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Quick ECG Analysis for On-Line Holter Monitoring Systems

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Abstract— **Computer-aided bedside patient monitoring requires real-time analysis of vital functions. On-line Holter monitors need reliable and quick algorithms to perform all the necessary signal processing tasks. This paper presents the methods that were conceptualized and implemented at the development of such a monitoring system at Medical Clinic No. 4 of Târgu-Mureş. The system performs the following ECG signal processing steps: (1) Decomposition of the ECG signals using multi-resolution wavelet transform, which also eliminates most of the high and low frequency noises. These components will serve as input for wave classification algorithms; (2) Identification of QRS complexes, P and T waves using two different algorithms: a sequential clustering and a neural-network-based classification. This latter also distinguishes normal R waves from abnormal cases; (3) Localization of several kinds of arrhythmia using a spectral method. An autoregressive model is applied to estimate the series of R-R intervals. The coefficients of the AR model are predicted using the Kalman filter, and these coefficients will determine a local spectrum for each QRS complex. By analyzing this spectrum, different arrhythmia cases are identified. The algorithms were tested using the MIT-BIH signal database and own multi-channel ECG registrations. The QRS complex detection ratio is over 99.5%.**

I. Introduction

ON-LINE ECG processing systems require a reliable and fast QRS complex detection algorithm. Most on-line algorithms apply a direct, time-domain method, which sometimes leads to mediocre results. Parameter estimation methods are mostly too complex to be implemented in microcontroller-driven devices. Transformation-based algorithms are usually reported to work off-line, because of the enormous amount of calculations. These are the key problems to be solved using the new QRS detection method [1–3].

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The time between the R-waves for an ECG signal varies with time. In the case of a normal subject, this variability may depend on blood pressure and respiration rate [4]. More extreme cases are when some kind of arrhythmia occurs, such as bigeminy or atrial fibrillation. Many techniques have been developed for the automatic detection and identification of such kind of phenomena. Most of them are based either on the direct analysis of the ECG signal itself, or on analyzing the statistics of the R-R intervals. It has been suggested, that various sorts of cardiac arrhythmia may be studied by applying spectral analysis techniques [5]. In this paper we investigate whether the Kalman filter identifier can be used to study the onset and termination of arrhythmia [6], whether arrhythmic disturbances lasting only a few beats may be detected using this method.

The present paper proposes a chain of signal processing methods, which can perform an automated, quick and accurate segmentation of the ECG and localize several kinds of artifacts and arrhythmic phenomena, and which will reliably support an on-line monitoring system in intensive healthcare. First a multi-resolution wavelet decomposition is performed, to get a multiple-resolution filtered ECG signal, in which the QRS complexes, P and T waves are directly and accurately recognizable using a direct time domain method. An artificial neural network is trained as well for peak classification in order to find the exact location of several kinds of artifacts. An autoregressive (AR) model is applied to predict the obtained series of QRS complexes. The coefficients of the AR model are predicted using the Kalman filter. The obtained coefficient values will define a local spectrum for each QRS complex. This local spectrum will be used to localize the onset of different rhythm disturbances. The outputs of these methods serve as input for heart rate variability and turbulence analysis, which support the physician in establishing the diagnosis.

II. Methodology

A. Multi-resolution wavelet decomposition

Wavelet transform is a linear operator, which decomposes the input signal into components that appear at different resolutions. The first thing needed for a wavelet transform is to choose a convenient mother wavelet. The function $\Psi(t)$ is said to be a wavelet if it has a finite spectrum and has no dc component, that is, it is oscillatory and its area is zero. The wavelet transform of the function $\varphi(t)$ at scale a and position τ is given by the following expression:

$$W\varphi(a,\tau)=\frac{1}{\sqrt{a}}\int_{-\infty}^{+\infty}\varphi(t)\Psi^{*}\left(\frac{t-\tau}{a}\right)dt\,, \tag{1}$$

where $\Psi^{*}(\alpha)$ denotes the complex conjugation of $\Psi(\alpha)$. In its digitized form, the formula gets the following aspect:

$$W\varphi_{\tau}=\sum_{k=-\delta}^{\delta}c_k\varphi_{\tau+k}\,, \tag{2}$$

where δ reflects the length of the interval in which the wavelet is defined, and the coefficients c_k contain the wavelet and the energy normalizing factor $1/\sqrt{a}$ [7]. The proposed wavelet is a Mexican hat given by the following formula:

$$\Psi(t)=\exp\left(-t^2/\beta^2\right)\cos(2\pi ft)-\lambda\,, \tag{3}$$

being defined on a single period of the cosine function, where β is the attenuation factor of the wavelet, f defines its basic frequency, while λ helps eliminate the dc factor.

The output of this wavelet transform will be a filtered signal that contains mostly the spectral components having the frequency around f. The parameters of this decomposition are the attenuation factor β, the basic frequency f, and the width of the definition interval that depends on δ. The detection of different waves from the ECG signal requires different parameter values. These values are shown in Table I.

TABLE I
PROPOSED PARAMETERS FOR WAVELET DECOMPOSITION

Wave to be detected	Basic frequency (f)	Interval width (δ)	Attenuation factor (β)
P and T	5-6 Hz	320 ms	0.06
QRS	16-18 Hz	120 ms	0.03

A positive side effect of this wavelet filtering will be the elimination of low and high frequency noises from the signal, in fact it will be similar to a band-pass filtering around the basic frequency f, without causing phase delay.

B. Event recognition: direct method using peak selection

The QRS complex detection is accomplished using the decomposed signal. First we determine the series of consecutive minima and maxima. Then the maxima, which occur after a long ascent and are followed by a long descent, will be declared the peaks of the R waves. The exact threshold value of the criterion "long" is determined at the beginning from the maximum value of the ascents in the first few seconds. Tests have confirmed that any threshold value situated between 40% and 60% of the tallest ascent leads to acceptable results. P and T waves are detected similarly, using a different wavelet component of the signal.

The stability, efficiency and reliability of this method have been studied by varying the value of the main parameters (β, f, δ), and checking how the detection ratio depends on them.

C. Local spectrum analysis based on Kalman filter

There has been suggested a wide variety of representation methods of the R-R interval time series. In the followings, we will use the interval tachogram, which represents the difference in the time of occurence of the R-waves for beats n and $n+1$ plotted against n. Let us denote by τ_n, the difference in time between the n-th and $n+1$-th beat. As we intend to study only the variations of the length of the R-R intervals, we subtract from each value τ_n, the mean T_n, of the R-R interval time series, computed over a moving window of length N:

$$T_n=T_{n-1}+\left(\tau_n-\tau_{n-N}\right)/N\,. \tag{4}$$

By performing the subtraction $t_n=\tau_n-T_n$, the spectral frequencies below the cutting frequency $1/N$ are being filtered from t_n. The parameter N should be chosen small enough, so that (4) can follow sudden changes in the R-R interval time series, and large enough, so that the subtracted series $\{T_n\}$ does not contain important low-frequency components that should not be eliminated. The time series $\{t_n\}$ can be modeled as an AR series of order k: $t_n=\theta_n X_n+\nu_n$, where $\theta_n=\left(t_{n-1},t_{n-2},\cdots,t_{n-k}\right)$ contains the previous k values from the time series $\{t_n\}$, $X_n=\left(a_n^1,a_n^2,\cdots,a_n^k\right)^T$ contains the AR coefficients for beat n, and $\{\nu_n\}$ represents the residual signal, which is a white noise series.

One of the quickest methods that can estimate X_n is the Kalman filter. Before applying this method, we need to define a model for the variation of X_n, between the data points $n-1$ and n. Let us define the model in the following way: $X_n=X_{n-1}+q_n$, where q_n is a vector representing a white noise series. If $q_n=0$, the AR coefficients do not vary in time, which would be appropriate for a stationary signal. The presence of a non-zero q_n models the changes in the AR coefficients due to the presence of non-stationarities in the data.

The discrete Kalman filter is a set of recursive equations that estimates the value of the AR coefficient vector X_n at time point n. The Kalman filter is given by the following equations:

$$\begin{aligned}
&X_{n/n}=X_{n-1/n-1}+K_n(t_n-\theta_n X_{n-1/n-1})\\
&P_{n/n-1}=P_{n-1/n-1}+Q_n\\
&\{s_n\}^2=\sigma_R^2+\theta_n P_{n/n-1}\theta_n^T\\
&K_n=P_{n/n-1}\theta_n^T\left(\{s_n\}^2\right)^{-1}\\
&P_{n/n}=\left(I-K_n\theta_n\right)P_{n/n-1}
\end{aligned} \tag{5}$$

where $X_{n/n}$ is the estimated value of the vector X_n of AR coefficients at time point n, $P_{n/n}$ is the estimated error covariance matrix, $P_{n/n-1}$ is the predicted error covariance matrix, σ_R^2 the variance of the prediction error ν_n, and Q_n is the error covariance matrix of the plant noise vector q_n, K_n represents the Kalman gain matrix, which determines the weight put on the new measurements as they come in. Once the AR coefficients are determined, we can define the local power spectrum at time point n, as follows:

$$G(n,f) = \sigma_R^2 \left(\left| 1 + \sum_{i=1}^{k} a_n^m \exp(-2\pi f i j) \right| \right)^{-1} . \quad (6)$$

The Kalman filter needs several properly chosen parameters. First, we need a model for the plant noise covariance matrix. A common approximation is to let $Q_n = I\sigma_Q^2$, where I is the identity matrix and σ_Q^2 is the variance of each element of the plant noise vector q_n. The performance of the filter depends on the ratio σ_Q^2 / σ_R^2. If this ratio is zero, the signal is considered to be stationary, and it would not be possible to follow any non-stationary behavior of the signal. If this ratio is too large, the filter will be able to follow the non-stationary behavior, but it will give too noisy estimates for the AR coefficients. Tests have led to a compromise value of 0.25 for this ratio.

Let us consider the order k of the AR model next. In general, for autoregressive analysis, if there are m peaks in the spectrum, a model of order $k = 2m+1$ should be chosen. Tests have showed, that most of the studied arrhythmia cases manifest one or two peaks in the local power spectrum, consequently a model order of $k = 5$ is appropriate. Other values for the model order should also be tested, because the power spectra obtained can be very sensitive to the model order.

The initialization of the Kalman filter is also an important task, which can be properly resolved using the maximum entropy method.

D. Local spectrum analysis based on Kalman filter

ECG waveform classification is performed by an artificial neural network that uses radial basis function (RBF). The input of the network is provided by the multi-resolution wavelet transform. These transformed values for several consecutive samples are applied as input to the RBF network, which gives as output the classification of the actual event if any: normal QRS complex, P wave, T wave, and different kinds of artifacts (e.g. ventricular premature beats (VPB), etc). The RBF network is trained using the MIT-BIH arrhythmia database, which contains thousands of examples for all normal events and dozens of most arrhythmia types [7].

III. RESULTS

The QRS complex detection algorithm has been tested using ECG registrations from the MIT-BIH database and registrations measured with the Holter system at the Medical Clinic No. 4 of Târgu-Mureş [9]. The detection ratio varies between 99% and 100%. The threshold value of the peak detection criterion, if chosen in a certain, considerably wide interval, does not influence the detection ratio, which provides stability for the algorithm. Most arrhythmia-free sections had no failed detections.

The basic frequency has a strong influence on the detection ratio. Its value has to be around the dominant frequency of the R wave. By choosing a value between 12Hz and 21Hz, we obtain a very good detection ratio; the optimal value, even if it depends from registration to registration or from patient to patient, in every case is very close from 17Hz [7]. The width of the interval, in which the mother wavelet is defined, should be chosen as 1-1.5 periods of the cosine function in the mother wavelet's definition. The attenuation factor β should be chosen such a way, that it limits the mother wavelet's values at the boundaries of the interval to 3-5% of its maximum. Table II gives a summary on the efficiency of the method, measured with ECG registrations from MIT-BIH database.

TABLE II
QRS COMPLEX DETECTION RATIO FOR DIFFERENT MIT-BIH RECORDS

Record number	Total beats	Failed detections	Detection ratio
104	2230	6	99.73 %
105	2572	19	99.26 %
108	1763	17	99.03 %
201	1963	7	99.63 %
203	2982	16	99.46 %
222	2484	7	99.72 %
228	2053	8	99.61 %
Total	16047	80	99.50 %

The following four arrhythmia types are studied with the Kalman filter: bigeminy, trigeminy, second degree block and ventricular flutter. The main goal is to determine the effectiveness of the Kalman filter identifier in the detection of the onset and termination of arrhythmia, to see whether short segments of signal, which contain arrhythmia, can be detected. We study the local power spectra obtained with the Kalman filter and plotted in a logarithmic scale.

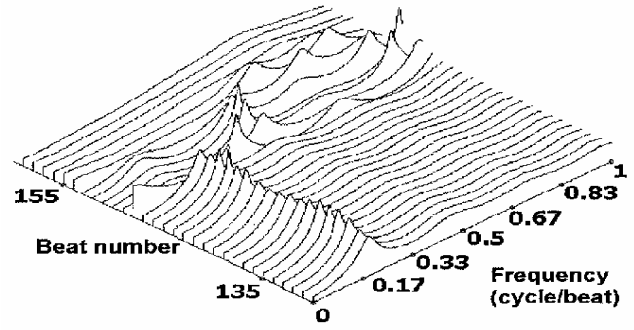

Fig. 1. Time varying power spectrum in case of bigeminy

Bigeminy occurs when the R-R interval time series contains such segments, in which long and short beats are following each other. The local power spectrum of such a time series, over a stationary segment of signal, has a single peak at the frequency of half cycle per beat.

Figure 1 represents the time varying spectra computed for $N = 20$, of a registration from our database. The ECG signal contains a segment of bigeminy between beats 148 and 151. It can be observed, that the spectral criterion detects this event, even if with a delay of one beat. Consequently we can say that the onset of bigeminy has been detected, but we also have another event, which seems not to have any medical significance. The detection rate of bigeminy depends on the length of the segment, that is, the number of pairs of long and short beats. The spectra obtained are shown in Table 3.

TABLE III
BIGEMINY DETECTION RATE DEPENDING ON THE LENGTH OF ARRHYTHMIC SEGMENT

Length of bigeminy (pairs of beats)	Detection rate (percent)
2	92.5 %
3	94.0 %
4	95.0 %
5 or more	97.5 %

Trigeminy occurs when the time series $\{t_n\}$ contains repeated segments, where within each segment a long beat is followed by two short beats. The power spectrum of such a time series has a peak at 0.33 cycles per beat. Figure 2 illustrates the time varying spectra of MIT-BIH case 201, between beat numbers 1090 and 1110. In this interval the trigenimy occurs between beat numbers 1095 and 1104, and the peak at around 0.33 cycles per beat can be observed for this data segment. The spectra computed for other beats have peaks at other frequencies.

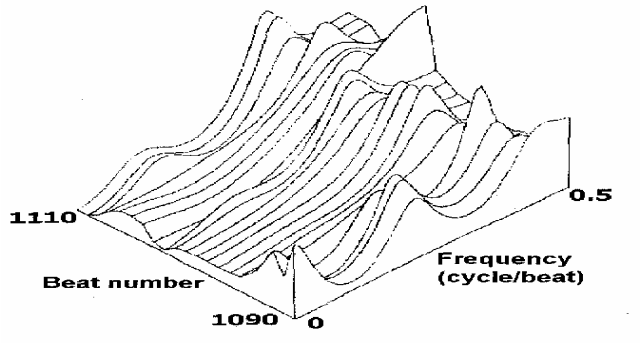

Fig. 2. Time varying power spectrum in case of trigeminy

This spectral method has also been tested for more complicated arrhythmia cases. The amount of available such cases in the MIT-BIH database is not enough to create a reliable criterion for their characterization.

Using the output of the above mentioned methods, the on-line monitor system performs heart rate variability (HRV) and heart rate turbulence (HRT) analysis, which can help the diagnosis and can predict dangerous states of the patient [6–8, 10].

IV. DISCUSSION AND CONCLUSIONS

Having the QRS complex detection ratio over 99.5%, this method can be called a reliable one, and can be implemented into Holter systems. Wavelet-transform-based methods have been reported many times to require a lot of calculation, which makes it hard to use in on-line signal processing systems. Using modern computers, this method can process a 10-minute registration in a few hundreds of milliseconds. Therefore it can be applied even in case of multi-channel ECG. Experiments show that the algorithm can work even in a microcontroller-driven Holter system.

One of the objectives of this paper was to investigate whether the study of time varying spectra of the R-R interval time series can give us information about the identification of short segments of arrhythmia and the detection of the onset and termination of such phenomena. The Kalman filter identifier algorithm has been used to compute such spectra. The investigations carried out suggest that this algorithm gives accurate information about the presence of bigeminy or trigeminy. Short segments of such arrhythmias can be detected, although in a few cases the arrhythmia does not manifest itself clearly in the spectra until several beats after the onset. The detection rates between 92% and 98% are quite a promising result. The early recognition of such phenomena, which can cause sudden death, is of key importance in intensive care. Tests have shown, that the proposed methods can detect in time most (85–90%) cases of the frequent events that can cause ventricular fibrillation.

The RBF network based event classifier, with its accuracy of 99.5% is a reliable tool in this signal processing chain.

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