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An Improved Method for ECG Morphological Features Extraction from Scanned ECG Records

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Abstract. Electrocardiogram (ECG) has been the preliminary diagnostic tool to detect cardiovascular diseases. ECG is generally recorded on a thermal paper which cannot be stored for a long time for analysis, as the thermal trace gets erased gradually. To store the trace, the records are scanned and saved as images to maintain medical record. The memory occupied by this method is high and the regeneration of signal accuracy is less.

This paper aims to extract the ECG morphological feature extraction, in addition to extraction of ECG trace from the paper and converting it to a digital time series signal. Thus an improved method of morphological feature extraction technique has been adopted in this paper. Digital time series signal and morphological feature extraction were tested on a database of 25 paper records and the accuracy is 95% and 97.5% respectively. Further work is extended to perform an automatic arrhythmias classification using DTW from the obtained morphological parameters.

Keywords: ECG Morphology, ECG to Digital, EMR, Adaptive Binarization, Iterative morphological image processing, DTW

1. Introduction

Cardiovascular disease (CVD) is one of the widely spread lifestyle disease worldwide. Electrocardiogram (ECG) system has been adopted for almost a century to monitor the heart. Thus, to monitor the heart's condition and measure progress continuously, ECG is recorded on a regular basis on thermal paper. These ECG records are scanned and stored as images in hospitals for the assessment of patient's rehabilitation. The storage space required for these images is high and increases as the number of records per patient increases. Further, the retrieval time also increases, which plays a key role in the Electronic Medical Record (EMR) systems. On the other hand, regeneration of scanned image accuracy is less. To overcome this problem, the ECG trace from the scanned image is extracted using an improved method of binarization. The extracted trace is converted into a digital time series signal for further processing.

Majority of the ECG's clinically information is said to be found in the intervals and amplitudes defined by its features (characteristic wave peaks and time durations). According to author's knowledge, few researchers [1]–[4] have approached ECG digital time series signal extraction as a research problem. Lawson et al., [5], chose a scanning resolution of 200 dpi and used global threshold to separate the ECG trace from the background grid lines. The low resolution results in loss of data accuracy and global threshold results in missing pixels which are replenished by linear interpolation. Fabio Badilini et al., [6] developed an application for extraction of the ECG trace from the image. But the method requires the user to fix anchor points for missing peaks and thus the accuracy comes down. Shen et al., [7] separated the ECG trace from the background grids using the histogram. The missing pixels are replenished by checking the value of the pixel in the original image. This is a tedious process. Tsair Kao et al., [1] employed a colour filter to remove the background gridlines in the colour image. There was a problem of missing pixels in the process which was replenished by linear interpolation. Jalel Chebil et al., [3] did a comparative study of the extracted trace accuracy by scanning the image at various resolutions. Global thresholding and median filtering were employed to remove background grids. The threshold to separate the trace from the background should be selected based on the nature of the image to avoid any missing pixels. All conventional techniques use morphological operations such as erosion, dilation, thinning etc. to extract the ECG trace from the background. However, all the above work addresses the issue of one-dimensional time series signal alone.

This paper aims to develop a simple, robust and improved technique that would (a) derive digital time series ECG waveform from the scanned ECG image and (b) extract the ECG clinical information like amplitude and time interval of ECG parameters (characteristics wave peaks and time duration) using proposed first derivative technique. The added advantage of the proposed technique is, (1) it addresses the issues of various paper record scanning resolutions; which were previously unaddressed, as a novelty, (2) it eliminates the noise reduction and baseline wandering pre-processing stage in morphological interpretation; leading to reduction in the computational time and improvement in the accuracy. This would help in automatic ECG report generation like the heart rate and morphological features such as duration of P, QRS and T wave, intervals of PR, ST and QT and amplitudes of P, R and T waves and disease classification. In addition this would act as a second opinion tool to the physician.

2. Methodology

The process of extraction of the thermal ECG trace from the image, conversion to a time series signal and morphological feature extraction is as shown in the flowchart in Figure. 1.

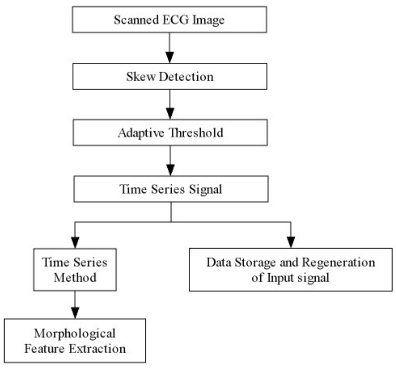

Fig. 1: Overview of ECG Morphological feature extraction from Scanned ECG traces

2.1. Scanning, Skew detection, Adaptive thresholding and Time series signal generation

Jain –Xiong et al., [8] reports as an effort of human error, the scanning of the ECG paper record result in skew. This could be overcome by skews detection and correction. Based on Prasanth et al., [4] an improved method of binarization for accurate extraction of trace from the scanned image and conversion of the trace envelope to a time series signal was performed. The paper records are scanned at 600 dpi resolution for accurate trace extraction. The ECG is recorded at a paper speed of 25 mm/sec. The large boxes in the paper are 5mm wide measuring 0.5 mV in the amplitude scale and 0.2 seconds in the time scale [3]. The scanning resolution plays a major role in the conversion of the ECG trace into digital time series signal. For example let us assume the scanning resolution of ECG trace was scanned with 600 dpi resolution, it implies there are 600 pixels in an inch. As the thermal record has the grid dimensions specified in mm, number of pixels in mm is derived using the Equation (1). The amplitude and time scaling of a pixel in terms of mV and ms is calculated as shown in (2) and (3).

$$1 \text{ mm} = 600/25.4 \text{ pixels} = 23.622 \text{ pixels} \quad (1)$$

$$\text{Amplitude scale: } 10 \text{ mm} = 1 \text{ mV} = 236.22 \text{ pixels.} \quad (2)$$

$$\text{Time scale: } 25 \text{ mm} = 1 \text{ second} = 590.55 \text{ pixels} \quad (3)$$

$$1 \text{ pixel} = 4.233 \text{ mV}$$

$$1 \text{ pixel} = 1.693 \text{ ms}$$

An improved method of binarisation is employed to extract the ECG trace accurately from the background grids. The extracted trace is used to generate the digital time series signal using envelope detection. The envelope is scaled in amplitude and time

2.2. Morphological Feature Extraction

In this method, first derivative of the Digitized ECG signal within a window frame is performed and stored in an array of size "N-n", where "N" is the total number of ECG signal samples. First derivative of the signal is calculated using Equation (4).

$$S(i)=\tan^{-1}(S(i+n)-S(i))/n \quad (4)$$

Where i =1, 2...N-n, s = Extracted ECG Signal with samples 1 to N, S = First Derivative signal with samples 1 to N-n, n = Window size.

The window size '[ ]'is chosen to be equal to the number of samples between the Q and R peaks, as the QR slope is found to be the steepest in ECG waveform signals [9] , as compared other slope which are wide and less steep. In addition, the standard range of inclination angle of the P wave, QRS complex and T wave for both normal and abnormal ECG [9] are well know; the first derivative array elements with values less than 30 are eliminated. Thus from the defined range of S values between the minimum positive value and maximum negative values are removed to eliminate noise. The entire S(i) array is plotted for single ECG lead is shown in figure 2a.

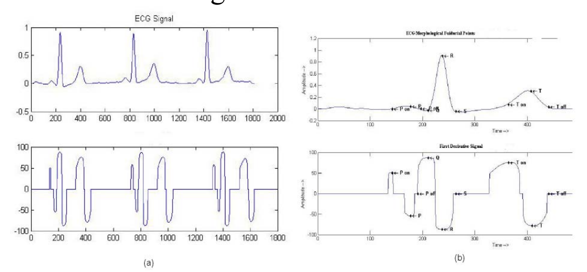

Fig. 2: Derived digital ECG from Scanned ECG Image

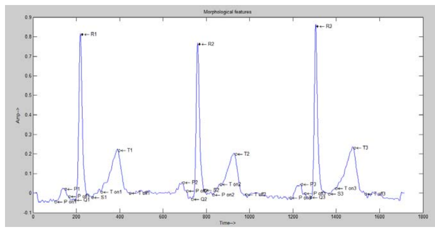

Fig. 3: First derivative based morphological feature extraction

As shown in figure 2a in a single cycle of ECG waveform, each of the P peak, QRS complex and T peak, a pair of positive and negative peak appears in the first derivative ECG waveform plot. The positive peak appears when the moving window starts at the P onset point of ECG cycle and ends at the P peak and thus the plot is positive in this position. Similarly a negative peak appears when the moving window is placed at the P peak and ends at the P offset point as it is a descending slope and the plot is negative in this position. Based on ECG waveform plot various peaks and fiducial points were detected as shown in figure 2b.

3. Result and Discussion

A database containing 25 ECG records was created. Each ECG record has 12 leads, recorded for duration of 3 seconds. The paper record is scanned at 600 dpi resolution and saved in JPEG format. Based on the scanning resolution the image is segmented into 12 different regions thus separating the 12 leads for further processing. Lawson et al., method the low resolution results in loss of data accuracy and global thresholding results in missing pixels which are replenished by linear interpolation thus reducing the accuracy of the ECG trace extracted. Fabio Badilini et al., is time consuming and misplacement of anchor points affects feature extraction and shen et al., and Tsair Kao et al., methods led to missing pixels are replenished by interpolation after checking the darkness or color threshold of that pixel in the original image respectively. Jalel Chebil *et al.,* employed global thresholding and median filtering to remove background grids these also result in missing pixels.

The drawbacks found in the previous work performed have been overcome in this paper by choosing providing adaptive scanning resolution to retain the trace information and a threshold was chosen based on the nature of the image to extract the trace accurately. Further, this paper has been extended to morphological feature extraction from the time series data. Chouhan *et al.,* employed a magnitude based threshold technique to detect QRS wave. A number of adaptive thresholds have been employed to detect the QRS peaks in different leads. Sigmoid function is used to enhance steep peaks. In this method, detection of waves was performed but their amplitude or time intervals were not detected.

In this paper, morphological features of the ECG signal were extracted using the first derivative method. The morphological feature extraction method employed in this paper is not based on any amplitude threshold but purely based on the ascending and descending nature of the ECG waveform. The peaks, onset and offsets of each peak is obtained using first derivative method were marked on the signal and is as shown in Figure. 6. The accuracy of the feature extraction method is found by comparing first derivative method with the manually obtained morphological features by reading the paper record as shown in Table 1.

Table 1. Comparison of first derivative method with the manually obtained values for one lead patient record

MORPHOLOGY	HR	P Duration	QRS Duration	T Duration	PR Interval	QT Interval	ST Interval	P Amplitude	R Amplitude
MANUAL	66	0.12	0.11	0.24	0.16	0.42	0.3	0.1	0.86
First Derivative Method	66	0.12	0.12	0.24	0.16	0.42	0.31	0.11	0.85

The accuracy of the first derivative method based morphological feature extraction methods is found for the database containing 25 records and it was found to be 97.5%. The entire operation from scanning to digital time series ECG signal and ECG morphological feature extraction took 23 sec for a single lead. For performance evaluation four cases are considered, as there are four classes of data being classified. In case 1, normal data is assigned as one class and the other three data i.e. Sinus Bradycardia (SB), Sinus tachycardia (ST) and Premature Ventricular Contraction (PVC) belong is assigned as the second class. In case 2, SB is assigned as one class and the other three data is assigned the second class. Based on the classification results and the two cases possible, 2 confusion matrices are evaluated as follows.

Table 2. Confusion matrix

Case 1			Case 2		
	Normal	SB + ST + PVC		SB	Normal+ST+PVC
Normal	24	1	SB	7	0
SB+ST+PVC	0	20	Normal+ST+PVC	1	37

A limitation of the derived digital ECG waveform from scanned ECG image is that the digitization process is performed for lead at a time after performing lead segmentation. However this may lead to lose of the relative timing between the different leads [6], in addition to vital information like patient detail and other analytical reports. In future, this work can be extended to use character recognition technique to prevent the vital information loss. One criticism towards efforts aimed at deriving the ECG waveform from scanned ECG image is that paper ECG analysis is an obsolete technique today in western countries. However, according to authors opinion, a) there are number of clinically valuable ECGs that are still stored on paper records and the number of them that are often retrieved to derive measurements is still very huge [6], b) In the developing countries like India and China, electronic ECG machine migration is under progression and this justifies the need of digitize these valuable tracings to be stored in digital archives.

4. Conclusion

The extraction of ECG waveform from scanned ECG records and converting it to a one-dimensional time series signal has been performed with an improved method of binarisation with high accuracy of 95%. The morphological features were extracted using first derivative method with an accuracy of 97.5%. Correlation study has proved that the first derivate method produced accurate results. DTW classification provides Sensitivity of 99% and Specificity of 98.04% for automatic arrhythmias detection.

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