Analysis of Extracting Distinct Functional Components of P300 using Wavelet Transform

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Abstract: This paper investigates P300 features extracted through wavelet transform for BCI systems. Feature extraction is one of the key issues of signal processing for P300 based brain-computer interface systems (BCI). This paper examines and highlights the significance of using wavelets in P300 based BCI systems. We also mention various methods of feature extraction from P300 signals. The analysis suggests that wavelet transform is the best-suited tool for non-stationary signals like P300 signals.

Key-Words: P300 signal, Brain-Computer Interface, Fourier Transform, Wavelet Transform, Short Term Fourier Transform, Feature Extraction.

1 Introduction

Research have proved the utility of EEG based Brain Computer Interface Systems (BCIs) for unblussed people [1] [2]. The electroencephalogram (EEG) signal when recorded for a particular stimulus, called as evoked related potential (ERP). The most popular evoked related potential (ERP) signal is P300, acquired from the central-parietal region of the brain [3]. These signals are non-stationary in nature and do not allow the accurate retrieval of the signal frequency information. These signals reflect only time-domain information i.e. Time-Amplitude representation. Therefore, to extract frequency information, signal transformations are required. The common techniques for this are Fourier Transform (FT), Short-Time-Fourier Transform (STFT), Wavelet Transform (WT); Continuous Wavelet Transform (CWT) and Discrete Wavelet Transform (DWT). The most common technique is Fourier Transform (FT), introduced by J.Fourier. Nevertheless, it provides only frequency domain information of the signals, minus time domain information. Therefore, it is merely used for the signals whose frequency content does not change in time called stationary signals [4] [5]. Fourier Transform transformation technique shows any periodic function as an infinite sum of periodic complex exponential function defined by the following two equations [5]:

$$X(f) = \int_{-\infty}^{\infty} x(t) \times e^{-2j\pi ft} \, dt$$

$$x(t) = \int_{-\infty}^{\infty} X(f) \times e^{2j\pi ft} \, df$$

where \(x\) denotes signal, \(t\) denotes time, \(f\) denotes frequency, \(X(f)\) denotes signal in frequency domain i.e. FT of \(x(t)\), \(x(t)\) denotes signal in time domain i.e. inverse FT of \(X(f)\) and \(\int_{-\infty}^{\infty}\) means integral correspond to all time instances and treated as window function of FT.

The limitation of Fourier analysis is the loss of brief information in the frequency domain. Hence, it cannot use for non-stationary signals whose frequency content varies over the time. Electroencephalography (EEG), Electromyography (EMG), Electrocardiography (ECG) signals etc. are non-stationary in nature. The time-frequency
information is required for such signals. Here, P300 signal is of particular interest that is an event-related potential (ERP). The P300 signal is the response of the brain to a specific stimulus like flash-light, occurrence of rare or surprising task-relevant stimuli [6]. There may be some situation when some portion of a non-stationary signal is stationary, then the Short-Time-Fourier Transform (STFT) is applied. In STFT, the signal is separated into small segments and a window function ‘w’ is chosen. The width of this window function ‘w’ is equal to the portion of the signal that is stationary. Different slide windows exist like the Hamming, Bartlet, or Kaiser windows [6]. The window function ‘w’ is applied to the signal and overlap with the stationary portion of the signal. When these two are overlapped, apply Fourier transform on the product of window function ‘w’ and signal, which produces another signal. Then this window function ‘w’ is shifted and the process is repeated until the end of the signal. Therefore, STFT is windowed version of the FT that gives different FT’s of frequencies at different times or STFT= FT (signal* w).

The shortcoming of STFT is the resolution problem in which a time window is chosen and applied, same for all frequencies of the signal. Due to this important information is lost at very low or high frequencies. The difference between Fourier Transform and Short-Time-Fourier Transform (STFT) is in former window function ‘w’ is infinite therefore, wide window is chosen that gives good frequency resolution but poor time resolution where in later window function ‘w’ is finite therefore, narrow window is chosen, to obtain stationary signal in non-stationary signal, that gives good time resolution but poor frequency resolution. The information provided by STFT is limited by the fixed size window that causes the frequency resolution to get poorer. Therefore, wavelet transform (WT) provides solution to this resolution problem. In WT, choosing the window function ‘w’ is totally application dependent. The time-frequency window known as mother wavelet that is flexible and important information is not lost at very low or high frequencies. The window functions ‘w’ are chosen and derived from the main mother wavelet window using translation and dilation operations. It involves the concept of multi-resolution analysis (MRA) that analyzes the signal at different frequencies with different resolutions. WT allows the use of the long time windows for producing good frequency localization at low frequency, and short time windows for producing good time localization at high frequency [7]. The advantage of WT is the size of window that changes as the transformation is performed. The STFT has a constant resolution at all times and frequency, where the WT gives a variable resolution. Therefore, WT is best EEG signal analysis tool which provide time, frequency and amplitude information. There are two variations of wavelet transform: continuous wavelet transform (CWT) and discrete wavelet transform (DWT). CWT is an alternative to STFT, is a form of wavelet transform that was developed to overcome the resolution problem. Later, in 1976 Croiser, Esteban and Galand devised a technique to decompose time signals, known as discrete wavelet transform (DWT). The CWT is based on mother wavelet and computed by the convolution operation of the signal and the mother wavelet (basis function) where the DWT is based on sub-band coding and computed by successive low-pass and high-pass filtering. The computation of CWT may consume significant amount of time and resources, depending on the resolution required where DWT is easy to implement and reduces the computation time and resources required, therefore a fast computation of Wavelet Transform [5] [8]. This paper focuses on the research done by various authors using wavelet transform for feature extraction. The organization of this paper is as follows. The pre-processing, feature extraction methods and classifier of various existing P300 based BCI system is described in Section 2. Section 3 emphasizes on the use of wavelets for feature extraction in P300 based Systems. Finally, Section 4 concludes the paper with discussion of how Wavelet Transform is the best tool for P300 signals.

2 P300 Based Systems

A typical P300 signal is obtained by presenting uncommon target stimulus to the subject that is entrenched in sequence of non-target stimulus. The P300 is an endogenous event related potential (ERP) signal, retrieved from parietal lobe of the brain. The occurrence of P300 signal is directly proportional to the infrequency of target stimulus. P300 is a positive ERP signal with a latency of about 300ms. The advantage of P300 signal is it occurs suddenly or unintentionally so no training is required and best suited to synchronous type of BCI system. The cue-based means the subject just need to concentrate on
one out of several stimuli. The prominent and erotic content based signal leads to an excellent P300 signal [9]. This section discusses the pre-processing, feature extraction and classification phases of various P300 based BCI systems in Table 1.

3 Feature Extraction of P300 signal using Wavelet Transform

The brain signal patterns are described by specifying the set of features using feature extraction methods like Fourier Transform, Short-Time-Fourier Transform (STFT), and Wavelet Transform etc. Due to the spontaneous i.e. self generated and non-stationary nature of EEG signals, the wavelet transform is the best signal analysis tool. Wavelet Transform gives the best interpretation of the EEG signal in terms of time and frequency. This section discusses the last 14 years survey of using wavelet transform for P300 based BCI systems and their limitations.

In 1998, the Quadratic B-spline wavelet transform (WT) was used to analyze the functional components of P300 ERP. The analysis was performed by repeated measures ANOVA [21]. In 2006, the features were extracted through quadratic B-spline wavelets which differentiated deceptive and truthful responses. The signals were evaluated up to 6th scale i.e. d4 (~15–31 Hz) roughly corresponds to beta, d5 (~7.5–15 Hz) roughly corresponds to alpha and d6 (~3.75–7.5 Hz) roughly corresponds to theta. The d5 and d6 failed to show any significant difference between ‘target’ and ‘truth’ cards. But in d4, 10 out of the 31 coefficients that are d4_8, d4_10, d4_16, d4_17, d4_20, d4_21, d4_24, d4_27, d4_29, d4_31 showed statistically significant differences [22]. In 2007, two estimation models were used for P300 detection i.e. Kalman filtering and Daubechies-4 wavelet as Wavelet Transform. The discrimination analysis was performed using; linear discriminant analysis, Mahalanobis distance, and Bayes’ theorem. The data precision problems in processing the P300 estimation, the feature extraction, the classification and the discrimination still remain in the future [23]. In 2009, a Brain-Computer Interface application, Mind Speller, developed for disabled patients. Three types of features extracted were down sampled signals, CWT and Common Spatial Pattern. The Least-Squares Support Vector Machine was used for classification. The tuning of the LSSVM classifier is very time consuming [14]. In 2009, the db4, bior2.4, bior4.4, bior5.5, coif2, sym4, and sym6 are used for recognizing and classifying P300 signals. In this work, 20-30 coefficients were extracted using these wavelets. A five-octave wavelet transform was performed which produced five sets of coefficients in the 60-120 Hz, 30-60 Hz (gamma), 1530 Hz (beta) , 8-15 Hz (alpha) and 4-7 Hz (theta) frequency ranges and the residues in the 0.5-4 Hz frequency band. The quadratic discriminant analysis had been performed as classification [24]. In 2009, three different types of features were extracted for Guilty Knowledge Test (GKT). One Morphological features, second Frequency features and finally the Wavelet features using Quadratic B-spline functions. The features extracted were evaluated using statistical method i.e. t-test and selected using genetic algorithm (GA). The linear discriminant analysis (LDA) was used for classification of innocent and guilty subjects [25]. In 2010, wavelet transform and Fisher distance was used for P300 feature detection. Here, first wavelet transform was applied to EEG signals and then Fisher distance had been calculated in order to analyze the divisibility of the feature to obtain the optimal features. The neural network was used as classifier to classify the selected features [26]. In 2011, Daubechies-4 wavelet was used for P-300 rhythm detection which then fed to the ANFIS system. The experiment became tedious which result in generating low-level P300 signals [27]. In 2012, the discrete Daubechies4 (db4) wavelet was used to obtain coefficients of P300 component. The Bhattacharyya distance was used for selecting minimal channels. The pre-processing had been performed using windsorizing method to remove the outliers. For classification, Bayesian linear discriminant analysis (BLDA) was used [8]. The survey of using WT for P300 based BCI systems, showed that the wavelet analysis can effectively used to extract the distinct components of P300 signals. Further, wavelet transform helps in removing the noisy and non-meaningful information from ERP signals [28].
Table 1: P300 BCI Systems

<table>
<thead>
<tr>
<th>S.No.</th>
<th>Pre-processing</th>
<th>Feature Extraction</th>
<th>Classifier</th>
<th>Year</th>
<th>Ref</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>bandpass digital filtering (0.5-50 Hz) and normalized to an interval of [-1,1]</td>
<td>the value of samples of filtered data as feature, PCA</td>
<td>Linear Support Vector Machine (LSVM), Gaussian Support Vector Machine (RSVM), Neural Network (NN), Fisher Linear</td>
<td>2006</td>
<td>[10]</td>
</tr>
<tr>
<td>2</td>
<td>with almost no preprocessing</td>
<td>GA features are encoded in variable-length chromosomes, where each gene encodes one feature</td>
<td>Logistic Classifier</td>
<td>2008</td>
<td>[11]</td>
</tr>
<tr>
<td>3</td>
<td>sampled at 240Hz</td>
<td>ICA</td>
<td>simple classification method</td>
<td>2008</td>
<td>[12]</td>
</tr>
<tr>
<td>4</td>
<td>sampled at 256 Hz using the EEG amplifier Mindset24 by Nisan Computer Systems LLC</td>
<td>PCA</td>
<td>Fisher’s Linear Discriminant Analysis (FLDA)</td>
<td>2009</td>
<td>[13]</td>
</tr>
<tr>
<td>5</td>
<td>sampling frequency of 1000Hz</td>
<td>Features based on down-sampled signals, CWT, and the Common Spatial Pattern technique</td>
<td>Least-Squares Support Vector Machine</td>
<td>2009</td>
<td>[14]</td>
</tr>
<tr>
<td>6</td>
<td>data were filtered using the moving average technique and decimated by a factor of 16</td>
<td>PCA</td>
<td>Step Wise Linear Discriminant Analysis (SWLDA)</td>
<td>2009</td>
<td>[15]</td>
</tr>
<tr>
<td>7</td>
<td>Signals were sampled at 256 Hz, and filtered by a 0.1-50 Hz bandpass filter and a 50 Hz notch filter.</td>
<td>twelve input channels are transformed into two high SNR projections for P300 &amp; μ and β band powers as features for left imagery vs. right imagery and imagery vs. rest</td>
<td>native Bayes classifier (NB) for P300 &amp; two-class Fisher linear discriminant (FLD) for motor imagery</td>
<td>2011</td>
<td>[16]</td>
</tr>
<tr>
<td>8</td>
<td>PCA is used for reducing the dimension of EEG signal, ICA is used for removing EEG artifact</td>
<td>AR model and FastICA algorithm</td>
<td>—</td>
<td>2009</td>
<td>[17]</td>
</tr>
<tr>
<td>9</td>
<td>low-pass filtered with cut-off frequency at 25 Hz, downsampled to 50 Hz</td>
<td>Canonical Correlation Analysis</td>
<td>Linear Discriminant Analysis</td>
<td>2009</td>
<td>[18]</td>
</tr>
<tr>
<td>10</td>
<td>filtered with an S order bandpass Chebyshev Type I Filter with 0.1 Hz low cutoff frequency and 20 Hz high cutoff frequency</td>
<td>extracted all data samples between 0 and 687 ms poston of each intensification, assuming that this period will</td>
<td>Weighted ensemble of SVM's, Channel selection with optimized SVM's, Row and column based SVM ensemble</td>
<td>2010</td>
<td>[19]</td>
</tr>
<tr>
<td>11</td>
<td>6th-order band-pass filter (BPF) &amp; the signal was downsampled from 2048 Hz to 32 Hz</td>
<td>AR model</td>
<td>adaptive neural network classifier (ANNc)</td>
<td>2012</td>
<td>[20]</td>
</tr>
</tbody>
</table>

4 Conclusion

This paper discusses various P300 based BCI systems and the use of wavelets for extracting distinct wavelet features from P300 signals. As the P300 (or EEG), signals require thorough study of features in terms of time-frequency analysis, Fourier Transform (FT) have limitation while dealing with the signals that change abruptly. As discussed the wavelets use variable size window functions that help in providing the time-frequency information of a signal. Thus, the wavelets are highly suited to brain signal analysis. The wavelets also help in improving the speed and accuracy of
BCI systems. Table 2 compares the accuracy result of various wavelet methods achieved. Based on the comparison, in 2012 the Daubechies4 (db4) wavelet has achieved the highest accuracy of 97.50% than other techniques. This survey concludes that the wavelets are the best analysis tool for the signals that has discontinuities.

Table 2: Comparison of Wavelet Methods

<table>
<thead>
<tr>
<th>Wavelet Method</th>
<th>Accuracy</th>
<th>Year</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kalman filtering</td>
<td>97.13%</td>
<td>2007</td>
</tr>
<tr>
<td>CWT, CSP and Down-sampled</td>
<td>94.50%</td>
<td>2009</td>
</tr>
<tr>
<td>Quadratic B-Spline</td>
<td>86.00%</td>
<td>2009</td>
</tr>
<tr>
<td>Daubechies4 (db4) wavelet</td>
<td>85.00%</td>
<td>2011</td>
</tr>
<tr>
<td>Daubechies4 (db4) wavelet</td>
<td>97.50%</td>
<td>2012</td>
</tr>
</tbody>
</table>

References:


