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ECG Analysis in the Time-Frequency Domain

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Abstract— **The Electrocardiogram (ECG) has been established as a powerful diagnostic tool in medicine which provides important information about the patient's heart condition. The correct identification of the QRS complexes is a fundamental step in every automated or semi-automated ECG analysis method. A major problem that is often encountered in automatic QRS detection is the presence of artifacts in the ECG data, which cause considerable alterations to the signal. In this work, the objective was to develop a method, based on Time-Frequency Analysis (TFA), which would be able to automatically detect and remove artifacts in order to increase the reliability of automatic QRS detection. The TFA method used for the analysis of the ECG data, was based on a time-varying Autoregressive (AR) model whose solutions were obtained using Burg's method. The algorithm could detect and remove 95.6% of the artifact areas and correctly identify 92.0% of QRS complexes (322 out of 335 annotated QRS complexes). The proposed method was compared with one of the most commonly used methods in ECG analysis, which is based on the use of wavelets. The wavelet-based method resulted in an accuracy of QRS detection of 65.3% mainly due to the large number of false positive detections in the regions of artifact.**

Keywords— **Electrocardiogram, ECG, Time-Frequency Analysis, spectrogram, artifact detection, QRS detection**

I. INTRODUCTION

Heart disease is one of the main causes of death in the western world and much effort is expended on its diagnosis and treatment. Electrocardiography is considered to be one of the most powerful diagnostic tools in medicine that is routinely used for the assessment of the functionality of the heart. Different waves reflect the activity of different areas of the heart. A normal electrocardiogram (ECG) consists of a P wave, a QRS complex, and a T wave. The P wave is caused by electric currents produced by the depolarization of the atria before their contraction, while the QRS complex is caused by electric currents produced by the depolarization of the ventricles prior to their contraction, during the extending of the depolarization in the ventricular myocardium. The detection of the QRS complex is the crucial first step in every automated algorithm for ECG analysis. Due to their characteristic shape, the QRS complexes serve as the reference point for automated heart rate monitoring and as the starting point for further evaluation [1].

Numerous approaches have been proposed for automatically finding the QRS complexes in as ECG [2]. Such algorithms include artificial neural networks [3-6] and genetic algorithms [2]. Other approaches included signal derivatives, for detection of the steep slope of the QRS complex, [7-11], cross-correlation methods, where an initial template was aligned to the current ECG signal [4,5], and syntactic approaches, where the ECG signal was represented as a piecewise linear approximation and was analyzed using syntactic rules. The wavelet transform method is currently considered to be a state-of-the-art method for automatic ECG analysis and QRS detection [12-16]. Almost all of the proposed algorithms so far, share a common algorithmic structure, that is, a preprocessing stage, including filtering, a feature extraction stage, and a decision stage in which peak detection and decision logic are included [2,17-19].

Time-Frequency Analysis

Many methods of signal processing assume stationary signals. However, most biological processes are, in general, non-stationary, that is, they dynamically change over time [20, 21]. In such cases, analyzing the signal in the time or frequency domain separately might not be so comprehensive. Time-Frequency Analysis (TFA) effectively provides a description of the spectral content as a function of time [22]. Time–Frequency Representations (TFRs) are two-dimensional (2D) functions, which describe the signal temporally and spectrally and contains both the time variations and frequency bands which define the signal.

II. DATA

The ECG data used for the development and testing of the algorithm was taken from the MIMIC II database. The MIMIC II database consists of over 25 thousands intensive care unit (ICU) patient recordings of physiologic and vital signs, captured in real-time, and comprehensive clinical data obtained from hospital records. The ECG waveforms were sampled at 125Hz and they typically lasted over 20 hours each [23]. A set of 45 ECG segments was chosen randomly from eight different MIMIC II patients. Each segment lasted from 5 to 10 seconds and contained normal and abnormal beats as well as artifacts (Fig. 1) which were manually annotated. Accurate annotation was a critical part of the evaluation of the results of the developed algorithm. Twenty of the data segments contained ECG beats as well as various types of artifacts of different durations. Another 20 segments contained only normal QRS complexes and the remaining 5 contained both normal and abnormal beats.

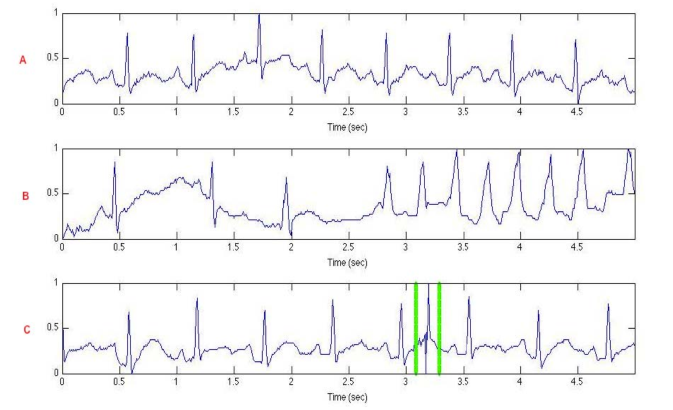

Figure 1. (A) Normal ECG waveform. (B) Abnormal ECG events from 2.5 to 5seconds. (C) Artifact between 3 and 3.5 seconds. (The green lines indicate the start and end point of the artifact area.)

III. Methodology

The TFA of the ECG signals was performed with autoregressive (AR) spectral estimation using Burg's method to estimate the AR coefficients [24]. An important parameter is AR spectral estimation is the model order since it determines the amount of spectral information that can be predicted from the input data. The most important advantages of Burg's method are the faster convergence for short data records, better resolution of closely spaced sinusoids with low noise, and smaller divergence of the PSD estimates from the true values. For the different tasks of the ECG analysis described below, different spectral bands of the estimated spectrogram were used. The choice of window size and overlap and the AR model order were chosen after extensive experimentation to optimize the performance of the algorithm.

The analysis of ECG signals was based on the mean image of the spectrogram. This statistical measure improved the noise robustness of the artifact detection and removal. The mean image was calculated using 15x15 neighborhood, overlapping, windows with no padding. The choice of mean, as opposed to higher order moments, and its parameters was also based on the best performance of the algorithm.

Automatic thresholding was necessary in two cases: (i) for detecting the level that optimally separates the spectral value populations in the mean image and (ii) for detecting the QRS complexes. Otsu's automatic threshold method was used to optimally separate the populations [25]. This method was used to convert gray scale images to binary.

The algorithm for artifact detection assumed that these parts of the signal occupy relatively wide areas in the spectrogram. Narrow components, like the heart beats, should not be detected as artifact. For this purpose, two morphological operations were performed, image closing and opening, in order to remove narrow areas and accurately detect artifacts.

IV. Algorithm Details

The complete algorithm developed is illustrated as a flow chart in Fig. 2. It includes the following, main, steps:

1. Load the ECG signal from the database.
2. If there are any missing values, interpolate to fill in the gaps.
3. Check whether the signal contains artifact or not ("Artifact Hypothesis Testing").
4. If there is no artifact, proceed with QRS detection (step 6). If there is artifact, find it and remove it (step 5).
5. Find the areas of artifact and remove them from the spectrogram ("Artifact Detection and Removal").
6. For the artifact-free signal (either directly from step 4 or cleaned from step 5), find the QRS complexes.

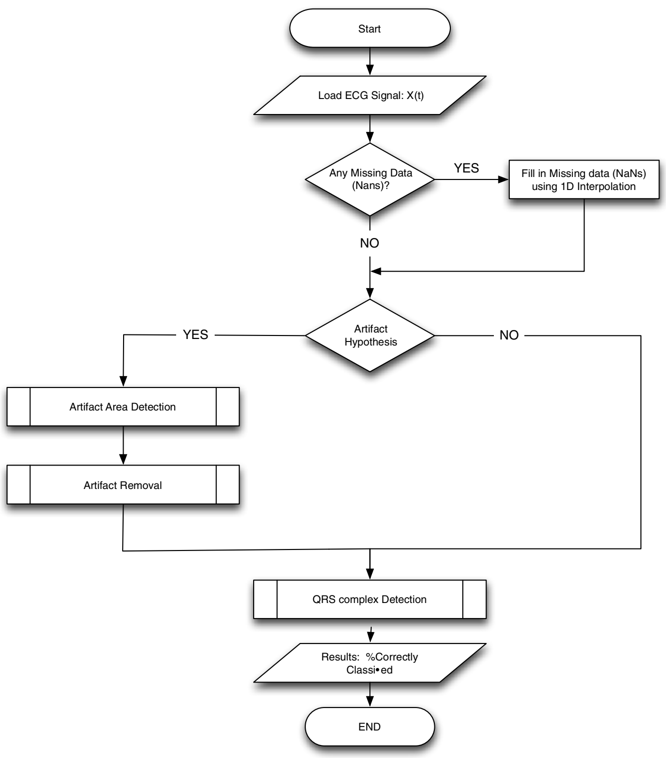

Figure 2. Flow chart of the proposed algorithm.

A. *Artifact Hypothesis Testing*

The purpose of this portion of the algorithm is to correctly decide whether there is an artifact in the ECG signal or not. The steps of the algorithm are described below.

1. Calculate the time-frequency representation of the signal using Burg's method (window: 15 samples, overlap: 5 samples, AR model order: 2, length of FFT: 2^{10})
2. Use the band of the spectrogram from 55 to 60Hz. (The band choice was a result of the observation that most of the PSD of the artifact was in the high frequency portion of the spectrum).

3. Convert the spectrogram to a binary image using Otsu's automatic threshold.
4. Perform morphological opening in the horizontal direction of the binary image, in order to eliminate objects with a width less than 30% of the sampling frequency.
5. If the number of 1s (true values) was greater than 150 pixels, then the hypothesis is that artifact exists in the image (YES), otherwise the hypothesis is that the signal does not contain artifact (NO).

It must be noted that the spectrogram's parameters and the threshold (150 true values), for optimal detection of artifact presence in the image, were found experimentally, with the help of statistical testing (t-test) to optimally separate the images with and without artifact.

B. Artifact Area Detection & Removal

Artifact detection is an important step in automatic QRS detection. The purpose of this algorithm is to accurately detect the area of the artifact. Ideally, the signals that reach this step do contain artifact, based on the decision of the previous step. The steps of the algorithm are shown below.

1. Calculate the time-frequency representation of the signal using Burg's method (window: 15 samples, overlap: 10 samples, AR model order: 2, length of FFT: 2^{10})
2. Calculate the mean image using a 15x15 neighborhood. The frequency band chosen was again that between 55 and 60 Hz where the artifact has greater power than the other components of the signal.
3. Convert the mean image to a binary image using Otsu's automatic threshold.
4. Perform morphological operations, first closing and then opening, to eliminate objects such as heart beats.
5. The output of the algorithm is a binary image ("Artifact Mask"). The pixels corresponding to the locations of artifact have the value 1, whereas everywhere else, the value is 0.

Each spectrogram, which contains the artifact, is multiplied by the logical complement of the artifact mask. The multiplication is performed element-wise converting the area of artifact to 0s. An example is shown in Fig. 3.

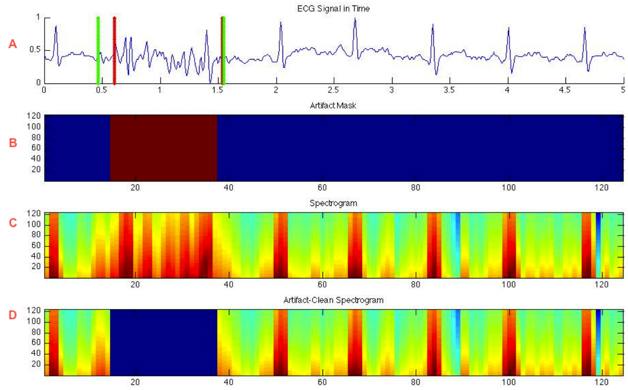

Fig. 3 (A) ECG signal with artifact. The green vertical lines indicate the manually marked end-points of the artifact area. The red vertical lines indicate the automatically detected end-points. (B) The "Artifact Mask". Red indicates logical values of one and blue logical zeros. (C) Spectrogram Image. Red corresponds to high spectral power while blue corresponds to low power. (D) The artifact-free spectrogram image. Blue corresponds to zero values.

QRS Complex Detection

QRS complex detection is the last step of the proposed algorithm. Artifact-free signals reach this step directly, while artifact-containing signals undergo artifact detection and removal first. The results of the algorithm are described below and shown in Fig. 4.

1. Calculate the time-frequency representation of the signal using Burg's method (Window: 10 samples, overlap: 5 samples, AR model order: 2, length of FFT: 2^{10})
2. Sum the spectral intensity between 5 and 20 Hz for each time point.
3. Normalize the summed data between so that it takes values between 0 and 1.
4. Calculate an automatic threshold, using the Otsu's method, of the summed values to separate the peaks that correspond to QRS complexes from noise.
5. Get their locations of the peaks which are above the threshold from the ECG signal.
6. Find the Q-wave and S-waves by finding the minimum peaks in the range of -10 and +10 samples around each R respectively.

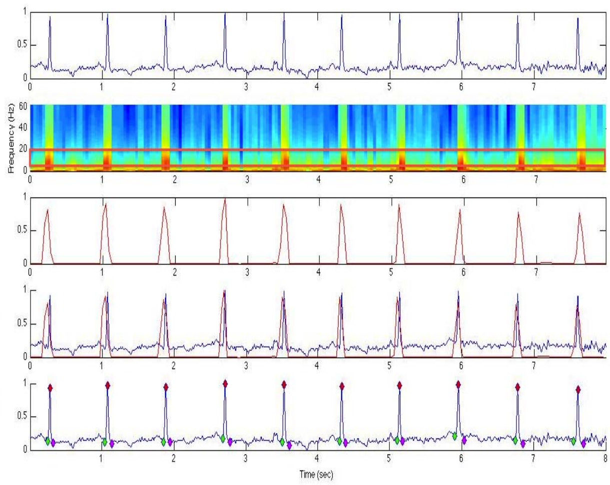

Figure 4. (A) Normal ECG signal without artifacts. (B) Spectrogram of A. The red rectangle indicates the frequency band 5-20Hz. (C) The thresholded and normalized sum of the values of each column of the spectrogram. (D) Overlay of the summation data and the ECG signal. (E) Q, R and S waves automatically detected and noted with different color diamonds.

V. RESULTS

A. Artifact Hypothesis Testing Results

The “Artifact Hypothesis Testing” algorithm was used to decide whether the signal under consideration contained artifact or not. Based on this decision, the signal was classified as Artifact or Normal and was further processed accordingly. Hence, this was a very important step for achieving improved accuracy of QRS detection. The correct classification rate was 95.56 %.

Table 1 shows the results of this algorithm on 45 ECG segments of which 20 contained artifacts. The correct classification rate was 95.56 %.

TABLE 1. RESULTS OF THE CLASSIFICATION OF THE SIGNALS INTO THE CLASSES ARTIFACT AND NORMAL.

		ESTIMATED		
		Artifact	**Normal**	**Total**
ACTUAL	**Artifact**	18	2	20
	Normal	0	25	25
	Total	18	27	45

B. Artifact Detection and Removal Results

The “Artifact Detection and Removal” algorithm was applied to signals that were classified, during the previous step, as artifact-containing. In order to evaluate the performance of the algorithm, its results were compared to the manually annotated data. If a point was classified as artifact and was in the actual artifact area was considered a True Positive, otherwise it was considered a False Positive. Similarly, True Negatives and False Negatives were calculated from points classified as not artifact. The overall accuracy of the artifact detection algorithm, after testing on the 18 ECG signals that were identified as artifact-containing in the previous step was 95.60 % as shown in Table 2.

TABLE 2. RESULTS OF ARTIFACT DETECTION ALGORITHM

		ESTIMATED	
		Artifact	**Not Artifact**
ACTUAL	**Artifact**	29.89%	1.66%
	Not Artifact	2.74%	65.71%

C. QRS complex Detection Results

QRS detection is the last step of the proposed algorithm. The algorithm was applied to all 45 ECG segments which contained both normal and abnormal beats. Ideally, both should be recognized as QRS complexes. The performance of this portion of the algorithm is presented in Table 3. The correct classification of QRS complexes of artifact free signals is an impressive 100 % (173 beats all correctly identified.) The performance degrades for ECG signals containing either artifact or abnormal beats.

TABLE 3. RESULTS OF QRS COMPLEX DETECTION.

	True Positive	**False Negative**	**False Positive**	**% Correct Classification**
Segments with normal beats	173	0	0	100%
Segments with artifact	113	6	13	85%
Segments with abnormal beats	36	7	2	80%
Overall	322	13	15	92%

VI. DISCUSSION

Given the results presented in the previous section, it is evident that the proposed algorithm is very successful in QRS detection. The proposed algorithm yields an overall score of 92% correct classification. Particularly, if the signal contains only normal QRS complexes the QRS complexes are 100% correctly classified although the performance is poorer for signals with artifacts and abnormal beats (85% and 80% respectively). These results are significantly more accurate than those achieved using a wavelet-based QRS detection algorithm. When applied to the same data, the overall accuracy of such an algorithm is only 65.3 % (96.2 % for segments with normal beats and no artifacts, 38.4 % for segments with artifacts, and 49.5 % for segments with abnormal beats.) It is obvious that the results are significantly affected by the presence of artifacts an issue alleviated to a large extend by the artifact detection and removal algorithm proposed here.

The performance of the proposed algorithm is significantly improved because of its artifact testing, detection, and removal features. The segments of ECG signals which did not contain artifact were all classified correctly as did most of the artifact-containing ECGs. However, signals with missing data artifact or saturations were misclassified as clean. Although this did not affect the QRS detection significantly, this limitation can be alleviated by detecting and removing these artifacts in the time domain.

Artifact Detection is an important step in minimizing the False Positives of QRS detection in the case of artifact containing signals. However, the artifact area has to be detected as accurately as possible in order to not only avoid false positives (artifact being detected as a QRS complex) but to limit false negatives (normal QRS being removed as artifact) as well. This can be achieved by minimizing the difference between the detected edges and those of the actual artifact area. This problem requires appropriate adjustments of the parameters of the algorithm.

For the results of this study to be generalized, a much larger data set is needed. In that way there will be a much larger and more varied number of cases so that the statistical conclusions can be drawn safely. An important parameter that could possibly affect the results is the accuracy of the manual annotations. In that case, more than one annotators should be used to validate the annotations between them.

VII. CONCLUSIONS

In conclusion, a method based on Time-Frequency Analysis was developed in order to automatically analyze ECG data. This method includes:

a. Determining the presence of artifact in the signal.
b. Detecting the artifact area and removing the artifact.
c. Detecting the QRS complexes of both normal and abnormal beats.

The proposed method yields 92% correct QRS detection. The improved performance is a result of the detection and removal of ~ 96% of the artifact, when it exists in the signal, thus avoiding the majority of possible false detections. To our knowledge, this is the first case where artifact detection and rejection in ECG signals have been so successfully implemented.

In the future this work could be extended in order to also detect the P and T waves, which provide additional information about specific functions of the heart. In addition, successful detection and classification of the various types of abnormal beats could also be performed using TFA features. When these functionalities are fully implemented will result in an ECG-based, accurate, automated, diagnostic tool for various diseases of the cardiovascular system.

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