ADAPTIVE FILTERING OF ECG SIGNAL FOR DERIVING RESPIRATORY ACTIVITY

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Summary

This paper introduces a new approach for deriving the respiratory signal from a single-lead ECG by adaptive filtering. The method uses the R-R interval and the R-wave amplitude time series, extracted from the ECG signal, as inputs to the filter: the respiratory activity is estimated at its output. The adaptive filtering is able to enhance the common component between the above series (namely, the respiratory influence), attenuating the uncorrelated noise. More than 170 hours of ECG and respiratory signal were collected both in CCU and during Holter ambulatory monitoring. LMS (Least Mean Square) and RLS (Recursive Least Squares) adaptive filtering methods were applied to obtain the estimate of the respiratory signal. Visual inspection and spectral analysis were used to evaluate the performance of the filtering by comparison with a true respiratory signal obtained by a piezoelectric transducer.
RLS adaptive filtering technique was more effective than LMS in producing an 'ECG-derived' respiratory signal. This approach adds clinically important information to conventional ECG analysis.

Introduction

Monitoring of the respiratory activity is clinically useful in many patients affected by cardiac, pulmonary, and neurological diseases.
Furthermore, the knowledge of the respiratory variability allows a more accurate evaluation of the autonomic nervous system influence on the cardiovascular system: respiration modulates sympathetic and parasympathetic influence on the heart rate and blood pressure variability [1].
Respiratory activity can be monitored directly by appropriate equipment (air flow, chest electrical impedance, or body volume change measurements) or indirectly extracting the respiratory activity by processing related signals like multi-lead ECG [2].
We describe a filtering approach to the ECG signal for deriving respiratory activity, based on the analysis of a single-lead ECG.
A biological series is often the result of combined contributions from different sources. The adaptive filtering is a powerful tool to separate the contribution of interest (signal) from other contributions (noise). The applications of this methodology can be classified in two schemes: noise canceler and signal enhancer. The former is applied when, besides the previous series, a new series is available containing components correlated with the noise but not with the signal. This filter is able to cancel the correlated noise and the output will not suffer from any distortion [3,4].
The latter is applied when a new series is available containing components correlated with the signal but not with the noise; this filter enhances the signal related components. In this case, the signal passing through the filter can suffer of some distortion [5].
Many biological series contain a respiratory component; for what concerns the electrocardiogram, both the heart rate and the QRS complex amplitude show periodical fluctuations due to the respiratory activity. This may be considered as a common component, which could be estimated by a signal enhancer filter applied to R-R and R-wave amplitude time series. We should observe that the noise and artifacts on the R-R interval and on the R-wave amplitude series are uncorrelated being obtained in two different domains; the first is a time difference, the other is an amplitude level.

Methods

ECG and respiratory signals were collected using both multichannel FM (Racal) and ambulatory Holter FM recorders (Remco-Cardioline). The respiratory signal was obtained by a thoracic belt with piezoelectric transducer (Fig.1).

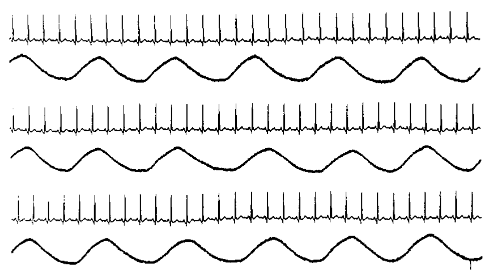

Figure 1. An example of a one minute long ECG and respiratory signal recording.

The signals were derived from six 24-hour 2-channel Holter recordings (modified-V4 ECG lead plus respiration) and from five 6-12 hour recordings in the CCU (V4 and D3 ECG leads plus respiration). The signals were then digitized at 250 samples/sec with 12-bit resolution and stored into hard disk for further analysis.
All these signals were processed to obtain the series of the R-R interval (RR), of the R-wave amplitude (RW), and of the respiratory signal level (RA).
Each series was analyzed by parametric and not parametric spectral analysis estimators: the respiratory component was present in all the series but often embedded in other contributions.

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Adaptive filtering is an implementation of the Optimum Filtering methodology when the stationary condition of the input series is not satisfied. The term "optimum" refers to the minimization of the Mean Square Error criterion (MSE). In order to simplify the discussion we consider the optimum filtering case first. Let us assume the following hypothesis:

1) the stochastic processes RR, RW, RA are stationary;
2) the contribution of the respiratory signal to the RR and RW series is additive and its propagation path is assumed to be equivalent to a linear filter;
3) the "noise" components of the RR and RW series are uncorrelated. They are uncorrelated with the respiratory signal, too.

The fig.2 shows a model of the propagation of the respiratory activity versus RR and RW series and the optimum filter which minimizes the MSE=$E[e_k^2]$. The filter predicts the RW series using the RR series as input: it tries to cancel the correlated components between the two series in order to minimize the MSE.

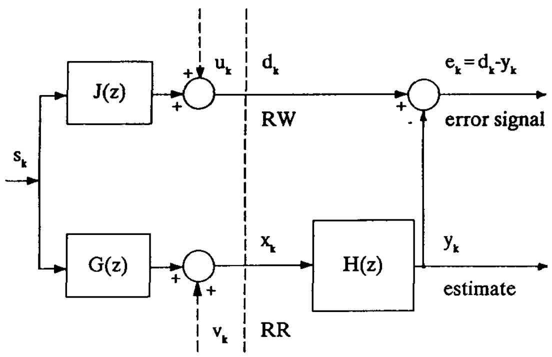

Figure 2. Model of respiration signal propagation (left side) and optimum filtering scheme (right side).

To studying the behavior of the filter transfer function we assumed the length of filter = ∞ (i.e. unconstrained Wiener solution, no causality condition). The optimal unconstrained Wiener transfer function is [3]

$$H^*(z)=\frac{\Phi_{xd}(z)}{\Phi_{xx}(z)}$$

Where $\Phi_{xx}(z)$ is the auto-power spectrum of the x_k and $\Phi_{xd}(z)$ is the cross-power spectrum between x_k and d_k series.

Since the noise v_k is uncorrelated with s_k the spectrum of the reference input x_k results

$$\Phi_{xx}(z) = |G(z)|^2\Phi_{ss}(z) + \Phi_{vv}(z)$$

where $\Phi_{ss}(z)$ is the signal power spectrum, and $\Phi_{vv}(z)$ is the noise power spectrum.

Since u_k and v_k are uncorrelated with each other and with s_k the cross-spectrum between the reference and the primary input results

$$\Phi_{xd}(z)= J(z)\Phi_{xs}(z)= J(z)G(z^{-1})\Phi_{ss}(z)$$

The unconstrained Wiener transfer function becomes:

$$H^*(z) = \frac{J(z)\,G(z^{-1})\Phi_{ss}(z)}{|G(z)|^2\Phi_{ss}(z) + \Phi_{vv}(z)}$$

The frequency response can be obtained by substituting $e^{j\omega}$ to z.

In stationary conditions, the respiratory signal s_k is a narrow band signal, so $\Phi_{ss}(j\omega)$ is near zero for $\omega\notin(\omega_0-\Delta\omega,\omega_0+\Delta\omega)$. Under the assumption that $\Phi_{vv}(z)$ is a wide band noise the $H^*(z)$ becomes the transfer function of a narrow band pass filter centered on the respiratory frequency ω_0.

In our application the filter H(z) has been implemented as a FIR filter. The output y_k of the filter ("estimate" signal) is given by

$$y_k = W_k^T X_k$$

where $X_k^T=[x_{0,k},\dots,x_{L-1,k}]$ is a L-length vector of the input sequence and $W_k^T=[w_{0,k},\dots,w_{L-1,k}]$ is a L-order weight vector, characterizing the H(z) transfer function of the filter.

The error signal is given by

$$e_k = d_k-y_k = d_k-W^T X_k$$

and therefore the MSE can be expressed by

$$MSE = \xi(W) = E[e_k^2] = E[(d_k-W^T X_k)^2]$$

Generally the stationarity condition is not fulfilled; in our case adaptive implementation of the optimal filtering permits to follow slow changes of the respiratory frequency. Two adaptive algorithms have been tested: Least Mean Squares (LMS) and Recursive Least Squares (RLS).

The LMS algorithm derives from the gradient method and it attempts to minimize the statistical error measure (Mean Square Error). Moreover, it has a stochastic behavior, converging towards the minimum error with a random oscillatory path. This algorithm is very simple and fast, but its convergence rate is slow.

The weight vector is updated by

$$W_{k+1}= W_k+ 2\mu e_k X_k$$

with $\mu=\mu_n/(L+1)\sigma_k^2$ $\qquad 0<\mu_n<1$

σ_k^2 is the input signal power, continuously updated according to $\sigma_k^2=\alpha x_k^2+(1-\alpha)\sigma_{k-1}^2$ $\qquad 0<\alpha<<1$

The parameter μ controls the rate of convergence. A large μ could result in an iterative process that never converges to the optimum solution; on the other hand if μ is too small the coefficient vector adaptation could be very slow.

Actually the LMS algorithm uses the instantaneous error e_k instead of the MSE in the gradient estimation for updating of the weight vector. It has been demonstrated that this form of updating moves the coefficients towards the minimum MSE on the average, which means that considerable error can be contained in a single updating. This produces a jitter of the weights which is still present after the convergence. High μ value causes the mean weights to converge more quickly but makes the instantaneous weights to fluctuate more.

The RLS algorithm derives from the Least Squares Method where the sum of the squared error is minimized without any statistical assumption on the input time series. We used the exponentially windowed Recursive Least Squares algorithm which minimizes the cumulative squared error:

$$\varepsilon_k = \sum_{i=1}^{k} \lambda^{k-i} e_i^2$$

where $e_i= d_i- W_k^T X_i$

The parameter λ, with $0<\lambda\leq 1$, is a forgetting factor used to weight more heavily the recent data. It is worth nothing that the cumulative square error is a function of the actual data vector X; this error is computed and reoptimized at every iteration. For this reason the RLS filters are exactly optimal for the acquired data rather than statistically optimal. The RLS algorithm converges much faster than the LMS. The superiority of the RLS relies in its search for the optimal weight vector at each point in time by minimizing an exact error, using the actual data. The LMS algorithm, instead, finds the minimum MSE weight vector in the asymptotic case only (for $n \to \infty$).
The conventional RLS filter requires on the order of L^2 operations per iteration, this is due to the complexity of recursively computing the inverse of the sample covariance matrix. Fast Transversal Filter (FTF) implementation of RLS algorithm results in a substantial reduction in computational complexity [6] (approximately 7 L arithmetic operations). However, many FTF algorithms show instability due to the use of finite precision arithmetics, especially

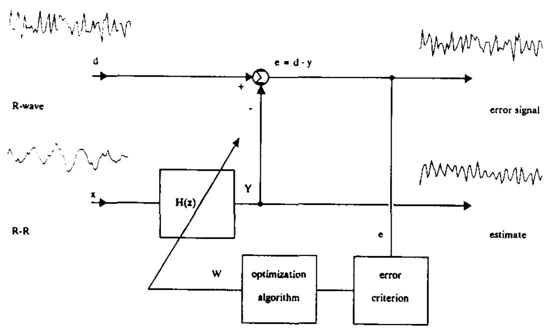

Figure 3. Adaptive Filter Scheme (Signal Enhancer). The R-wave series is the "reference" input and the R-R series is the "primary' input. The filter output is the estimate of the correlated components between the two input series.

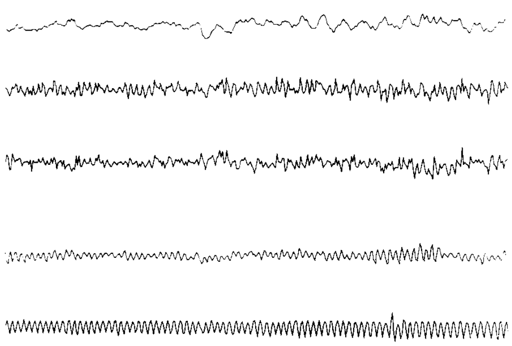

Figure 4. RLS adaptive filter application. Top-down: R-R interval series ("reference" input), R-wave amplitude series ("primary" input), error output of the filter, estimate of the respiratory signal, actual respiratory signal collected by the piezoelectric transducer. All the series are 360 beats long.

when the exponential weighting factor is chosen less than unity for purpose of fast adaptation.
The expression of the optimal transfer function it was obtained without any assumption of causality and finite length filter. The not causal condition can be approximately satisfied using a delay in the primary input. In our applications we used a delay equal to about an half of the filter length.
Both LMS and RLS methods were applied to obtain the estimate of the respiratory signal according to the scheme of figure 3. The filter enhances the correlated components in the two series of data, in this case the respiratory activity, attenuating the uncorrelated noise. Both methods were tested by comparison of the estimate output with the true respiratory signal. We used a filter length of 20 points; an updating factor μ=0.01÷0.05 for LMS algorithm and a forgetting factor λ=0.99÷0.996 for RLS algorithm. These values are not critical.

Results

The analysis of the ECG recordings showed a good correspondence between the filter output and the actual respiratory signal (Fig.4).The adaptive filter application is powerful in estimating the respiratory frequency also when the respiratory component in the R-R series is very low. Anyway the estimate is affected by the smoothing effect of the filter and its waveform could be distorted.
Parametric and non-parametric spectral analysis have been applied to evaluate the enhancement of the respiratory component in the output of the filter in comparison with the input time-series (Fig.5). The spectrum of the filter output shows a main peak at the same frequency of the actual reference respiratory signal.
The correspondence between the output of the filter and the respiratory signal is proven by the autoregressive spectral analysis performed over longer period of time, disclosing the same frequency component in both spectra (fig. 6, 7). This filtering application is able to follow precisely any change in respiratory frequency, because of its adaptive implementation.

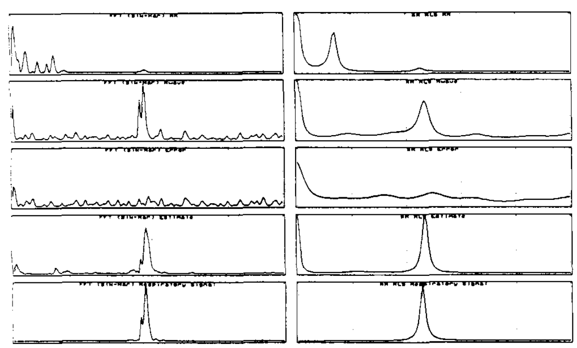

Figure 5. Power spectra of the series displayed in Fig.4. On the left: FFT approach (Blackman-Harris window); on the right: parametric autoregressive MEM spectral estimation (model order = 12). Top down: R-R interval series, R-wave amplitude series, error output, estimate output, and actual respiratory signal.

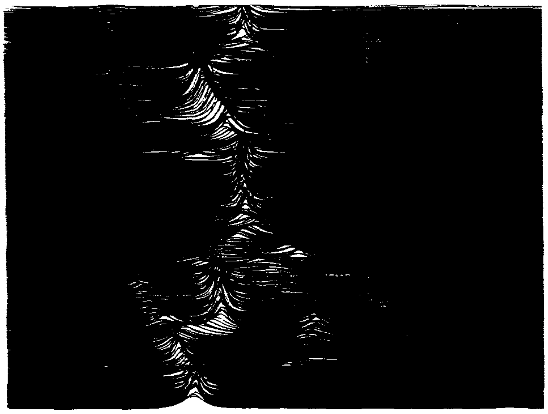

Figure 6. Compressed Spectral Array representation (AR approach) of 512 spectra sequence of the respiratory estimate obtained by the filter.

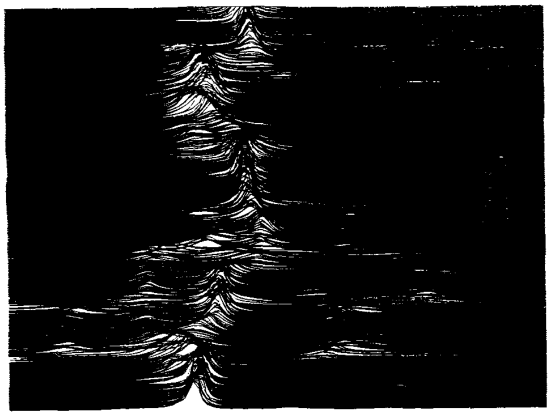

Figure 7. Compressed Spectral Array representation (AR approach) of 512 spectra sequence of the actual respiratory signal.

RLS (Recursive Least Squares) adaptive filtering technique was more effective than LMS (Least Mean Square) in obtaining the 'ECG-derived' respiratory signal (Fig. 8). RLS technique converges faster but it is more computing and time consuming. Fast RLS implementation suffers from instability.

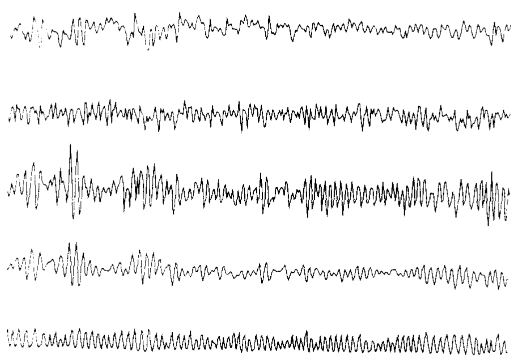

Figure 8. Comparison of LMS and RLS adaptive filtering methods. Top-down: R-R interval series ("reference" input), R-wave amplitude series ("primary" input), respiratory estimate obtained via RLS algorithm approach, via LMS algorithm approach and the actual respiratory signal.

For what concerns the filter structure we note that it is not symmetric with reference to its inputs: using the RR interval series as the reference signal and RW series as the primary signal, it attempts to predict the RW; vice versa using RW as the reference and RR as the primary input, it attempts to predict the RR series. The choice of the input configuration depends by the length of the filter, and by noise and signal frequency distribution. Both configurations have been tested, the first resulting more effective.

Conclusions

There are important effects of respiration on the heart and the circulatory system. The respiratory activity interacts, at the central nervous system level, with the efferent autonomic tone which directly affects heart rate and blood pressure variability by modulating sympathetic and parasympathetic nerve traffic. The methods of spectral analysis currently applied to investigate the autonomic nervous system influence on the cardiovascular system, by the study of heart rate and blood pressure variability can be usefully integrated by the information on the respiratory activity.

Moreover the knowledge of the pattern of respiration and cardiac activity is useful for the diagnosis of many pulmonary and heart affections characterized by the association of disturbances of respiratory activity (apnea, periodic breathing, etc.) and cardiac arrhythmias.

Adaptive filtering technique can be applied as a useful tool to obtain a respiratory-related signal derived from a single ECG-lead monitoring, providing an additional clinically relevant information to conventional ECG analysis, even to long-term Holter recordings, when a direct respiratory signal is not accessible.

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