COMPARATIVE STUDY OF SOME BASIS FUNCTIONS IN WAVELET SHRINKAGE ECG DENOISING

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ABSTRACT

The applicability of basic functions from different wavelet families to Wavelet Shrinkage ECG denoising has been investigated. A method for ECG denoising based on Wavelet Shrinkage with Time-frequency Dependent Threshold has been applied. The experimental results have been compared on a wide ECG database and they have shown existence of strong relationship between the wavelet function support and denoising quality.

I. INTRODUCTION

One of the most serious problems in the registration of electrocardiographic (ECG) signal is the parasite interference of muscle active potentials – electromyographic (EMG) signals. The EMG spectrum is wide-band and overlaps the ECG spectrum [1]. This leads to difficulties in determining ECG signal parameters important in medical diagnostics.

The ECG contains pulses with different frequencies and amplitudes – high-frequency Q, R, S waves (forming QRS complex) and the "slow" low-pass P and T waves (Fig.1). Their time-varying behavior determines ECG as highly nonstationary signal.

The noise presence problem can be partially avoided by low-pass signal filtering. This approach improves SNR but decreases the amplitudes of high frequency Q, R and S waves, which is undesirable in diagnostics of some diseases.

Recently a new technique named Wavelet Shrinkage (WS) have become very popular for signal denoising [2]. In this approach the signal is first decomposed into wavelet domain and then the coefficients are "shrinked" using a nonlinear threshold depending on the noise characteristics. There are two crucial steps in applying this procedure:

Appropriate choice of expansion basis function

We need a function that efficiently uncouples the signal from the noise. Wavelets are appropriate candidates for such functions since they have good time and frequency localization as well as good decorrelation properties [3].

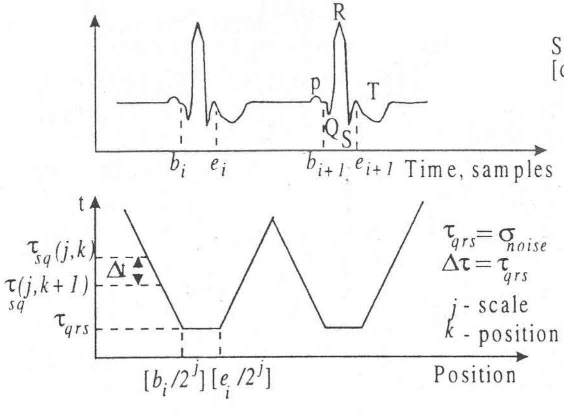

Fig.1: Threshold function for scales 1, 2 and 3

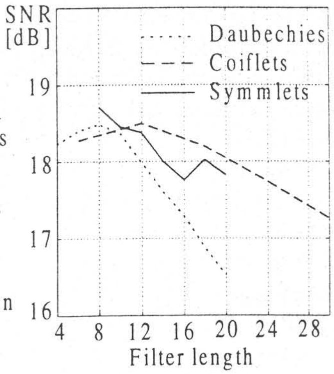

Fig.2: Average SNR versus the filter length for different wavelet families

Appropriate choice of shrinking threshold

The threshold must be function of the statistical characteristics of the noise in order to preserve the informative signal parts. The shrinking threshold for WS ECG signal denoising proposed in [4] is shown in Fig.1. It is high for the non-informative wavelet coefficients (which are harder influenced by noise) and low for the informative coefficients, representing important signal features.

The following questions arise: 1. Does there exist best wavelet basis for WS ECG signal denoising when using the threshold in [4]. 2. What is the optimal filter length for such denoising approach.

The presented work gives the answers of these questions, based on comparative study of wavelet shrinkage applicability. A database of ECG signals with different behavior - pathological and healthy - have been used in the experiments.

Part two of the paper briefly describes the wavelet basis functions and their properties important for denoising tasks. Part three presents the experimental results obtaining by denoising with WS using different wavelets from several wavelet families. Conclusions are formulated in Part four.

II. WAVELET BASIS FUNCTIONS

Wavelet Transform has localization, multiresolution and decorrelation properties, which make it a powerful technique in many signal processing applications [5], [6]. From mathematical point of view they represent an admirable relationship between continuous time basis functions and discrete time digital filters, working on discrete signals and allowing fast algorithms [3].

Wavelet Transform decomposes the analyzing signal in a small number of significant coefficients, while the rest amount of small coefficients is considerable

[2]. When a signal noise-mixture is decomposed, the signal features are represented by large wavelet coefficients and the noise is spread over all coefficients. Thus the small coefficients are harder influenced by noise. Donoho has been explored this wavelet property in denoising of different (mostly synthesized) signals, and has proposed several shrinkage thresholds [7].

There are many wavelet families, designed in different mathematical constraints for different practical applications.

Daubeshies has recently developed its famous family of *minimum phase wavelets* with *compact support* and *maximum number of vanishing (zero) moments* [6]. The Daubechies wavelets are compactly supported and can be obtained by iterated regular filters. The degree of regularity represents the function continuity and continuity of its derivatives. A necessity condition for regularity is a presence of zero at frequency $\omega=\pi$ in the iterated filter. There are also several sufficient conditions developed in [6]. Roughly speaking they represent the relation between the filter length and the number of vanishing moments -the longer the filters have more vanishing moments.

However the phase of the Daubeshies' filters is not linear. It is impossible to construct orthogonal and compactly supported wavelet with linear phase, as shown in [6]. But the symmetrical wavelets (linear phase wavelets) are preferable in some applications where non-symmetrical filters can make the phase distortions around edges more visible.

Looking for more symmetry two other groups of orthogonal wavelets have been constructed [6]. *Coiflets* have maximum number of vanishing moments for both the wavelet and the scaling function. *Symmlets*, called also least asymmetrical wavelets, have almost linear phase and are the least asymmetrical in the group of orthogonal wavelets.

Relaxing the orthogonality conditions [5] one can construct biorthogonal wavelet pair, where the analysis and synthesis decomposition functions are different and both symmetrical. This changes the number of vanishing moments and the support of analysis and synthesis wavelet.

In the case of ECG signal the wavelet choice problem becomes more difficult because of its nonstationary behavior. Therefore one need to use all wavelet properties while some of them are mutually exclusive. More smoothed wavelets (longer filters) are needed especially for good P and T waves representation. But longer filters could not time localize the fast QRS complexes. Linear phase wavelets are preferable in order to spread the distortions symmetrically but we trade the single wavelet for pair of analysis/synthesis (symmetrical!) wavelets.

These preliminary assumptions emphasize our experimental effort in this task.

Table 1 summarizes the wavelets used in our investigations.

Family	Daubechies	Coifflets	Symmlets	Spline	Villasenor
Ortho-gonality	Orthogonal	Orthogonal	Orthogonal	Biorthogonal	Biortho-gonal
Compact support	Yes	Yes	Yes	Yes	Yes
Filter Order	N=2,...,10	N=1,...,5	N=4,...,10	Nd=1;Nr=1,3,5 Nd=2;Nr=2,4..8 Nd=3;Nr=1,3..9	[Nd, Nr] = [7,6], [3,2], [3,5], [5,4]
Support width	2N-1	6N-1	2N-1	2Nd+1 2Nr+1	2Nd+1 2Nr+1
Filter lengths	2N	6N	2N	[2Nd, 2Nr]	[2Nd, 2Nr]
Symmetry	far from	close to	close to	yes	Yes
Vanishing moments	N for ψ	2N for ψ 2N-1 for φ	N for ψ	Nr-1 for ψ	Nr-1 for ψ

Table 1: Wavelet's basic features

III. RESULTS

The ECG database used in our experiments contains 192 8-channels signals with 3,6 sec duration, 200 Hz sampling rate and 8 levels of quantization. They include different patients records with heard deceases and healthy.

Each of the signals has been mixed with white noise achieving SNR=14dB. The signals have been denoised using the WS procedure described in Part I, and the residual signals (the difference between the noise free signal and the denoised signal) have been obtained. The corresponding SNRs have been averaged over all signals and channels. They have been used as objective measures in comparison of different wavelet's applicability.

The results show that there is strong relationship between the filter length and the noise suppression level when orthogonal wavelets have been used. Best results are obtained using filter lengths between 8 and 12. Increasing the length of the filter the wavelet smoothness capability grows but time localization around QRS areas fails. As a result some oscillations may occur in the ends of the QRS areas. Decreasing the length of the filter may produce artifacts in the areas of P and T waves.

Fig. 1 shows the average SNR versus the filter length after WS denoising using Daubechies wavelets, Symmlets and Coiflets.

Similar results arise in the case of biorthogonal wavelet denoising. For Villasenor wavelets the best working filters are 7 and 6-order filters. Despite their symmetry the shorter filters lead to worse results as in the orthogonal case. The biorthogonal spline wavelets produce best results for filters' lengths 2 and 8.

In each family the "favorites " are as follows: Daubechies8, Coiflet2, Symmlet4, Spilne28 and Villasenor67 where the numbers after the wavelet's name

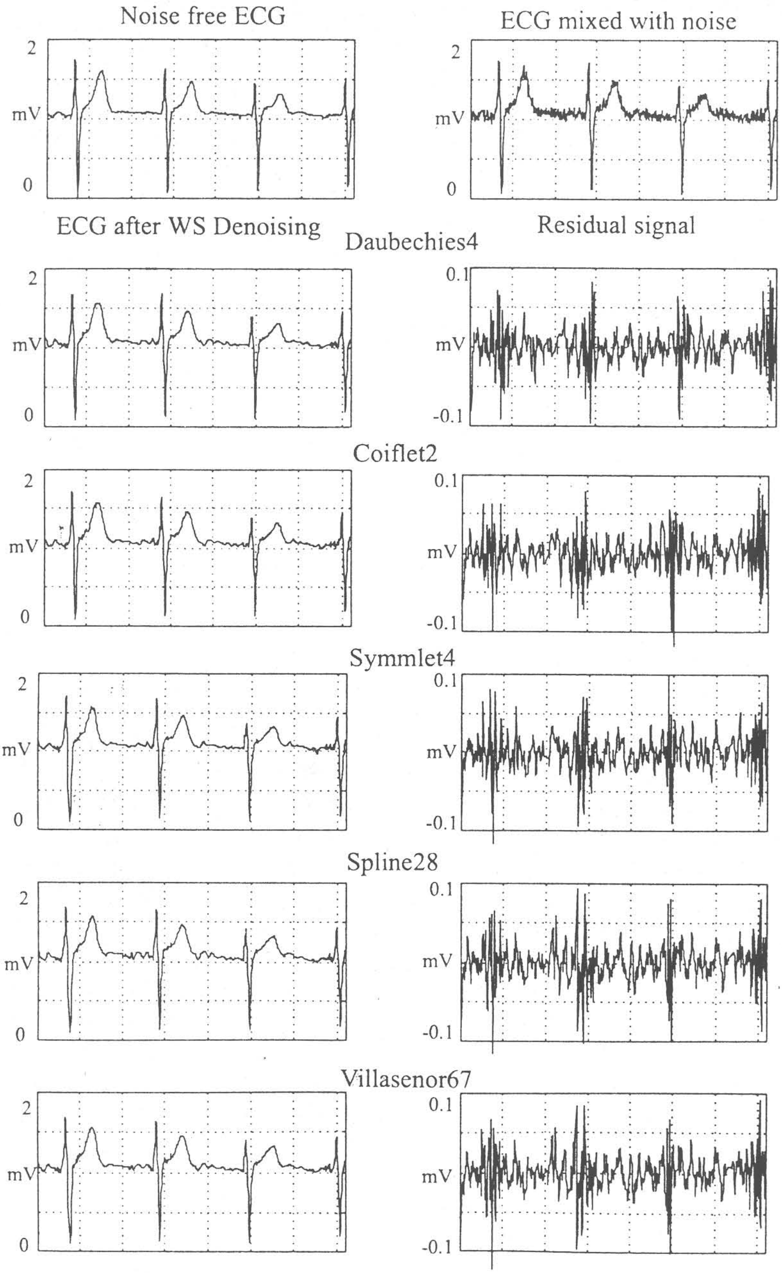

Fig. 3: Denoising Results

represents the order of the filters. This group of "winners" leads to very similar results. The difference between the best and the worst average SNRs are less than 0.25dB. That's why we cannot point best wavelet for this application. In the same time the choice of the filter length is very important, because the filter order represents the smoothness and regularity properties of the wavelet.

The denoising results for the five "winners" are illustrated in Fig.3. We can see from the figure that all wavelets have given good results – the amplitudes of the high frequency Q, R and S waves have been preserved and in the same time the high frequency noise outside the QRS area has been suppressed successfully.

IV. CONCLUSION

The capabilities of the algorithm for WS ECG denoising proposed in [4] have been investigated. Different wavelet families have been theoretically and experimentally compared due to their applicability as basis functions in wavelet shrinkage denoising.

The important role of the wavelet support (the length of corresponding filter) has been pointed out. Best results are obtained using filter length between 8 and 12. The small differences in the results between the best wavelets from each family show that the choice of wavelet type is not critical in this application.

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