A DIGITAL FIR FILTER FOR QRS COMPLEX DETECTION

تصميم مرشح رقمى ذو استجابة محدوده للتعرف على مواضع الـ QRS

Fatma E.Z. Abou-Chadi*, M. M. Elzalabani*, and Manal. M. Saleh**
* Department of Electrical Communications
Faculty of Engineering - Mansoura University
** Mansoura Electronic Exchange

الخلاصه ــ يقدم هذا البحث خوارزم لمرشح رقمى يناسب التعرف على مواضع الـ QRS وقد صممنا المرشح ذو استجابة محدوده ليستبعد الترددات المنخفضه والتى تمثل التغيرات فــــى خط الاساس لاشارات رسم القلب وكذلك ليعظم نسبة الاشاره الى الضوضاء بدرجة تقترب من تلك التى يحققها المرشح الموائم المثالى ولكنه يتميز عنه بسهوله تنفيذه واختصار وقت الحساب وكذلك يتميز بخصائص خطية لطيف زاوية السطور بحيث لا يؤثر على مواضع وأزمنة حدوث الـ QRS . وقد اختبرنا فاعلية عمل هذا المرشح على نوعين من البيانات الاولى لتسجيلات محاكيه لاشـــارة رسم القلب والثانيه لتسجيلات حقيقيه لعدد أشخاص وقد وجد ان معدل التعرف على الـ QRS يصل الى ١٠٠٪ حتى فى حالة التسجيلات ذات المستوى العالى من الضوضاء .

ABSTRACT- A digital filtering algorithm is presented that is suitable for automatic detection of QRS complexes. A bandpass nonrecursive finite impulse response (NRFIR) filter is used to suppress lower frequency frequencies of the ECG signal, which are inherently nonstationary, and to model the frequency response of the optimal matched filter. This digital filter is time saving and it provides linear phase characteristics so that the time of QRS occurrences is not affected. Its capability is demonstrated by applying the filtering to simulated and true ECG records. The detection rate for very noisy records reaches 100 percent.

I. INTRODUCTION

Several arrhythmia monitors that analyze the ECG in real time for ambulatory patients have been developed [1, 2]. When an arrhythmia appears, such a monitor can be programmed to immediately store an interval of the abnormal ECG for subsequent transmission to a central station where a physician can interpret it. Such a device requires a very accurate QRS recognition capability. False detection results in unnecessary transmission of data to the central station or requires an excessively large memory to store any ECG segments that are unnecessarily captured. Thus, an accurate QRS detector is an important part of many ECG instruments.

QRS detection is difficult, not only because of the physiological variability of the QRS complexes, but also because of the various types of noise that can be present in the ECG signal [3]. A matched filter can maximize the signal-to-noise ratio (SNR) of a known signal in noise. Therefore, it may be used successfully to identify the location of a QRS complex. However, the design of an optimal matched filter requires knowledge of both the signal and the correlation statistics of the noise. The nonstationary nature of the signal and noise in ECG represents an obstacle in application of matched filtering to QRS detection. Therefore, an essential step before applying a matched filtering procedure is to remove or reduce the influence of nonstationarity.

In a previous work [4], an attempt has been made to develop a QRS detection algorithm that eliminates nonstationaty effects by using a variable threshold which adapts itself to variations in the baseline. However, this technique may fail to detect ventricular ectopic beats with small amplitude. Also, in case there exist several QRS complexes with different amplitude and

T-waves with high amplitude at the same time, it is difficult to set up the boundary to distinguish between these two different waves.

In the present paper, we propose a new QRS detection algorithm which achieves the two goals, namely the removal of nonstationarity and maximization of SNR in one operation. By finding the optimum bandpass filter whose upper frequency characteristics give the same performance of the matched filter, we assure that the two goals have been achieved.

Another important consideration, apart from the combination of nonstationarity removal and maximization of SNR, is the phase distortion. In many cases, it is essential to use filters which cause no phase distortion; this is particularly important when some features of the waveform (such as the time of occurrence or the amplitude of the QRS peak) are to be subsequently examined. Keeping this consideration in mind, we restrict ourselves here only to symmetric nonrecursive finite impulse response NRFIR filters causing no time delay and no phase distortion within the passband [5]. Such filters also have the important advantage of being free from stability problems [6].

The organization of the paper is as follows. In section II, we review the theoretical matched filter background, which is essential to our algorithm. Then, in Section III, we presented our new algorithm. The application of the algorithm to ECG signal and the experimental results obtained for QRS detection are reported in Section IV.

II. THE MATCHED FILTER AND ITS CHARACTERISTICS

The matched filter can be used to detect a signal embedded in noise where the signal is known and where the noise is a stationary random process. The filter is so designed to maximize output SNR at a particular time t_k. It is easily shown that, if the noise is white, the impulse response of the matched filter takes on the form of a mirrored version of the input signal [7,8]. That is $h(t) = s(t_k-t).u(t)$, where $h(t)$ is the impulse response, $s(t)$ is the signal, and $u(t)$ is the unit step function. The desired response is simply the signal waveform reversed in time and delayed by t_k seconds. The block diagram of the matched filter system at typical input and output is shown in Fig.1. The impulse response of the matched filter can be obtained by coherent averaging an ensemble of individual beats aligned to their peak.

In practice, however, the noise $n(t)$, is neither white noise nor stationary. The output SNR will be adversily affected since the background noise is not white; the background noise includes portions of the ECG signal such as the P and T waves, instrument noise, and electromyographic noise. In some applications, for instance, the detection of radar target returns in a background clutter, a prewhitening filter is used to whiten the background noise and then a matched filter is designed whose impulse response is matched to the signal output from the whitening filter [9, 10]. In our case, however, we shall adopt a different, simpler approach as described hereafter.

The matched filter is actually a very special type of bandpass filter centered at the expected frequency band of the incoming signal. Although it is the theoretical optimum linear filter, it is argued that other types of bandpass filter, if centered at the proper band of frequency, would also enhance the

SNR, not as much, of course, as would the matched filter. In many systems, the construction of an ideal matched filter would be impractical so that the degradation incurred by an easily constructed bandpass filter in lieu of a matched filter is tolerated [9].

There are two major drawbacks of applying matched filtering to ECG signals. First, the long computation time caused by the large number of multiplications involved in the filtering in the time domain (about 230 multiplications or so are required to process an ECG, that is, sampled at a rate of 250 Hz, with a filter having an impulse response length of one ECG beat). Second, the possibility of causing phase distortion to the output filtered signal as a result of using unsymmetrical impulse response (in our case, it is a complete ECG beat reversed in time). Seeking for a convenient method to circumvent these drawbacks, a symmetric NRFIR bandpass filter suggests itself. The design of this filter is described in the next section.

III. BAND-PASS FILTER DESIGN

III.1 Frequency Characteristics of the Filter

Our goal is to design an NRFIR bandpass filter whose frequency characteristics approximate the frequency response of the matched filter. This would require a priori knowledge of the frequency response of the matched filter. As stated before, the impulse response of the matched filter is the signal template reversed in time and delayed t_k seconds. In this work, a typical template of the ECG beat is obtained by coherent averaging of an ensemble of 25 beats aligned to their maxima (namely the R-wave). In real time application, template formation is to be carried out at the beginning of the recording for each individual subject from about 25 second recording (sampled at 250 Hz) judged to be normal for that subject. The decision of normality of these beats should be made by the physician.

Having determined the impulse response of the matched filter (Fig.1.b), the next step is to calculate (through an FFT) its frequency response which determines, in turn, the frequency characteristics of the desired bandpass filter. Fig.2 illustrates the frequency response of the matched filter for a normal subject. However, it is also desired to remove the nonstationarity in the ECG signal resulting from base-line wander due to respiration or motion artifacts. It has been established [11] that these factors contribute to the low frequency band of the ECG spectrum. Therefore, the ECG signal should be high-pass filtered in order to reduce the nonstationarity effects. A Convenient lower cutoff frequency value obtained in previous studies is 5 Hz [11, 12].

Designing a filter whose frequency response is of complexity like the one shown in Fig.2 is impractical as it requires large number of coefficients. Therefore, a simple approach based on the approximation of the desired frequency response by two plateaus having different lengths was adopted. The first plateau extends from 5 Hz up to the frequency above which all frequency components are 3 dB below the maximum. The second extends from the 3 dB point up to the frequency f_s above which all frequency components have a magnitude greater than -30 dB below the maximum value of the frequency components lying in the range of (5 Hz and up).

Therefore, as an illustrating example, the filter ideal characteristics corresponding to the frequency response of Fig.2 would be as follows:

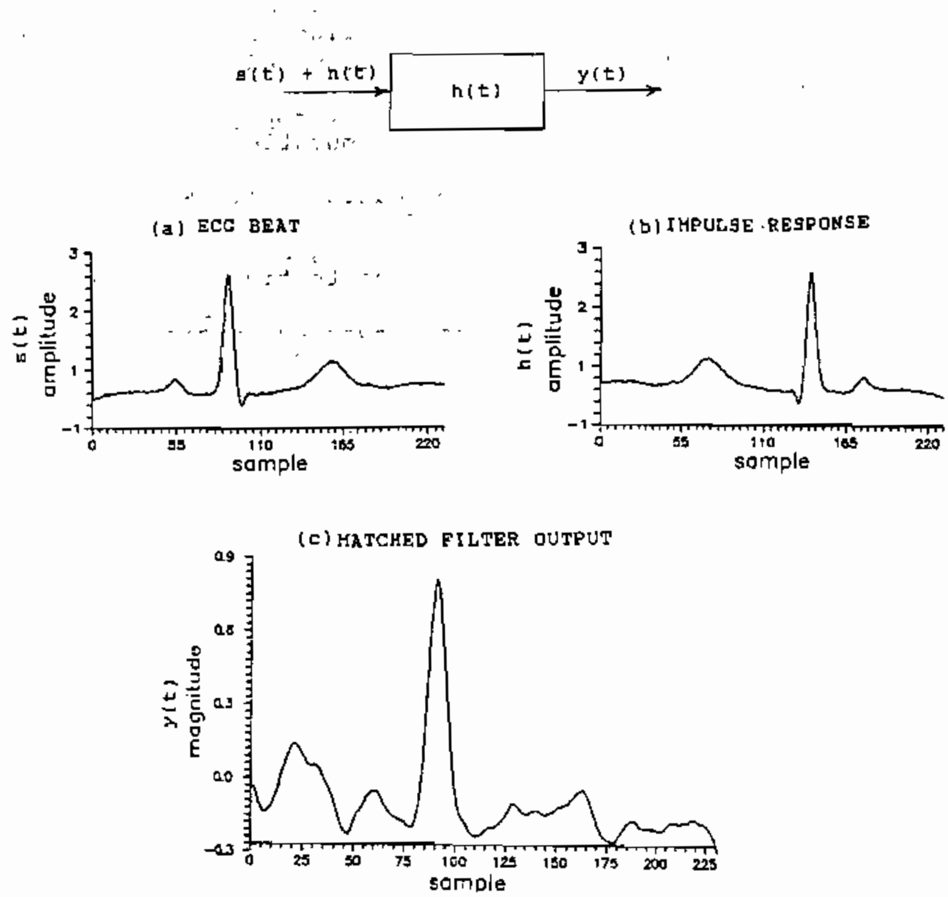

Fig.1 A matched filter system

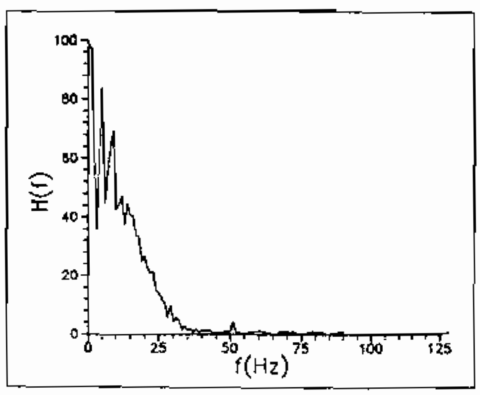

Fig.2 The frequency response of the matched filter of Fig.1.b

- to stop frequency components from 0 - 5 Hz
- to pass compeletely frequency components lying in the range greater than 5 Hz and less than 10 Hz
- to attenuate frequency components lying in the range 10 - 20 Hz A convenient attenuation factor was found to be equal to the ratio between the mean value of the frequency components lying in that range and the value of the maximum frequency component lies in the range of 5 Hz and up.
- to stop completely all frequency components above 20 Hz.

A formulation of the above specifications (using normalized values of frequency) is

$$\begin{aligned} H(f) &= 0 & 0 &< |f| \leqslant 0.02 \\ &= 1 & 0.02 &< |f| \leqslant 0.04 \\ &= 0.3 & 0.04 &< |f| \leqslant 0.08 \\ &= 0 & &\text{otherwise} \end{aligned} \tag{1}$$

III.2 Determination of the Filter Impulse Response Cofficients

The Fourier series of the band-pass filter of (1) can be written as

$$H(f) = \frac{a_o}{2} + \sum_{n=1}^{\infty} \left[a_n \cos(2\pi fn)\right] + \left[b_n \sin(2\pi fn)\right] \tag{2}$$

where

$$a_n = 2 \int_{-0.5}^{0.5} H(f) \cos(2\pi fn)\, df \tag{3}$$

and

$$b_n = 2 \int_{-0.5}^{0.5} H(f) \sin(2\pi fn)\, df \tag{4}$$

Because of the symmetry of H(f) with regard to f = 0, all coefficients b_n are zero. Substitution of (1) in (3) gives the values of the coefficients a_n.

Inverse Fourier transformation of the Fourier series describing the continuous spectrum (1) with coefficients a_n results in a discrete infinite noncausal impulse response h_c

$$h_c(nT) = h_c(-nT) = \frac{a_n}{2}$$

$$n = \ldots, -3, -2, -1, 0, 1, 2, 3, \ldots \tag{5}$$

and T = sampling interval

This impulse response is symmetric as a result of the reality of the spectrum defined in (1). In order to obtain from (5) an impulse response which can be implemented as an NRFIR filter, the impulse response must be finite and causal.

After truncation, the impulse response becomes finite with length NT, which is achieved by limitation of n in (5) as follows:

$$|n| \leqslant (N-1)/2, \qquad N \text{ is odd} \tag{6}$$

The truncation is performed symmetrically with respect to n = 0 in order to maintain symmetrical impulse response. The truncation of the discrete impulse response causes distortion of the desired frequency spectrum of the filter. Ripples are found to occur in the pass and stop-bands (Gibbs phenomenon).

To improve the pass and stop-band ripples, the impulse response h(nT) is multiplied by a Kaiser window [6].

$$h_w(nT) = h(nT) \;.\; W(nT) \tag{7}$$

where W(nT) is the Kaiser window

$$W(kT) = \frac{I_o\left[\alpha \sqrt{1 - \left[\frac{(N-1-2k)T}{(N-1)T}\right]^2}\right]}{I_o(\alpha)} \; ; \quad 0 \leq k \leq (N-1)/2$$

$$= W((N+1-k)T) \qquad \frac{N+1}{2} \lesssim k \lesssim N-1$$

$$= 0; \qquad k < 0; \qquad k > N-1 \tag{8}$$

where

$$\alpha = 0.1102\,(a - 8.7); \qquad a > 50$$

$$= 0.5842\,(a-21)^{0.4} + 0.07886\,(a-21); \; 21 < a \leqslant 50$$

The parameter (a) determines the shape of Kaiser window. Here a value of 40 was chosen to obtain the required specifications.

The filter becomes causal by shifting the impulse response over a time interval with length (N - 1) T/2. This operation introduces an exact delay between output and input of the filter which is also (N - 1)T/2. After the shift operation, the spectrum $H_w(f)$ of the truncated impulse response becomes $H_{wp}(f)$

$$H_{wp}(f) = \exp\left[-j2\pi f(N-1)T/2\right] H_w(f) \tag{9}$$

However, the obtained filter (9) was found not to have its minimum stopband amplification being zero, at the frequency f = 0; the stopband does not touch the $H_{wp}(f) = 0$ level but crosses it so that the attenuation decreases.

A simple method for correcting the impulse response coefficients was reported by Van Alste [13]. Therefore, the whole spectrum of $H_{wp}(f)$ was lifted by adding a certain constant factor q so that $H_{wp}(0) = 0$ and the increased pass-band amplification was corrected by multiplying with $1/(1 + q)$ so that it again becomes unity. The corrected spectrum $H_{cor}(f)$ is

$$H_{cor}(f) = \frac{1}{(1+q)} \left[H_{wp}(f) + q\right] \tag{10}$$

Thus, the existing impulse response coefficients $h_{wp}(nT)$ corresponding to (9) were changed in the following way into a new impulse response $h_{cor}(nT)$:

$$h_{cor}(nT) = \frac{1}{(1+q)} h_{wp}(nT); \qquad 0 \le n \le \frac{N-3}{2}, \quad \frac{N+1}{2} \le n \le N-1$$

$$= \frac{1}{(1+q)} \left[h_{wp}(f) + q \right]; \qquad n = \frac{N-1}{2}$$

$$= 0 \qquad \text{elsewhere} \tag{11}$$

where

$$q = -\sum_{n=1}^{N-1} h_{wp}(nT) \tag{12}$$

The impulse response coefficients $h_{cor}(nT)$ of (11) were calculated using N = 33. Using the impulse response symmetry the number of multiplications becomes 16 (N = 230 in case of matched filtering). Thus the number of multiplications is reduced by a factor of about 14. The resultant frequency spectrum $H_{cor}(f)$ is shown in Fig.3.

Generation of the filter output makes use of the following equation:

$$y(nT) = \sum_{i=0}^{N-1} x((n-i)T) \cdot h_{cor}(iT) \tag{10}$$

where

T = sampling interval
y(nT) = output signal samples
x(nT) = input signal samples
h(iT) = filter impulse response coefficients
N = number of filter coefficients

IV. APPLICATION AND PERFOMANCE

We evaluated the performance of the proposed algorithm by applying the NRFIR bandpass filter to two types of ECG signal: simulated ECG signal (used as a gold standard) corrupted with four levels of each of six types of noise and an ensemble of true ECG records.

IV.1 The Synthesized ECG

The synthesized ECG signal was obtained using the approach adopted by Friesen et al. [3]. We simulated six types of noise:
- electromyographic noise,
- powerline interference,
- baseline drift due to respiration,
- abrupt shifts in the baseline,
- motion artifacts, and
- a composite of all of the above.

Fig.4 shows the contaminated ECG signal with each type of simulated noise. We did not simulate other types of noise such as electrosurgical and instrumentation noise as they behave similarly to the random model used for EMG.

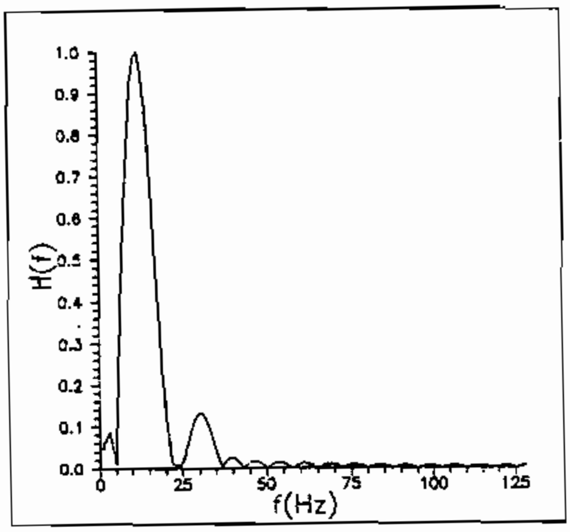

Fig.3 The resultant frequency response of the NRFIR filter (N = 33)

Each of the six types of noise is added to an uncorrupted ECG at four different levels: 0, 50, 75, and 100 percent of the ECG maximum amplitude. Fig.5 shows an example of simulated signal and itsthe corresponding filtered version. Note that the nonstationarity has been almost completely removed and that the locations of the QRS complexes are clearer.

IV.2 Recorded ECG

Four 35-sec Lead II ECG records were obtained from 4 normal volunteers using a Philips ECG monitoring system type XV1503. The subject was lying down and breathing quietly.

It has been important to evaluate the filtering performance with noisy ECG signals. Therefore, the bandwidth of the true signal was chosen to be 100 Hz thus assuring that the recorded signal includes the 50 Hz component. Moreover, the subject was asked to breathe deeply and to move his hands several times so that respiratory, abrupt change in baseline, and motion artifacts are included.

The output of the ECG recorder was then connected to a 12-bit analog-to-digital converter with a built-in 8-channel capacity. The output was transmitted separately to a single channel at a rate of 250 sps. The digital data were transferred to an IBM PS2/80 computer by a program written in Basic. Fig.6 shows an example of ECG record before and after filtering.

IV.3 QRS Detection and Evaluation

QRS complexes were detected by searching for the global maxima of y(nT) of (10). The classification was carried out based on the values of these maximal points. A number of decision rules were adopted in the classification section. For example, a simple threshod logic was used for classifying QRS's and non-QRS's. Other common components of QRS decision rules such as blanking, where events immediately following a QRS detection are ignored for a set time, and search back, where previously rejected events are reevaluated when a significant time has passed without a detection, were also considered.

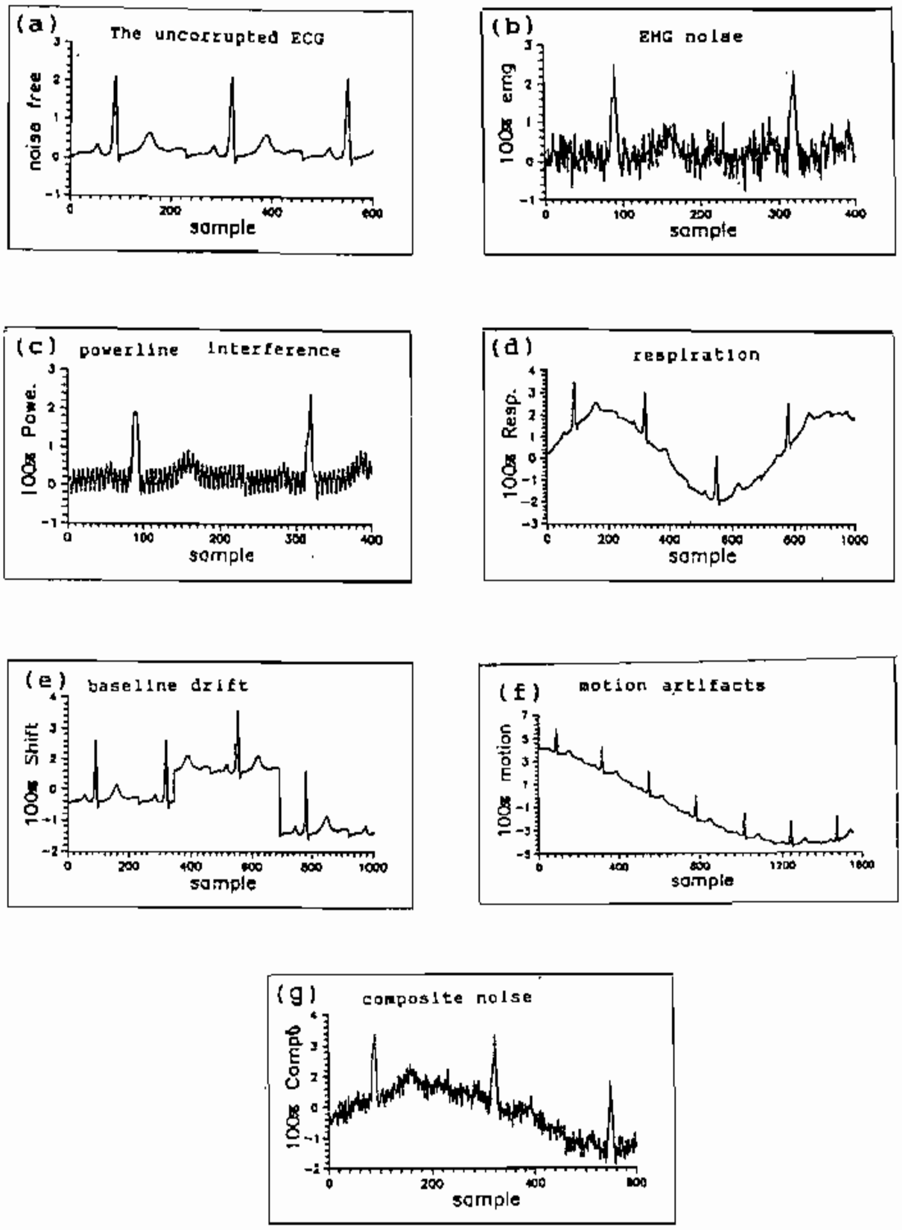

Fig.4 Synthesized ECG signal contaminated with six different types of noise

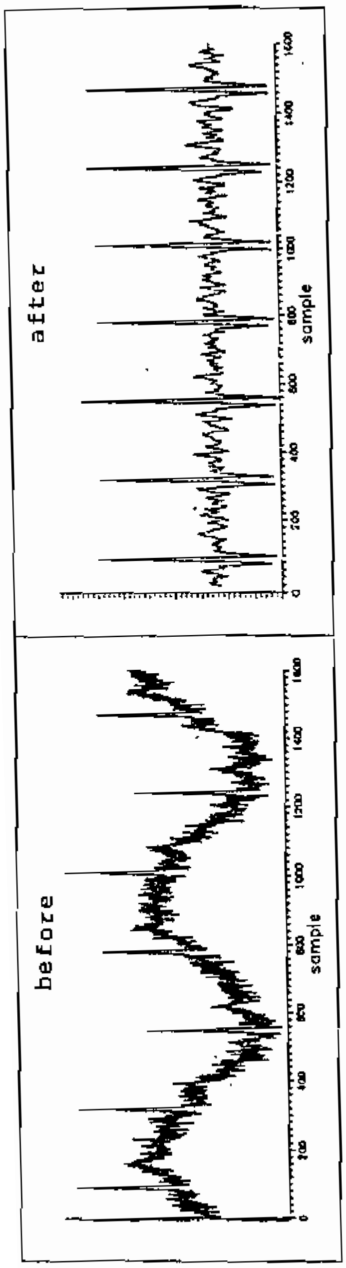

Fig.5 An example of the influence of digital filtering of ECG signal contaminated with composite noise (100% level)

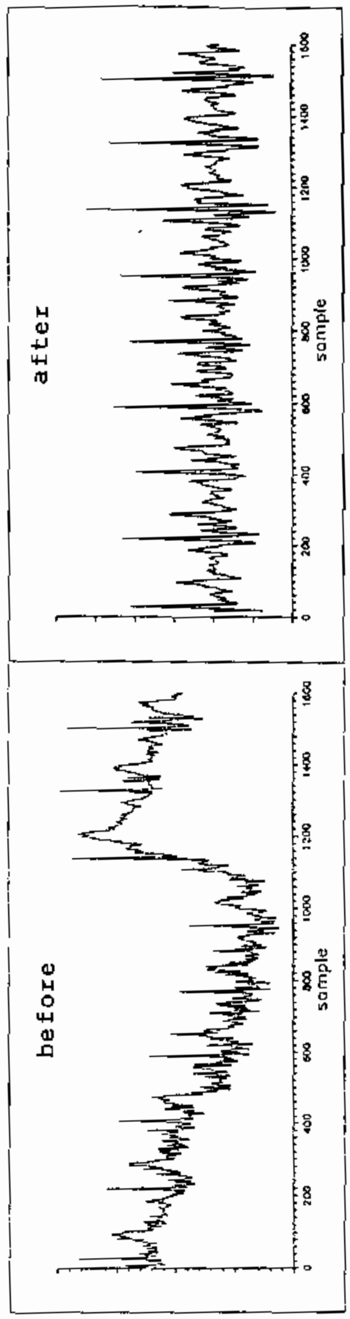

Fig.6 An example of the influence of digital filtering of true ECG record

As a verification of the surpassing performance of the developed method in detecting QRS complexes, an evaluation procedure was carried out. Following the same criteria developed by Hamilton [14], our scoring algorithm compares the onset of the QRS candidate to a key file containing the locations of all of the valid QRS onsets in case of synthesized data. Also, for the true data, the correct locations of the QRS complexes was determined by a visual search and then stored in another file.When a QRS complex occurs, a detection algorithm either indicates or fails to indicate the event. Proper detection of a valid QRS complex represents a true- positive (TP) event. Missing a valid QRS complex represents a false-negative (FN) event. Similarly a false-positive (FP) event is an indication of a detection in the absence of any QRS complex. Multiple detection (MD) occurs when the QRS detector triggers more than once within the same QRS window. Moreover, an indication of the time delay (TD) required for detection is also calculated after each run. If the detection occurs after the actual onset but before the end of the QRS complex, it is classified as a late detection. The number of sample points between the onset and the detection are summed for all of the detections of that run.

IV.4 Results

The results of the application of the described detection method to the synthesized ECG signal are listed in Tables I-IV. Each table gives the results of one level for the six types of noise. Satisfactory results are obtained.

Table I Resulting performance using synthesized ECG (0% noise level)

TP	FP	FN	MD	TD	% QRS (Detected)
37	0	0	0	0	100

Table II Resulting performance using synthesized ECG (50% noise level)

Noise Type	TP	FP	FN	MD	TD	% QRS (detected)
EMG	37	0	0	0	0	100
Powerline	37	0	0	0	0	100
Respiration	37	0	0	0	0	100
Baseline drift	37	0	0	0	1	100
Motion	37	0	0	0	0	100
Composite	37	0	0	0	1	100

Table III Resulting performauce using synthesized ECG (75% noise level)

Noise Type	TP	FP	FN	MD	TD	% QRS (detected)
EMG	37	0	0	0	2	100
Powerline	37	0	0	0	0	100
Respiration	37	0	0	0	0	100
Baseline drift	37	0	0	0	1	100
Motion	37	0	0	0	0	100
Composite	37	0	0	0	1	100

Table IV Resulting performance using synthesized ECG (100% noise level)

Noise Type	TP	FP	FN	MD	TD	% QRS (detected)
EMG	37	0	0	0	4	100
Powerline	37	0	0	0	0	100
Respiration	37	0	0	0	0	100
Baseline drift	37	0	0	0	1	100
Motion	37	0	0	0	0	100
Composite	37	0	0	0	1	100

As for the recorded data, a total of 142 beats was analyzed in the four files considered. As a result, detection of QRS complexes was successfully reported with absent (FP) and (FN). The algorithm succeeded to detect 100 percent of the beats.

V. CONCLUSION

In this paper, a digital filter is presented, which is very well suited for the automatic detection of QRS complexes. An NRFIR bandpass filter whose frequency characteristic approximate those of an optimal matched filter provided the reduction of interferences caused by various types of noise. It appeared that drawbacks resulted from conventional matched filtering such as long computation time and phase distortion could be circumvented. The filtering procedure permits the use of low amplitude threshold, thus increasing the detection sensitivity. Its performance was evaluated using synthesized and true recorded ECG signals and satisfactory results of nearly 100 percent have been obtained.

REFERENCES

[1] N.V. Thakor, J.G. Webster, and W.J. Tompkins. Design, implementation, and evaluation of a microcomputer-based portable arrhythmia monitor. Med. Biol. Eng. Compt., Vol.22, 151-159, (1984).

[2] M. L. Ahlstrom and W. J. Tompkins. Automated high-speed analysis of Holter tapes with microcomputers. IEEE trans. Biomed. Eng., **BME-30**, 651-657, (1983).

[3] G. M. Friesen et al. A comparison of the noise sensitivity of nine QRS detection algorithms. IEEE Trans. Biomed. Eng., **BME-37**, 85-98, (1990).

[4] F.E.Z. Abou-Chadi and M.M. Saleh. An adaptive QRS detection algorithm with variable threshold. Mansoura Engineering Jounal (MEJ), vol.17, no.4, E1-E12, Dec. 1992.

[5] P. Laguna, N.. Thakor, P. Caminal, and R Jane. Low-pass differentiators for Biological signals with known spectra: Application to ECG signal processing. IEEE Trans. Biomed. Eng., **BME-37**, 420-425, (1990)

[6] A.V. Oppenheim and R.W. Schafer. Digital Signal Processing. Englewood Cliffs, NJ: Prentice-Hall, (1975).

[7] G.L. Turin. An introduction to matched filters. IRE Trans. Inform. Theory, **IT-6**, 311-329, (1960).

[8] A.C. den Brinker, H.A.L. Piceni, and F.E.W. Vervuurt. A pseudomatched filter model applied to the transient system of human vision. IEEE trans.Biomed. Eng., **BME-38**, 502-510, (1991)

[9] M.D. Srinath and P. Rajeskaran. An introduction to statistical signal processing with applications. New York: Wiley, (1979).

[10] H.R. Raemer. Statistical communication theory and applications. Prentice Hall, (1969).

[11] J. Pan and W. J. Tompkins. A real-time QRS detection algorithm. IEEE Trans. Biomed. Eng., **BME-32**, 230-236, (1985).

[12] H.G. Goovaerts, H.H. Ros, T.J. vanden Akker, and H. Schneider. A digital QRS detector based on the principle of contour limiting. IEEE trans. Biomed. Eng., **BME-23**, 154-157, (1979).

[13] J. A. van Alste and T. S. Schilder. Removal of base-line wander and power-line interference from the ECG by an efficient FIR filter with a reduced number of taps. IEEE trans. Biomed. Eng., **BME-32**, 1052-1060, (1985).

[14] P. S. Hamilton and W. S. Tompkins. Evaluation of QRS detection algorithms using the IBM PC. Proc. of the IEEE/seventh Ann. Conf. of the Eng in Med. and Biol. Society, 830-833, (1985).