ITERATIVE ECG SIGNAL FILTERING FOR BETTER QRS RECOGNITION

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Abstract: This paper presents an adaptive, iteratively functioning ECG signal filtering method. After a conventional pre-filtering, the waves from the signal are localized and the model's parameters are determined. The gained information allows an iterative-type filtering in permanent concordance with the aimed processing manner. The structure of the algorithm allows real-time adaptation to the heart's state. Using these methods for one channel of the MIT-BIH database, the detection rate of QRS complexes is above 99.8%. The negative influence of various noise types, like 50/60 Hz power line, abrupt baseline shift or drift, and low sampling rate was almost completely eliminated.

Introduction

The computerized ECG signal processing, after several years of significant progress, can be considered a well-developed application. An efficient real-time analyzer system, based on filtering, beat detection (recognition and clustering), classification and diagnosis must be able to evaluate the signal with maximum few seconds delay to recognize in time the potentially dangerous and life threatening arrhythmia. Despite the presence of serious noise, a reliable analysis must involve at least the detection of QRS complex, T and P waves, automatic rhythm analysis, classification and diagnosis, allowing physicians to derive more information for cardiac disease diagnosis. All parameters used in clinics for diagnosis can be deducted from this information. It is important to determine the correct position and amplitude of every characteristic event (if it exists).

An optimal computerized ECG filtering algorithm's performance criterion mainly depends on the ability to separate the signal from artefacts, and from the amount of distortion introduced by the filter. The post-filtering step is essential to reduce the signal distortion. Both guidelines are quite hard to evaluate, because the diagnosis is subjective and depends on the shape of the ECG signal.

The most important task in the ECG signal processing is the accurate detection of the QRS complexes. All further processing steps are based on the position of the QRS waves as basic information. Unfortunately the recorded ECG is often disturbed from different kind of noises. Data corrupted with noise must be pre-filtered or discarded. The ECG quality assurance requires human and artificial noise detection schemes in order not to lose clinically significant information. During ECG recording the noise can only be diminished but not eliminated, so it is important to use a method with good noise susceptibility.

ECG filtering algorithms generally contain a band-pass filter with a centre frequency in the range of 11-16 Hz. After passing through the filter, the signal may be squared or averaged over a number of samples to obtain the place of QRS waves. Unfortunately these static techniques suffer from two major problems:

- QRS waveform varies from patient to patient, and depends on the state of the patient;
- Noise and QRS complex pass bands overlap.

Due to the non-linear behaviour of the human body all processing methods must be capable to change their state during the measurement, otherwise they introduce a huge amount of artificial noise. The design of an optimal matched filter can increase the signal-to-noise ratio, but the non-stationary nature of the signal and noise in an ECG represents an obstacle in the application of these filters for QRS detection. A linear filter cannot whiten the non-linear ECG signal effectively.

Artificial neural networks [3] are inherently non-linear models, so an ANN-based filtering is potentially useful. For complicated non-linear signals we should use at least two hidden layers, which theoretically enable us to approximate any real signal. In practical use the ANN model can adapt far better than linear models. The number of input units corresponds to the filter order. We should not increase too much the parameter number in order to allow constantly good transient properties. It is important to choose the right number of hidden layers to allow good learning speed and adaptation at the same time.

At the first time the algorithm needs only a basic (short) template bank and in time of usage a patient-specific classifier is created without human supervision. For significant performance improvement, a maximum 1-3 minute manually supervised ECG record is needed.

After pre-processing, filtering, evaluation and model's parameter estimation the signal reconstruction is needed. In this step the post-filtering method knows the main ECG specific information, and can better separate all artificial noises. For a high performing filter it is necessary to use all ECG and patient depending information. This problem can be handled only if the computer knows the formation of the ECG signal.

Materials and Methods

The filtering is tested on the ECG registrations of MIT-BIH database (sampled at 360 Hz with 11-bit resolution) and our own recordings (sampled at 200-500 Hz with 8-12 -bit resolution). Most of these files contain one or two channels.

A complex filtering process can be divided to the following steps:

- Pre-filtering;
- Segmentation into R-R intervals;
- Build up or update a temporal template bank for QRS beats;
- Perform optimal filter by using QRS wave pattern database;
- Determine all recognizable characteristic point (for R, T and P waves);
- Extract the model's parameters;
- Perform a post-filter using pattern database and the model-based estimation;
- Complete the template bank for all recognized waves.

Pre-filtering

An accurate R, T and P wave detection and ECG signal segmentation needs the pre-filtering in order to eliminate the noise caused by the electrical network, the rejection of the noise caused by bad contacts, motion or breath.

The elimination of the noise caused by the electrical network is recommended by windowed FFT and IFFT combined with a parameter estimator and filter which contains the following steps:

- Windowed FFT execution, for an interval of length between five and twenty seconds. All intervals are overlapped by at least fifty percent of their length;
- Estimate the amplitude and phase of the 50 (60) Hz component and its higher harmonics from the amplitudes and phases of the adjacent frequencies;
- Modify the signal spectra;
- Process the IFFT algorithm;
- Post-filter by a regressive method the artificial noise caused by modifications in signal's spectra.

After the electric noise is eliminated, it is possible to estimate the signal. In our approach, because the studied signal has a non-linear behaviour, we define a non-linear adaptive estimation algorithm. The first drawback of this method is that, it is hard to determine the optimal phase of the 50 (60) Hz component of the measured ECG signal.

The next three paragraphs shortly present a realization of this estimation.

Let $A_{EN,Arm1}$ be the amplitude of the first harmonic of the electrical noise calculated for a window of length *N*, from sample *BegPos*-$\frac{N}{2}$. The amplitude contains the effect of the 50Hz (60Hz) component of the real ECG. This representation has the advantage, that the sum of the sine components is zero. For cosine components at the same place/time this property cannot be guaranteed. That is why we must effectuate the previous computing for the window shifted with one position to left and right.

Theoretically from two vectors we could be able to determine the cosine component, but for a higher precision we should use both shifted windows. The amplitude for *i*-th harmonic is given by equation 1:

$$A_{EN,Arm.i} = \frac{1}{N} \cdot \sum_{k=0}^{N-1} X\left(BegPos + k - \frac{N}{2}\right) \cdot \sin\left(\pi \cdot \frac{ENFrq_{Arm.i}}{SmpFrq} \cdot (1 - N + 2 \cdot k)\right) \qquad (1).$$

BegPos represents the first element's position and *SmpFrq* is the sampling rate. To determine the estimated amplitude and phase for *i*-th harmonic, we must choose two from the three vectors. The selection highly depends on the angles between these vectors (the angle between the projection of the selected two vectors must be maximal for the most robust estimation). Figure 1. visualize the determination process of the amplitude and phase for a higher harmonic.

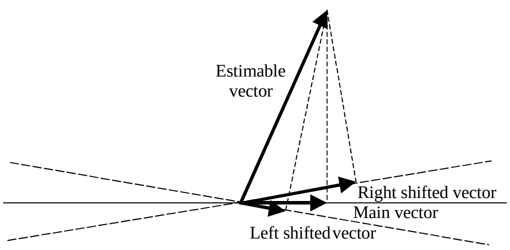

Figure 1: The estimable vector can be determined more exact if the angle between perpendicular projections of the selected vectors is higher (always less than π).

To eliminate the high frequency noise the non-linear parameter estimation methods could reach better performance, than transformation methods.

Let the set S of basic functions:

$$S(X) = \left\{ \begin{array}{l} f_1(X) = X;\ f_2(X) = \frac{1}{N_2} \cdot X^2;\ f_3(X) = \frac{1}{N_3} \cdot X \cdot \left(X \cdot q^{-1}\right);\ f_4(X) = \frac{1}{N_4} \cdot \sqrt{X}; \\ f_5(X) = \frac{1}{N_5} \cdot e^{\alpha \cdot X};\ f_6(X) = \frac{1}{N_6} \cdot e^{\alpha \cdot \left(a \cdot X - b \cdot \left(X \cdot q^{-1}\right)\right)};........ \end{array} \right\} \qquad (2).$$

The symbol q^{-1} represents one sample period long dead time. α , a and b are internal parameters, where $a^2 + b^2 = 1$.

Let $X_L(n)$ and $X_R(n)$ the *n*-th left and right aimed estimation, defined as:

$$X_L(n) = p_L \cdot \tilde{X}_L(n) = p_L \cdot \sum_{i=-q}^{q} a_{L,i} \cdot X(n-i) +$$

$$(1-p_L) \cdot \sum_{i=1}^{q} b_{L,i} \cdot X_L(n-i) \quad (3)$$

$$X_R(n) = p_R \cdot \tilde{X}_R(n) = p_R \cdot \sum_{i=-q}^{q} a_{R,i} \cdot X(n-i) +$$

$$(1-p_R) \cdot \sum_{i=1}^{q} b_{R,i} X_R(n+i), \quad (4)$$

$a_{L,i}$, $a_{R,i}$, $b_{L,i}$ and $b_{R,i}$ are prediction coefficients, p_L and p_R are balance probabilities determined by the dispersions $\sigma_{X_L - X}(n,l)$, $\sigma_{X_R - X}(n,l)$, $\sigma_{\tilde{X}_L - X}(n,l)$ and $\sigma_{\tilde{X}_R - X}(n,l)$. For better separation of the signal from the noise, the length l should select more than one R-R period.

During on-line processing the estimation is delayed with at least $3 \cdot q$, but preferably with more than one R-R interval, in order to minimize the differences of the efficiency between $X_L(n)$ and $X_R(n)$; $(p_L \geq p_R; p_L + p_R = 1)$.

The resulting sample $X(n)$ obtained by formula:

$$X(n) = p \cdot \sum_{i=-q}^{q} a_i X_L(n-i) + (1-p) \cdot \sum_{i=-q}^{q} b_i X_R(n-i) \cdot \quad (5)$$

Segmentation into R-R intervals

In a heavily noise tainted environment a parameter extraction model could be less robust, than a good transformation algorithm. One of the best transformation methods for R wave detection uses wavelets.

The selected wavelet is:

$$\Psi(t) = \frac{1}{\sqrt{2\pi}\sigma} \cdot \exp\left(-\frac{t^2}{2\sigma}\right) \cdot \sin(\alpha \cdot t \cdot \exp(-\beta|t|)) \quad (6)$$

where α and β is selected according to the highest frequency in ideal (noise free) ECG signal and σ is the dispersion, used to modify the wavelets shape.

Analysing more than 100 recordings we obtained as a good robust result $\alpha = 200 \cdot \pi$, $\beta = 1/3$. The robustness in this step is far more important, than a local performing index. The WT depends upon two parameters, scale s and position τ.

The dyadic wavelet is determined using a scale $s = 2^j$, where $j \in Z$ and Z is the integral set. The WT (equation: 6) at scale $s = 2^j$ is obtained by:

$$Wf(2^j, \tau) = \frac{1}{2^j} \cdot \int_{-\infty}^{\infty} f(t) \cdot \Psi^*(\tfrac{t-\tau}{2^j}) dt \quad (7).$$

Experiments show that with this kind of wavelet, more robust algorithms can be realized than with the conventional wavelets. This property is due to the sinusoidal term, which can realize a correlation not only with the adjacent beats (the ECG signal is more or less semi-periodical).

Build up or update a temporal template bank for QRS beats

Largely the signal's power is included in the QRS beats so a template collection is essential. During signal processing, the pre-constructed wave database should be modifiable. Although automated waveform classification based on a decision-tree algorithm could perform remarkable results, the new self-organising (SO) adaptive clustering based method has several advantages:

- It is not susceptible to variations of beat morphology and temporal characteristics;
- It can perform a real-time unsupervised learning;
- It needs much less amount of knowledge for the same performance

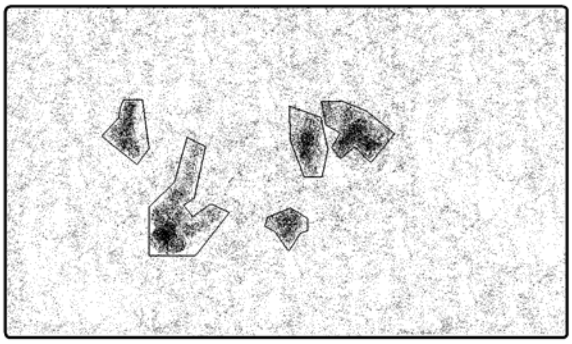

Figure 2: The normal QRS beats, artifacts, abnormal beats, P and T waves in plain representation (the space has 32 dimensions)

The clusters are built up according to the following rules:

- $\sigma_i \leq \sigma_{Max}$; σ_{Max} is predetermined; i=0..n;
- M_i is determined in such a way, than σ_i to be minimal;
- For every R (T and P) wave, which belongs to a cluster $\|X\| = \sum_{i=0}^{n} \left(\frac{X_i - M_i}{\sigma_i} \right)^2 \leq R_{MAX}$; (8)

  R_{MAX} is predetermined; X is a vector, representing a wave in the space;
- X can belong to more cluster;
- The total number of the clusters for a predetermined R_{MAX} is minimal;

In this case, for every wave we can obtain an indicator vector $\overline{X}^t = (p_0(X), ..., p_{n-1}(X))$, where n is the number of clusters and $p_I(X)$ is the probability to belong to the cluster C_I, having the value:

$$p_I(X) = \prod_{k=0}^{7} \frac{1}{\sigma_{I,k}} \exp\left(-\frac{(X_k - M_{I,k})^2}{2\sigma_{I,k}}\right). \quad (9)$$

The major problem is to resolve the cases when the patient's QRS wave's pattern differs much from the "average waveforms". In this case a deeper analysis is necessary, which is processed using hearth model based signal estimation. This is an unavoidable step of the filtering and detection.

Perform optimal filter by using QRS wave pattern database

The optimal filter is based on the pre-processed signal and the template bank.

Let $\overline{X}(n) = \sum_{k=0}^{nr-1}\left(s_k \cdot \sum_{i=-q}^{q} a_{F,i} \cdot f_k\left(X(n-i)\right)\right)$ and

$$\widetilde{X}(n) = p_{F,X-\widetilde{X}}(n) \cdot \overline{X}(n) +$$

$$(1 - p_{F,X-\widetilde{X}}(n)) \cdot \sum_{i=-q}^{q} b_i B(m,i) \qquad (10)$$

be the processed data. The low value of p_F $(p_F < 0.2)$ justifies the need of the collection B, whose *m*-th element has the maximal correlation value with $\overline{X}(n)$.

In the case of fast isoelectric line movement the shape of the waves can be deteriorated. The separation in clusters will eliminate that bed effect and the deteriorated samples can enter in the template bank. All modified waves must be judged with care. For them we will re-estimate the isoelectric line, but we will not include them into the template bank.

Determine all recognizable characteristic point (for R, T and P waves)

The determination algorithm of the characteristic points is almost the same, than the template bank building method. The major difference is that, the method is applied for the pre-filtered data. In first step the template bank is realized for every recognizable event.

Due to the pre-filtered data there is no more problem with the isoelectric line movement. For this reason it is much easier to perform the algorithm. The mathematical treatment of the problem was presented before.

Extract the model's parameters

There are more than 100 important parameters (statistical, spectral, etc.) which can be studied during the analysis of the signal. The determination of these parameters usually need simple mathematical algorithm (statistical analysis). Doctors to determine the correct treatment for patient use these results. The effect of different medicaments is tested also. Most parameters can be seen in Figure 3.

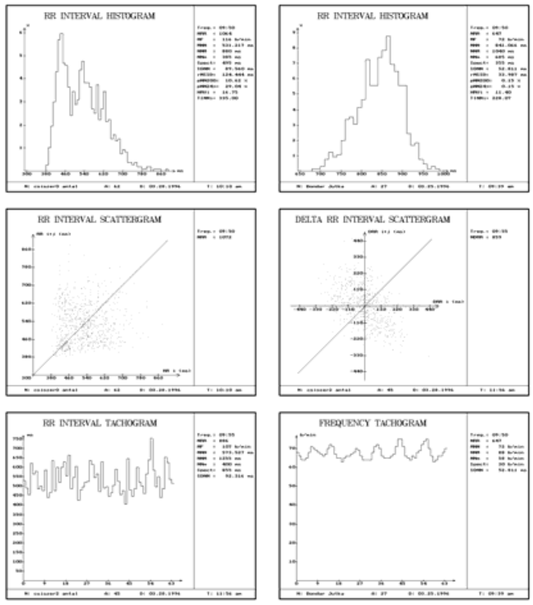

Figure 3: These extracted parameters and graphic representations could help physicians to determine a treatment.

Perform a post-filter using pattern database and the model-based estimation

The non-linear intermediate result is:

$$Z_p(t) = f\left(\sum_{k=-j}^{j} c_{pk}(t) \cdot X(t+k)\right). \qquad (11)$$

$X_k(t) = Y(t+k)$ and f ( ) is a normalized Gauss function. The c_{pq} weight coefficients connect the input and the hidden layers. The output of the filter is:

$$Y_w(t) = Y(t) - Y(t) = Y(t) - \sum_{p=-i}^{i} c_p(t) \cdot f\left(\sum_{k=-j}^{j} c_{pk}(t) \cdot X(t+k)\right). \qquad (12)$$

The adaptive behaviour of the filter [4] is assured by the permanent variance of the genetic search method based upon least mean square (LMS) algorithm computed coefficients.

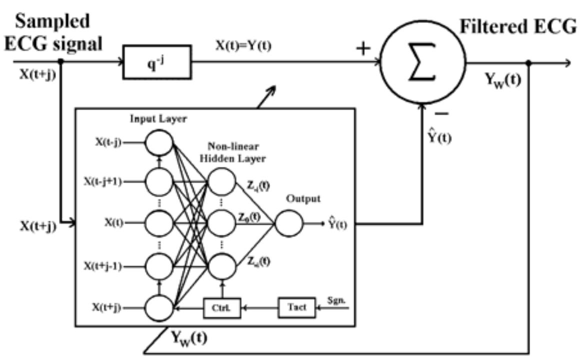

Figure 4: The structure of the adaptive filter

Both the input signal and the selected template are processed through the whitening filter. During this process the template bank is changing adaptively.

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The whitened template is:

$$T_{w,r}(t) = T(r) - \sum_{p=-i}^{i} c_p(t) \cdot f\left(\sum_{k=-j}^{j} c_{pk}(t) \cdot T(r+k)\right) \quad (13)$$

where $r=j,\ldots L\text{-}j$, and L is the size of the template.

The output of the matched filter will be:

$$Y_m(t) = \sum_{r=j}^{L-j} T_{w,r}(t) \cdot Y_w(t-L+r). \quad (14)$$

Complete the template bank for all recognized waves

The main characteristic shapes of a normal ECG signal are R, T and P waves. While performing real-time analysis, the wave-bank can be slightly modified. The changes are based on auto-correlation of the pre-filtered signal and the template's elements.
If the obtained results cannot accomplish the aimed results, the pre-filtering must be repeated (the best obtained results are permanently saved). As the processing computer is faster, the final real-time performance is better.

Results

For better comparison possibility with other methods we used the MIT-BIH recordings. These files were selected from the arrhythmia database due to their high noise or artefact level. At these ECG recordings, the efficiency is higher then in the case of the QRS detection technique presented in [2].

Table 1: Representation of the QRS detection rates for the noisiest MIT-BIH registrations

Records number	Total beats	Failed forward	Failed iteratively
104	2230	9	1
105	2572	23	4
108	1763	21	4
201	1963	11	3
203	2982	22	5
222	2484	8	2
228	2053	8	2
Total	16047	102	21

Figure 5 demonstrates that, the output of the post-filter is almost free of artefacts. In this experiment our 8-bit resolution and 200 Hz sampling rate measurements were used. It is clear, that at higher sampling rate and resolution the filtering with the same quality is much easier.

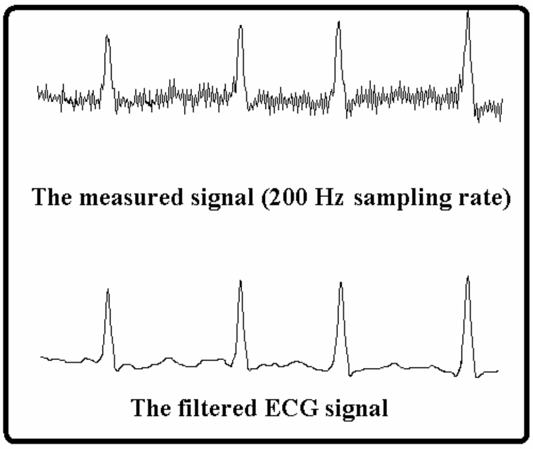

Figure 5: Comparison of the measured signal and the post-filter's output

Discussion

The ANN-based adaptive matched filter [6][7] and the wavelet-transform-based QRS detection algorithm were applied for the noisiest ECG signals. The distinct features of these methods are:

- A multi-layer neural network structure can model the inherently non-linear ECG signal better than linear models-based filtering methods;
- The QRS templates used for filtering is updated by a parameterised wavelet-based algorithm, which provides better adaptation to the signal changes than any other static structure techniques;
- Wavelet-based analysis could be more robust than parameter extraction methods;
- With the parametrical estimator it is possible to choose permanently the optimal size of the neural network for real-time processing. It is able to remove the redundancy introduced by the increased number of the hidden units,
- The networks learning step may vary in time in order to adapt in time to the eventually changes in the measured signals structure.

The major advantage of this method is the ability to change its behaviour in time, if necessary. Table 1 demonstrates the superiority of the iteratively filtering methods. Although the forward method ensures good results and no better transformation algorithm is known, the iterative algorithm easily overtakes its performance. This is because the post-filtering is much more complex, and can recline on all still that moment obtained information.

Figure 2 demonstrates that the normal beats and the normal T and P waves (surrounded in the figure) are easy to separate from abnormal beats. The problem is not so simple, when we want to classify the abnormal beats. With this parameter estimation model we could form beat specific clusters in a plain representation (where was selected for both coordinate an optimised combination of the parameters).

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Figure 6. shows how efficient could be a classification-based post-filtering. To reach such a performance the method should identify as much as possible fix characteristic point from the signal.

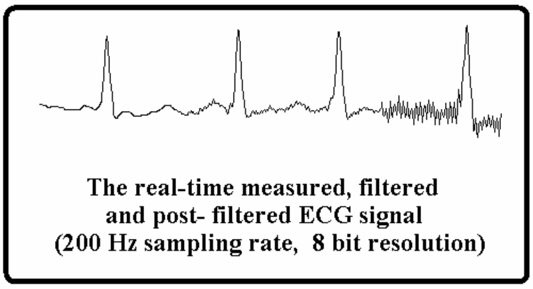

Figure 6: The effect of filtering and post-filtering during measurement

Conclusion

The post-filter algorithm for beat recognition is more efficient than the one presented in [2]. For other waves, the detection rate is also higher then the earlier developed Wavelet and Neural-Network-Based recognition methods.

Normally the Wavelet could solve the recognition task, because P and T wave power spectra are between 0.5-10 Hz. According to this, it can be investigated at scale between 15-35. Although the baseline movement is dominant between 0.4-8 Hz, the P and T waves can be detected. Then PR, ST and QT intervals can be simply calculated.

In case of QRS detection the filter of the genetic estimator removes baseline movement and the bulk of the artefacts, suppresses the P and T waves and increase the R wave. The QRS complex can be easily recognized from the output of the adaptive estimator. The P and T waves cannot be accurately detected without additional processing steps based on wavelet transform.

The major advantages of post-filtering method usually rise in trouble, when the patient has unique behaviour. In clinical health care [5], these situations are the most dangerous. A better malfunction recognition [9] during real-time measurements and diagnosis could save human lives.

Experiments show that this adaptive filter [1] can model the non-linear ECG signal better, than linear algorithms. The combination of the recognition [8] separation and classification methods allows new perspectives in the field of reliable full-automated ECG signal classification.

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