A Wavelet Based Algorithm for the Identification of Oscillatory Event-Related Potential Components

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Abstract

Event Related Potentials (ERPs) are very feeble alterations in the ongoing Electroencephalogram (EEG) and their detection is a challenging problem. Based on the unique time-based parameters derived from wavelet coefficients and the asymmetry property of wavelets a novel algorithm to separate ERP components in single-trial EEG data is described. Though illustrated as a specific application to N170 ERP detection, the algorithm is a generalized approach that can be easily adapted to isolate different kinds of ERP components. The algorithm detected the N170 ERP component with a high level of accuracy. We demonstrate that the asymmetry method is more accurate than the matching wavelet algorithm and t-CWT method by 48.67 and 8.03 percent respectively. This paper provides an off-line demonstration of the algorithm and considers issues related to the extension of the algorithm to real-time applications.

Keywords: Single-trial EEG, Wavelet asymmetry, N170 ERP detection

1. Introduction

The ability to detect single-trial event related potentials (ERPs) in real-time EEG signals has many clinical and research applications, particularly in

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the field of brain computer interfaces (Barret, 2000; Birbaumer et al., 2008). ERPs appear as dynamic alterations in ongoing EEG frequency components that are very feeble signals compared to background EEG and have low signal-to-noise ratio when recorded from electrodes attached to the scalp. Detection of ERP components from real-time EEG is therefore a challenging problem.

Studies based on unique ERP features (Wilkinson and Seales, 1978) and conventional anomaly detection algorithms like filtering (Cong et al., 2011) and matching pursuit have given limited success for the detection of ERPs (Rondik and Ciniburk, 2011). However, use of a band-pass filter specifically tuned for EEG/ERP frequencies improves signal to noise ratio. While Thesasiri et al. (2008) have shown that linear FIR filters may not perform optimally, filters tailor made for the particular ERP, such as Woody filters and matched filters provide better detection accuracy (Ford et al., 1994; Serby et al., 2005). Also Ciniburk and Mautner (2008) have shown that the Hilbert-Huang transform (Huang and Shen, 2005) could further improve the discrimination power of filter based approaches. But these filtering variations are limited in their success rate with real time signal detection.

The joint time-frequency analysis of signals is a solution to overcome the limitations of conventional filtering techniques. Wavelets can be used for the joint time-frequency analysis of EEG signals and they provide more robust measures for the detection and analysis of ERP components (Blanco et al., 1998).

Samar et al. (1999) and Quian Quiroga et al. (2001) have presented evidence that wavelets may improve the extraction and analysis of ERP waveforms. The applications of wavelets to ERPs are broad ranging, including joint time-frequency analysis of ERPs (Samar et al., 1992), artifact removal (Jiang et al., 2007) and event detection (Demiralp et al., 1999; Samar et al., 1995). Furthermore, features derived from wavelet coefficients (Merzagora et al., 2006; Trejo and Shensa, 1999) perform well in preprocessing (Kalayci et al., 1994) stages of classification problems using statistical learning algorithms (Abootalebi et al., 2006; Browne and Cutmore, 2002).

A variety of wavelet based methods have been used to study different aspects of EEG/ERP signals. Methods based on the discrete wavelet transform (DWT)(Burger et al., 2007; Herrera et al., 2000) and continuous wavelet transform(CWT) (Bostanov and Kotchoubey, 2004), in combination with other statistical measures (Lim et al., 1995), have been tried for the detection as well as the analysis of ERPs. Variable threshold schemes

(Fatourechi et al., 2004) and wavelet packet analysis (Graimann et al., 2004) have shown reasonable results when there is no background noise. A more accurate method proposed by Chapa (1995); Chapa and Rao (2000) for the detection and multiresolution analysis of ERPs is computationally expensive and at times gave unbounded errors.

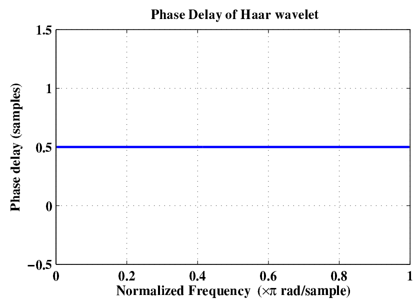
We propose a generalized, yet simple and powerful scheme using wavelets to detect specific ERP components from EEG data. The algorithm makes use of a less-used asymmetry property of wavelets along with time base properties of the target ERP component. Asymmetry is associated with the observed phase shift of wavelet coefficients when the wavelet transform is performed on a signal. The amount of phase shift produced by a wavelet for a specific ERP is unique and can be used for its detection. A detailed description of wavelet asymmetry is given in section 2.

Our method can be used to detect different ERP components by changing the wavelet basis function and time base parameters. It is also automated with self-correction and validation mechanisms using wavelet features and time-based properties of the ERP components as a guide. This paper outlines the general approach, provides an off-line demonstration of the detection performance of the algorithm using the N170 component of ERPs to 'face' versus 'non-face' stimuli, and considers issues related to the extension of the algorithm to real-time applications.

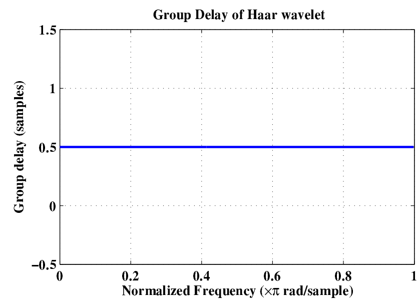
2. Asymmetry in wavelets

When the phase difference between the input and output signal is zero, the corresponding digital filter is said to be linear. Linear filters are symmetric. Wavelets behave exactly like filters and a wavelet function ψ when convolved with an input signal $f(t)$ will project the signal onto an orthogonal subspace ξ as $\hat{f}(\xi)$. In terms of symmetry, a wavelet filter with coefficients a_n is linear if the phase of the function $a(\xi) = \sum_n a_n e^{in\xi}$ is a linear function of ξ for some $l \in \mathbb{Z}$ (Daubechies, 1992). This essentially means that the filter delays each frequency in the input signal in equal amounts at the output. The phase delay and group delay of such filters will have a flat profile for all the input frequencies similar to the one shown in Figure 1a and 1b .

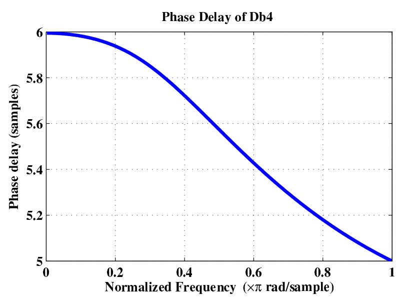
When the filter response is non linear, which means different frequencies are shifted by different amounts at the output, the filter is said to be asymmetric. The phase delay response and group delay response of asymmetric filters will not have a flat profile. An example is shown in Figure 1c and 1d



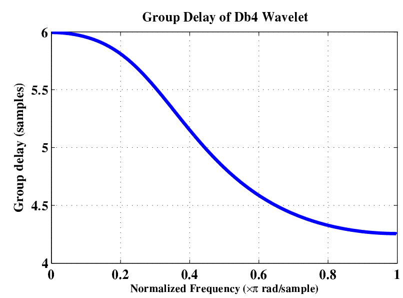
(a) Haar Phase Delay



(b) Haar Group Delay



(c) Db4 Phase Delay



(d) Db4 Group Delay

Figure 1: (a) and (b) shows the flat response of the Haar wavelet which is a symmetric filter. Db4 is an asymmetric filter whose phase delay and group delay are shown by (c) and (d). Since the wavelet filter is not symmetric, the filter responds with time delays.

where each frequency component of the signal is shifted by a specific number of samples.

2.1. Asymmetry as a measure

Filter phase response is quantified in terms of group delay $\tau(\omega)$ which is given as

$$\tau(\omega) = -\frac{d\theta(\omega)}{d\omega} \tag{1}$$

where $\theta(\omega)$ is the phase of the wavelet filter $H(\omega)$.

Let δ_k be the phase shift introduced by an asymmetric wavelet to a signal $f(t)$ at the analysis scale ϕ_k. t_k is the corresponding shift on the time scale due to δ_k. Both δ_k and t_k are due to group delay $\tau(\omega)$. When ERPs are convolved with asymmetric wavelet function ψ the output phase shift δ_k and the corresponding shift on timescale t_k will stay bounded within a unique value. This is because ERPs are band limited signal components and the corresponding wavelet coefficients generated will be shifted with respect to the phase response of the wavelet at those frequencies.

Therefore the value of t_k will be unique for a specific ERP when it is convolved with the best match of its wavelet function. When there is maximum resemblance of the wavelet with the signal under analysis, the wavelet coefficient generated will be maximum. This is because wavelet is a function that depends on the spectrum of the signal and not its amplitude.

In our method we combine the unique phase shift due to asymmetry and corresponding wavelet coefficients to detect ERP components from single trial EEG data. The only requirement of deriving the asymmetry measure is that the ERP should be oscillatory like a wavelet, so that the best fit wavelet does not have energy exceeding the non oscillatory components of the ERP. For ERP components that are not oscillatory, such as slow wave shifts, the group delay induced by the wavelet filter will be very minimal because there maybe no frequency components in the group delay band of the wavelet.

3. Application of Wavelet Asymmetry to detect N170 ERP Component

To demonstrate the feasibility of the asymmetry measure as a detection metric, we have chosen the N170 ERP as an example. The N170 is an ERP which is oscillatory and has possible wavelet candidate matches.

Currently, face recognition is one of the challenging and active research areas of cognitive science. The N170 ERP is a characteristic response to the presentation of a face stimulus and is used to illustrate the implementation of our algorithm. A face stimulus presented to a human observer elicits a large negative amplitude between two positive going peaks in the EEG between 130ms and 200ms following the stimulus as shown in Figure 2. This large negative amplitude N1 which is observed at the occipito-temporal sites is termed the N170 (Bentin et al., 1996).

3.1. Data Acquisition

The EEG data used in this study came from the study by Desjardins and Segalowitz (2013). Ten healthy right handed adults in the age range 22-37 (9 females) were presented with 26 images. The images were gray scale front views of 16 faces, 8 houses and two half-circle checkerboards. The face stimuli were of four identities with emotions of anger and fear either in upright or inverted orientations. The house stimuli comprised four identities which

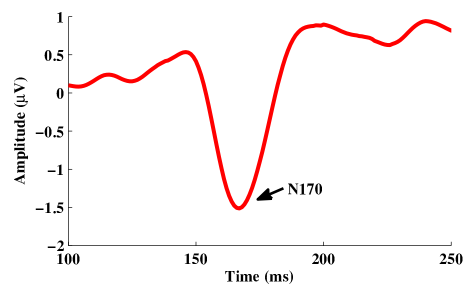


Figure 2: The typical N170 ERP has a negative dip that depends on the nature of the stimuli shown to the subject.

were also either upright or inverted. The stimulus samples can be seen in (Desjardins and Segalowitz, 2013). The stimuli were presented to the subjects in a dark room on a CRT monitor at 1024×768 resolution with a refresh rate of 60 Hz, with the images on a black background. The images were constantly shown for the duration of the task, where the subjects were to respond with both hands on a four-key keypad. There were 8 trial blocks with 300 trials in each block.

In addition we used 400 samples of resting EEG collected by Desjardins and Segalowitz (2013) while subjects passively watched the Windows XP star pattern screen saver. Each segment was 1 minute long.

The EEG data was recorded with 128 channels using the BioSemi ActiveTwo system at a sampling rate of 512 Hz. Artifacts and noise were removed from the EEG data using advanced data preprocessing techniques including Independent Component Analysis as described in Desjardins and Segalowitz (2013).

4. Methods

4.1. Selection of Wavelet & Scale for N170 ERP

The wavelet basis function and the scale are critical factors for any kind of component identification based on the CWT (Samar et al., 1995). Previous studies have shown various methods for selecting the best wavelet basis (Brechet et al., 2007; Flanders, 2002; Nielsen et al., 2006).

We have used a generalized algorithm for the selection of a wavelet basis function and scale which is illustrated by Rafiee et al. (2011). In this method, a wavelet basis function is chosen such that maximum wavelet coefficients are obtained when there is maximum resemblance between the wavelet and the signal in terms of its spectral features.

For example, consider the continuous wavelet transform of a signal $x(t)$ as :

$$C(a,b) = \int_R x(t)\psi_{a,b}\mathrm{dt} = \int_R x(t)\frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right)\mathrm{dt} \tag{2}$$

where $C(a,b)$ are the wavelet coefficients, $\psi(\cdot)$ the wavelet function, a the scaling factor and b the shifting parameter. The continuous wavelet transform gives a measure of correlation between the signal and the wavelet. A larger value of wavelet coefficient means a larger correlation between the signal and wavelet. Therefore by looking at the wavelet coefficients that are produced when an ERP signal is analyzed by different wavelet candidates, it is possible to determine the best wavelet basis for a particular ERP component detection application.

Given the shape and spectral profile of the N170 ERP, wavelets such as Daubechies 6, Daubechies 7, Daubechies 8, Symlet 5, Biorthogonal 3.9 are possible candidates. The CWT coefficients of these wavelets at specific scales were examined with respect to the representative averaged N170 ERP shown in Figure 3f.

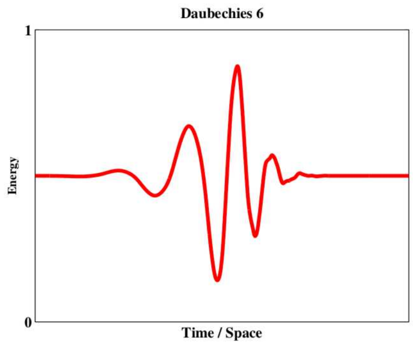
The large value of CWT coefficients revealed that Symlet 5 had the best match with the averaged N170 ERP.

The N170 ERP component has characteristic component peaks, namely P1, N1 and P2. The Symlet 5 has similar features in its profile which is why it matched the component better than others. This is illustrated in Figure 3.

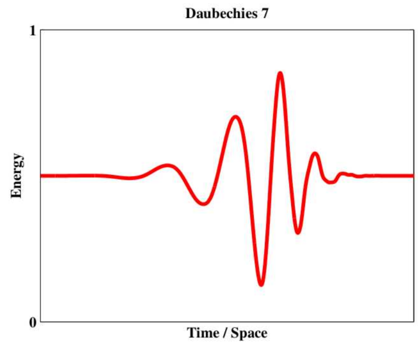
In the present study, to determine the best scale, the occipito-temporal signals from all 10 subjects who had prominent P1, N1 and P2 peaks comprising the N170 component were segmented manually. The segmented data were averaged for each channel across all the subjects to derive an averaged ERP. A full CWT was then done on each of the averaged segments. The scale at which the wavelet coefficients gives a maximum value (i.e., at which spectral matching is a maximum) was identified as the best scale for detecting N170 ERPs.

The sum of absolute values of the coefficients at each scale for every channel is then computed as:

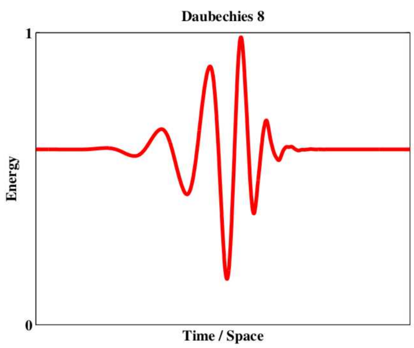
$$S_n(a) = \sum abs[C_n(a)] \tag{3}$$



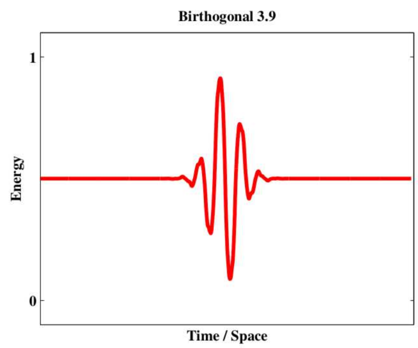
(a) Daubechies 6



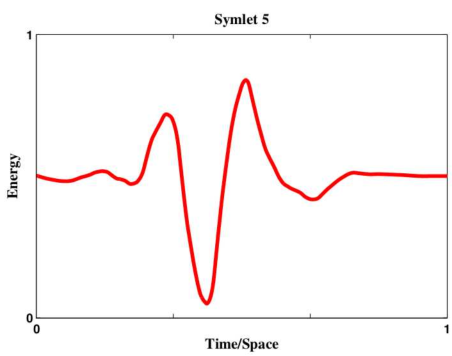
(b) Daubechies 7



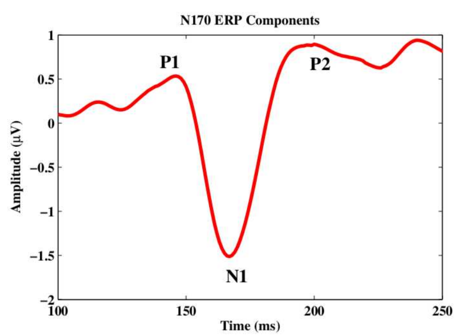
(c) Daubechies 8



(d) Biorthogonal 3.9



(e) Symlet 5



(f) N170 ERP

Figure 3: The Symlet 5 wavelet has the greatest similarity in terms of spectral content to that of the N170 ERP complex. This is also evident from their morphological similarity shown here.

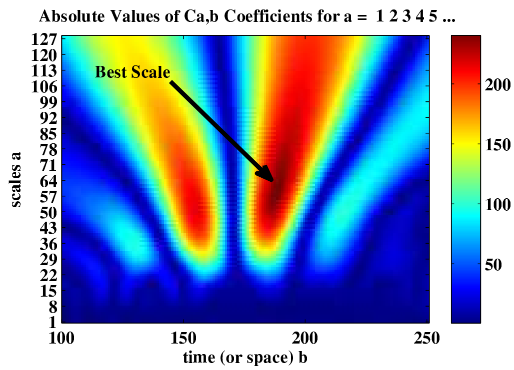


Figure 4: The CWT gives large coefficient values at regions where the scaling of the wavelet matches the structure in the input signal. The corresponding scale and time are marked by the darkest region in the time-scale Full CWT plot shown above.

Finally, the scale at which the value of the sum $S_n(a)$ is maximum is chosen as the best match (Rafiee et al., 2011) for the specific channel n. Due to the characteristic nature of the averaged ERP, we observed that the values for best scale varied across the channels. On average it was noted that a scale of 65 was the best scale returned for the different channels. Figure 4 shows the range of matching scales for the N170 ERP in this study.

4.2. Detection Algorithm

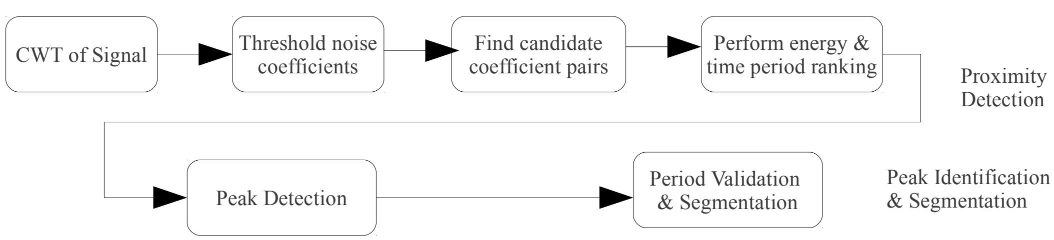
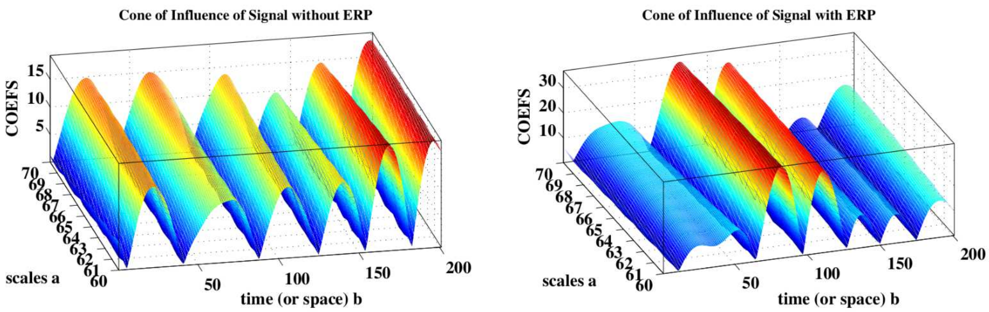


Figure 5: Detection Algorithm

The algorithm begins with the CWT of the input signal to detect the candidate locations for the N170 ERP and then marks the exact location of the ERP after a validation procedure. In a fully automated algorithm based on the CWT, the best scale of analysis should also be chosen automatically.

To resolve this issue we added an additional decision function prior to the main algorithm to determine the scale of analysis.



(a) Signal without ERP

(b) Signal with N170 ERP

Figure 6: (a) shows the spread of higher coefficients over a large area for different scales for a single trial EEG signal with just noise and no ERP. (b) shows the localization of higher coefficients over different scales for a signal with an N170 ERP.

The decision function now tests for the presence of large wavelet coefficient localization across the specified range of scales. This region is called the cone of influence (Torrence and Compo, 1998). In most of the cases where there is a highlighted anomaly similar to the ERP in the signal, the cone of influence will be narrow and well defined. See Figure 6.

Once the cone of influence is identified, the scale corresponding to the largest wavelet coefficient is chosen as the best scale of analysis. Selection of the best scale becomes a challenging issue when dealing with single trial EEG data. The original ERP will be modulated to a certain amount by the high alpha components and other noise sources.

4.2.1. Proximity Detection

The proximity detection stage finds a candidate location for an N170 component based on the wavelet coefficients. The signal is first preprocessed using a low pass filter designed with cut off frequency 65 Hz and stop band attenuation of 25 Hz to remove high frequency spikes within the data. These parameters are decided from the power spectrum of the signal.

After the preprocessing stage, CWT is done on the signal's n^{th} channel with the Symlet 5 wavelet at the specified scale a to generate wavelet coefficients $C_n(a)$. A threshold of wavelet coefficient C_τ is set such that all coefficients that satisfy the condition

$$\mathrm{C_n(a)} \geqslant C_\tau \tag{4}$$

are retained in the process. The value of C_τ is set to 50% of the average wavelet coefficient corresponding to the N170 peak of all the trials used to determine the range of scales in Section 4.1. Suppressing all remaining coefficients reduces the chance for false detection in the steps that follow. If no coefficient with a value greater than C_τ is found in the data, the algorithm reports the absence of an ERP and exits without going to the remaining processing stages.

The maxima of positive and negative coefficients appear in pairs with the negative coefficient preceding the positive coefficient where the N170 complex is present. When the wavelet is convolved with the signal on the time axis, there will be a point of minimum correlation and maximum correlation. The wavelet function being slightly asymmetric (Daubechies, 1992), the points of correlation will be shifted with respect to the alignment of the largest peak in the N170 versus the wavelet by a certain factor. This is the shift δ_k in terms of sample number introduced by the wavelet. Considering the band limited nature of the wavelet and the ERP, the shift will stay within a specific range.

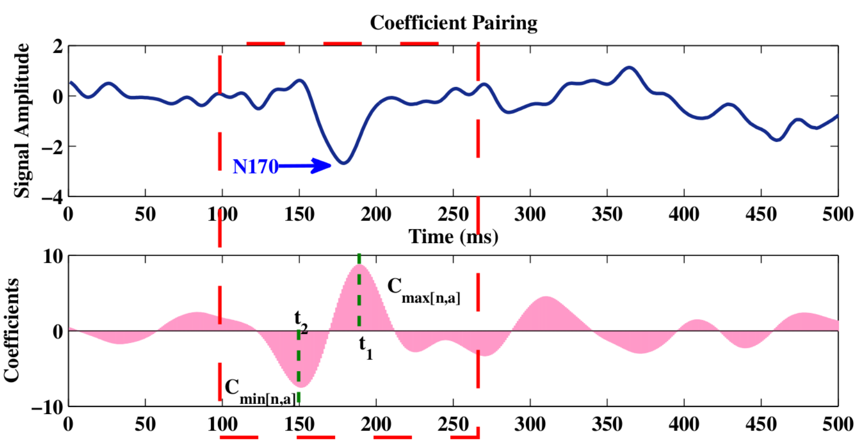


Figure 7: At regions where the N170 ERP complex is detected, the wavelet transform gives a pair of negative and positive coefficients. The strength of these coefficients depends on how well the match is.

According to the basic theory of wavelets, larger energy distribution corresponds to areas where an anomaly is present. In an ideal case this should be where the N170 ERP occurs. But in actual practice, due to noise and other factors, there could be multiple segments similar to N170 in an EEG.

If the algorithm finds more than two coefficients satisfying the condition in equation 4, all candidate coefficient pairs for which the negative coefficient precedes the positive coefficient are identified and ranked on the basis of the energy of the coefficients. To differentiate the N170 component from seemingly similar segments, we add a constraint that the time period between the maximum positive coefficient and negative coefficient must be such that,

$$\mathrm{t}_1 - \mathrm{t}_2 \approx T_{N170} \tag{5}$$

where T_{N170} is the approximate time period observed for N170 coefficient pairs in the data. See Figure 7. In our data, this time period is around 60ms - 88ms for single-trial EEG data. This is the asymmetry based measure derived from the wavelet coefficient.

We use a Gaussian weight function centered around 70 ms to give relative weighting to each of the detected segments as shown in Figure 8. Thus if the coefficient that is a maximum has a T_{N170} of about 70ms, it gets the highest ranking in the detection procedure.

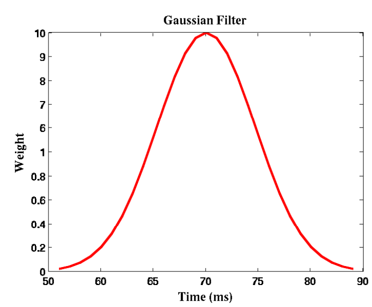


Figure 8: In most subjects, the positive and negative coefficients corresponding to the ERP complex are separated by about 70ms. However, this is not a magic number and may vary slightly across subjects and observations. We thus used a Gaussian Weight function such that any detection that does not match in time may be discarded. This reduces false detection resulting from noise when SNR is low.

In other words, the best coefficient pair will have maximum energy as well as the best value of T_{N170}. This strategy will reduce the chances of picking up false candidates having maximum energy distribution. Figure 9 shows an example of a selected coefficient pair within the proximity frame.

The time index values of successful detection candidates are saved and passed on to the next stage of the algorithm.

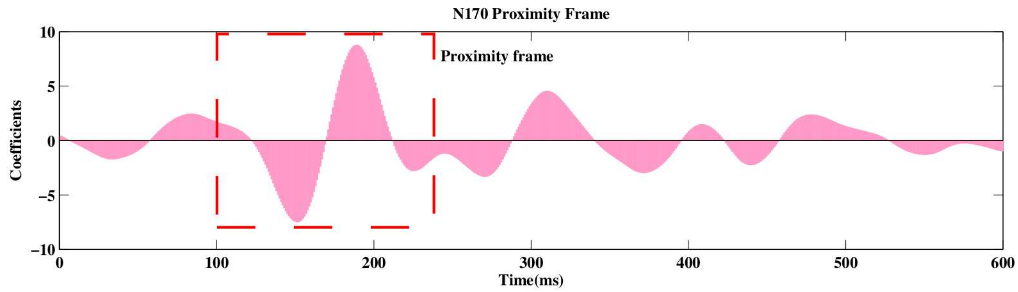


Figure 9: We use a Proximity Detection algorithm to pick up the best coefficients after applying the Gaussian weight function. The boundaries of the proximity frame spans the maximum value of T_{N170}. This procedure discards fake detections that do not match in either spectral content or scale, thereby improving the detection accuracy of the algorithm.

4.2.2. Peak Identification and Segmentation

The second stage of the algorithm constitutes a peak detection mechanism along with a final segmentation and validation. The peak identification algorithm basically detects the P1, N1 and P2 components of the N170 complex. A forward and backward slope detection mechanism is the heart of the peak identification algorithm. The peak detection first picks the N1 component which is the main component of N170. Once N1 is identified, the minor components P1 and P2 are detected. To minimize the effect of picking local peaks due to noise, a minimum peak period validation is performed. In this validation step, the time period between the candidate P1, N1 and P2 are checked. A detection is recorded if the time period between the 3 complexes satisfy the time period of the standard N170 positive and negative peaks. Once the peaks are identified, a final check on the period of the ERP is done to verify that it meets the N170 total period criterion. If it fails, the peak identification is re-run with modified parameters to recalculate the peaks. The algorithm finally marks the start and end positions of the segmented N170 ERP.

This final stage of the algorithm also makes sure that the basic morphology of the N170 component which are P1, N1 and P2 are conserved while segmenting. The segment is padded with a short period of 10ms at the start and end of the extracted data.

5. Results

We tested the algorithm on the occipito-posterior sites of the single trial data set of 10 subjects. Along with the EEG data, the wavelet name and sampling rate were given as input arguments to the algorithm. The test was done in two stages, namely 1) verifying that the algorithm does not detect false N170 components in resting EEG, and 2) comparing the ability of the algorithm to detect genuine single-trial N170 components associated with stimulus presentation against two commonly used wavelet detection algorithms.

5.1. Resting EEG data

It is desired that the ERP detection algorithm identify only real ERPs and not patterns that look similar to an ERP. To verify this, our algorithm was tested on 400 samples of resting EEG data without N170 ERP components. When a detection is made, the algorithm marks the start and end of the ERP with green and red arrow marks. When the algorithm is not able to find an ERP in the data, the arrows are placed at the beginning of the data stream, pointing at each other. The algorithm did not identify an N170 component in any of the resting EEG segments. A sample data segment used for the study is shown in Figure 10.

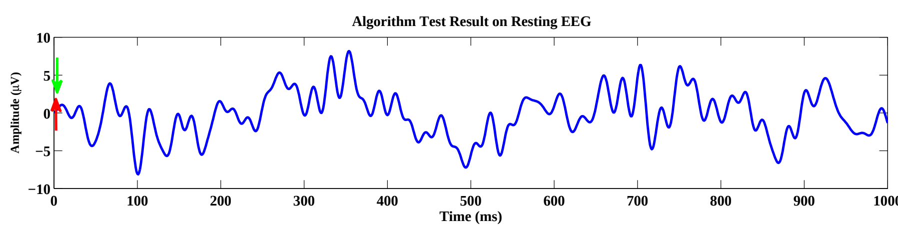


Figure 10: An example used to demonstrate that erroneous detections are not picked up by the algorithm is shown. Green and red arrows are used to mark the start and end of the N170 component. When no ERP is found, this is reported by the arrows positioned one on top of the other as shown.

5.2. Single trial EEG

The algorithm was tested for its ability to detect the N170 component in the single-trial EEG data that had been preprocessed to remove artifacts caused by eye movements, ECG spikes and muscle activity. For the single trial test, Twelve hundred single-trial ERP segments from the occipitotemporal channels of all the 10 subjects were used. Out of the 1200 trials, 600 were ERPs to face stimuli and the other 600 were ERPs to non-face stimuli (including house and checkerboard stimuli). The algorithm detected the presence of single-trial N170 ERPs to faces in the 600 positive samples with an accuracy of 96.7% and the accuracy with which it detected the absence of face-evoked N170 ERPs was 86%. With the total 1200 samples the overall accuracy was 91.33%. Figure 11 shows two examples in which the N170 ERPs were correctly detected by our algorithm.

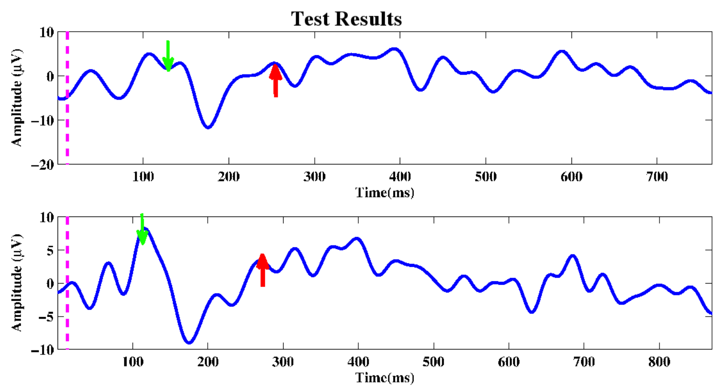


Figure 11: Two examples of N170 ERPs in single trial data that were correctly detected by our algorithm are shown. The dashed line shows the onset of the stimulus. The two examples are data from the O2 channel of two different subjects for which the best wavelet scales were different for the two subjects.

To evaluate how well our algorithm performs, it was compared against the spikelet technique proposed by Guido et al. (2006) and t-CWT proposed by Bostanov (2004). The Spikelet constructs wavelets matching a specified signal by deriving a system of linear equations from the Daubechies transform filter coefficients. A matching wavelet with the spikelet algorithm was constructed to match the N170 ERP and was used for detection. The t-CWT method uses a combination of t-statistics and wavelet scalogram called the t-value scalogram to extract features of a particular ERP. This measure can be used for ERP detection. The t-CWT method was modified such that the wavelet filter coefficients of the Symlet system were used to calculate the scalogram to detect the ERP. The results are tabulated in Table 1.

The first column in the table shows the three methods for ERP detection. The third column shows the number of predictions of the corresponding ERP type in column 2. The detection accuracy of each type of ERP is given in the fourth column and the last column gives the overall accuracy of each algorithm to detect the presence/absence of face-evoked ERP. As Table 1 shows, the proposed asymmetry based detection algorithm is more accurate in identifying ERP structures in the data.

Method	Real	Predicted as N170	Predicted as non-N170	Detection Accuracy	Overall Accuracy
Matching	N170	190	410	31.7%	
	Non-N170	278	322	53.7%	42.66 %
t-CWT	N170	512	88	85.3%	
	Non-N170	112	488	81.3%	83.3 %
Asymmetry	N170	580	20	96.7%	
	Non-N170	84	516	86.0%	91.33%

Table 1: Comparison of the ERP detection accuracy of the asymmetry method with two other algorithms using 1200 instances of single trial EEG data.

Detection failures were separately investigated in detail. Most of them occurred in cases where the original ERPs are severely distorted by high alpha components from noisy patterns that had spectral components similar to N170. Figure 12 illustrates how a fake pattern may generate larger wavelet coefficients above the detection threshold limit to result in the false detection of the ERP.

The time period check could not save the situation because the fake candidate pair matched the expected time period and gave a larger value for the wavelet coefficient.

With N170 single trial data, the majority of the failed detection cases were similar to the example in Figure 12 where the prominent features of the actual ERP were distorted by noise in the signal. This distortion reduced the value of wavelet coefficient and the time period of the actual N170 coefficient pair did not fall within the set of optimum values. The noise fluctuation had the value of wavelet coefficient and time period of an actual N170 ERP. In all those cases, the other detection algorithms also failed to correctly identify the ERP component.

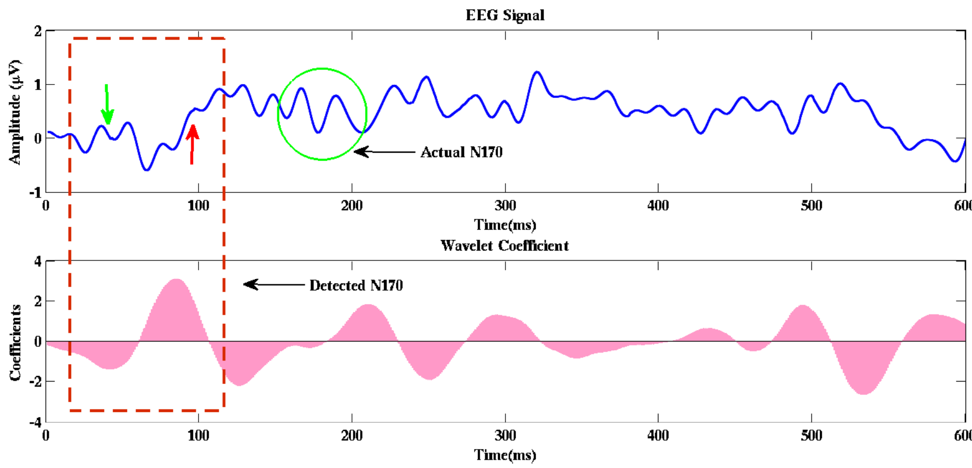


Figure 12: A typical failed case is shown. This failure resulted due to the distortion caused by the noise in the spectral components of the ERP complex and the resulting reduction in the strength of the coefficient of the actual ERP.

6. Discussion

This study demonstrates that the wavelet coefficients at different scales and the corresponding phase shift are unique for a particular ERP component, and can be used for detection of event-related potentials in single trial data.

The efficiency of the algorithm was tested by detecting N170 ERPs in single trial data. The algorithm robustly detected the N170 ERPs except in the few situations where the noise component presented a more faithful match to the actual ERP component or distorted the prominent features of the actual ERP component.

The detection of wide variety of single-trial ERP components has many potential applications, including to reveal fluctuations in the information content across trials(Rousselet et al., 2011), to disentangle the contribution of single-trial amplitudes and latencies to changes in mean ERPs(Navjas and Quiroga, 2013) and to model covariation across recording modalities, for instance EEG and fMRI(Nguyen and Cunnington, 2014).

Nevertheless, there are limitations to the types of ERP components that the algorithm can detect with high accuracy. The algorithm may not be useful for detecting slow wave ERP components. This is because the asymmetry measure requires that the selected ERP component should be oscillatory. When wavelets with asymmetric response are convolved with slow wave

ERPs, the induced group delay will be very minimal making it impossible to obtain the asymmetry measure. Therefore the asymmetry measure may fail due to the lack of a good wavelet match.

We have shown that the algorithm gives good results in offline mode. The offline detection of a specific ERP component on single trials is an extremely useful procedure with many applications, both in basic neuroscience research comparing neural responses to cognitive information processing in one condition versus another, and in clinical neuroscience research designed to determine symptoms associated with compromised brain functions. In both cases, standard ERP methods that depend on averaging many single trials in order to eliminate EEG responses not associated with the stimulus manipulation also end up eliminating important information only available when single trials are scored, namely, the degree to which the brain response is consistent across trials. For example, intra-individual variability of behavioral responses (MacDonald et al., 2006) and of ERPs (Segalowitz et al., 1997) relate to important cognitive and neural control functions, and potentially inform us of the progress of variable disease processes (Kiiski et al., 2012). However, the methods currently available to detect this variability are relatively crude. One such method is to apply a severe low-pass filter that eliminates everything except a low-frequency large component such as the P300(Segalowitz et al., 1997).Others have specific parameter requirements, such as independent component analysis (ICA) which requires having an adequate number of electrode channels (e.g., 64 sites) and having stationery signals (Kiiski et al., 2012). The algorithm presented here permits the scoring on single-trials of the amplitude and latency (with respect to a stimulus-onset time) of an ERP component, thus yielding a latency-consistency measure. It also permits one to examine the statistical reliability of an amplitude difference (of a specific ERP component) between two conditions for each research participant, thus removing the need to assimilate to the error term differences in EEG response magnitude across individuals. This is a useful aspect of the algorithm that has great potential for cognitive and clinical neuroscience.

The implementation of this algorithm in real time potentially offers opportunities to improve brain computer interfaces for augmenting human cognitive and motor abilities and for advancing the field of neuroprosthetics. This is a topic for future research. There are a number of limitations that must be overcome in order to achieve a real time implementation. First, the algorithm is based on the CWT which in general is a computationally expensive technique, and because the algorithm must perform multiple CWTs during a single detection, processor speed may be a limiting factor to real-time implementation. Currently the algorithm execution takes nearly 80ms on a PC with 2.2GHz Intel i3 processor and 2GB RAM. Second, artifacts caused by eye movement and muscle movement were removed from the data used in this study by an independent components analysis (ICA), a computationally intensive off-line procedure. However real time EEG data are highly contaminated with such extracerebral artifacts and the detection performance of the algorithm under conditions of currently available real-time artifact rejection remains to be determined in future research.

7. Conclusion

We have introduced a novel wavelet-based algorithm based on wavelet asymmetry for detecting single-trial oscilatory ERP components and have shown that it provides more accurate off-line detection than two common previous methods. The algorithm is accurate even when moderate noise is present in the data.

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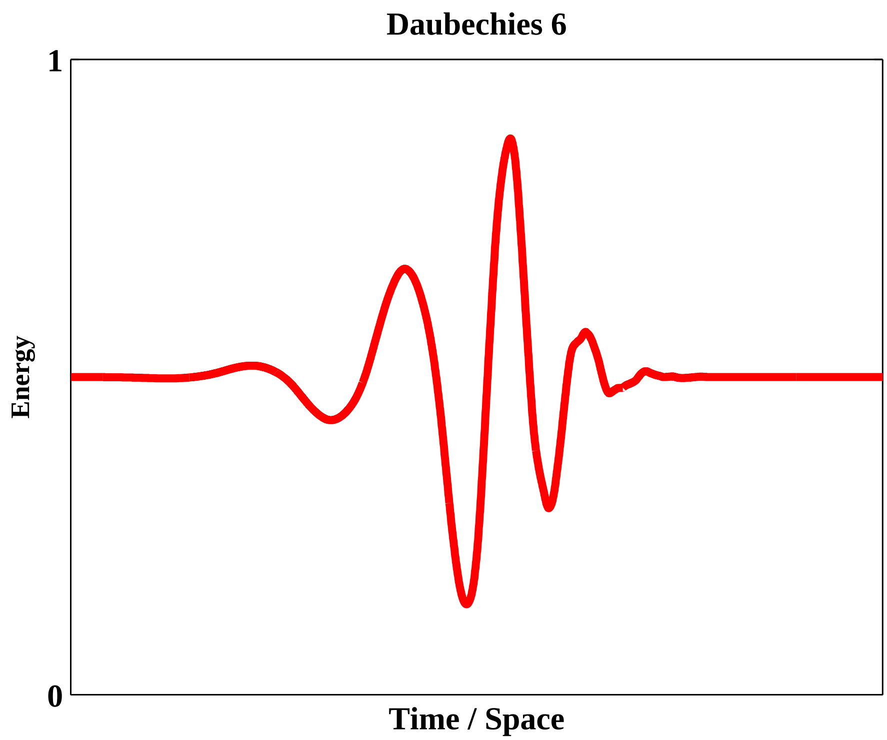
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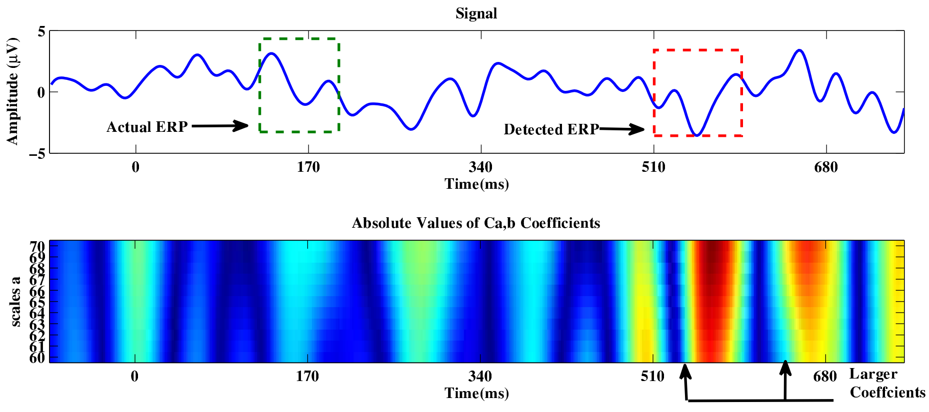
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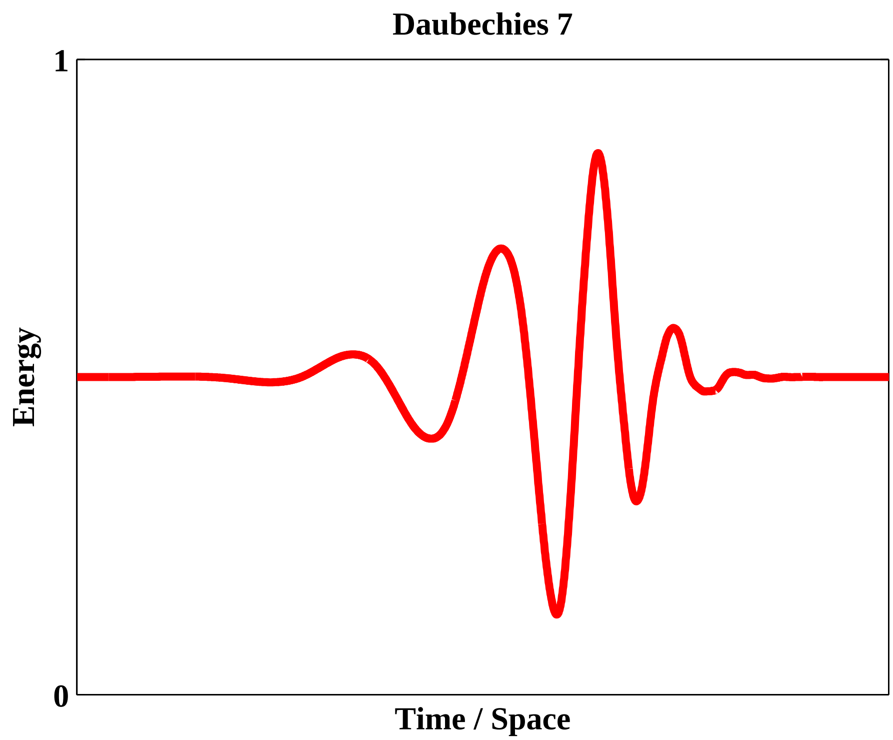
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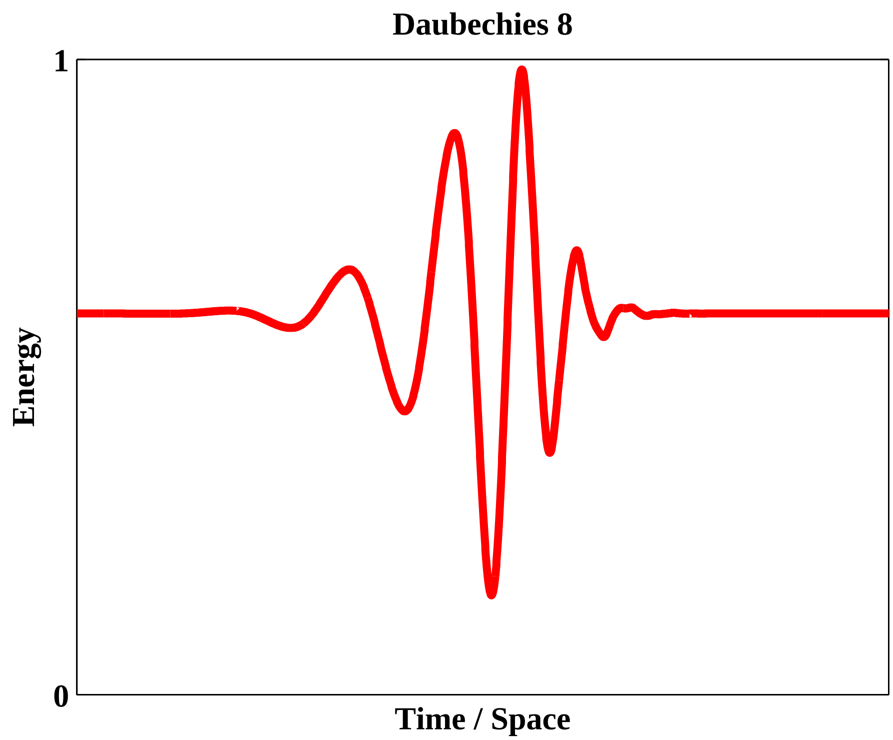
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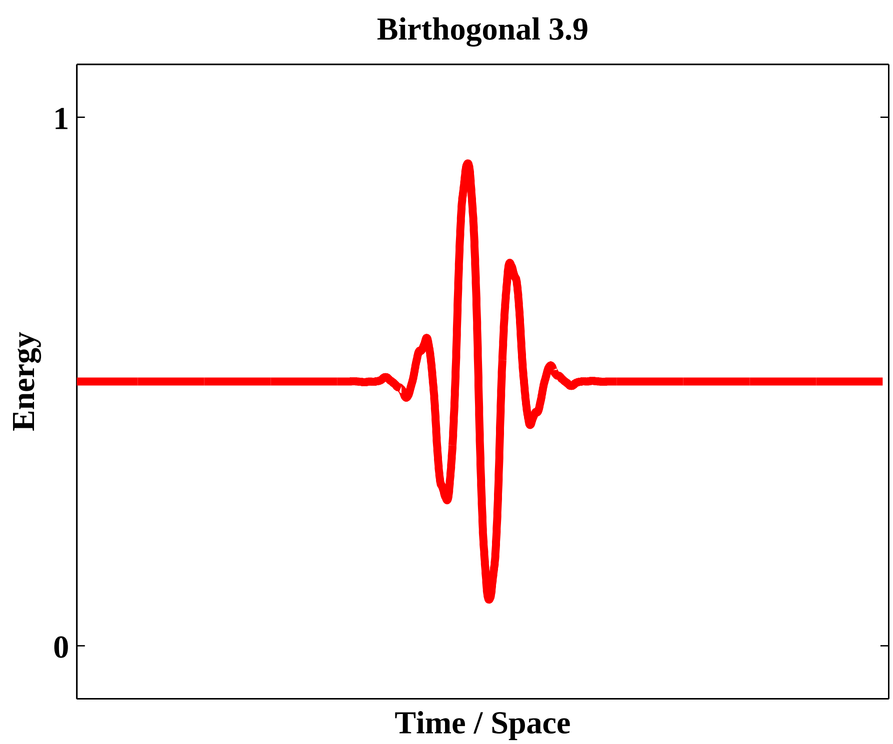
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