LOCAL ADAPTIVE DE-NOISING TECHNIQUES IN TRANSFORM DOMAIN FOR EMCG DE-NOISING

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ABSTRACT

There are various de-noising algorithms and optimization methods for different signal and noise characteristics. However, the signals used in real application may have deviations from the model. For example: signal and/or noise may not be stationary or a proper model for them may not be available. MCG (magnetocardiography) is an example signal, where conventional de-noising methods are not giving satisfactory results. Local adaptive processing allow to modify filtering parameters according to the specific properties of different “portions” of a signal. In this paper a methodology for adopting the transform domain local adaptive processing to the specific task of MCG signal de-noising is introduced.

1. INTRODUCTION

The electrocardiography (ECG) and the magnetocardiography (MCG) are fully non-invasive, totally harmless, safe and quick methods for measuring the electric activity of the heart. However, diagnostic information conveyed by the ECG and MCG signals is limited. Also differences in the ECG and MCG waveforms induced by a diagnostic event may overlap with normal inter-individual variability. The simultaneous ECG and MCG recordings convey extra information associated with the distribution of the volume source (electric activity of the heart) with respect to the single ECG or MCG measurement [3][6][11]. Combining the information conveyed by the ECG and MCG leads, at least theoretically, may improve the accuracy and the content of the diagnostic information extracted from the recordings. However, this requires proper characterization of the waveform morphologies and this needs better preservation of the signal details and higher attenuation of corrupting noise. Furthermore, especially the MCG signals may be highly distorted by the environmental noise interfering with the signal spectrum. This brings the necessity of improved de-noising. A transform-based non-linear filter for fulfilling the requirements of combined electromagnetocardiography (EMCG) analysis is introduced.

Low frequency noise, line frequency interference and Gaussian noise corrupting MCG recordings are not stationary. The MCG signals are also corrupted by arbitrary noise components induced by the sensor movement in the geomagnetic field of the earth and a proper model for noise in the MCG recordings is not available [3][6][11]. Those facts bring problems in applicability of conventional de-noising algorithms for MCG. The transform-based non-linear filtering was adapted to the de-noising requirements of combined electromagnetocardiography (EMCG) analysis by employing a signal based suitable threshold estimation method [11].

2. LOCAL ADAPTIVE PROCESSING IN TRANSFORM DOMAIN

Processing the signals in an orthogonal transform domain rather than time domain suggests certain advantages, when the spectra of the signal and the noise can be separated in an orthogonal transform domain, in terms of incorporating the available a priory information about the signal to the design of the filter. Performing the transform domain de-noising give better results when it is applied locally rather than globally [12].

When the spectrum of the signal and the noise can be separated in any invertible transform domain, de-noising the signal in the transform domain and performing the inverse transform is an efficient method of removing the noise [1][12].

General filtering algorithm consists of the following three steps:

1. Computing spectral coefficients

   $\mathbf{a} = \mathbf{T}\,\mathbf{b}$

   of the observed signal period **b** within the window over the chosen orthogonal transform **T**.

2. Modifying the spectral coefficients

   $a'_r = f(a_r, r)$

3. Performing the inverse transform

   $\mathbf{b}' = \mathbf{T}^{-1}\,\mathbf{a}'$

The signal and noise spectra may be partially overlapping in most of the real applications. Therefore, the higher levels of noise attenuation are possible only at the cost of the lower detail preservation. The local filtering of the signals with the variable modification of the spectral coefficients can dynamically optimize the noise attenuation with acceptable detail preservation [11].

Most of the signals carrying information are highly correlated. Therefore, in most cases where a noisy signal spectrum coefficient is over a threshold value associated with noise variance σ^2 the original signal has significant component [1][4][5][7][10][12].

Generally the modification is done by hard or soft thresholding. Hard thresholding corresponds to removing all coefficients whose absolute value are lower than the threshold and leaving the other coefficients unchanged. The soft thresholding modifies all coefficients lower than the threshold to zero and subtracts the threshold from the absolute value of the remaining coefficients. When the threshold values are chosen correctly, the noise attenuation can be optimized locally with a negligible distortion of the signal details. Furthermore, performing the de-noising in a running window and averaging all of the results returned for the same sample suppresses the artifacts induced by de-noising [4][10][12].

The proper threshold estimation method is the main tool for adoption of the algorithm to the requirements of a specific application.

A de-noising algorithm can be applied if a priori information considered in the algorithm is available.

When the noise is white Gaussian and stationary, a constant threshold $t \cong 3*\sigma$ performs the best results. The noise variance for white Gaussian noise may be estimated by:

$$\overline{\sigma} = \sqrt{2}\,\text{median}(\text{abs}(\mathbf{Tb}))$$

The algorithm may be used with colored noise by frequency varying thresholding. Temporally varying thresholding with local estimation of noise variance may improve the de-noising performance for varying noise variance σ^2. However, in some applications the noise may not be stationary (the distribution of the noise spectral components is also non-stationary). In this case a proper noise model is not available and the only available a priori information for any de-noising algorithm can be extracted from the signal.

3. MCG DE-NOISING

The main problems of MCG signal de-noising are as follows:

1. The noise in MCG recordings is high and has non-stationary components.
2. Some local portions (QRS complex) of the signal have important and significant components in 30-54 Hz. band, while there is considerable noise components in the same bands.
3. Commonly used method for de-noising the MCG signals is ensemble averaging triggered by ECG signals. However, intra-subject anatomical variability, motion artifacts, etc do not allow a perfect template matching and cause smoothing of important details.
4. Filtering by a temporally varying algorithm according to the local spectral characteristics may perform noise attenuation with negligible distortion in the features of the characteristic waveforms of the signal.
5. The conventional ECG analysis does not need very high de-noising accuracy. However, improving the content and accuracy of the diagnostic information on the basis of simultaneous ECG and MCG is under investigation and this improvement require accurately de-noised ECG and MCG signals.

A transform domain adaptive filter employing a signal based proper threshold estimation methodology was used for final de-noising of the MCG signals to attenuate the noise components interfering with the characteristic waveforms of the signal.

The suitable threshold estimation method employs the following steps.

- Dividing a sufficient portion (sufficiently long for occupying at least one heart beat) of the signal into *N* non-overlapping blocks.
- Performing the transform for each non-overlapping window.
- Computing the maximum of absolute value of each spectral coefficient calculated in different windows.
- Setting the threshold for each spectral coefficient as:

  $$t_i = c_i.\max(\text{abs}(b_1(i)),\text{abs}(b_2(i)),...,\text{abs}(b_N(i)))$$

  Where c_i corresponds to the ratio of the threshold to the maximum of the spectral coefficient

The following selections were used for MCG de-noising:

1. The **DCT** was selected as the transform for processing [8].
2. A window size of 32 was used for signals sampled at 500 Hz sampling frequency.
3. The first four **DCT** coefficients belonging to the frequencies lower than 23 Hz are passed without thresholding mainly for preserving P-wave details.
4. The ratios from 5. to 8. **DCT** coefficients were set as:

   c(5)=0.6, c(6)=0.8, c(7)=0.9, c(8)=1
5. The 9. to 32. **DCT** coefficients corresponding to frequencies higher than 54 Hz were set to zero without thresholding.

Keeping the distortions negligible was mainly considered in selection of the filtering parameters. Line frequency interference and low frequency noise can be removed by conventional methods (notch filtering, linear interpolation, etc) prior to final de-noising. The continuos recording version of the algorithm uses the median of first three beats in setting of the thresholds and the same threshold is used for the whole recording [11].

4. EXPERIMENTAL RESULTS

4.1 Comparative results

A filtered MCG waveform is considered as the clean signal. The clean signal was corrupted by different levels of additive Gaussian noise. The corrupted signals were filtered by different filters and the results are presented in Table 4-1.

Signal	SNR1 (dB)	SNR2 (dB)	SNR3 (dB)
Clean Signal	inf.	inf.	inf.
Corrupted signal	4	7.7	10
LA filtered in transform domain	14	18	23
Filtered by Wiener filter	13	17.2	21
LAF using wavelet transform	14.1	18.1	23
LAF using noise variance	17	21	24
LAF using noise variance when band relations were considered	18.8	22.6	24
LAF using locally estimated noise variance	18.7	21.4	22.7
LAF using locally estimated noise variance when band relations were considered	18.9	22.3	23.9
LAF with varying transform size	17	21	24.4
Global wavelet de-noising	12.5	16.3	17.6
Translation invariant wavelet de-noising	17.9	20.1	22

Table 4-1: Comparative results

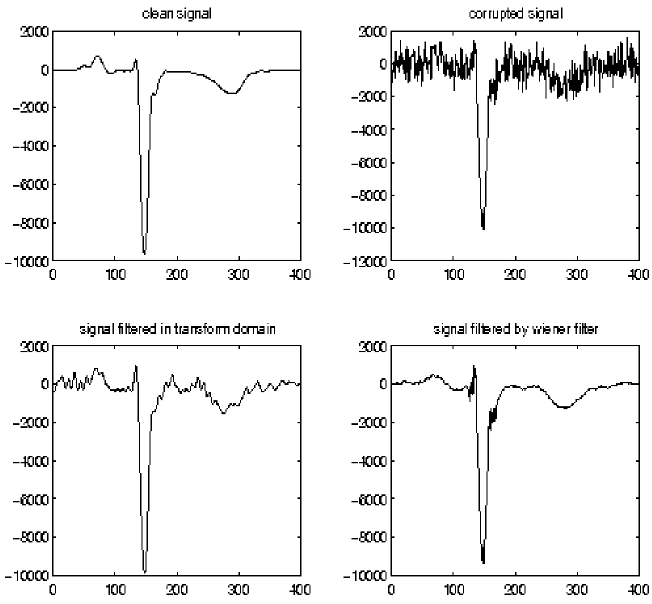

Figure 4-1: Plots of comparison. The remaining noise components in transform domain filtering is distributed, while most of the remaining error in Wiener filtering is in beginning, R-peak and end parts of the QRS complex which are important in characterization of the waveform.

'LA (local adaptive) filtered in transform domain' corresponds to the developed filter. An optimal 'Wiener filter' of size 32 was used in comparison. 'LAF using wavelet transform' was the same algorithm only using a local full wavelet decomposition by Daubechies 4. 'LAF using noise variance' was performed by using a fixed threshold of 3*σ and application needs the information on noise variance. The 'band relations' were considered by thresholding all spectral coefficients which represent an equal or higher frequency then the lowest frequency below a threshold of 1.5*σ. 'LAF using locally estimated noise variance' was performed by using a median based local noise variance estimator [5]. Its application does not need the information on noise variance. But adoption to colored noise needs information of the noise model. 'LAF with varying transform size' was performed by local noise variance estimation and switching between transform sizes of 32 and 64 according to the variance of the corrupted signal. Global and translation invariant wavelet de-noising was performed by using full decomposition by Daubechies 8. The main difference between the achieved and possible performances was due to the selections for keeping the desired detail preservation. For example frequencies lower than 23 Hz were passed for preserving P-wave. P-wave has a negligible contribution to the total signal power but has a diagnostic importance.

The clean, corrupted and filtered waveforms by transform domain and Wiener filters are plotted in figure 4-1.

4.2 Experimental results from application point of view

252 MCG and 229 ECG waveforms were filtered by the developed filter as a final de-noising. A wavelet based characteristic wave detection algorithm [2][9][11] detected all QRS complexes and T-waves without any error for a total of 481 recordings after filtering. This filter removed the local extrema in QRS complexes induced by noise. The T-waves and P-waves in the filtered signals were visible. Accurate evaluation of the P-Q segments and S-T segments was possible in the filtered signals. Four MCG samples filtered by developed filter and Wiener filter are plotted in Figure 4-2 to 4-5.

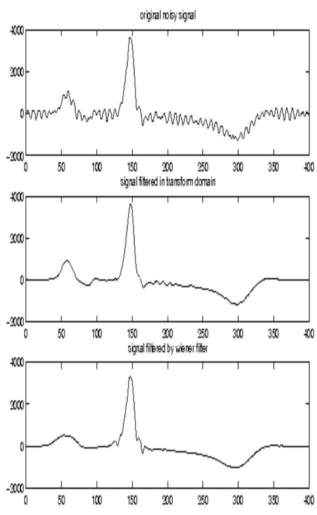

Figure 4-2

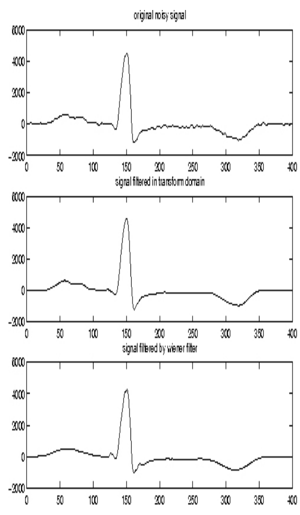

Figure 4.3

Significant noise components may be left after notch filtering, baseline correction and template averaging of the MCG signals. Remaining noise may be attenuated successfully by transform domain filtering (Figure 4-4 is a good example) with negligible distortion in signal waveforms. The filtered MCG signals are sufficiently clean for proper characterization necessary for investigating the probability of extracting extra diagnostic information (for example spatial properties of myocardial infarction, etc.) from the simultaneous ECG and MCG.

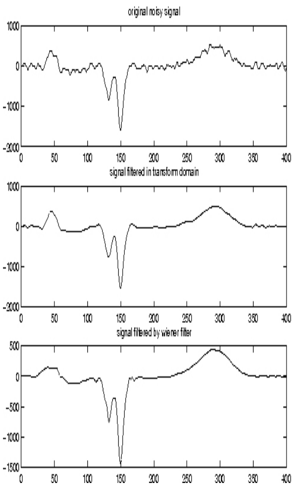

Figure 4-4

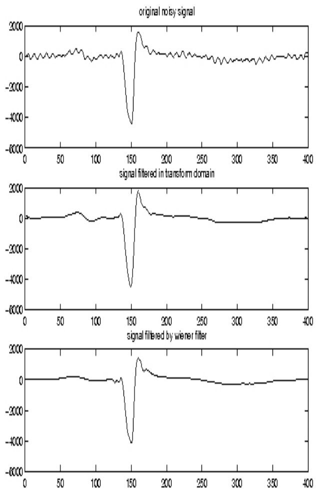

Figure 4-5

5. SUMMARY AND CONCLUSIONS

When the signal is corrupted by random noise, which can not be separated in frequency or time domain, local adaptive filtering of the noisy signal in a suitable orthogonal transform domain is a promising solution for improving the balance between detail preservation and noise attenuation.

The algorithm can be adjusted for the requirements and available a priori information of a specific task by the selected threshold estimation method. Especially when the noise is non-stationary and a proper noise model is not available signal based suitable threshold estimation method may be employed. This fact makes the algorithm available for some applications where most of the conventional algorithms considering a noise model fail. The methodology can be used in similar problems where a proper model for noise is not available.

The future research in this area may include development of combination methods of the values computed for the same sample in different windows rather than simple averaging, incorporating the filtering algorithm with post-processing and pre-processing methods where necessary (like image enhancement, impulse removal, etc).

6. REFERENCES

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