Denoising Functional MRI: A Comparative Study of Different Temporal Techniques

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Abstract - **In this paper, we present a comparative study of different denoising techniques applied to functional magnetic resonance imaging (*fMRI*) sequences. The performance of these techniques was investigated using a simulated *fMRI* time series data with noise levels. The performance of these techniques was evaluated with respect to two quantitative measures; signal-to-noise ration (*SNR*), and shape preservation. As a result of the comparative study it has been found that denoising using Wavelet transform with reverse biorthogonal basis functions provides the best performance among all denoising techniques.**

Keywords - **Functional Magnetic Resonance Imaging (*fMRI*), Signal-to-Noise-Ratio (*SNR*), Hemodynamic Response Function (*HRF*), and Statistical Parametric Mapping (*SPM*)**

I. Introduction

Functional neuroimages often need preprocessing before being subjected to statistical analysis [1]. A common preprocessing step is denoising. In this paper we study different *fMRI* temporal denoising techniques. The performance of these techniques is compared with respect to (i) the improvement of the *SNR*, and (ii) the shape preservation of active region.

The remainder of this paper is organized as follows: Section-II presents an overview of *fMRI* imaging techniques; Section-III presents modeling of *fMRI* data, Section-IV a discussion of the performance evaluation criteria. Classification of different denoising techniques was presented in Section-V. Section-VI presents time domain denoising techniques. Section-VII provides transformed domain techniques. In Sections IIX and IX the results and conclusions were presented, respectively.

II. Overview of FMRI

Functional neuro-imaging is a fast evolving area aimed at measuring brain activity during task performance [2]. *FMRI* is the most recently developed modality, which distinguishes itself from earlier methods (e.g. *PET*, *SPECT*, etc.) in that no exposure to ionizing radiation is evolved, better spatial and temporal resolution is achieved, and a relatively straightforward co-registration to anatomical MRIs acquired on the same machine can be attained.

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The main problem associated with *fMRI* techniques is the poor signal-to-noise ratio (*SNR*), where the intensity of the detected *MRI* signal is mainly dependent on the applied static field, (e.g. the maximum signal change is 5% for $B_0 = 1.5T$). Therefore, a preprocessing step for noise reduction is necessary, in order to improve the *SNR*.

In general, *fMRI* time-courses can be modeled as the summation of the activation signal, physiologic and random noise components [3, 4]. Let us assume the observed signal $x(k)$, the activation signal $s(k)$, and the composite noise $n(k)$, representing all types of artifacts, then

$$x(k) = s(k) + n(k) \tag{1}$$

III. Modeling FMRI Data

Simulating a set of *fMRI* time series representing the brain function under both resting and activated states would cover, in general, both temporal and spatial variations in time courses, in this work only temporal variations are considered [3, 4].

A. Modeling the HRF

HRF refers to the local changes in blood oxygenation as an effect of increased neuronal activity [4, 5]. The *HRF* to a sensory input is transient, delayed and dispersed in time. Fig.1 shows the simulated *HRF* of the from

$$s(k) = \left(1 - exp\left(-\frac{k}{T_1}\right)\right)^3 .exp\left(-\frac{k}{T_2}\right) \tag{2}$$

where T_1 and T_2 are constants that can be adjusted to obtain the desired shape, and k represents the sampling time (i.e. the number of samples within each epoch). In the described simulation $T_1 = 5.0$ and $T_2 = 7.5$.

B. Physiologic Noise

Physiologic noise is composed of respiration, a signal of high amplitude and long duration, and cardiac pulsation; a signal of low amplitude and short duration [3]. This noise type was simulated as a periodic signal consisting of two fundamental frequencies, $1\,Hz$ and $0.2\,Hz$, and the first three harmonics superimposed on a small dc as shown in Fig.2. The choice of these frequencies is based on a heart rate of *60 beats/min,* and respiration rate of *12 breaths/min.*

C. Random Noise

Random noise introduced to *fMRI* due to imaging system itself, subject motion, etc. Random noise was simulated using random number generator, shown in Fig.3.

D. Composite Noise

During the measurement of real *fMRI* signals all types of *MRI* artifacts simultaneously corrupt the measured signal. Therefore, the composite noise is the summation of scaled versions of all previously simulated artifacts [2]. Fig.4 shows a simulated *HRF* corrupted with composite noise.

IV. The Performance Evaluation Criteria

The performance of all the denoising techniques was evaluated using two different quantitative measures. These measures are shortly described below.

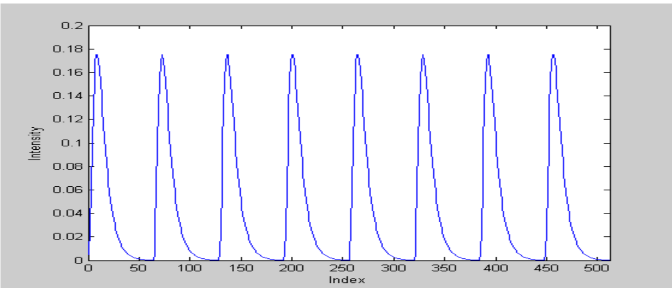

Fig.1 The simulated HRF for 8 epochs each has 64 samples.

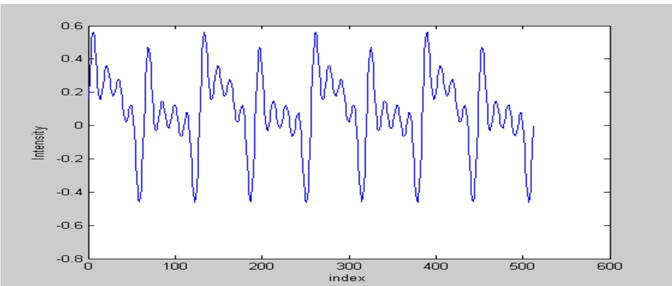

Fig.2 Simulated physiologic noise for 8 epochs each has 64 samples.

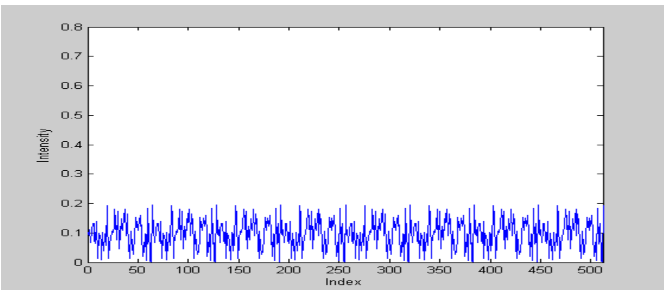

Fig.3 Simulated random noise for 8 epochs each has 64 samples.

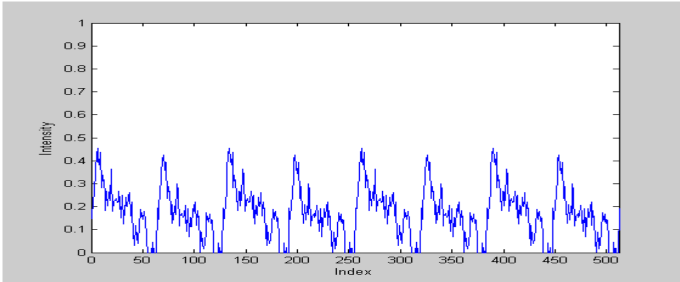

Fig.4 Simulated random noise for 8 epochs each has 64 samples.

A. Signal-to-Noise-Ratio (SNR)

SNR is an important quantitative measure for evaluating the performance of the applied technique. In which, *SNR* is computed and compared before and after denoising [1]. In this article the *SNR* is defined as

$$SNR = \left(\frac{Variance\ of\ Pure\ Information}{Variance\ of\ Additive\ Noise} \right) \tag{3}$$

B. Shape Preservation

This parameter may be estimated using the correlation coefficient (*R*) between the original *x* and output *y* signals [1, 6]:

$$R = \frac{\sum_i (x_i - \tilde{x})(y_i - \tilde{y})}{\sqrt{\sum_i (x_i - \tilde{x})^2 \sum_i (y_i - \tilde{y})^2}} \tag{4}$$

V. Denoising Techniques

Denoising techniques can be classified into temporal and transformed techniques. Here, two temporal denoising techniques will be discussed; (i) linear, and (ii) nonlinear. On the other hand, in transformed domain (i) frequency domain, and (ii) wavelet domain techniques, will be discussed.

VI. Temporal Denoising Techniques

A. Linear Filters

Linear filters tend to destroy oscillations and other fine details, and perform poorly in the presence of signal dependent noise, physiologic noise [7, 8].

1. Mean Filters

The mean techniques is a simple, intuitive and easy to implement method of smoothing data, *i.e.* reducing the amount of intensity variation between one sample and its neighbors [7].

2. Gaussian Filters

The Gaussian smoothing operator is a convolutional operator, similar to the mean filter [7], but it uses different weights representing the shape of a Gaussian distribution

$$h(i) = \frac{1}{\sqrt{2\pi}\sigma} exp\left(-\frac{(i-m)^2}{2\sigma^2}\right) \tag{5}$$

where σ is the standard deviation, and m is the mean value.

3. Wiener Filter

Wiener filter is the solution of the linear minimum squared error problem of estimating a signal s, from a measured signal x using a filter, $h(k)$. It can be shown easily that the frequency response of the non-causal Wiener filter is

$$H(w) = \frac{P_s(w)}{P_s(w) + P_n(w)} \tag{6}$$

where $P_S(w)$ and $P_n(w)$ represent the power spectral density of the original signal and noise, respectively. Intuitively, the action of Eq.6 is to keep frequency bands where the signal power is much stronger that that of the noise and to severely attenuate frequencies where noise predominates. A natural extension of the Wiener filter is to allow it to be time-varying. In principle, this should only require substituting the signal and noise power spectral densities with their time-dependent counterparts [5].

4. Coherent Average

Coherent average (*CA*) assumes that a series of M equidistant and identical stimuli are applied to the system, and the following assumptions were satisfied [9]; (i) The response $s(k)$ will be complete before the next stimulus occurs, and invariant with time, (ii) The delay time between stimulus and the start of the response is constant, and (iii) The noise $n(k)$ has the properties; additive, uncorrelated with either the stimulus or the response, stationary. The *CA* signal $y(k)$ follows from

$$y(k) = \frac{1}{M} \sum_{i=0}^{M-1} x(k + iT) \tag{7}$$

5. Robust Weighted Average (RWA)

In case non-stationary artifacts, it is better to use an adaptive weighted average filter; called robust weighted average. *RWA* should have a set of properties given by Huber et al in [10]. Here, the main problem is the estimation of the noise power spectrum, in order to evaluate the adaptive weight. The weighted average is given by

$$y(k) = \tilde{x}(k) = \sum_{i=1}^{N} w_i x_i(k) \tag{8}$$

where w_i is the weight matrix.

B. Non-Linear Filters

In non-linear filters, noise is removed without any attempt to identify it [7, 8], where, the filters employ a low pass filter on groups of samples with the assumption that the noise occupies the high frequency spectrum.

1. Median Filters

Median filter often does a better job than the mean filter of preserving useful detail in the data. Like the mean filter, the median filter considers each sample in the data in turn and looks at its nearby neighbors to decide whether or not it is representative of its surroundings [8].

2. Weighted Median (WM) Filters

Weighted median filters can be defined in two distinct ways; however both definitions give exactly the same output [11]. *WM* filters are special case of weighted ordered statistic filters. There are two familiar weighted median techniques; positive integer weights and positive non-integer weights [11].

$$y(k) = med\left[\sum_{i=1}^{N} w_i x(k+i)\right] \tag{9}$$

VII. TRANSFORMED DOMAIN TECHNIQUES

A. Frequency Domain Techniques

In frequency smoothing methods the removal of noise is achieved by designing a frequency domain filter. These methods are time consuming and depend mainly on the filter characteristics [8].

1. Spectrum Subtraction (SS)

The spectral subtraction provides an estimate of the signal spectrum as the difference between the noisy spectrum and an estimate of the noise spectrum [12]. The corresponding power spectra would therefore related by

$$P_S(w) = P_X(w) - P_N(w) \tag{10}$$

where $P_{S(w)}$ and $P_X(w)$ are the power spectra of the original and measured pixel time-course, respectively. The power spectrum of the noise, $P_N(w)$, can be estimated from locations where the deterministic signal is absent. Here, the amplitude square of the Fourier transform is used as the periodgram estimate of the power spectrum. Spectrum subtraction may result in negative estimated of the power spectrum, in which case they would have to be mapped to non-negative values, here mapped to zero. The estimate Fourier transform of the recovered signal, in terms of power and phase, is given by

$$Y(w) = \sqrt{P_s(w)}.e^{j\theta_X(w)} \tag{11}$$

Finally, the signal $y(k)$ can be obtained by taking the inverse *FFT* of the Fourier transform of Eq.11.

B. Wavelet Domain Filters

Wavelet bases are bases of nested function spaces, which can be used to analyze signals at multiple scales. Wavelet coefficients carry both time and frequency information, as the basis functions varies in position and scale. The wavelet transform efficiently converts a signal to its wavelet representations; in one level a signal x is splitted into an approximate part cx_1 and a detail part dx_1 [7, 8, and 13]. In multilevel decomposition, only the approximate part is further decomposed.

1. Thresholding Wavelet Coefficients

The wavelab package contains a number of schemes for the wavelet-based denoising [14], based on thresholding detail coefficients in the wavelet domain. There are two main thresholding techniques; (i) soft thresholding, and (ii) hard thresholding [15].

2. Wavelet Packet Transform

Wavelet packets *(WP)* are waveforms indexed by three naturally interpreted parameters: position, scale, and frequency [16] for a given orthogonal wavelet function, a library of bases called *wavelet packet bases* were generated. The decomposition parameters of a given dataset are chosen based on an entropy-based criterion. The main difference between wavelet transform and *WP* is that, in *WP* both approximate and detail coefficients are decomposed, instead of approximate coefficients in the case of wavelet transform.

3. Smoothing Wavelet Coefficients

Major interests of the recent papers on the noise reduction using wavelet transform are the determination of the wavelet transform and the choice of thresholding parameters [16]. Thresholding in wavelet domain is to smooth or to remove some coefficients of wavelet transform of the measured signal. Through the thresholding operation, the noise content of the signal is reduced effectively under the non-stationary environment. In this part, a *LPF* was used to smooth the wavelet transform coefficients instead of thresholding method.

VIII. RESULTS

The following set of tables and figures show the results of applying different denoising techniques in both time domain and transformed domain. Six levels of *SNR* were used. These are: 0.25, 0.50, 0.75, 1.0, 2.0, and 3.0. Some techniques require certain parameters, which are determined via trial and error approaches. Tables from 1 to 3 give the output *SNR*, while tables from 4 to 6 provide the values of *R* between noisy input and the filtered signal at each level of noise. It has been found that using a transformed technique based on wavelet transform of mother function reversed biorthogonal of order 2.8 and soft thresholding of balanced sparcity norm will give the best performance from the point of view of *SNR* and *R*.

IX. CONCLUSION

We have compared temporal smoothing and transformed denoising techniques for a simulated *fMRI* time-series. Summarizing all the presented results of the comparative study, it was found that the wavelet transform based on reversed biorthogonal of order 2.8 basis function and soft thresholding with balanced sparcity norm, provides the best denoising from the point of view of *SNR*, and correlation coefficient.

Table.1: Results of applying temporal filters

Filter Type	SNR_i					
	0.25	0.50	0.75	1.00	2.00	3.00
Mean	3.46	5.15	5.89	6.33	7.07	7.32
Med	2.84	4.00	5.05	5.98	8.74	10.66
Wiener	7.74	7.36	7.18	7.06	6.84	6.75
Gaus	6.65	6.65	6.65	6.65	6.65	9.23
C.A.	1.27	2.67	3.99	5.13	8.60	11.01
RWA.	4.68	4.83	4.99	5.29	6.18	6.94
S.S.	1.10	2.00	2.75	3.39	5.24	6.44

Table.2: Results of applying wavelet transform

Filter Type	SNR_i					
	0.25	0.50	0.75	1.00	2.00	3.00
DB.3	1.31	2.48	3.52	4.47	7.55	10.15
Sym.5	1.31	2.48	3.52	4.47	7.55	10.15
Mey.	1.36	2.66	3.93	5.15	9.68	13.74
Haar	1.33	2.36	3.19	3.92	6.41	8.62
Bior	1.33	2.63	3.91	5.16	10.02	14.60
Rbior	1.47	2.91	4.31	5.69	10.91	15.72
Coif.3	1.47	2.90	4.31	5.69	10.91	15.72

Table.3: Results of applying wavelet packet

Filter Type	SNR_i					
	0.25	0.50	0.75	1.00	2.00	3.00
DB.3	1.11	2.21	3.24	4.18	7.58	10.16
Sym.5	1.11	2. 21	3.24	4.18	7.58	10.16
Mey.	1.16	2.36	3.57	4.80	9.61	14.00
Haar	1.14	2.14	3.03	3.85	6.57	8.54
Bior	1.20	2.50	3.82	5.13	10.68	15.63
Rbior	1.11	2.30	3.46	4.72	9.88	14.99
Coif.3	1.21	2.40	3.58	4.74	8.70	11.69

Table.4: Correlation coefficients of temporal filters						
Filter	SNR_i					
Type	0.25	0.50	0.75	1.00	2.00	3.00
Mean	0.56	0.65	0.70	0.78	0.81	0.87
Median	0.60	0.67	0.73	0.79	0.86	0.91
Wiener	0.72	0.79	0.82	0.87	0.91	0.94
Gauss.	0.67	0.73	0.80	0.85	0.90	0.92
C.A.	0.70	0.73	0.81	0.87	0.90	0.91
R.W.M.	0.69	0.71	0.82	0.85	0.87	0.89
S.S.	0.67	0.70	0.76	0.80	0.84	0.88

Table.5: Correlation coefficients of wavelet transform						
Filter	SNR_i					
Type	0.25	0.50	0.75	1.00	2.00	3.00
DB.3	0.69	0.78	0.86	0.91	0.94	0.95
Sym.5	0.69	0.78	0.86	0.91	0.94	0.95
Meyer	0.71	0.81	0.85	0.88	0.93	0.96
Haar	0.64	0.74	0.78	0.82	0.88	0.91
Bior	0.71	0.81	0.86	0.88	0.94	0.95
Rbior	0.73	0.83	0.87	0.89	0.94	0.96
Coif.3	0.71	0.80	0.85	0.87	0.92	0.94

Table.6: Correlation coefficients of wavelet packet						
Filter	SNR_i					
Type	0.25	0.50	0.75	1.00	2.00	3.00
DB.3	0.69	0.80	0.85	0.88	0.94	0.96
Sym.5	0.66	0.77	0.82	0.85	0.91	0.93
Meyer	0.68	0.79	0.84	0.88	0.93	0.95
Haar	0.62	0.73	0.78	0.82	0.88	0.91
Bior	0.69	0.80	0.86	0.89	0.94	0.96
Rbior	0.67	0.79	0.84	0.87	0.94	0.96
Coif.3	0.68	0.79	0.84	0.87	0.94	0.96

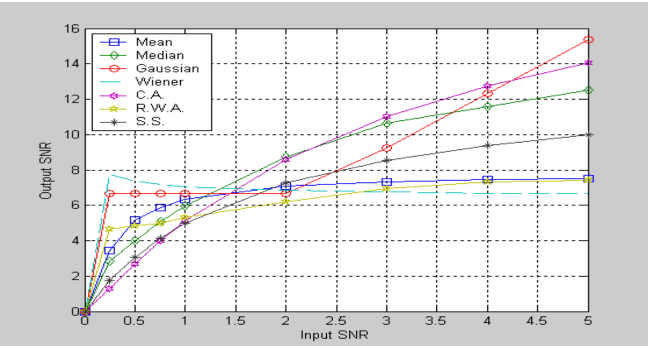

Fig.5 The results of SNR_o for temporal techniques.

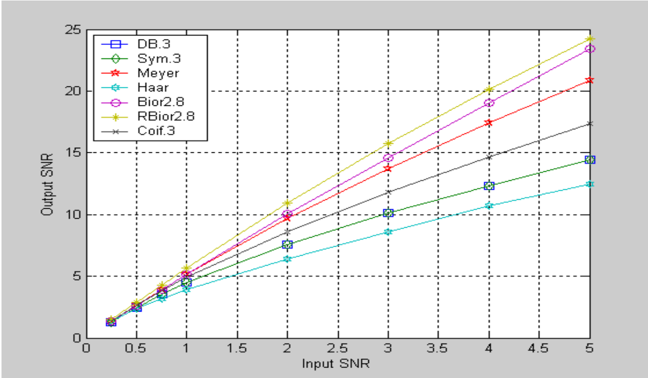

Fig.6 The results of SNR_o for wavelet transform.

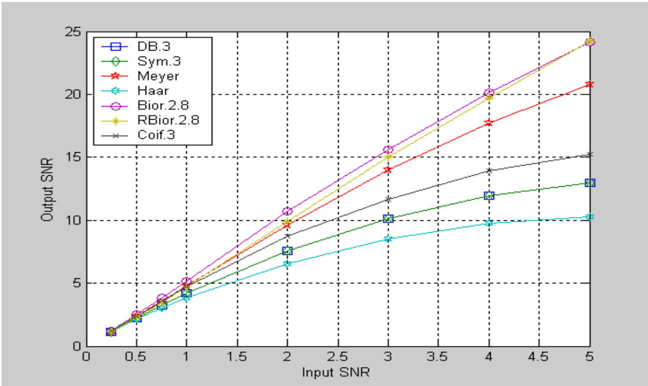

Fig.7 The results of SNR_o for wavelet packet.

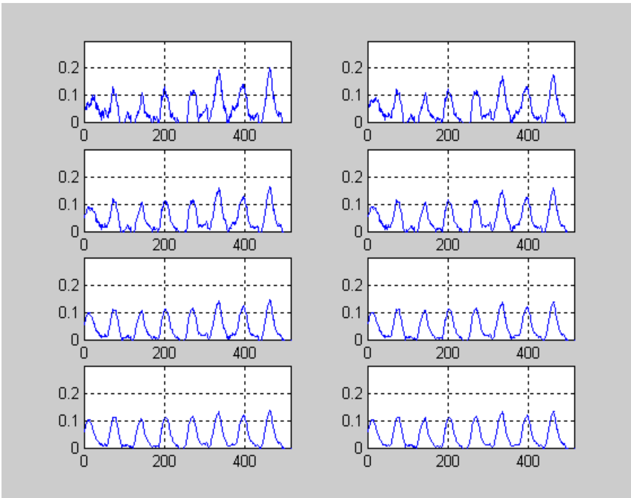

Fig.8 The output signal of robust weighted average.

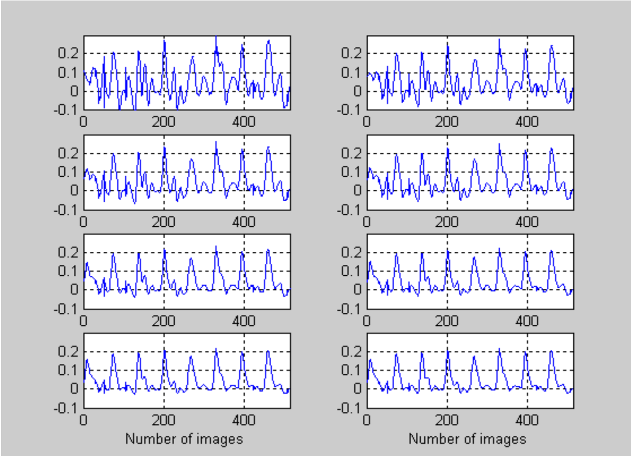

Fig.9 The output signal of wavelet transform based on reversed biorthogonal.

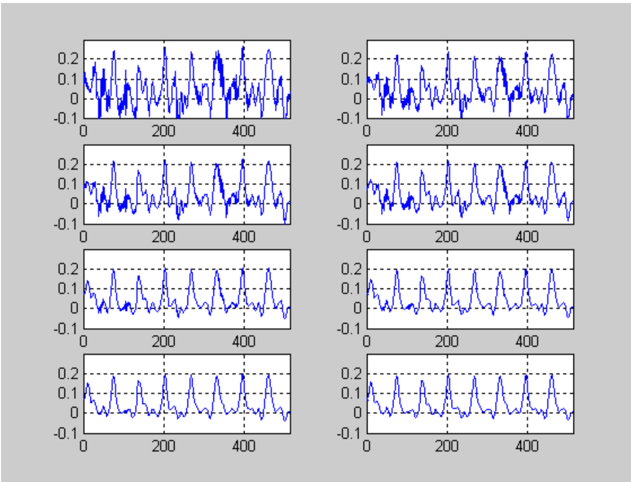

Fig.10 The output signal of wavelet packet based on reversed biorthogonal.

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