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Timely and Error Free Detection and Elimination of Violation in ECG

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ABSTRACT: Cardiac signal processing is usually a computationally demanding task as signals are heavily contaminated by noise and other artifacts. In this paper, an effective approach for peak point detection and localization in noisy electrocardiogram (ECG) signals is presented. Six stages characterize the implemented method, which adopts the BPF filter (Hamming Window) and a thresholding technique for the detection of zones inside the ECG signal which could contain a peak. Subsequently, the identified zones are analyzed using the wavelet transform for R point detection and localization. The conceived signal processing technique has been evaluated, adopting ECG signals belonging to MIT- BIH Noise Stress Test Data base, which includes specially selected Holter recordings characterized by baseline wander , muscle artifacts and electrode motion artifacts as noise sources. The experimental results show that the proposed method reaches most satisfactory performance, even when challenging ECG signals are adopted. The results obtained are presented, discussed and compared with some other R wave detection algorithms indicated in literature, which adopt the same database as a test bench. In particular, for a signal to noise ratio (SNR) equal to 6 dB, results with minimal interference from noise and artifacts have been obtained, since Se e +P achieve values of 98.13% and 96.91, respectively.

I. INTRODUCTION

The electrocardiogram (ECG) is often contaminated by noise and/or interference that is external (i.e ., electrode contact noise) or internal in origin (i.e., other physiological processes in the body),which could impair the reliability of diagnoses in clinical applications and practices. ECG signal variability and its morphology change over time and are dependent on each individual. Due to its dynamic nature, the ECG exhibits stochastic and non-stationary behavior. Therefore, the study of such a signal is a time-consuming task, with a high probability of physicians missing vital information. Various approaches have been implemented to improve the accuracy of QRS complex detection. Without aiming to provide an exhaustive review of R peak detector procedures indicated in literature, some examples of the most recent and popular tools that adopt the standard MIT-BIH arrhythmia database are described below. The well-known Pan and Tompkins method, which is a benchmark in the R peak detection field, is based on the slope, amplitude and width of the ECG signal . After a preprocessing phase aimed at removing the noise, smoothing the waveform and amplifying the QRS slope and width, two sets of thresholds are applied to the signal in order to localize true positive R peaks. An evolution of the Pan and Tompkins method is indicated in , which reproduces the same preprocessing stage of but optimizes the decision rules by the performance test of three estimators (mean, median and an iterative peak level) for the adaptive threshold placing. A real time algorithm for QRS detection which is composed of four stages is proposed in. To remove baseline wander and power-line interference from the ECG, a band-pass filter is applied, while to enhance the QRS complex, a five-point first-order differentiation, absolute and backward accumulationoperation was used. For an accurate location of local maxima in ECGs with different morphologies, A K-nearest neighbor-based peak-finding algorithm and particle swarm optimization method were implemented. For muscular artifact removal, the ECG signal is filtered by adopting a band-pass Finite Impulse Response (FIR) filter window, adopting a Kaiser Bessel window, while for the elimination of motion artifacts and base line noise, the first differential of the filtered signal is

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performed. . A multiresolution analysis is used in for the ECG signal enhancement and the signal mirroring is designed to avoid missing detections. To locate R peaks, local maximums are calculated by the first-order forward differential approach and are truncated by the amplitude and time interval thresholds. In [8], authors applied simplification methods from computer graphics for data reduction, based on the observation that the ECG is essentially a graphical representation of heart electrical activity. In particular , a method named the vectorization process is applied , which is similar to that of converting bit map images into vector images in computer graphics. After vectorization , the ECG signal is reduced to 11 slope types and the signal sequence of slopes is treated as a sequence of alphabetic symbols that can be recognized by a finite automata recognizer. To eliminate false positive detections of R peaks, a probabilistic analysis is performed. A four stage R peak detection method which implements nonlinear transformation and a peak-finding strategy is presented in [9]. With the aim of enhancing QRS complexes and reducing out-of- band noise, the band-pass filtering and differentiation operations are implemented in the first stage, while for limiting the false positives/false negative detections, a nonlinear transformation based on energy thresholding, Shannon energy computation and smoothing processes is performed in the second stage. A peak- finding strategy based on the first order Gaussian differentiator is developed in the last two stages. In [10], the similarity between a template QRS pattern and potential QRSs is exploited through the use of a matched filter. In case of multiple ambiguous R peaks, the possible occurrences in time are limited by a dynamic time window which depends on the standard deviation of previously detected R intervals. Subsequently, the selection of the R peaks is computed using the cross- correlation between potential QRSs and the selected template. Dual tree complex wavelet and transforms was adopted for the QRS enhancement. The combination of first and second derivative was applied on the signal obtained from the wavelet transform to accentuate the QRS complex and suppress P and T waves. Further, the Hilbert transform was applied to have an envelope for R peaks for a single sided threshold mechanism. The envelope peak was then detected by adding a high-frequency signal whose amplitude depended on the QRS complex. With the aim to implementing a real-time system which is able to monitor the heart rate every few seconds, an adaptive thresholding - based ECG R peak detection procedure which combines the ECG segmentation method. The signal under test is initially band-passed through a zero-phase filter to remove baseline wander and high-frequency noise, and then differentiated to enlarge high-frequency components of QRS complexes and to suppress low-frequency components of P and T waves. The signal is successively squared and integrated to emphasize the correlation between samples and to merge the multiple peaks. The integrator, using the adaptive threshold algorithm, produces a smooth, pulse-like peak for each QRS peak which is used to detect the R peaks. Instead of using a threshold based on amplitudes as in the previous paper, a threshold based on the sampling frequency is adopted in the peak detection logic, which is based on the second derivative. As the presence of noise makes the extraction of accurate features from the ECG signal difficult, a hybrid linearization method involving the extended Kalman filter and the discrete wavelet transform is adopted for denoising. Thereafter, principal component analysis is applied to noise-free ECG signals for R peak localization.

II. DUAL TREE COMPLEX WAVELET TRANSFORM

The wavelet transform is a suitable tool for studying non-stationary signals. Therefore, it can identify useful information for R point detection and discard signal bands which provide a scant contribution to the study. Since wavelet functions are compact, wavelet coefficients only measure the variations around a small region of a data array. This feature makes wavelet analysis particularly useful for signal processing; the “localized” nature of the wavelet transform allows us to pick out features in analyzed data with ease, such as spikes (i.e., noise or discontinuities), discrete objects, edges of objects and so forth. Moreover, wavelet coefficients at one location are not affected by coefficients at other locations in the data understudy.

The Dual-tree complex wavelet transform (DTCWT) calculates the complex transform of a signal using two

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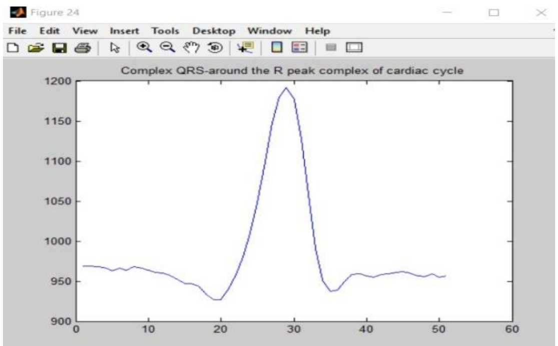
separate DWT decompositions (tree 'a'and tree 'b'). If the filters used in one are specifically designed different from those in the other it is possible for one DWT to produce the real coefficients and the other the imaginary. This redundancy of two provides extra information for analysis but at the expense of extra computational power. It also provides approximate shift invariant (unlike the DWT) yet still allows perfect reconstruction of the signal. The design of the filters is particularly important for the transform to occur correctly and the necessary characteristics are:

- The Low Pass Filter the two trees must differ by half a sample period
- Reconstruction filters are the reverse of analysis
- All filters from the same orthonormal set
- Tree 'a' filters are the reverse of tree 'b' filters
- Both trees have the same frequency response



III. PROCEDURE

An ECG signal consists of many cycles of P, Q, R, and S waves, with each cycle comprising many sample points. In MIT-BIH record 100, a cycle comprises approximately 280 sample points. There are up to 10 fiducial points that determine the overall characteristics of a cycle of ECG signal. Among various existing SEE-based methods, band-pass filters, such as the Chebyshev type I filter and Butterworth filter, are used for denoising input ECG signals as

preprocessing steps. In the proposed method, wavelet transform replaces the band-pass filters by level 2 down-sampling, soft thresholding for denoising detailed coefficients, and reconstructing the level 1 signal. By applying this procedure, we can reduce the size and time required for extracting R peaks.

- Read ECG signal from standard bio-library.

- ECG signal is passed through amplitude normalization refers to a process that makes something more normal or regular.

- Normalized signal is passed through the Band pass filter(BPF)that passes frequencies within a certain range and attenuate frequencies outside that range.(FL=4 Hz & FH=22Hz)

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- Filtered signal is passed through the Hamming window which function is a mathematical function that is zero-valued outside of some chosen interval, normally symmetric around the middle of the interval, usually near a maximum in the middle, and usually tapering away from the middle).

The output is taken from the hamming window function comparison between

- Original ECGsignal
- Amplitude normalizedsignal
- BPFsignal

The original ECG signal is processed and amplitude normalization is done. After that this signal is filtered using Band Pass Filter to get rid of the unwanted low frequency components.Then the processed signals is processed using Dual Tree Wavelet Transform and R peak detection is done in this step.

IV. RESULT AND ANALYSIS

A. ECG Database Used as Test Bench

The proposed method is evaluated using the MIT-BIH Noise Stress Test Database which includes twelve- and half-hour ECG recordings and three- and half-hour recordings of noise typical in ambulatory ECG recordings. The ECG recordings were created by adding calibrated amounts of noise to clean ECG recordings from the MIT-BIH Arrhythmia Database. Baseline wander, electrode motion artifact and muscle noise are the type of noises considered in MIT-BIH. In order to evaluate the worst situation, only the files provided directly from the database (files 118 and 119) are used in the test. They are only affected by noise of EM type (electrode motion artifact noise). Noise was added beginning after the first 5 minutes of each record, during two-minute segments, alternating with two-minute clean segments. Instead, the three noise records were assembled from the recordings by selecting intervals that contained an electrode motion artifact, which is the most difficult to handle because it can mimic the appearance of ectopic beats. With the aim of comparing the performance of the implemented method with the results of some significant R peak detectors indicated in literature, only the first channel of each ECG record is processed. Moreover, a two-fold cross-validation procedure has been used: File 118 was used to choose the best parameters and file 119 for testing the system.

B. Performance Evaluation and Results

For the performance evaluation, the sensitivity, positive prediction and detection error rate are taken into account. The sensitivity (Se) is defined as the probability of detecting a R point when a R point actually exists; the positive prediction (+P) represents the probability of detecting a R point among the detected ECG peaks. They are computed by adopting the following expressions:

Sensitivity:

$$Se = TP/ TP + FN \qquad (1)$$

Positive Prediction:

$$P = TP/ TP + FP \qquad (2)$$

Detection error rate:

$$DER = FP+FN/TP+FN \qquad (3)$$

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where TP (the number of true positives) is the number of correct identifications of R points present in the signal under test; FN(the number of false negatives) is the number of R points present in the signal that the algorithm is not able to detect; FP (the number of false positive) is the number of R points detected by the algorithm that are not actually in the signal. Different signal to noise ratio (SNR) levels for the same ECG record are analyzed. In particular values ranging from 24 dB to 0 dB are tested. A tolerance window of 150 ms, centered at the reference annotation, has been used in order to classify peaks detected by the procedure. With the aim of comparing the performance of the implemented method with the results of some significant R peak detectors indicated in literature, only the first channel of each ECG record is processed. Moreover, a two-fold cross-validation procedure has been used. File 118 was used to choose the best parameters and file 119 for testing the system.

An analysis of performance shows that when increasing the noise contribution, FN remains almost constant while a small growth in FP is observed, which makes the performance worse. It is evident that the Se parameter is almost constant, depending on FN parameter, therefore it is rather unaffected by noise corrupting the ECG signal. The obtained performance confirms that the algorithm is immune to noise up to SNR values equal to 6dB. In fact, for SNR = 6 dB, results with minimum interferences from noise and artifacts have been obtained, since Se e +P achieves values of 98.13% and 96.91%, respectively. More specifically, during the test phase, 1987 beats have been analyzed, obtaining TP = 1950, FN = 37 and FP= 62. For SNR values lower than 6 dB, +P and Se are dependent on the amount of noise signal, decreasing as FP and FN grow. By an assessment of the results achieved for SNR values equal to 0 dB, it is noted that FN and FP raise by almost identical proportions if compared with the corresponding values obtained with a SNR equal to 6dB. In particular, Se and +P reach values of 78.98 and 75.25, respectively.

The procedure presented in this work shows good results compared to other methods indicated in literature. More specifically, it achieves the most effective +P value compared to all the analyzed algorithms and a quite satisfactory Se value comparison with a noise resistant procedure in the existed methods. The method implemented in this proposed work reaches better performance and has lower computational complexity, avoiding signal reconstruction in the time domain.

V. CONCLUSION

Bioelectrical signals are very useful in detecting pathological conditions and in controlling the effectiveness of drugged treatments. In particular, ECG signal processing is an important diagnostic tool for the monitoring of heart functional status. The proposed system adopts the Hilbert transform combined with a threshold technique and the wavelet transform to localize R peaks, even if noisy signals and peaked T and P waves are present. The noise robustness of the implemented method is quantified adopting the MIT-BIH Noise Stress Database as a test bench. Experimental results show the method's validity. In fact, results with minimum interferences from noise and artifacts have been obtained up to SNRs equal to 6 dB. For SNR values lower than 6 dB , the method performance gets worse , sincean increase of FP and FN is observed. The method is suitable to be used in parallel architecture for real-time analysis applications. The method's weakness is related to the sampling rate and the resolution of the ECG records: In fact, the method has poor performance as soon as the ECG sampling rate and resolution decrease, compared to the parameters of the MIT-BIH database.

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