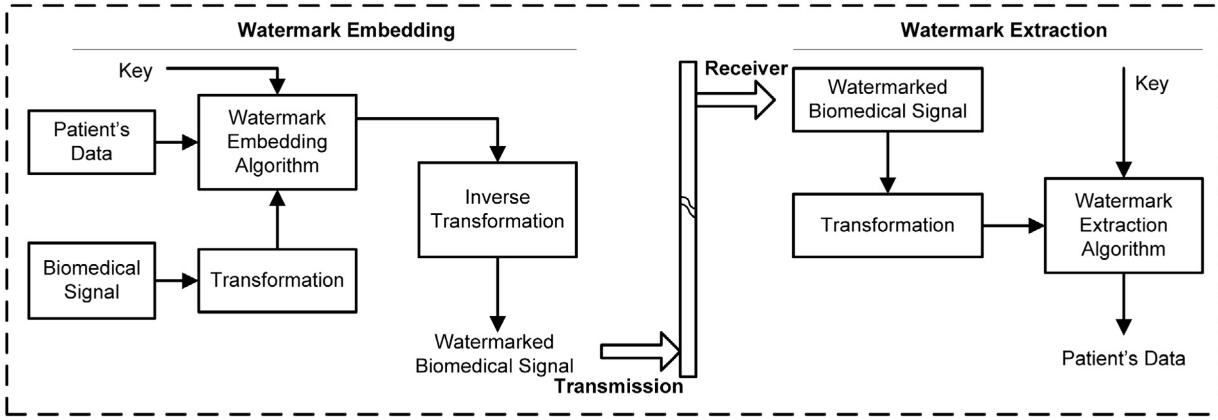

Fig. 1. Biomedical signal steganography architecture.

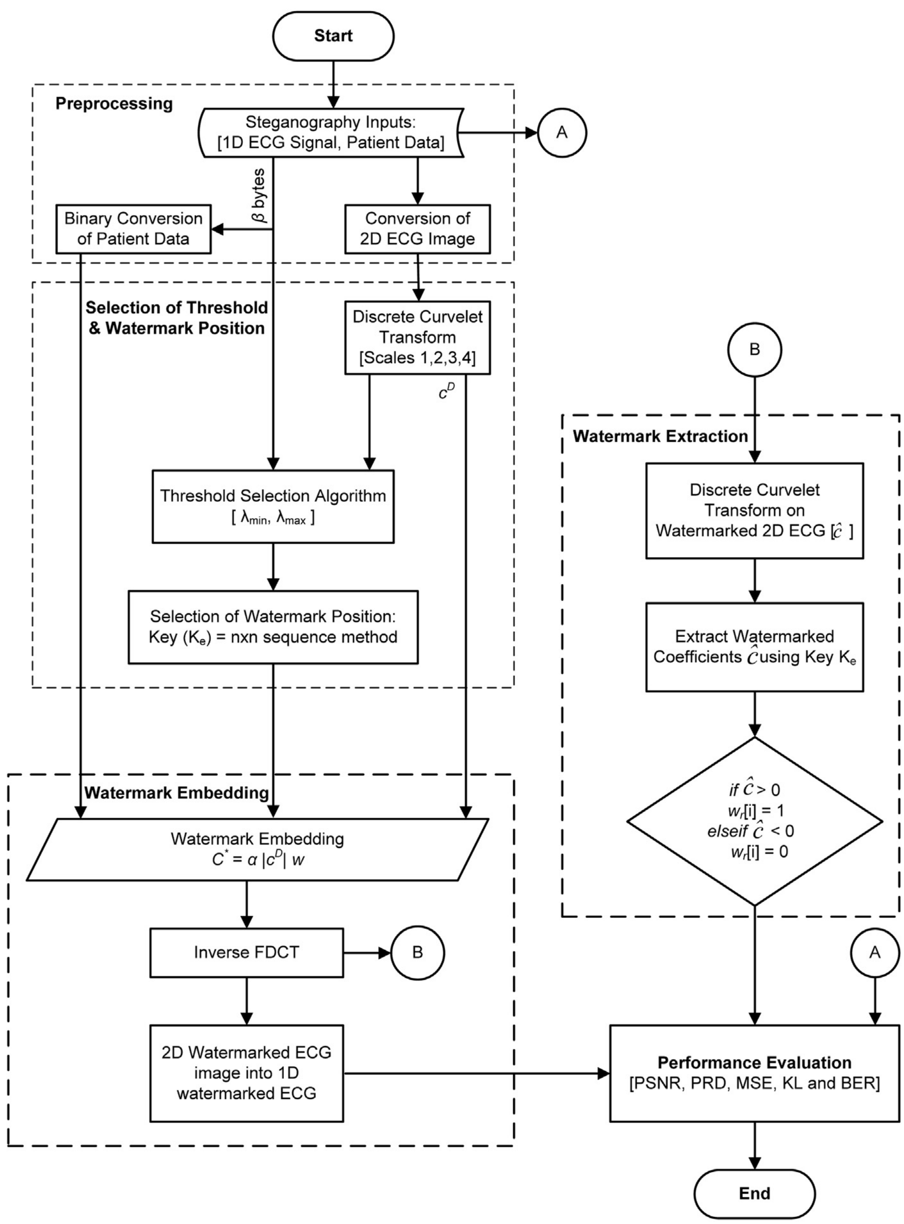

Fig. 2. Curvelet transform based ECG steganography architecture.

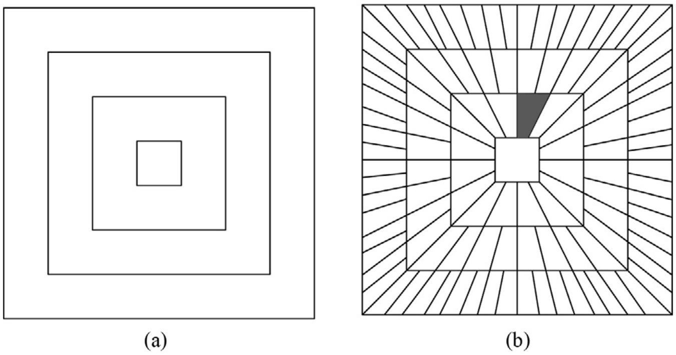

Fig. 3. Segmentation in frequency space (a) concentric square, (b) wedges.

(2) Threshold selection.
(3) Selection of $n \times n$ sequence watermark position.
(4) Watermark extraction and performance evaluation.

2.1. Preprocessing

The 1D ECG signal is converted into the 2D ECG image based on the fiducial mark of each QRS complex according to Tompkins algorithm [22]. The image is transformed by FDCT following Eq. (2). FDCT converts the image from time domain to frequency domain using Fast Fourier Transform. The frequency space is then divided into scales which are pictorially depicted by concentric squares in Fig. 3(a). Usually, the relationship $\log_2(n)$ is used to determine the number of scales; where n is the image size. Then, digital tiling of scaled frequency space, wedges are constructed using Cartesian window as given in Eq. (5). Digital tiling is depicted in Fig. 3(b).

$$\tilde{U}_j(\omega) = W_j(\omega) V_j(S_{\theta l}\omega) \tag{5}$$

where $S_\theta = \begin{pmatrix} 1 & 0 \\ -\tan\theta & 1 \end{pmatrix}$ $W_j(.)$ is a radial window and $V_j(.)$ is an angular window.

The curvelet coefficients of each wedge can be found using Eq. (2). These are sensitive to the frequency components of the image. Low frequency components are grouped at scale 1. Scales 2 and 3, wedges of second and third concentric squares contain the coefficients of intermediate frequency. Scale 4, the outermost, contain the high frequency components. The patient data, upon conversion to binary form need to be embedded in the obtained coefficients. The coefficients chosen for embedding patient data play a vital role in the deterioration. In order to preserve diagnosability information, modifying the coefficients in scale 4 is a good choice [17].

2.2. Threshold selection

The number of coefficients to be modified is dependent on the size of the patient data. In ordered c^D the coefficient indexed with the size of watermark is chosen as threshold [13]. Let β be the number of watermark bits and N is the number of finest scale coefficients ($\beta < N$). In the case of negative coefficients, if the coefficients below the threshold value are to be modified, a coefficient value indexed with size of the watermark is selected as threshold value $\lambda_{\min}$. The minimum of the coefficient is $\lambda_{\max}$ (maximum in magnitude) as shown in Fig. 4(a) and the coefficients in this range are modified. Similarly, the complement is done if the coefficients larger than a threshold are to be modified as shown in Fig. 4(b).

The proposed approach selects a threshold range ($\lambda_{\min}$, $\lambda_{\max}$) which is approximately $n/2$ coefficients on either side of a coefficient which is very near to zero (C_{zero}). This is pictorially represented in Fig. 5. Since the edges are represented by absolute high coefficients, this arrangement minimizes the chances of modifying a curve.

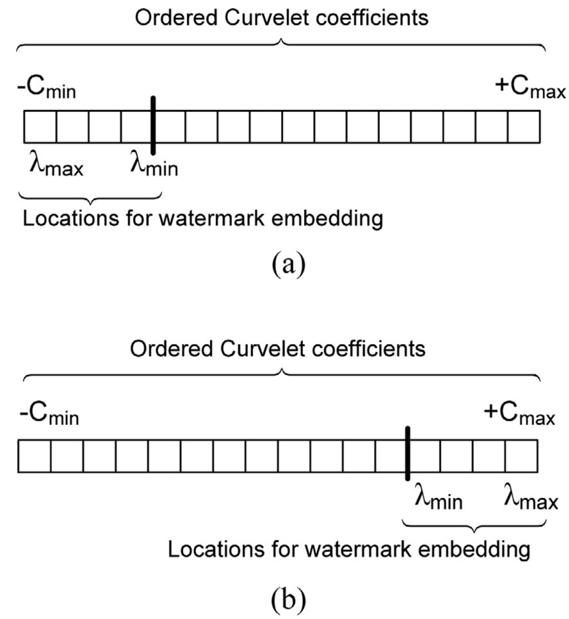

Fig. 4. Threshold value selection based on (a) lowest coefficients, (b) highest coefficients.

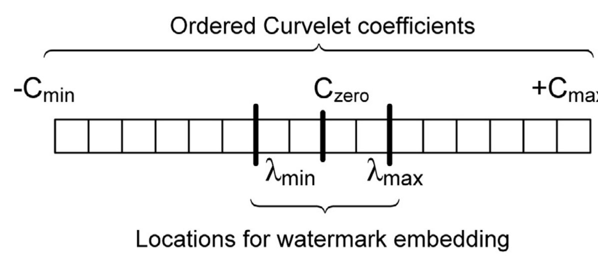

Fig. 5. Threshold selection with coefficients around zero.

2.3. Selection of n × n sequence watermark position

In order to avoid overlapping of watermark allocation and modification of coefficient values, $n \times n$ sequence method is proposed by Hong et al. [18] and also reported in [15,23]. A typical representation on an $n \times n$ sequence rule with the various watermark positions and their neighbors, is presented in Fig. 6. The watermark position $c^D{}_{(i,j)}$ prevents its neighbors $c^D{}_{(i-1,j-1)}$, $c^D{}_{(i-1,j)}$, $c^D{}_{(i-1,j+1)}$, $c^D{}_{(i,j-1)}$, $c^D{}_{(i,j+1)}$, $c^D{}_{(i+1,j-1)}$, $c^D{}_{(i+1,j)}$, and $c^D{}_{(i+1,j+1)}$ from being embedded with a watermark bit. However, the watermarking capacity is reduced in this approach. Usually, the $n \times n$ sequence is exercised in a blind manner. In other words, random keys are generated and neighbors around chosen locations are locked from change. An adaptive technique is proposed here where coefficients near C_{zero} are selected for watermarking. Then, $n \times n$ neighbors around it are locked. The subsequent watermark bit will be embedded in the next available coefficient. By doing this, we are trying to modify coefficients that are not too far from C_{zero}. This allows for not modifying coefficients that represent the curves.

2.4. Watermark extraction and performance evaluation

The hidden patient data can be extracted using Eq. (4). The performance of an ECG steganography algorithm can be measured using metrics such as PSNR, PRD and KL distance [24–29]. These metrics measure the imperceptibility of the watermark. High PSNR, low PRD and KL values are interpreted as better imperceptibility of

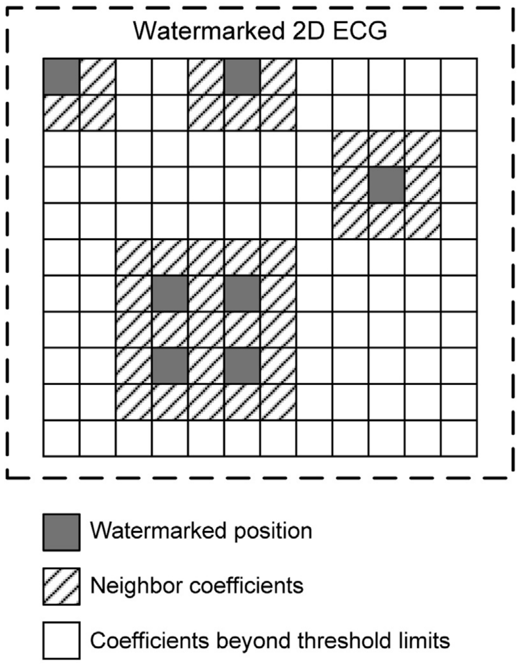

Fig. 6. Skeleton of adaptive watermark embedding using $n \times n$ sequence.

watermark. The efficiency of the algorithm for data losses during retrieval of hidden data is measured using Bit Error Rate (BER). The increase in data loss increases the BER value. The expressions for the metrics are provided in Appendix A.

3. Results and discussion

In order to construct 2D ECG image from 1D ECG data, it is subjected to bandpass filtering followed by differentiation which

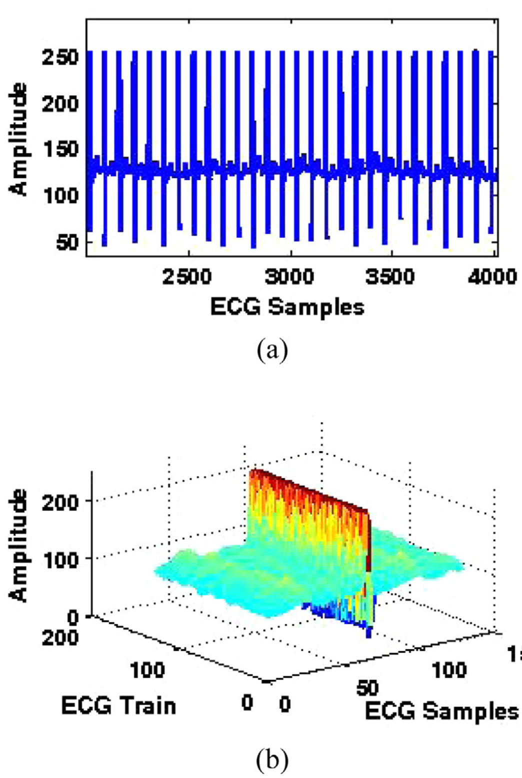

Fig. 7. 1D to 2D ECG image conversion (a) 1D ECG signal, (b) 2D ECG image.

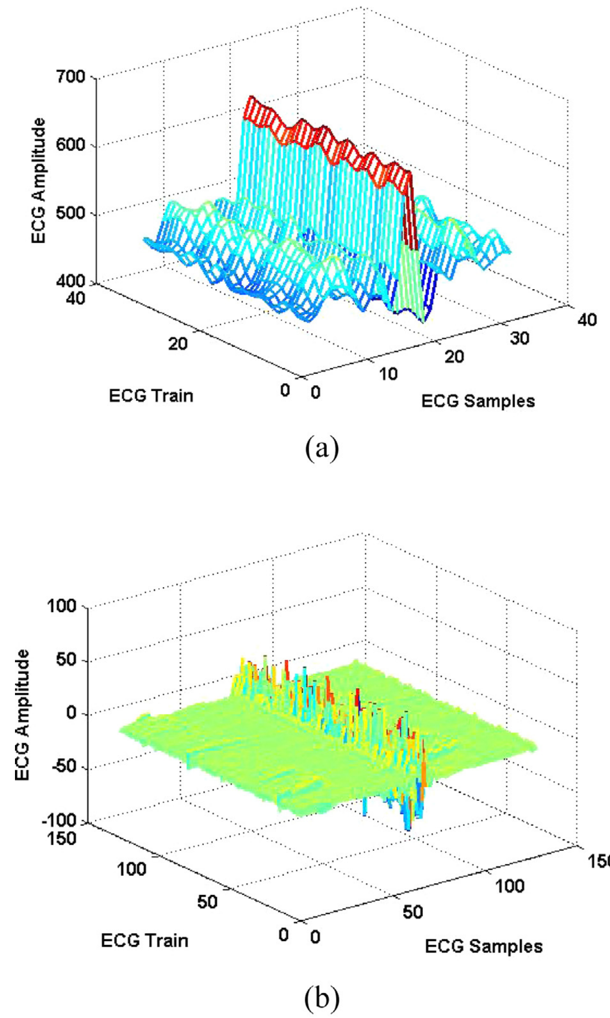

Fig. 8. FDCT coefficients of (a) coarsest scale, (b) finest scale.

allows distinguishing the QRS complexes. The signal is then subjected to a point-by-point squaring which makes the entire data positive ahead of the subsequent integration. The fiducial mark for temporal location of QRS complex is the maximum slope of QRS complex or peak of *R* value. Since the sampling rate of 1D ECG signal is 128 Hz, 64 points are taken at both sides of fiducial point to arrange each ECG train [22,30,31] as shown in Fig. 7. Fiducial points are also used to reconstruct the 1D ECG signal from the 2D ECG image. The 2D conversion process causes negligible data loss in 2D ECG image. The resultant 2D ECG image is taken as the cover ECG image and subjected to FDCT to obtain its coefficients.

Scales 1 and 4 contain the coefficients of low and high frequency components, respectively. This is presented in Fig. 8. Since the ECG features remain with low frequency components, similar to [17] we choose the high frequency components to embed patient data. Next, a threshold needs to be selected.

3.1. Adaptive watermark embedding method

3.1.1. Effects of threshold range

In order to understand the effect of modifying the coefficients at different levels, the following study was performed. The cover 2D ECG data consists of 128 ECG trains. We consider a single train of ECG data and its corresponding coefficients as shown in Fig. 9(a)

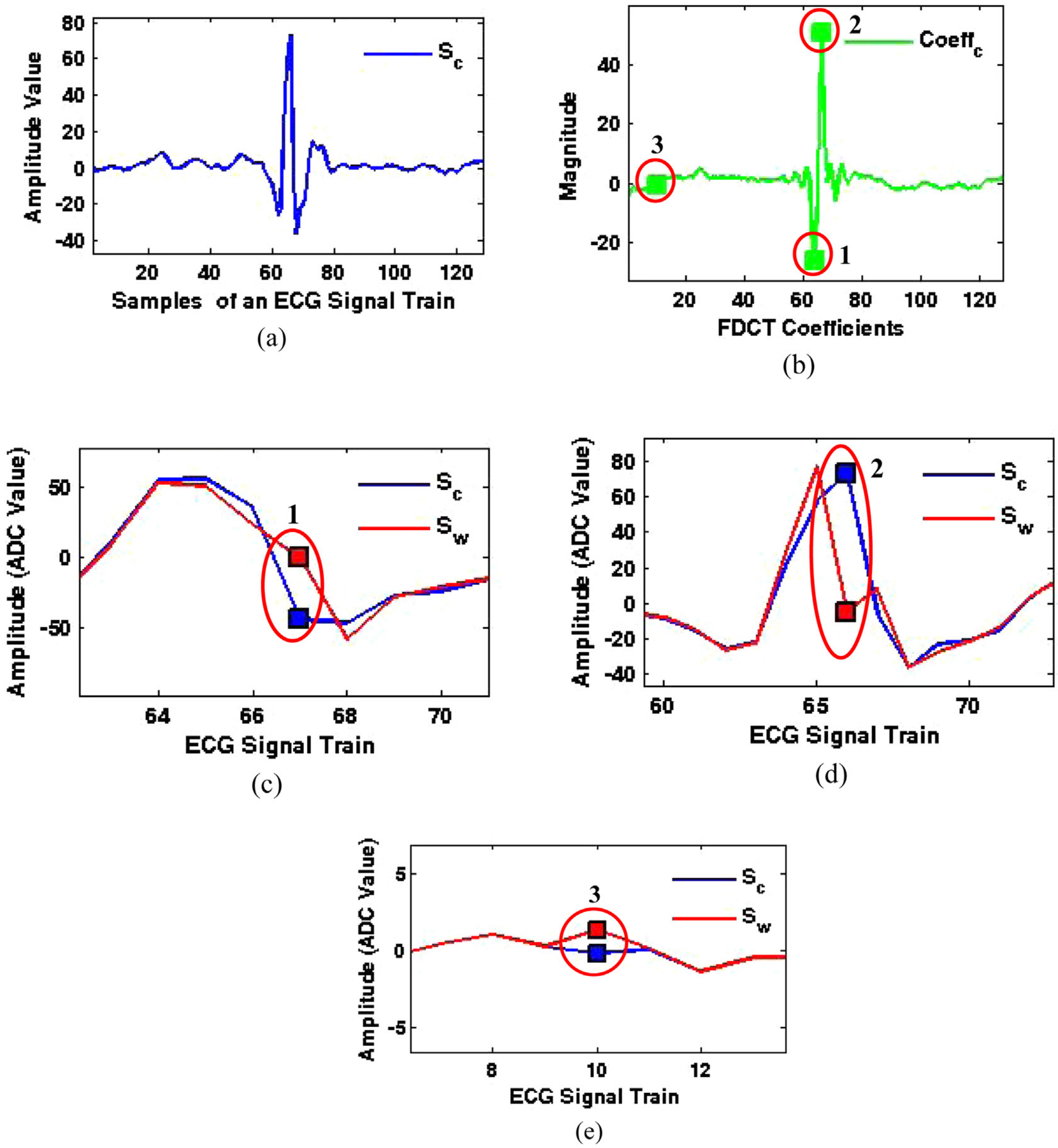

Fig. 9. (a) An ECG train of cover image, (b) FDCT coefficients of ECG train in (a). ECG train after modifying a coefficient at different locations: (c) minimum, (d) maximum, (e) near zero.

and (b), respectively, where, S_c, S_w are cover and watermarked ECG signals, respectively. Coeff$_c$ is the FDCT coefficients of cover ECG signal. The goal is to understand the effect on the shape of the cover signal by modifying coefficients at three different levels, one at a time. First, the minimum coefficient is modified by multiplying it with −1. This results in the water marked signal and it can be readily observed that it deviates from the cover signal as shown in Fig. 9(c). Similarly, the maximum coefficient was modified and it resulted in the modified watermarked signal whose peaks changed considerably as shown in Fig. 9(d). However when the coefficients around zero were modified, the changes were very less as shown in Fig. 9(e). The deterioration can be evaluated using PSNR, PRD and KL distance. The ability to extract secret data is measured by BER. This exercise was performed on 128 trains and their metrics

Table 1
Performance metrics of $n \times n$ sequence.

S. no	λ_{min}	λ_{max}	$n \times n$ Sequence method					
			Watermark size (bytes)	PSNR	PRD	KL	MSE	BER (%)
1	−0.397	0.396	83	75.56	3.27e − 4	0	0.0018	0
2	−0.808	0.809	167	66.17	9.66e − 4	3.72e − 5	0.01	0
3	−1.336	1.335	251	60.68	0.0018	0.0027	0.05	0
4	−2.128	2.144	335	56.04	0.0031	0.0031	0.16	0
5	−3.431	3.301	418	51.53	0.0052	0.0146	0.45	0
6	−18.640	18.465	502	43.44	0.0132	0.1448	2.94	0

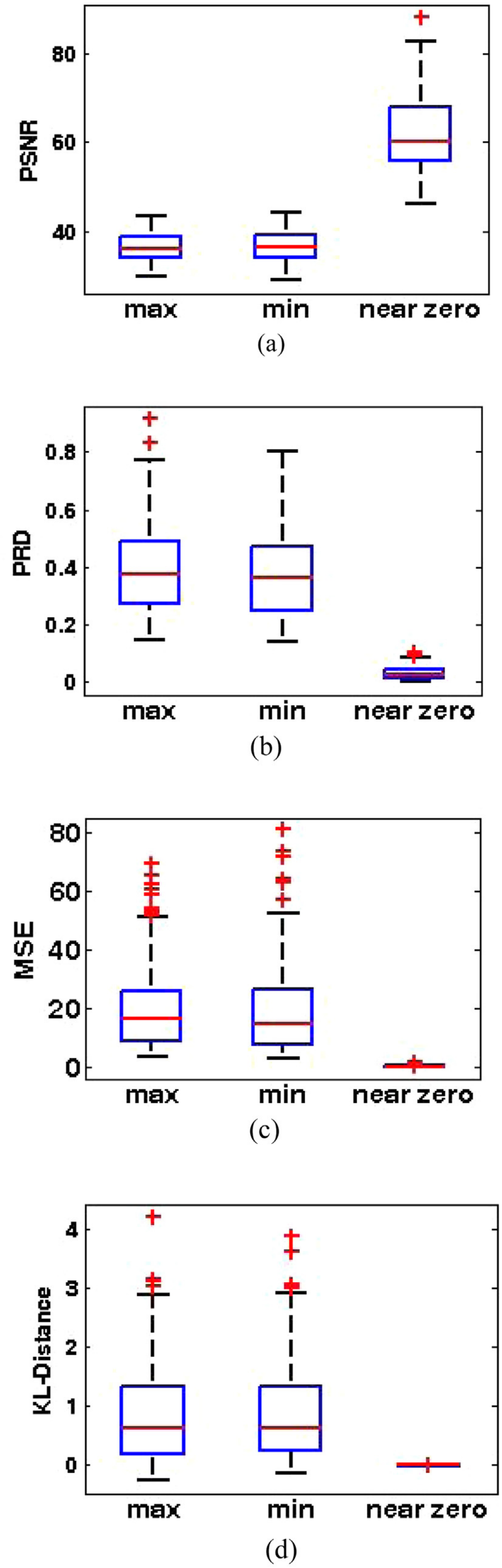

Fig. 10. Boxplot for metrics (a) PSNR, (b) PRD, (c) MSE and (d) KL distance.

are presented as box plots in Fig. 10. The PSNR value is about 65% higher when the coefficients near zero are modified compared to the modification at the other two levels. Similarly, PRD, MSE and KL distance are almost zero. It is clear from this study that for ECG type data, watermarking at coefficients which are very near to zero will result in less deterioration of the cover signal.

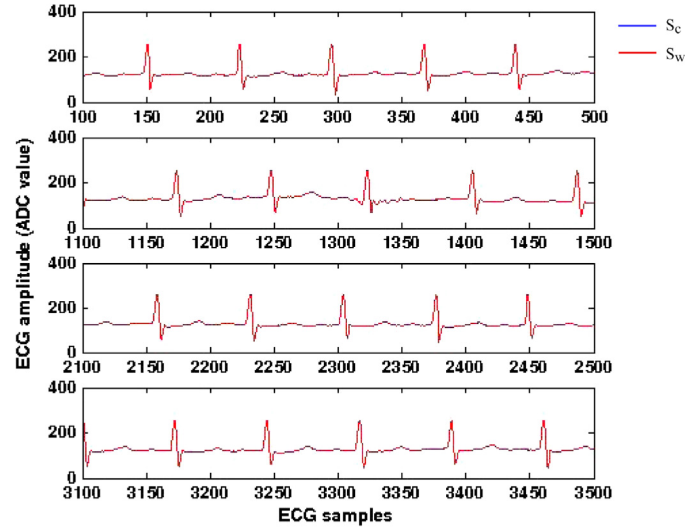

Fig. 11. 1D cover and watermarked ECG signal.

3.1.2. *Performance of adaptive* n × n *sequence watermarking*

Six different patient information (watermark) sizes are embedded into the ECG image one at a time and the performance of the proposed method is tested. The watermark sizes in bytes are: 83, 167, 251, 334, 418 and 502. One window of the resultant watermarked ECG signal with different time instances are shown in Fig. 11. S_c and S_w denote the cover and watermarked ECG signals, respectively. Since the differences between the two signals are negligible, they are indistinguishable in Fig. 11. An embedding strength $\alpha = 0.5$ was selected during watermarking. The effect of different alpha values is discussed subsequently. The performance metrics for each case is listed in Table 1.

It is observed that the PSNR value is good throughout which ensures the imperceptibility of watermark. For increase in watermark size, there is decrease in the PSNR value. This decrease is due to the increase in threshold range λ_{min} and λ_{max}. There is always a tradeoff between imperceptibility and watermarking capacity. For an increase in data size by about 1.5 times, the signal deterioration increased by about 10%. The 0% BER for all watermark sizes shows that the proposed approach retrieves the patient data without any loss. The watermark capacity can be improved by increasing the size of the cover ECG image.

3.2. *Effect of alpha* (α)

Alpha (α) is a watermark embedding strength which affects the performance of steganography algorithm. A low value of α affects the signal shape minimally but BER might be large. On the other hand, if a value closer to 1 is chosen, it increases the signal deterioration especially for amplitudes with higher coefficients. Here, we have studied the effect of α on the watermarked ECG signal. Performance of the current technique is measured for four different α values: 0.3, 0.5, 0.7 and 1.0. The results are presented in Fig. 12. It can be observed that performance of the $n \times n$ sequence is almost independent for alpha values greater than 0.5. For an α value of 0.3, large errors in retrieved patient data is observed. This is reflected in the BER as shown in Fig. 12(d). The large error is due to the fact that the signal value reduces and sign changes.

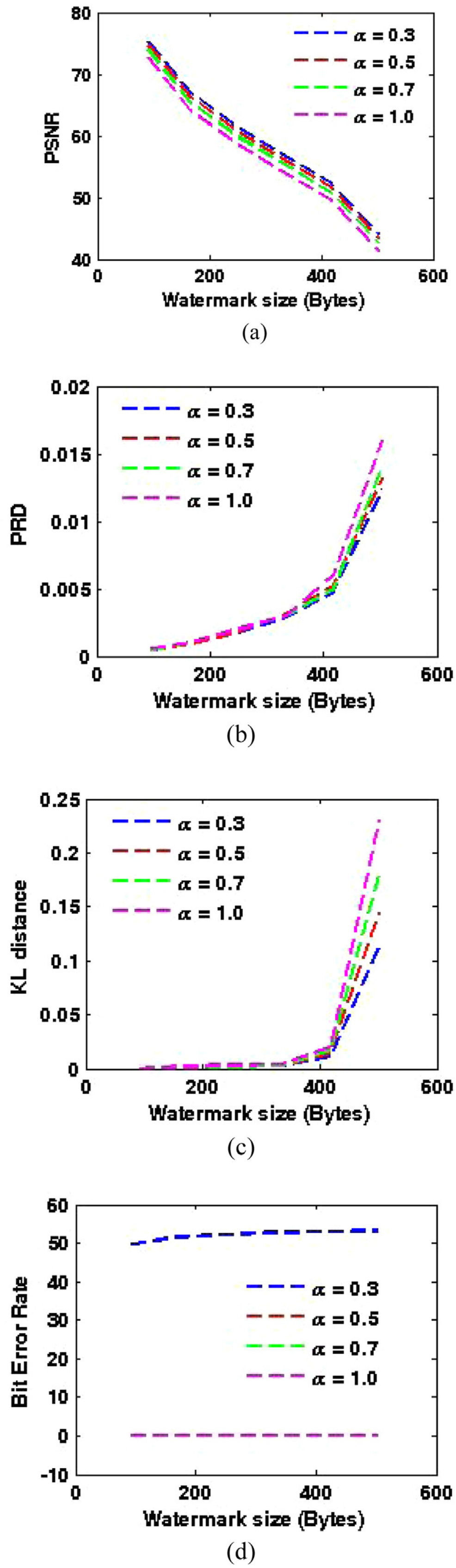

Fig. 12. Performance metrics for various α (a) PSNR, (b) PRD, (c) KL distance, (d) Bit Error Rate.

4. Conclusion

Performance of FDCT based ECG steganography algorithm using adaptive $n \times n$ sequence watermarking technique was studied in this work. FDCT of cover signal results in a set of coefficients and patient data can be hidden in these coefficients. When the coefficients are modified, the cover signal deteriorates and affects the diagnosability. The focus of this work is to minimize the deterioration while preserving the diagnosability. We study the effect of modifying coefficients at three different levels: near zero, minimum and maximum, on the final deterioration of cover signal. It is shown that modifying coefficients near zero yielded better results than the other two choices. Therefore we propose modifying coefficients around zero in an $n \times n$ adaptive sequence technique. The signal deterioration is minimum while there is no loss in the data retrieved. The performance of the proposed approach is confirmed by the metrics such as PSNR, PRD and KL distance. As the patient data size is increased, the cover signal deteriorates but the Bit Error Rate is zero. It is observed that for about 1.5 times increase in the patient data, the signal deterioration is about 10%. Therefore the proposed methodology can be used for reliable steganography. Currently, there are commercially available wearable sensors such as SHIMMER [32] and Alivecor iPhone [33] which are capable of transmitting ECG signals over internet. Often, these come with Application Programming Interfaces which supports user program. The proposed algorithm can readily be used in such cases for successful ECG steganography.

Appendix A.

A.1. Performance evaluation metrics

PSNR is the ratio of maximum amplitude of the cover ECG signal to the mean squared deviation between cover and watermarked ECG signals. Higher the value of PSNR, better is the quality [26]. PSNR represents a measure of peak error and expressed in terms of the logarithmic decibel (dB) units in the following equation:

$$\mathrm{PSNR} = 20\log_{10}\left(\frac{\max[x_c]}{\sqrt{1/N\sum_{n=1}^{N}[x_c - x_w]^2}}\right) \tag{A.1}$$

where N is the total number of samples. $x_c(.)$ is the amplitude of the cover signal and $x_w(.)$ is the amplitude of the watermarked signal.

PRD is a percentage of relative squared difference between two signals. PRD increases linearly with increase of difference between the cover ECG and watermarked ECG [7] and is given in the following equation:

$$\mathrm{PRD}\,\% = \sqrt{\left(\frac{\sum_{i=1}^{N}(x_c - x_w)^2}{\sum_{i=1}^{N}(x_c)^2}\right)} \times 100 \tag{A.2}$$

BER is the ratio between the extracted patient information and the original patient information [7] as given in Eq. (A.3). This metric measures the percentage of data loss. BER increases with increase in data loss.

$$\mathrm{BER} = \frac{\text{Bits retrieved correctly}}{\text{Total Bits}} \times 100 \tag{A.3}$$

Kullback–Leibler divergence (KL) measures the distance between histograms of the cover and watermarked signals [27–29]. It can be expressed as the following equation:

$$D(p_c, p_w) = \int p_c(x) \log \frac{p_w(x)}{p_c(x)} \mathrm{d}x \tag{A.4}$$

where D is KL divergence, p_c is the probability of the cover signal and p_w is the probability of the watermarked signal. The advantage of using KL is that it works in the frequency domain while the other metrics presented are in the time domain. Therefore, this can be used in conjunction with the other metrics.

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