SPATIALLY SELECTIVE WIENER FILTERING OF EVOKED POTENTIALS IN THE WAVELET DOMAIN

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ABSTRACT

We propose a spatially selective Wiener (SSW) filtering method in the wavelet domain for enhancement of evoked potentials corrupted by stationary correlated noise. The proposed filtering scheme uses inter-scale correlation in the wavelet domain to identify signal and noise regions and uses their strengths to compute the Wiener filter transfer function. This computed function is used in a spatially selective fashion to filter noisy brainstem auditory evoked potential (BSAEP) signals. The filter entails signal component enhancement while avoiding visual artifacts around the edges. Results for both simulated and actual BSAEP signals indicate a significant improvement in the signal-to-noise ratio (SNR) of filtered sweeps.

1. INTRODUCTION

Evoked potentials (EP) are electrical responses of the central nervous system to sensory stimuli applied in a controlled manner. The stimuli are applied in the form of auditory clicks, visual patterns or electrical pulses, depending upon the neural pathway being tested. The resulting responses are called auditory (AEP), visual (VEP) and somatosensory evoked potentials (SEP), respectively. These responses are essentially electrical potential differences and are picked up at different identified locations on the scalp using surface electrodes. The amplitudes, occurrence times and durations of the various characteristic components of the EP's convey diagnostically important information about the corresponding sensory neural pathway. Based on the analysis time segment chosen from the time of application of the stimulus, evoked responses are classified as short, middle and long latency responses. Short latency auditory responses have both high and low frequency components in the analysis time length and have very low SNR in comparison with the other modalities of EPs. They are more complex with more number of components and hence are better suited to study any filtering or estimation algorithm. Hence, we restrict our attention to this subclass of EPs, namely,short latency auditory evoked potentials, which are also known as brainstem auditory evoked potentials (BSAEP) because they originate in brainstem. They are more stable and are clinically used to distinguish between conductive and sensory hearing loss.

EP occurs as an additive process to the natural brain activity known as electroencephalogram (EEG) and other physiological noise. The major problem in the acquisition of evoked potentials lies in their unfavourable signal-to-noise ratio (SNR) as the evoked signal is very low in amplitude in comparison with the spontaneous brain activity, namely the electro encephalogram (EEG). Usually, stimulus-synchronous averaging of a few hundreds to few thousands of responses to identical stimuli is carried out to increase the SNR. This is effective, since the stimulus induced changes in the EEG are negligible. Various attempts have been made by different research groups either to reduce the number of sweeps to be averaged to obtain a meaningful signal in order to reduce the recording time or to recover the information lost by averaging. Some of the other EP estimation methods include linear filtering in time domain [3], frequency domain [7], other non-parametric methods [6]. The AEP's consist of low-frequency components of relatively long duration and higher frequency components of shorter duration. For a correct description of the signal power, we must take into account not only its spectral distribution, but also its temporal distribution. In other words, although EP is considered stationary across an ensemble, it can be considered as non-stationary within a sweep, during which the frequency characteristics of the various temporal components vary. Hence, the analysis of EPs requires filters possessing time-varying characteristics.

Wavelets have become increasingly popular tools to efficiently deal with such nonstationary signals. Wavelet transform is found to be most suitable for analysis of the time varying structure of EP signals having both high and low frequency components [4, 5]. Thakor et al. [8] used multi-resolution wavelet analysis of the EP signals using orthogonal wavelets to characterize complex changes in their shape during neurological injury. The present work suggests methods to improve the SNR of ensemble averaged AEP's by reducing the residual noise. The objective is to obtain a smoother and improved estimate, which facilitates component measurement. We use a combination of two different wavelet methods for signal estimation, namely, a hierarchical Wiener filtering which is a parametric approach, and a thresholding method which is a non-parametric approach. Initially we briefly explain the different wavelet domain signal estimation methods in the following section.

2. SIGNAL ESTIMATION METHODS IN WAVELET DOMAIN

Signal estimation approaches in the wavelet domain may broadly be classified as thresholding approaches and filtering approaches. Thresholding algorithms are based on the energy compaction property of the wavelet transform and assume noise to be white with Gaussian distribution. In filtering approaches, the fundamental philosophy is to consider the set of wavelet coefficients as a stationary random process and use statistical estimation techniques for denoising the signal. Both these schemes tend to manipulate individual wavelet coefficients in order to denoise the observed signals. We briefly explain these two approaches in the following subsections.

2.1. Thresholding methods

Wavelet thresholding procedures exploit the energy compaction property for effective signal denoising, and are optimal in a minimax mean-square-error (MSE) sense for a variety of signal classes. In general, the wavelet coefficients of a function are large in regions where the function is irregular and small in smooth regions. If a function is corrupted by additive noise, the noise dominates the wavelet coefficients at small scales. Thus, most of those coefficients contain the noisy part of the signal and only a few large coefficinets are related to strong singularities in the underlying function. The thresholding schemes generally assume identically and independently distributed white Gaussian noise with unit variance corrupting the signal of interest. Due to this, small coefficients are more likely to be due to noise, while the large coefficients are due to important signal features. The essence of a threshold is that it should be large enough to eliminate noise, but small enough to keep the signal features.

In the most basic form of *wavelet thresholding* for denoising, if a coefficient is smaller than the threshold, it is set to zero; otherwise, it is kept or modified. The process of thresholding wavelet coefficients can be divided into two steps. The first step is the choice of the thresholding scheme. Two standard choices are: **hard** and **soft** thresholds [9]. The second step is the choice of the threshold, λ. Hard-thresholding zeroes every coefficient that falls below a defined threshold, while in soft-thresholding, a smooth and continuous non-linear function is applied to the transform coefficients. The most straight forward approach is to additionally shrink all the surviving coefficients by the value of the threshold. Let

$$x_i(n) = s(n) + v_i(n), \qquad n = 1, \cdots, N \quad (1)$$

be a finite length i^{th} noisy EP observation wherein the evoked signal s_i is corrupted by i.i.d. zero-mean, white Gaussian noise v_i with standard deviation ϵ. If $\{d_{j,k}\}$ are the wavelet coefficients of the signal $x_i(n)$, where j is the scale parameter and k is the translation parameter in the wavelet domain. Different thresholding functions are defined as follows:

- "Hard thresholding:"

$$T_{\lambda}^{HARD}(d_{j,k}) = d_{j,k}, [|d_{j,k}| \geq \lambda]+$$

- "Soft thresholding:"

$$T_{\lambda}^{SOFT}(d_{j,k}) = sgn(d_{j,k})(|d_{j,k}| - \lambda)+$$

A variety of methods have been proposed for the estimation of λ. The earliest method proposed by Donoho and Johnstone [9] is a universal threshold, which is a function of the noise variance and the length of decomposition. It is defined as,

$$\lambda = \sigma\sqrt{2log(n)}, \qquad where, \sigma = MAD/0.6745,$$

MAD is the median absolute deviation of the coefficients of the finest scale and n is the number of data samples. Often, the initial noise variance is estimated from the wavelet coefficients at the finest transform level, and a normalization by the MAD is applied. This method assumes the noise to be white with Gaussian distribution and the underlying signal of interest to be sufficiently smooth such that only noise is present at high frequencies. A level dependent thresholding of wavelet coefficients is more appropriate for correlated noise. Threshold selection is determined by the manner in which the denoising procedure is optimized: in a mean squared error, minimax, or visually appealing (Visu-shrink) [9] sense. The success of these methods depends entirely on the noise variance used to fix the threshold.

2.2. Filtering methods

The filtering approaches adopted for characterizing the signal vary slightly in different methods. Empirically designed wavelet-domain filters perform superior to those of other denoising algorithms using wavelet thresholding. The two important filtering approaches that are widely investigated in wavelet domain are Wiener filtering and spatially selective filtering, both of which exploit the statistical distribution of the wavelet coefficients. The design of the Wiener filter requires the knowledge of the strength of signal coefficients.

In the case of evoked potentials, this is obtained by using *a posteriori* data. A suboptimal Wiener filter transfer function in the frequency domain is written as,

$$H(\omega) = \frac{\hat{P}_s(\omega)}{\hat{P}_s(\omega) + P_v(\omega)} \quad (2)$$

where $\hat{P}_s(\omega)$ and $P_v(\omega)$ are the estimated power spectra of the signal and the noise, respectively. Similarly, an approximate form of the Wiener filtering in the wavelet domain may be written as [5],

$$\tilde{\theta}(i,j) = \frac{\hat{\Gamma}_s(i,j)}{\hat{\Gamma}_s(i,j) + \Gamma_v(i)} \quad (3)$$

where $\tilde{\theta}(i,j)$ is the Wiener filter transfer function at resolution level i and time j. $\hat{\Gamma}_s(i,j)$ and $\hat{\Gamma}_v(i)$ are the estimated energy density of the signal and noise components at resolution level i and time j. Filtering by (3) preserves time-frequency regions where the signal power is stronger than that of the noise, and attenuates regions where the noise predominates.

3. EP ESTIMATION USING SELECTIVE WIENER FILTERING IN WAVELET DOMAIN

The design of the Wiener filter in the wavelet domain requires the knowledge of noise-free signal coefficients which necessitate a data adaptive or empirical approach that infers the filter directly from the noisy observations. The challenging part is the estimation of smaller signal coefficients. It is felt that a spatially selective filtering strategy is needed because a uniform threshold may not be good enough if the noise is correlated. If we can use additional information, extracted from the noisy observations, to distinguish between the signal and noise coefficients, then spatially adaptive thresholds can be used to reap the benefits of keeping the important signal features while removing most of the noise.

Mallat et al. [12] introduced the concept of complete signal representation by WT domain maxima. They were able to distinguish signal maxima from noise maxima by analyzing the singularity properties of WT domain maxima of a signal across various scales. Witkin [11] first introduced the idea of using space-scale correlation of the subband decompositions of a signal to filter noise from the signal. They used the nonorthogonal wavelet decomposition using undecimated wavelet transform (UDWT. Mallat's multiresolution decomposition [12] and the à trous algorithm [14] are two separate implementations of the discrete wavelet transform. Mallat's method is based on the principle of reducing the redundancy of the information in the transformed data. Moreover, the transform is shift variant. The à trous algorithm results in a non-orthogonal and redundant data set. Depending on the application, each of these models can be advantageously used. Both the algorithms are observed to be special cases of a single filter bank structure [14]. A good improvement is possible in the case of denoising applications by giving up orthogonality and using a redundant and shift invariant discrete wavelet transform. Using direct multiplication of the coefficients across subband decompositions, Witkin was able to distinguish major edges from noise. Xu et al. [10] studied spatial filters in the wavelet domain using inter-scale correlation in the wavelet domain as an alternative to Fourier domain filters. They proposed a spatially selective filter (SSF) based on the space-scale correlations of the subband decompositions of a noisy signal. The major transitions in the signal are tracked from coarse scales to fine scales, thereby distinguishing major signal edges from the background noise. The method relies on the persistence property of the wavelet transform to accomplish the task of filtering noise from signals. A large spatial correlation between the scales is considered to indicate a signal edge. Direct l^{th} order spatial correlation across scales, $corr_l(m,n)$ is defined to be

$$corr_l(m,n) = \Pi_{i=0}^{l-n} w(m+i,n), \qquad n = 1,2,\cdots,N \quad (4)$$

where l is the number of scales involved in the direct multiplication and $m < M - l + 1$, where M is the total number of scales. An edge is identified at any position n for which

$$|corr_l(m,n) > |w(m,n)| \quad (5)$$

This algorithm, which iteratively identifies the important wavelet coefficients in each scale, is well explained in [10].

For the Wiener filter formulation, we use the inter-scale correlation in the wavelet domain as an index to group the wavelet coefficients in each scale into signal and noise dominant coefficients. The powers of signal and noise in each of these groups in each scale are used in (3) to compute a real, scale-dependent Wiener transfer function, in addition to discarding the noise dominant coefficients. The block diagram of the proposed scheme is presented in Fig. 1. The procedure is simple and easy to implement:

- *step 1:* Transform the data into the wavelet domain via the DWT: $\mathbf{y} = \mathbf{W}.\mathbf{x}$
- *step 2:* At each resolution level j, group the empirical wavelet coefficients into disjoint blocks $\{S^j = w(i,j), |w(i,j)| > corr_2(i,j)\}$ and $\{V^j = w'(i,j), |w'(i,j)| < corr_2(i,j)\}$.
- *step 3:* Compute the signal power from $\{S^j\}$ as $\hat{\Gamma}_s(i,j) = w^2(i,j)$ and the noise power from $\{V^j\}$ as $\hat{\Gamma}_s(i,j) = w'^2(i,j)$ to be used in the transfer function in (3).

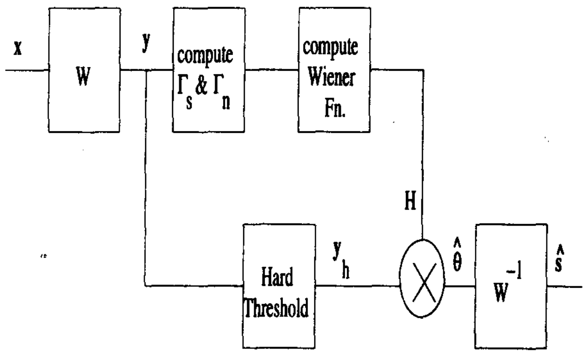

Fig. 1. Block diagram of the spatially selective Wiener filtering in the wavelet domain.

- *step 4:* Hard threshold the scale coeffcients obtained in *step 2* to eliminate the noise dominant coefficients and retain significant coefficients.
- *step 5:* Use the computed scale-dependent weighting factor in the significant signal regions to attenuate the noise.

It is observed that such a two level filtering results in an improved signal estimate. The algorithm is simpler than the one proposed in [13], which is based on multiple orthogonal bases. We present the results obtained using the proposed SSW filter in the next section.

4. DATA USED FOR THE STUDY

The filter technique is tested extensively on simulated and real AEP data. The simulation and the acquisition details of real data are presented in the following subsections.

4.1. Simulated data

A BSAEP which was obtained with the traditional techniques of averaging 512 sweeps of actual human responses sampled at 40 KHz, is used as the original signal, $s(n)$ in (1. To this, simulated EEG is added to generate an ensemble of noisy EP sweeps. The background EEG superimposed on the evoked signal was simulated as an autoregressive process [?] as follows:

$$v(k) = 1.5084v(k-1) - 0.1587v(k-2) - 0.3109v(k-3) - 0.0510v(k-4) + \theta(k) \quad (6)$$

where $\theta(k)$ is white Gaussian noise. The power spectrum of the simulated EEG noise is comparable to actual EEG. This is termed as BSAEP-Sim signal. In our experiments, ensembles of different SNR's are simulated by adding different amounts of noise to $s(n)$.

4.2. Real data

Beckman silver-silver chloride electrodes are applied with conductive paste to sites C_z, P_z, O_z and I_n according to the 10-20 system. All the electrodes are referenced to linked mastoids; the forehead is used as ground. The responses are recorded by repetitive sound stimuli applied as auditory clicks to the ear. In the case of BSAEP signals, the stimulus pulse of 0.1 ms duration is applied with an intensity of 60 dB above normal hearing level. Stimulus click rate is 17 Hz. The low voltage of AEP signals combined with relatively high background noise requires the use of highly sensitive amplifiers and computer averaging equipment. The data is first amplified, then sampled at 40 KHz and quantized to 12 bits. For each stimulus, the first 512 points (or equivalently 12.5 msec) of the response is recorded. The low filter is set to 100 Hz and the high filter to 3000 Hz. We evaluated the performance of the proposed estimator with data simulated at different SNR's. In the case of real data, since there is very little difference between the results obtained on the different normal data, we present the results for one typical case of BSAEP signal.

5. EXPERIMENTAL RESULTS

The proposed algorithm has been tested on both synthesised and real BSAEP signal. Experimental results show that this spatially varying wavelet thresholding yields significantly superior estimation of the signal. We have used mean square error (MSE) to evaluate the performance of the proposed estimator. If s is the required actual signal and $\hat{s}$ is the estimator's output, the MSE is defined as,

$$MSE = E[(s - \hat{s})^2] \quad (7)$$

We compute MSE for different SNR's of the input noisy signal both for simple ensemble average and compare it with the performance of the proposed estimator's output and also with the output obtained using hard thresholding in wavelet domain to objectively evaluate the performance of the proposed technique.

5.1. Results for simulated data

The BSAEP-Sim signal estimated using the proposed technique for different input SNRs is illustrated in Fig. 2. The SNR's of the input noisy signals shown in the first row of Fig. 2 are 1.75 dB, 3.0 dB and 5.0 dB, respectively. The corresponding signals, estimated using SS-W filter, are shown in the second row. The third row displays the original signal for comparison. The significant components of the BSAEP are clearly visible in the estimated output, and facilitate measurement even at a low input SNR of 1.75 dB, al-

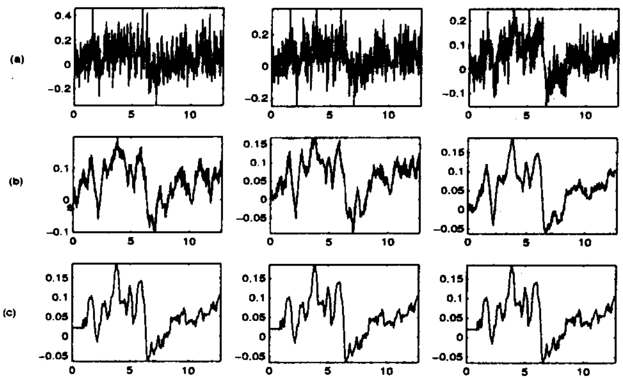

Fig. 2. Signals estimated from BSAEP-Sim at different SNR's. Row (a): BSAEP-Sim signal with input SNRs of 1.75 dB, 3.0 dB and 5.0 dB, respectively. Row (b): Signals estimated using SS-W filtering. Row (c): Original signal.

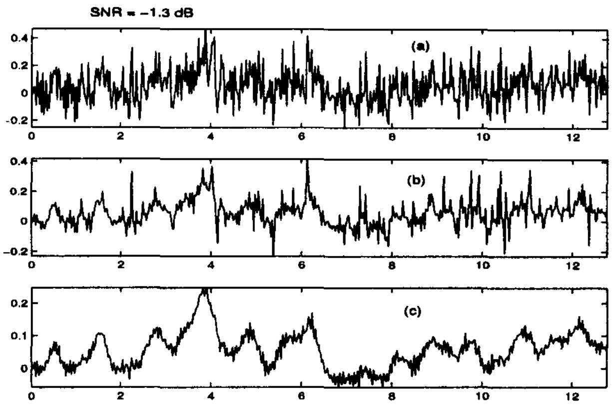

Fig. 3. Comparison of signals estimated from simulated BSAEP using two different techniques. (a) Ensemble averaged BSAEP-Sim signal at a SNR of 3 dB. (b) Output of hard thresholding. (c) Output of SS-W.

though it shows a small amount of residual noise. The residual noise in the estimated signal reduces with increase in the SNR of the input. Figure 3 compares the results obtained by our technique on BSAEP-Sim signal simulated at a SNR of 3 dB to the results achieved by simple hard thresholding. Fig. 3(a) presents the noisy input signal; the corresponding signals estimated using hard thresholding and the SS-W filter are shown in Figs. 3 (b) and (c), respectively. The output of the hard threshold estimator has a large amount of impulse noise and spurious fluctuations at the boundaries of the thresholding masks. This phenomenon is observed for input SNRs less than 3 dB. However, this noise is not present in the signals estimated using our technique.

The performance of the two estimators is also studied in terms of the MSE of the estimated output for different input SNRs. The results of comparison are presented

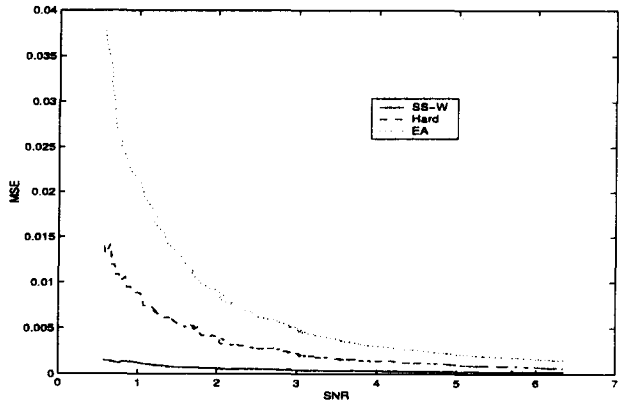

Fig. 4. MSE of the estimated output for different input SNRs. Solid line: SSW filter. Dashed line: Hard thresholding. Dotted line: EA. Input: BSAEPSim.

in Fig. 4, along with the MSE of the simple ensemble average. At any instant, the input to the SS-W filter is the ensemble average up to the current sweep, which may also be termed as current ensemble average (CEA). The SNR for the CEA increases with larger ensemble length. In Fig. 4, the x-axis shows the different input SNR's studied and the y-axis shows the corresponding MSE obtained. It can be seen that for any given CEA or SNR, the MSE of the signal estimated using SS-W is smaller than that obtained using the hard threshold estimator.

5.2. Results for real data

The proposed technique has been tested on a set of real brainstem AEP and middle latency responses. The results obtained are presented in Fig. 5, along with those of hard thresholding. Good and well defined components have been estimated from the noisy observations with the proposed technique. As seen from the figure, the SS-W is clearly superior in estimating the signal.

6. DISCUSSION

Thresholding in a shift-invariant or translation-invariant (TI) expansion eliminates some of the unpleasant artifacts introduced by modifying the coefficients of the orthogonal wavelet expansion. Hence denoising in a shift-invariant, redundant representation outperforms that by the orthogonal basis [?]. The wavelet transform based Wiener filter as described above improves the EP data from repeated trials. A substantial reduction in noise has been observed. This reduction is expected to improve subsequent quantitative analysis for extracting characteristics such as amplitude, width and onset time of individual responses. Spatially selective Wiener filtering is found to be giving better results both vi-

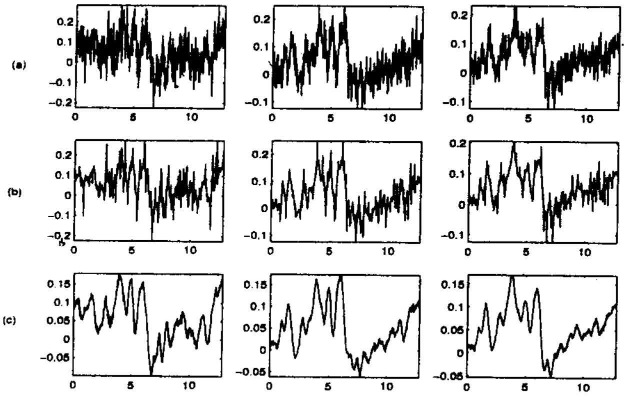

Fig. 5. Real BSAEP signals estimated using SS-W and hard threshold estimators for ensembles of different lengths. row (a): EA of 200, 300 and 400 sweeps, respectively. row (b): Signals estimated using hard thresholding. row (c) Signals estimated using SS-W filter.

sually and in terms of mean square error in comparison with hard thresholding.

Fig. 5 clearly illustrates the effectiveness of the proposed technique. For example, the first column shows that the filtering scheme is able to recover all the signal maxima and minima even from a highly noisy average of an ensemble of just 200 sweeps. Compared to the normal case of a BSAEP which requires a minimum of 2000 sweeps, this is a reduction by a factor of 10. Further, as seen from Fig. 3, hard thresholding introduces unwanted sharp spikes in the resultant waveform, because of which the principal peaks and valleys of the response are not always unambiguously identified. This is because of the phenomenon akin to the Gibbs oscillations. Hard thresholding is equivalent to applying a rectangular window in the wavelet domain, which entails the oscillations seen in the signal (time) domain. On the other hand, the proposed spatially selective Wiener filter results in smooth, clear peaks and valleys, from which measurements can be made easily. For the same input SNR, the MSE of the SSW estimate is always less than that obtained with hard thresholing by a factor of at least 5. This is a significant improvement in performance. In fact, as seen from Fig. 4, at low input SNR's of the order of 0.5 dB, SS-W filter gives rise to a very low MSE, which is comparable to that given by the hard threshold estimator at SNR's of around 4 dB. Results shown in Figs. 5 and **??** confirm that the technique produces equally valid results for real data too.

7. CONCLUSION

In this chapter, we have proposed a two level filtering method for estimating AEP signals. A Wiener filter is formulated exploiting the inter-scale correlation in the wavelet domain. The wavelet transform data at a given scale is compared to its correlation with the data at larger scales. Signal features are identified and retained because they are strongly correlated across scales in the wavelet domain; noise is removed since it is poorly correlated across scales. The signal features remain relatively undistorted because they are very well localized in space in the wavelet domain. The spurious fluctuations normally caused near the end points of the thresholding window in the hard thresholding scheme, and the smearing of the high frequency data due to Wiener filtering are both nullified by using a combination of the two approaches, resulting in an estimated signal far superior to that obtainable by either of them individually.

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