Suppression of electromyogram interference on the electrocardiogram by transform domain denoising

N. Nikolaev[1] A. Gotchev[2] K. Egiazarian[2] Z. Nikolov[1]

[1]Institute of Information Technologies, Bulgarian Academy of Sciences, Bulgaria
[2]Tampere International Center for Signal Processing, Tampere University of Technology, Finland

Abstract—*A method for suppression of electromyogram (EMG) interference in electrocardiogram (ECG) recordings is presented. By assuming that the EMG is long-term non-stationary Gaussian noise, two successive decompositions were proposed, and the data transformed for Wiener filtering. Successive ECG cycles were rearranged and aligned by the R-wave, forming a matrix containing separated heart cycles in its rows. A short-window discrete cosine transform (DCT) was applied to the columns of the matrix for inter-cycle de-correlation. Next, Wiener filtering in a translation-invariant wavelet domain was performed on the DCT-transformed matrix rows for de-correlation of the data into each ECG cycle. The method resulted in an improvement in the signal-to-noise ratio of more than 10 dB, a threefold reduction in mean relative amplitude errors and reduced ripple artifacts around the signal transients, thus preserving the waveform in diagnostically important signal segments.*

Keywords—*ECG, EMG, Wavelet transform, Discrete cosine transform, Wiener filtering*

Med. Biol. Eng. Comput., 2001, **39**, 649–655

1 Introduction

ONE OF the most serious problems in the acquisition and recording of electrocardiogram (ECG) signals is the presence of unwanted interference signals. Power-line noise and the baseline can be strongly suppressed by different filtering procedures, but superimposed electromyogram (EMG) signals require special attention. They behave like random wide-band spectrum signals, considerably overlapping the ECG spectrum. Most of the ECG signal energy is concentrated in the QRS complex, but there are diagnostically important changes in the low-amplitude PQ and ST intervals, the P- and T-waves, that could be completely masked by EMG noise.

The problem of EMG noise suppression becomes extremely important when ECGs are recorded during physical exercise, for long-term recording by portable devices (for example, ambulatory Holter-type recording) or for ECG recording of children or of people with injured extremities etc. In such cases, it is not possible to ensure relaxed conditions for the patient, and the muscular activity is reflected in high-amplitude EMG noise. Thus automatic interpretation, which is strongly dependent on accurate detection of characteristic ECG points and waves and measurement of signal parameters, becomes an extremely difficult, and often virtually impossible, task.

Adequate ECG denoising algorithms and procedures should

(*a*) improve the signal-to-noise ratio (SNR) to obtain clean and readily observable recordings, allowing the subsequent use of straightforward approaches for correct automatic detection of characteristic points in the ECG signal and recognition of its specific waves and complexes
(*b*) preserve the original shape of the signal and especially the amplitudes of sharp Q, R and S peaks, without introducing distortions in the low-amplitude ST-segment and P- and T-waves.

The use of low-pass (smoothing) filtering for EMG noise suppression is not a good solution as it reduces the sharp wave amplitudes and could also produce ripple effects around QRS complexes.

A noise suppression filter, namely a time-domain Wiener filter, can be designed as adaptive (THAKOR and ZHU, 1991). The adaptation requires preliminary knowledge of the second-order statistics of the EMG noise and the ECG signal. In the time domain, an additional EMG input as a reference signal is needed. This limits the application of the method. Another drawback is that the procedure needs a time-delay for adaptation.

A method using approximation filtering with a dynamically varied number of samples and weighting coefficients depending on the ECG signal slope has been proposed (CHRISTOV and DASKALOV, 1999). The results reported show adequate preservation of the QRS complex amplitudes and reduction in the EMG noise. The drawback is a possible slight widening of some QRS complexes.

Several transform domain methods for suppression of unwanted signal components have been proposed in the literature (LANDER and BERHANI, 1997; ACAR and KÖYMEN, 1999; PAUL *et al.*, 2000). ACAR and KÖYMEN (1999) proposed to exploit the redundancy in a 12-lead ECG and to separate the

Correspondence should be addressed to Dr A. Gotchev; email: Atanas.Gotchev@tut.fi

Paper received 10 April 2001 and in final form 1 August 2001

MBEC online number: 20013617

multichannel signals into two time-orthogonal sub-spaces (one containing the information signal and the other containing the unwanted components) by singular value decomposition (SVD). A similar idea of reducing the signal space by applying an SVD smoothing on a discrete cosine transform (DCT) matrix of the ECG signal appeared in Paul *et al.* (2000). The method works for a single-lead ECG recording and it has been compared with sub-optimum DCT domain Wiener filtering. The performance of the Wiener filtering for ensemble-averaged high-resolution ECGs has been extensively studied by LANDER and BERHANI (1997).

An algorithm for ECG signal denoising in the wavelet domain was proposed by NIKOLAEV and GOTCHEV (1998). The signal was decomposed in a wavelet domain, and the coefficients were shrunk by applying a time- and frequency-dependent threshold. The approach preserved the amplitudes of the QRS complexes and considerably reduced the noise in the 'flat' TP area, but some artifacts could arise in the transient PQ and ST areas. The problem was partially avoided by applying wavelet domain Wiener filtering (NIKOLAEV and GOTCHEV, 2000) and denoising in the translation invariant wavelet domain (NIKOLAEV *et al.*, 2000), which led to a reduction in the oscillations around the QRS onset and offset.

In the present work, we have extended the above-mentioned methods (NIKOLAEV and GOTCHEV, 2000; NIKOLAEV *et al.*, 2000) by embedding an inter-cycle decorrelation scheme as the first step of the denoising algorithm. Split and merge operators have been designed to form two-dimensional data by a beat-synchronous approach. The horizontal dimension represents the cycle interval, and the vertical one is formed by the successive cycles, further designated as 'channels'. The decorrelation transform redistributes the information between the channels, forming one 'most' important cycle-length channel and several 'less but still important' supplementary channels. They all form the input for the next transform domain Wiener filtering. The experimental results obtained showed improved performance both in SNR and subjective visual evaluation.

2 Method

We consider the signal/noise mixture $\boldsymbol{r}$ formed of the informative ECG signal vector $\boldsymbol{x}$ and the EMG interference vector $\boldsymbol{e}$

$$\boldsymbol{r} = \boldsymbol{x} + \boldsymbol{e} \quad \boldsymbol{r}, \boldsymbol{x}, \boldsymbol{e} \in \boldsymbol{R}^N \tag{1}$$

Here, the EMG noise is assumed to be short-term stationary Gaussian noise.

Our basic idea is to apply some transforms aimed at efficient signal decorrelation. Given well decorrelated data, an approximate Wiener filter, being optimum in the mean-squared error (MSE) sense, can be applied in the transform domain to suppress the undesired noise components (GHAEL *et al.*, 1997). We recognise two types of signal correlation, namely inter-cycle and intra-cycle correlations. Our technique is oriented towards a rearrangement of the data in a way that helps to handle those correlations in a separate manner.

The block diagram of the method is presented in Fig. 1, and the different modules are described below.

2.1 *Cycle splitting and alignment*

We establish a cycle-splitting operator $\boldsymbol{B}$ that forms two-dimensional data segments from M heart cycles with maximum L samples

$$\boldsymbol{B}(\boldsymbol{r}) = \boldsymbol{y} = \begin{bmatrix} y_1(1) & \cdots & y_1(L) \\ \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots \\ y_M(1) & \cdots & y_M(L) \end{bmatrix} = \boldsymbol{B}(\boldsymbol{x} + \boldsymbol{e}) = \boldsymbol{s} + \boldsymbol{n}$$

$$\boldsymbol{s} + \boldsymbol{n} = \begin{bmatrix} s_1(1) & \cdots & s_1(L) \\ \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots \\ s_M(1) & \cdots & s_M(L) \end{bmatrix} + \begin{bmatrix} n_1(1) & \cdots & n_1(L) \\ \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots \\ n_M(1) & \cdots & n_M(L) \end{bmatrix} \tag{2}$$

Here, L is the length of the longest cycle among the M successive cycles.

Let us designate by QRS_i the position of the R peak in the ith QRS in the signal $\boldsymbol{x}$. The beginning of each cycle is calculated according to its position

$$y_i(1) = r(QRS_i - L_0) \tag{3}$$

where $L_0 = t_0 F_s$. The constant t_0 represents the distance between the R-wave peak and the region in the beginning of the cycle where no heart activity could exist (in practice, we have set $t_0 = 200$ ms); F_s is the sampling rate. The end of the cycle is taken with respect to the beginning of the next cycle

$$y_i(j_{END}) = r(QRS_{i+1} - L_0 - 1) \tag{4}$$

To align the separated cycles, we concatenate to the end some number of zeros determined by the longest cycle $\{y_i(j_{END}) \ldots y_i(L)\} = \{0\}$. Thus, we can obtain a two-dimensional matrix with successive cycles at each row, aligned by R peaks, and with some possible zeros at the end of shorter cycles.

We have used a QRS detector based on signal rectifying, amplitude clipping and threshold comparison with the ampli-

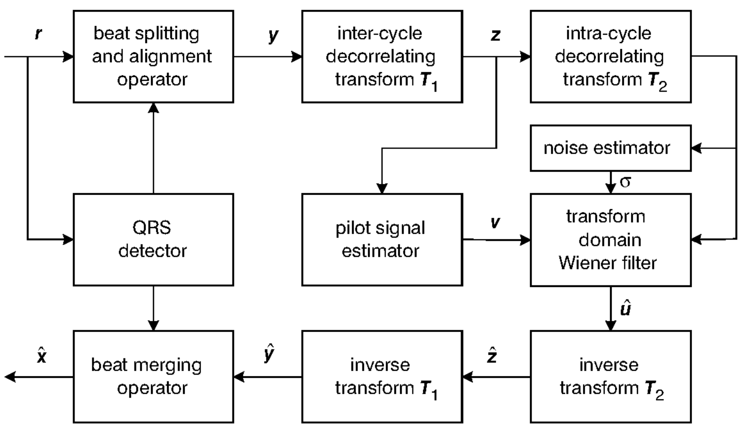

Fig. 1 *Block diagram of proposed method*

tudes of the first derivative on the rectified and clipped signal (FRADEN and NEUMAN, 1980). This QRS detector has shown very good performance in the presence of EMG noise (FRIESEN *et al.*, 1990). After finding the QRS positions, the operator $\boldsymbol{B}$ splits the signal into two-dimensional segments, each containing $M = 8$ aligned beats considered as different channels (see Fig. 2). Each segment overlaps the previous one by seven channels, meaning that the first two-dimensional segment contains the first M cycles, the second segment contains the cycles $2 \div M+1$ and so on.

We can assume the noise to be stationary in every cycle of the signal, i.e. $E\lfloor \boldsymbol{n}_i \boldsymbol{n}_i^T \rfloor = \boldsymbol{K}_i$, $\boldsymbol{n}_i$ being the ith row of the matrix $\boldsymbol{n}$ and $\boldsymbol{K}$ being the noise autocorrelation matrix.

2.2 *Inter-cycle decorrelation*

We apply a linear transform $\boldsymbol{T}_1$ on each of the columns of $\boldsymbol{y}$ to decorrelate the information between the different signal beats

$$z = \boldsymbol{T}_1 \boldsymbol{y} = \boldsymbol{T}_1 \boldsymbol{s} + \boldsymbol{T}_1 \boldsymbol{n} \tag{5}$$

As the data are highly correlated column-wise, the DCT is a proper choice as a de-correlating transform (RAO and YIP, 1990). Fig. 2 shows the content of each row of z after the DCT is applied to the columns of $\boldsymbol{y}$. It can be seen that the information about the signal is concentrated in the first row of z, as it contains the lowest-frequency components of the DCTs of each column and can be viewed as an averaged signal cycle. Hence, the noise variance there is already reduced by the factor $\sqrt{M}$ (JANSEN and BULTHEEL, 1999). The next plots, showing the remaining rows of z, contain information about the details in each cycle that are not presented in the first row of z. The advantage is that we keep, not only the average component, but also the details with information about the local changes in each cycle.

2.3 *Intra-cycle decorrelation*

According to Fig. 2, the intra-cycle decorrelating transform $\boldsymbol{T}_2$ should have good time-localising capabilities to keep the localised details in each row of z. The wavelet transform (WT) is a good choice

$$\boldsymbol{u} = \boldsymbol{T}_2 z^T = \boldsymbol{T}_2(\boldsymbol{T}_1 \boldsymbol{s})^T + \boldsymbol{T}_2(\boldsymbol{T}_1 \boldsymbol{n})^T \tag{6}$$

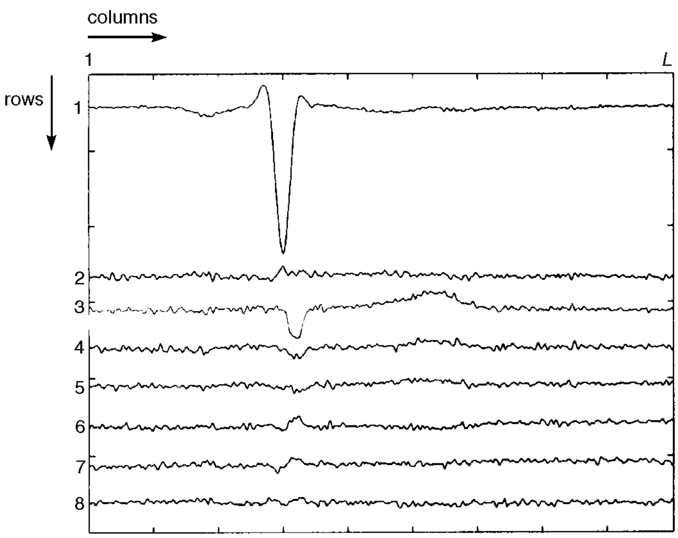

Fig. 2 *Eight channels of matrix z (from top to bottom) obtained after DCT on columns of matrix* $\boldsymbol{y}$

2.4 *Wiener filtering in transform domain*

The Wiener filter has been widely applied for noise suppression as it provides optimum signal estimation in the MSE sense (MERTINS, 1999). In general, it demands knowledge of the second-order statistics of the information signal and of the noise, represented by their corresponding correlation matrices (JAIN, 1989). The filtering manipulations can be simplified if the signal correlation matrix is diagonalised by a transform matrix formed by its eigenvectors, the so-called Karhunen–Loeve transform (KLT); for details, see JAIN (1989).

Unfortunately, the KLT is signal-dependent and not computationally acceptable, and hence, other linear transforms, i.e. near-optimum ones, have been investigated as approximates to the KLT, such as the DCT and WT (RAO and YIP, 1990; MALLAT, 1999). Choosing a transform that is near-optimum compared with the KLT, we can realise an approximate Wiener filtering (GHAEL *et al.*, 1997). For this sub-optimum filtering, the filter coefficients in some transform domain are given by

$$h_{Wiener}(i) = \frac{\varsigma^2(i)}{\varsigma^2(i) + \eta^2(i)} \tag{7}$$

Here, $\varsigma(i)$ is the ith transform domain coefficient of the signal (ith spectral line), and $\eta(i)$ is the ith transform domain noise component.

In practice, we do not know the true signal and noise statistics nor their transform domain expansions. Hence, we have to deal with their estimates, i.e. to make an empirical transform-domain Wiener filtering (GHAEL *et al.*, 1997).

In our case, we need signal and noise estimates when working in the $\boldsymbol{T}_2$ transform domain.

2.4.1 *Noise estimate:*

Passing through the linear system $\boldsymbol{T}_1$, the noise remains stationary in each row i of z. Then it can be proven that, after the transform $\boldsymbol{T}_2$, the resulting noise $\boldsymbol{T}_2(\boldsymbol{T}_1 \boldsymbol{n})^T$ is stationary for each column and for each scale of the wavelet decomposition (JANSEN and BULTHEEL, 1999). We estimate the noise variance in each column i of $\boldsymbol{u}$ and for each time position k and scale position j as

$$\begin{aligned} \hat{\sigma}_i^2(j) &= E[u_i^2(j, k-l)] \\ &= E[u_i^2(j, k)];\ k \in [1, 2^{-j}L_1] \cup [2^{-j}L_2, 2^{-j}L] \end{aligned} \tag{8}$$

where L_1 and L_2 are indexes, marking the regions where no coefficients corresponding to the QRS components are present.

2.4.2 *Filtering of the transform coefficients:*

The one-tap transform-domain Wiener filter is established as follows, according to eqn 7:

$$H_{WF(i)}(j, k) = \frac{\hat{v}_i^2(j, k)}{\hat{v}_i^2(j, k) + \hat{\sigma}_i^2(j)} \tag{9}$$

Here, $\hat{\boldsymbol{v}}_i$ are the transform coefficients of the pilot signal estimates for each row i of the transformed matrix z. They are obtained by applying preliminary wavelet shrinkage in the $\boldsymbol{T}_p$ wavelet domain (NIKOLAEV and GOTCHEV, 2000)

$$\boldsymbol{v}_i = \boldsymbol{T}_2 \boldsymbol{T}_p^{-1} \boldsymbol{H}_{HT(i)} \boldsymbol{T}_p (z_i)^T \tag{10}$$

Here, z_i is the ith row of the matrix z, and $\boldsymbol{H}_{HT(i)}$ are diagonal matrices performing hard thresholding

$$\boldsymbol{H}_{HT(i)}(j) = \alpha_i \hat{\sigma}_i(j) \tag{11}$$

α_i are empirically found constants (NIKOLAEV and GOTCHEV, 1998). As suggested by CHOI and BARANIUK (1998), $\boldsymbol{T}_p$ should be different from $\boldsymbol{T}_2$, and, for the case of ECG signals, it was found that the most localised wavelet bases (e.g. Daubechies4 or Haar) give the best results (NIKOLAEV and GOTCHEV, 2000).

(We have adopted the wavelet notations used in *Wavelab* toolbox, see BUCKHEIT *et al.* (1995).) The effects of the shrinkage operation $\boldsymbol{H}_{WF}$ (ripples around the PQ and ST areas) can be reduced by applying a translation-invariant wavelet transform (TIWT) for $\boldsymbol{T}_2$ (NIKOLAEV *et al.*, 2000). Fig. 3 represents Wiener filtering in the translation-invariant wavelet domain for each channel of z.

For the pilot signal estimate stage ($\boldsymbol{T}_p$ transform), we have used wavelet decomposition with a Daubechies4 wavelet involving a hard-threshold shrinkage scheme. For the Wiener filtering stage ($\boldsymbol{T}_2$-transform) we have applied a Symmlet4 wavelet.

The final signal estimate is obtained by applying the inverse transforms $\boldsymbol{T}_2^{-1}$, $\boldsymbol{T}_1^{-1}$ and the merging operator $\boldsymbol{B}^{-1}$

$$\hat{\boldsymbol{x}} = \boldsymbol{B}^{-1}\boldsymbol{T}_1^{-1}(\boldsymbol{T}_2^{-1}\boldsymbol{H}_{WF}\boldsymbol{u})^T \tag{12}$$

2.5 *Parameters for assessment of the results*

To evaluate quantitatively the proposed method, we have examined several measures on the denoising results. We have measured the following parameters:

(i) signal-to-noise ratio *SNR*, calculated as

$$SNR = 20\,\lg\frac{STD(\boldsymbol{x})}{STD(\boldsymbol{x}-\hat{\boldsymbol{x}})} \tag{13}$$

(ii) maximum relative error in the QRS areas E_{mean} averaged over all beats, calculated as

$$E_k = 100\frac{|\max(\boldsymbol{x}_k - \hat{\boldsymbol{x}}_k) - \min(\boldsymbol{x}_k - \hat{\boldsymbol{x}}_k)|}{|\max(\boldsymbol{x}_k) - \min(\hat{\boldsymbol{x}}_k)|} \tag{14}$$

where

$$\boldsymbol{x}_k = \{x(QRS_k - \Delta), x(QRS_k - \Delta + 1), \ldots \; x(QRS_{k+1} - \Delta - 1)\}$$

$$E_{mean} = \frac{1}{K}\sum_{k=1}^{K} E_k \tag{15}$$

(iii) maximum relative error in QRS areas E_{max}

$$E_{max} = \max_k(E_k) \quad k = 1, \ldots K \tag{16}$$

We have set $\Delta = 20$, which corresponds to a 50 ms interval.

We evaluate the amplitude measures, comparing them with the initial maximum relative amplitude ratio of the noise and the clean signal in the QRS areas E_{init}

$$E_{init} = E_{mean}|_{\hat{x}=r} \tag{17}$$

3 Experimental results

To test the proposed method, we have used three ECGs representing different heart pathologies and recorded from different patients. The records are from the standard lead II and are referred to as r0002, r0138 and r0352. The signals are 150 s long and sampled at 400 Hz, with a resolution of 4.88 μV bit^{-1}. The EMG noise has been recorded from two ECG electrodes placed on the forearm during sustained voluntary effort (CHRISTOV and DASKALOV, 1999). As the EMG signal was shorter than the ECG records, we concatenated several EMG segments to reach the ECG recordings' length. Then, the noise signal was filtered by a high-pass filter, with cutoff frequency of 1 Hz, to avoid the influence of baseline drift. Fig. 4 shows the spectrum of the EMG noise thus obtained.

In our experimental setup, we have mixed the 'clean' (noise-free) ECG signals with the EMG noise, achieving SNRs of 10, 15 and 20 dB. This is usually the case for ECG recordings under physical exercise conditions (the so-called stress-test ECG).

The results of denoising a part of the signal r0138 are shown in Fig. 5. The traces, from top to bottom, represent the signal–noise mixture, the clean signal, the signal after denoising and the residual (difference between clean and denoised signal). The initial SNR was set at 10 dB.

Fig. 6 shows the results after the denoising of a part of the signal r0352, a normal signal with sharp Q and R peaks. The traces are the same as in Fig. 5, and the initial SNR is 10 dB.

For comparison, we have suppressed the noise in the same signals by applying a fifth-order bi-directional low-pass Butterworth filter with cutoff frequency of 35 Hz (SUBCOMMITTEE, 1967). The results for the same part of the signal r0352 as in Fig. 6 are shown in Fig. 7.

Some quantitative results using the measures defined in Section 2.5 are shown in Table 1 for the proposed method and in Table 2 for the low-pass filtering.

4 Discussion

In our experiments we have tried to use ECG signals with some typical phenomena to check the applicability of the proposed denoising method. For example, in the signal in Fig. 5, the important detail, masked by the EMG artifact, is the slight ST depression. The noise in the important ST segment is completely removed, and its change can be easily detected. Some of the shapes of the extrasystoles are slightly distorted, but the effect is of no diagnostic significance.

The signal in Fig. 6 is characterised by very sharp Q and R peaks and a low-amplitude T-wave. It can be seen from the

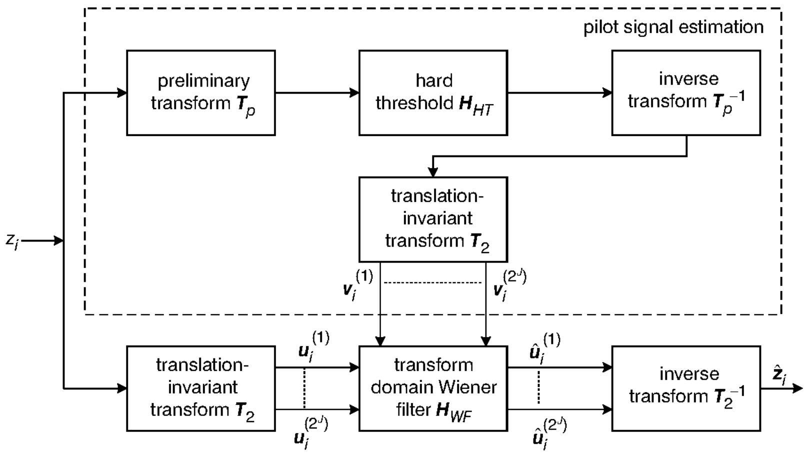

Fig. 3 *Wiener filtering in translation-invariant wavelet domain. Input signal: any column signal z_i; output signal: denoised version $\hat{z}_i$*

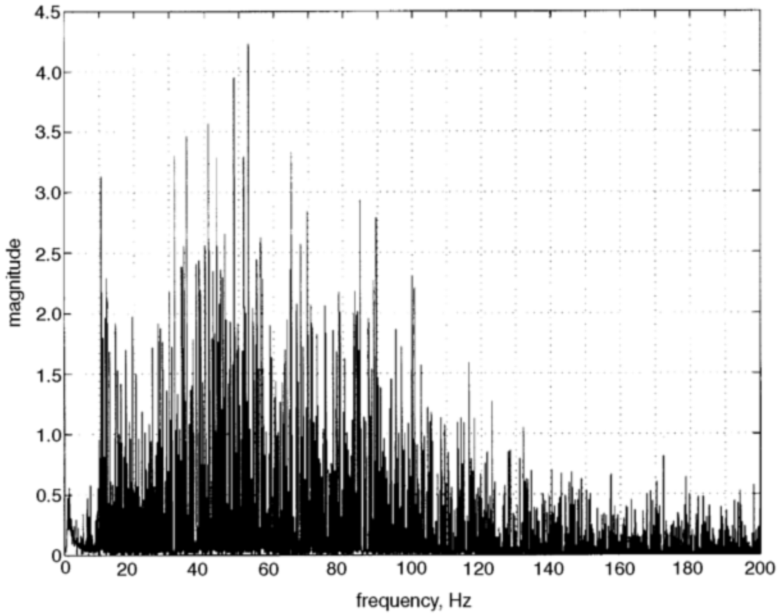

Fig. 4 *Spectrum of EMG noise used in experiments*

Fig. 5 *Denoising results for signal r0138 with proposed method: (a) noisy signal (clean ECG with added EMG); (b) clean ECG; (c) denoised ECG; and (d) residual signal (difference between clean ECG and denoised ECG)*

Fig. 6 *Denoising results for signal r0352 with proposed method. (a)–(d) as in Fig. 5*

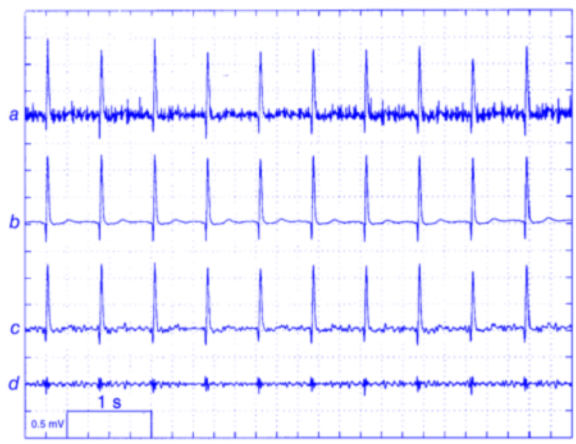

Fig. 7 *Denoising results for signal r0352 with fifth-order Butterworth filtering. (a)–(d) as in Fig. 5*

Figure that the noise is reduced and, at the same time, the amplitudes of the sharp Q- and R-waves are preserved. The low-amplitude T-wave, completely masked in the first trace, can be detected in the denoised signal, and the ST-segment can be easily assessed. In Fig. 7, the traditional low-pass filter almost completely failed, significantly reducing the sharp Q- and R-waves and moderately suppressing the noise in the 'flat' signal intervals. The QRS offset, the T-wave onset and the ST amplitude cannot be accurately detected.

A limitation of the proposed method is the limited ability to suppress low-frequency noise components. This effect can be observed in Figs 5 and 6, where some periodical artifacts are present in the denoised signals. The spectrum of these artifacts is concentrated in the 8–12 Hz band, which coincides with the peak at about 10 Hz in the noise spectrum (Fig. 4). The method limitation is due to the fact that the wavelet domain Wiener filtering procedure processes only the first four wavelet scales (the highest-frequency ones, above 12.5 Hz), and the fifth scale (below 12.5 Hz) is left unchanged. We did this with the aim not to disturb the low-frequency content of the P- and T-waves. Making this compromise, we obviously left unchanged the noise components below 12.5 Hz.

Table 1 Objective measures of denoising results using proposed method

	r00022				r0138				r0352			
Initial SNR, dB	*SNR*, dB	E_{init}, %	E_{max}, %	E_{mean}, %	*SNR*, dB	E_{init}, %	E_{max}, %	E_{mean}, %	*SNR*, dB	E_{init}, %	E_{max}, %	E_{mean}, %
10	22.5	35.0	9.0	7.4	20.2	23.3	12.7	10.4	21.3	31.0	16.7	9.0
15	25.5	20.8	8.9	6.3	22.3	13.8	10.8	8.2	23.4	18.4	12.6	7.9
20	27.8	11.7	7.1	5.1	24.0	7.8	9.0	7.1	24.5	10.3	8.9	6.4

Table 2 Objective measures of denoising results obtained by low-pass filtering with bi-directional fifth-order Butterworth filter

	r00022				r0138				r0352			
Initial SNR, dB	*SNR*, dB	E_{init}, %	E_{max}, %	E_{mean}, %	*SNR*, dB	E_{init}, %	E_{max}, %	E_{mean}, %	*SNR*, dB	E_{init}, %	E_{max}, %	E_{mean}, %
10	17.0	35.0	14.7	10.2	18.1	23.3	20.8	10.2	15.5	31.0	24.0	18.9
15	21.7	20.8	11.7	8.2	22.2	13.8	12.2	7.3	17.3	18.4	22.0	18.6
20	25.0	11.7	10.0	7.6	26.1	7.8	6.1	6.1	18.2	10.3	20.7	18.4

Finally, to prove that the above-mentioned periodical artifacts are noise components only and are not introduced by the proposed procedure, we performed the following experiment: we filtered the EMG noise by a high-pass filter with cutoff frequency of 20 Hz and then added it to the clean ECG signal. Performing our denoising procedure on this new mixture, we observed no periodical components in the denoised signal.

As far as the quantitative results are concerned, the SNR was improved by more than 10 dB, and the mean relative amplitude error in the QRS E_{mean} was reduced by more than three times for r0002 and r0352 and twice for r0138. However, E_{max} remains relatively high for r0138 and r0352, which means that some QRS complexes were more corrupted by noise (and, hence, not so well denoised).

The results for lower noise levels (initial SNR = 15 and 20 dB) are quite acceptable as well, although the advantages of the method are not so well emphasised in these cases and they are comparable with bi-directional filtering by a fifth-order low-pass Butterworth filter. For those noise levels, the low-pass filtering of the signal r0138 seems to perform better than the proposed algorithm. This is owing to the fact that the proposed procedure assumes that the successive beats are highly correlated. The presence of extrasystoles makes this assumption less adequate. The algorithm can recognise the extrasystoles as normal QRS complexes or not, but anyway, after the rearrangement, the two-dimensional data in matrix y are not as highly correlated column-wise, and the algorithm fails to concentrate the signal energy mostly into the first row of the matrix z (see eqn 5). As a result, the noise suppression thresholds α_i are not as well adapted to the signal energy distribution, which results in some increased distortion. On the other hand, ventricular extrasystoles have lower-frequency content than normal QRS complexes or supra-ventricular extrasystoles, and the low-pass filtering for those areas results in lower distortions (see Table 2).

5 Conclusions

By establishing the inter-cycle and intra-cycle processing in separate procedures, we can choose the most appropriate decorrelating decompositions for each stage. Thus, the DCT worked quite well on the aligned beats, producing channel signals that were very susceptible to the subsequent, adequately designed wavelet domain Wiener filtering. As a consequence, we achieved very effective suppression of the EMG noise and, at the same time, good preservation of the shapes and amplitudes of diagnostically important ECG waves. The method has shown its efficiency, especially for signals of high-frequency content and ones contaminated by high-amplitude noise, and the performance for low noise levels is comparable with simpler methods. A drawback could be the requirement for an efficient and fast-operating QRS detector. Otherwise, the decompositions proposed are fast, and, in the second stage, the data channels are processed separately, which is useful for parallel implementation in an ECG recording system.

Acknowledgments—We would like to thank Professor Ivan Daskalov from the Centre of Biomedical Engineering, Bulgarian Academy of Sciences, for his very helpful suggestions on interpretation of ECG features and for providing the ECG and EMG signal databases.

References

ACAR, B., and KÖYMEN, H. (1999): 'SVD-based on-line exercise signal orthogonalization', *IEEE Trans. Biomed. Eng.*, **46**, pp. 311–321

BUCKHEIT, J., CHEN, S., DONOHO, D., and JOHNSTONE, I. (1995): 'WaveLab reference manual'. Downloadable from http://www-stat.stanford.edu/~ wavelab/

CHOI, H., and BARANIUK, R. (1998): 'Analysis of wavelet-domain Wiener filters'. Proc. IEEE-SP Int. Symp. Time–Frequency and Time–Scale Analysis, pp. 613–616

CHRISTOV, I., and DASKALOV, I. (1999): 'Filtering of electrocardiogram artifacts from the electrocardiogram', *Med. Eng. Phys.*, **21**, pp. 731–736

FRADEN, J., and NEUMAN, M. (1980): 'QRS wave detection', *Med. Biol. Eng. Comput.*, **18**, pp. 125–132

FRIESEN, G., JANNETT, T., JADALLAH, M., YATES, S., QUINT, S., and NAGLE, H. (1990): 'A comparison of the noise sensitivity of nine QRS detection algorithms', *IEEE Trans. Biomed. Eng.*, **37**, pp. 85–98

GHAEL, S., SAYEED, A., and BARANIUK, R. (1997): 'Improved wavelet de-noising via empirical Wiener filtering', *Proc. SPIE*, **3169**, pp. 389–399

JAIN, A. (1989): 'Fundamentals of digital image processing' (Prentice Hall, 1989), pp. 293–294

JANSEN, M., and BULTHEEL, A. (1999): 'Multiple wavelet threshold estimation by generalized cross validation for images with correlated noise', *IEEE Trans. Image Process.*, **8**, pp. 947–953

LANDER, P., and BERHANI, E. (1997): 'Time–frequency plane Wiener filtering of the high-resolution ECG: development and application', *IEEE Trans. Biomed. Eng.*, **44**, pp. 256–265

MALLAT, S. (1999): 'A wavelet tour of signal processing' (Academic Press, 1999)

MERTINS, A. (1999): 'Signal analysis' (John Wiley & Sons, 1999), p. 119

NIKOLAEV, N., and GOTCHEV, A. (1998): 'De-noising of ECG signals using wavelet shrinkage with time–frequency dependant threshold'. Proc. European Signal Processing Conf., EUSIPCO-98, Island of Rhodes, Greece, pp. 2449–2453

NIKOLAEV, N., and GOTCHEV, A. (2000): 'ECG signal denoising using wavelet domain Wiener filtering'. Proc. European Signal Processing Conf., EUSIPCO-2000, Tampere, Finland, pp. 51–54

NIKOLAEV, N., NIKOLOV, Z., GOTCHEV, A., and EGIAZARIAN, K. (2000): 'Wavelet domain Wiener filtering for ECG denoising using an improved signal estimate'. Proc. Int. Conf. Acoustics, Speech and Signal Processing, ICASSP'2000, Istanbul, Turkey, pp. 2210–2213

PAUL, J., REDDY, M., and KUMAR, V. (2000): 'A transform domain SVD filter for suppression of muscle noise artifacts in exercise ECGs', *IEEE Trans. Biomed. Eng.*, **47**, pp. 654–662

RAO, A., and YIP, P. (1990): 'Discrete cosine transform, algorithms, advantages, applications' (Academic Press, 1990)

SUBCOMMITTEE OF INSTRUMENTATION COMMITTEE ON ELECTROCARDIOGRAPHY—AMERICAN HEART ASSOCIATION (1967): 'Recommendation for instruments in electrocardiography and vectorcardiography', *IEEE Trans. Biomed. Eng.*, **14**, pp. 60–68

THAKOR, N., and ZHU, Y. (1991): 'Application of adaptive filtering to ECG analysis: noise cancellation and arrhythmia detection', *IEEE Trans. Biomed. Eng.*, **38**, pp. 785–794

Authors' biographies

NIKOLAY NIKOLAEV obtained his MSc degrees in Biomedical Engineering and Applied Mathematics from the Technical University of Sofia (TUS), Bulgaria. Currently, he is working on his PhD thesis on the topic of ECG signal denoising and compression in the Institute of Information Technologies (IIT), Bulgarian Academy of Sciences (BAS).

ATANAS GOTCHEV received his MSc degrees in Communication Engineering and Applied Mathematics from TUS, and PhD in Communication Engineering from IIT, BAS. Currently, he is with the Institute of Signal Processing, Tampere University of Technology (TUT), Finland, where he specialises in transform methods for signal and image processing.

KAREN EGIAZARIAN received his MSc in Mathematics from Yerevan State University, Armenia, and PhD in Physics and Mathematics from Moscow Lomonosov State University, and DSc(Tech) degrees from TUT, respectively. Currently, he is Full Professor in the Institute of Signal Processing, TUT. His research interests are in the areas of applied mathematics, and signal and image processing.

ZDRAVKO NIKOLOV graduated in Communications Engineering from TUS. Currently, he is Associate Professor at IIT, BAS. His research interests are in the area of information theory and its application in biological and communications signal processing.