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Denoising of Transient VEP Signals Using Wavelet Transform

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Abstract: Transient Visual Evoked Potential (TVEP) is an important diagnostic test for specific ophthalmologic and neurological disorders. TVEP investigation is focused on the dominant peaks N75, P100, N145, a negative deflection followed by a positive deflection and then a negative deflection. Quantification of these latency changes can contribute to the detection of possible abnormalities. We have applied the wavelet denoising method to 100 pre-recorded signals using all the available wavelets in MATLAB wavelet toolbox to analyze the peaks (P100, N75 and N145). From the results it is clear that the positive peak is clearer in the denoised version of the signal using the wavelets Sym5 and Bior3.5. As opposed to the previous studies however our study clearly shows that the output using the former wavelet effectively brings out the P100 when compared to the latter. The first negative peak was clear in the denoised version of the signal using the wavelets Bior5.5 Bior6.8 and coif4. The second negative peak N145 was clear using all the above wavelets. In conclusion all the three peaks were fairly clear in the denoised output using the wavelet sym7. This would greatly help the medical practitioners. All the previous studies concentrated on the P100 only. Using the proposed method all three peaks could be analyzed in detail.

Key words: Transient visual evoked potentials, wavelet transform, denoising

INTRODUCTIONS

Eps are the alterations of the ongoing EEG due to stimulation (e.g., tone, light flash, etc.). They are time locked to the stimulus and they have a characteristic pattern of response that is more or less reproducible under similar experimental conditions. In order to study the response of the brain to different tasks, sequences of stimuli can be arranged according to well-defined paradigms. This allows the study of different sensitive or cognitive functions, states, pathologies, etc., thus making the EPs an invaluable tool in neurophysiology. Transient Visual Evoked Potential (TVEP) is an important diagnostic test for specific ophthalmologic and neurological disorders. TVEP investigation is focused on the dominant peaks N75, P100, N145, a negative deflection followed by a positive deflection and then a negative deflection. Quantification of these latency changes can contribute to the detection of possible abnormalities[1-3].

Due to the low amplitudes of EPs in comparison with the ongoing EEG, they are hardly seen in the original EEG signal and therefore several trials (i.e., data segments including the pre-and post-stimulus activity) are averaged in order to enhance the evoked responses. Since EPs are time locked to the stimulus, their contribution will add while the ongoing EEG will cancel.

However, when averaging, information related with variations between the single trials is lost. This information could be relevant in order to study behavioral and functional processes, habituation, refractoriness and it could also help to identify pathologies when the information from the average EP is not clear. Moreover, in many cases a compromise must be made when deciding on the number of trials in an experiment. If we take a large number of trials we optimize the EP/EEG ratio but if the number of trial is too large, then we could deal with effects such as tiredness, which eventually corrupts the average results. This problem can be partially solved by taking sub-ensemble averages (i.e. consecutive averages of a few single sweeps). However, in many cases the success of such procedure is limited, especially when not many trials can be obtained or when characteristics of the EPs change from trial to trial.

Several methods have been proposed in order to filter averaged EPs. The success of such methods would imply the need of less number of trials and would eventually allow the extraction of *single trial EPs* from the background EEG. Although averaging has been used since the middle 1950s, up to now none of these attempts has been successful in obtaining single trial EPs, at least in a level that they could be applied to different types of Eps and that they could be implemented in clinical

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settings. Most of these approaches involves Wiener filtering (or a minimum mean square error filter based on auto-and cross-correlations) and have the common drawback of considering the signal as a stationary process. Since EPs are transient responses related with specific time and frequency locations, such time-invariant approaches are not likely to give optimal results. For this reason, de Weerd and coworker introduced a time-varying generalization for filtering averaged EPs. The time-variant Wiener filter they proposed is clearly more suitable for the analysis of EPs but with the caveats that such filter bank implementation does not give a perfect reconstruction and that it is based on the Fourier transform (therefore the signal being decomposed in bases of sines and cosines with the drawbacks that this imposes, as we will describe later). Using the wavelet formalism can solve these limitations, as well as the ones related with time-invariant methods[4-6].

The wavelet transform is a time-frequency representation proposed first in, that has an optimal resolution both in the time and frequency domains and has been successfully applied to the study of EEG-EP signals. The objective of the present study is to follow an idea originally proposed and to present a very straightforward method based on the wavelet transform to obtain the evoked responses at the single trial level. The key point in the denoising of Eps is how to select in the wavelet domain the activity representing the signal (the EPs) and then eliminate the one related with noise (the background EEG[7-10].

In fact, the main difference between our implementation and previous related approaches is in the way that the wavelet coefficients are selected. Briefly, such choice should consider latency variations between the single trial responses and it should not introduce spurious effects in the time range where the EPs are expected to occur. In this respect, the denoising implementation we propose will allow the study of variability between single trials, information that could have high physiological relevance.

MATERIALS AND METHODS

Experiments were carried with subjects in the Neurology Department of the leading Medical Institute. TVEP was performed in a specially equipped electro diagnostic procedure room (darkened, sound attenuated room). Initially, the patient was made to sit comfortably approximately 1m away from the pattern-shift screen. Subjects were placed in front of a black and white checkerboard pattern displayed on a video monitor. The checks alternate black/white to white/black at a rate of approximately twice per second. Every time the pattern alternates, the patient's visual system generates an electrical response that was detected and was recorded by surface electrodes, which were placed on the scalp overlaying the occipital and parietal regions with reference electrodes in the ear. The patient was asked to focus his gaze onto the center of the screen. Each eye was tested separately (monocular testing). Scalp recordings were obtained from the left occipital (O1) electrode (near to the location of the visual primary sensory area) with linked earlobes reference. Sampling rate was 250 Hz and after band pass filtering in the range 0.1-70 Hz, 2 s of data (256 data pre-and post-stimulations) were saved on a hard disk.

Denoising of Eps: As proposed by Donoho, the conventional definition of denoising implies a thresholding criterion in the wavelet domain. The signal is recovered from noisy data just by setting to zero those wavelet coefficients below a certain threshold (*hard denoising*) or with the use of a smoother transformation (*soft denoising*). However, this procedure is not optimal for recovering the EPs because these ones are of the order or even smaller than the background EEG. Therefore, instead of using a thresholding criterion, we implemented a denoising based on the specific time and frequency localizations of the evoked responses.

The gray curves in Fig. 1 show the decomposition of an averaged (over 30 trials) VEP. In this we used five levels decomposition, thus having five scales of details (D1-D5) and a final approximation (A5). On the left-hand side we plot the wavelet coefficients and on the right-hand side the actual components/decomposition. The sum of all the reconstructions gives again the original signal (gray curve of the uppermost right plot). The lower levels give the details corresponding to the high frequency components and the higher ones correspond to the low frequencies.

Note in Fig. 1 that the P100 response is correlated mostly with the first post-stimulus coefficients in the details D4-D5. In consequence, a straightforward way to avoid the fluctuations related with the ongoing EEG and get only the peaks of interest, is just by equaling to zero those coefficients not correlated with the TVEPs. The black traces in the left-hand side of Figure show the coefficients kept for the reconstruction of the P100 response and the black curves on the right-hand side show the contributions of each level obtained by eliminating all the other coefficients. Note that in the final reconstruction of the averaged response (black curve in the uppermost right plot) background EEG oscillations are cancelled. We should remark that this is usually difficult

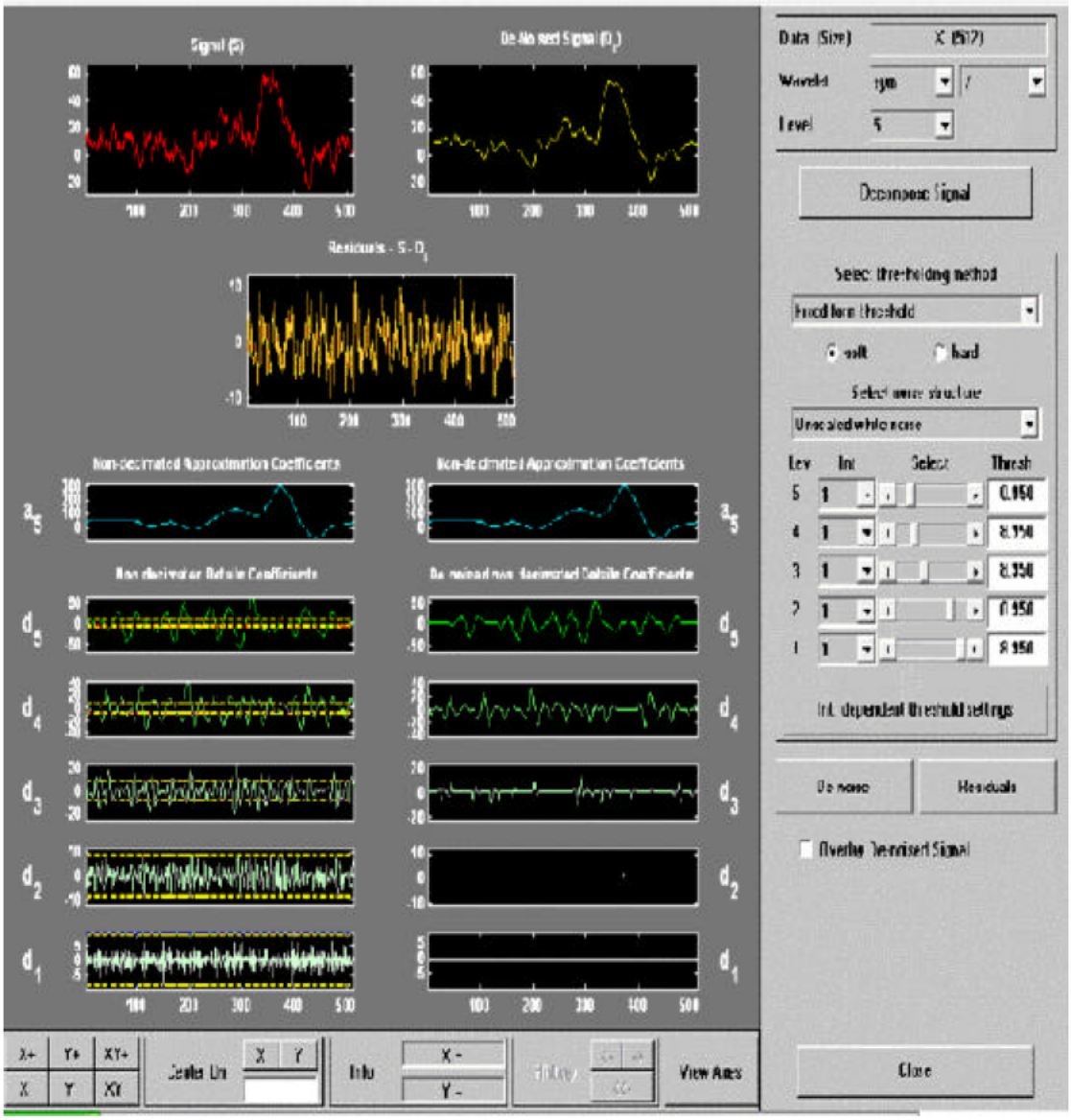

Fig. 1: MATLAB wavelet decomposition window

to achieve with a Fourier filtering approach (especially in averages of less number of trials) due to the different time and frequency localizations of the P100 response and overlapping frequency components of these peaks and the ongoing EEG. In this context, the main advantage of wavelet denoising over conventional filtering is that we can select different time windows for the different scales. Since TVEPs are activity time locked to the stimulation, we could use this feature to reconstruct the contribution of the single trials to the averaged TVEPs. This will allow the visualization of the TVEPs at the single trial level. Let us remark a critical point when implementing the denoising of the TVEPs. This is the choice of which coefficients to keep and which to eliminate. On one hand, choosing a wide range of scales (frequency window) allows a better reconstruction of the morphology of the TVEPs (again we remark that the selection of an appropriate wavelet function plays an important role in this respect). Also, choosing a wide time window of coefficients makes the method more sensitive to latency differences (jitters) between trials (in the extreme case of keeping one single coefficient, the denoised signal will be just the wavelet function with its amplitude proportional to the coefficient). On the other hand, if we choose a wide (conservative) range of coefficients we would not eliminate the background EEG activity in order to

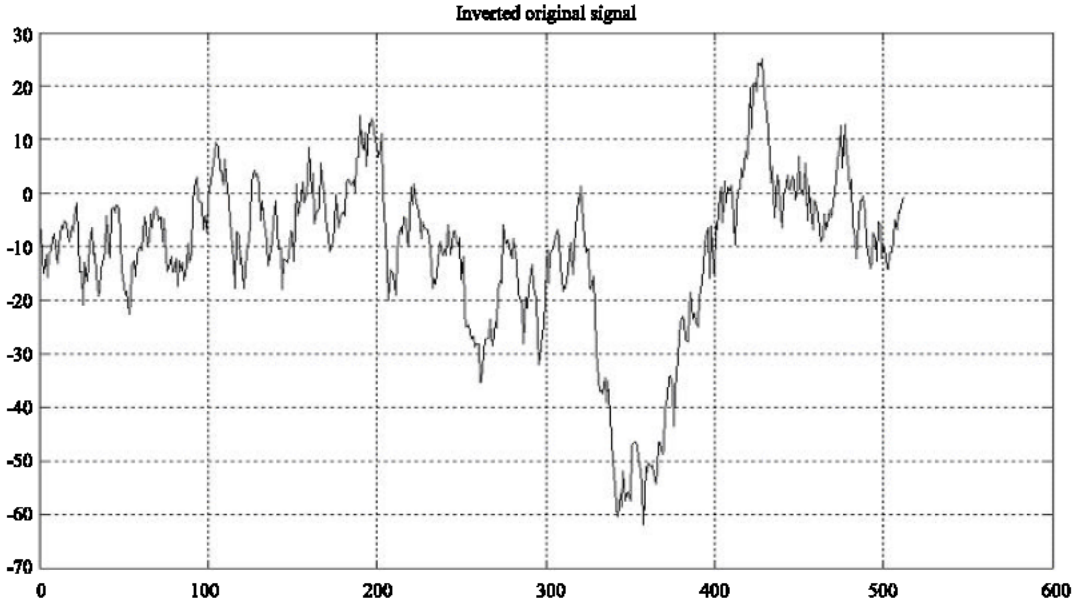

Fig. 2: TVEP without denoising

recognize the TVEPs (in the extreme case of keeping all coefficients we will just reconstruct the original signal). In this respect we propose to use test signals, such as a spontaneous EEG (or a pre-stimulus EEG segment) in order to check for eventual spurious interpretations due to an unfortunate selection of the coefficients. We heuristically found the selection of those coefficients remarked in black traces in Figure an optimal compromise between TVEP resolution and sensitivity to variations between trials. They allow the visualization of the single trial TVEPs and also they cover a reasonable time and scale ranges where the TVEPs are physiologically expected to occur. We should also mention that the wavelet coefficients to be kept could be smoothed by using, e.g. *soft thresholding* in order to decrease border effects. Although the *hard thresholding* we used can introduce spurious border fluctuations (e.g., in Figure the positive deflection in the denoised signal between-0:2 and 0 s), these are outside the time range of physiological interest of the evoked responses. In short the method consists of the following steps:

- The averaged EP is decomposed by using the wavelet multiresolution decomposition.
- The wavelet coefficients not correlated with the average EP (but also considering a time range in which single trial EPs are expected to occur) are identified and set to zero.
- The inverse transform is applied, thus obtaining a denoised signal.
- The denoising transform defined by the previous steps is applied to the single trials.
- Finally, validity of the results can be checked by applying the method to EEG test signals.

RESULTS AND DISCUSSION

We have applied the denoising method stated above to a number of pre-recorded signals using all the available wavelets to analyze the peaks (P100, N75 and N145) as they are of high importance in medical diagnosis.

From the waveforms shown in Fig. 2 and 3 it is clear that the positive peak is clearer in the denoised version of the signal using the wavelets Sym5 and Bior3.5. As opposed to the previous studies however our study clearly shows that the output using the former wavelet effectively brings out the P100 when compared to the latter. The first negative peak was clear in the denoised version of the signal using the wavelets Bior5.5 Bior6.8 and coif4. The second negative peak was clear using all the above wavelets. In conclusion all the three peaks were fairly clear in the denoised output using the wavelet sym7. This would greatly help the medical practitioners.

Here are some samples of the denoised signals using various wavelets. The first figure shows us the original signal recorded (inverted). The next figure shows us the denoised signal using different wavelets.

In fact, there are many different functions suitable as wavelets, each one having different characteristics that are more or less appropriate depending on the application.

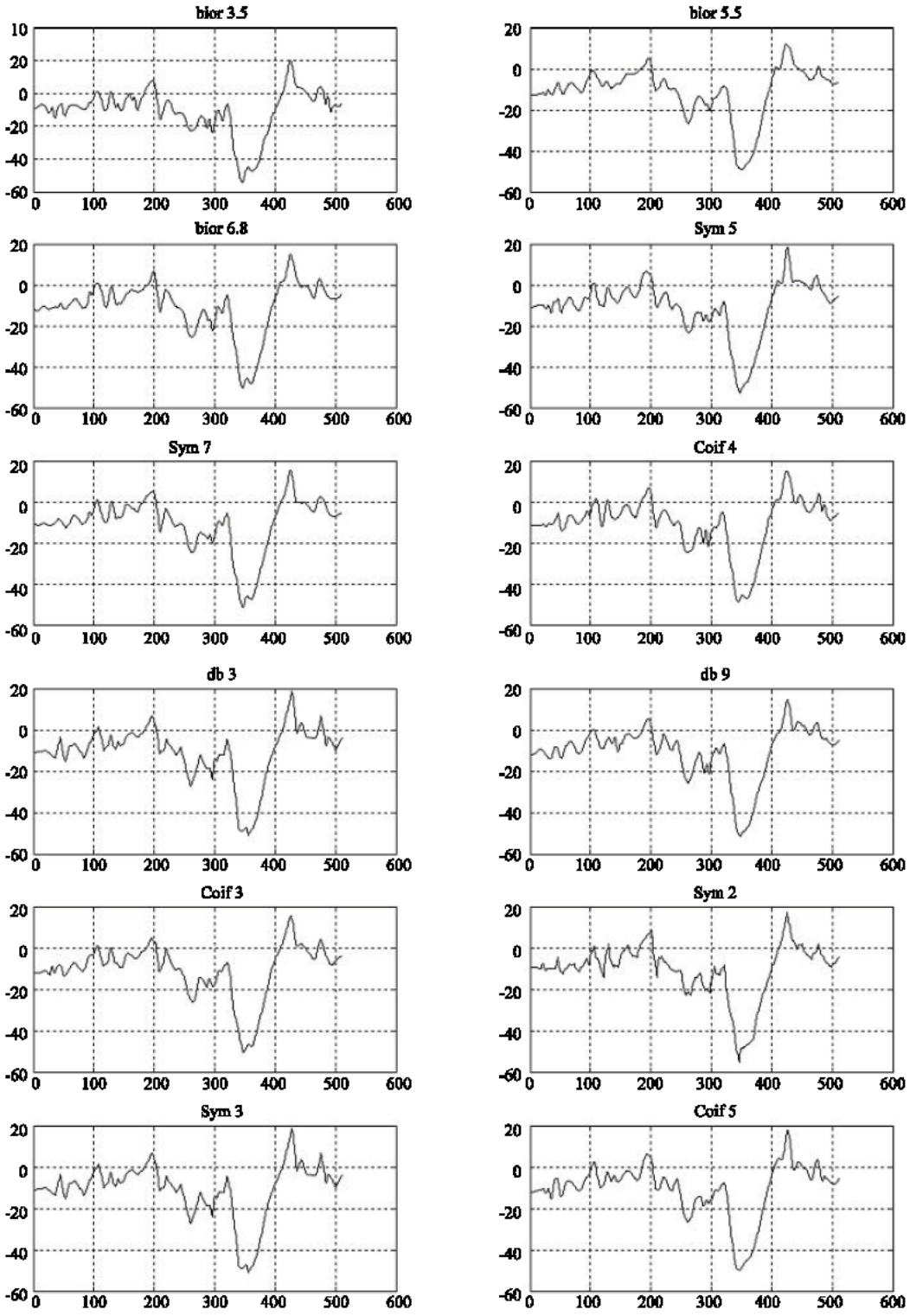

Fig. 3: Denoised TVEP with different wavelets

Irrespective of the mathematical properties of the wavelet to choose, a basic requirement is that it looks similar to the patterns we want to localize in the signal. This allows a good localization of the structures of interest in the

wavelet domain and moreover, it minimizes spurious effects in the reconstruction of the signal via the inverse wavelet transform. For this, the previous analysis have been done by choosing quadratic biorthogonal B-splines as mother functions due to their similarity with the evoked responses[7-9]. B-splines are piecewise polynomials that form a base in L^2. But our analysis says that there is more wavelets that can be used which are similar to TVEPs.

CONCLUSION

We presented a method for extracting EPs from the background EEG. It is not limited to the study of EPs/EEGs and similar implementations can be used for recognizing transients even in signals with low signal-to-noise ratio. The denoising of EPs allowed the study of the variability between the single responses, information that could have a high physiological relevance in the study of different brain functions, states or pathologies. It could also be used to eliminate artifacts that do not appear in the same time and frequency ranges of the relevant evoked responses. In passing, we showed that the method gives better averaged Eps due to the high time-frequency resolution of the wavelet transform, this being hard to achieve with conventional Fourier filters. Moreover, since trials with good evoked responses can be easily identified, it was possible to do selective averages or even jitter corrected ones, with a resulting better definition of the averaged EPs. These advantages could significantly reduce the minimum number of trials necessary in a recording session, something of high importance for avoiding behavioral changes during the recording (e.g., effects of tiredness) or, even more interesting, for obtaining Eps under strongly varying conditions, as with children, or patients with attentional problems. The main difference with these authors is in the criteria for selecting the wavelet coefficients. This is crucial for obtaining an optimal implementation that is physiologically plausible (e.g., allowing variations between trials) and that minimizes the presence of spurious effects in the time range of the evoked responses.

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