CHAPTER 2

LITERATURE SURVEY

Literature survey briefs out the work done by various researchers in the field of biomedical signal processing. Different mathematical and signal processing techniques developed to extract and analyze biomedical signals are outlined. It includes averaging number of similar signals, wavelet transforms, etc., to reduce background noise. Application of standard deviation, median distance, to remove artifacts in evoked potentials is also discussed.

2.1 INTRODUCTION

Alan Jhonson (1982) discussed about the latency using specificity of attention in the stroop test: An EP study. General models of attention differ in the degree of specificity which they predict. Stroop effect is a demonstration of the reaction time of a task [7]. When the name of a color (e.g., "blue," "green," or "red") is printed in a color not denoted by the name (e.g., the word "red" printed in blue ink instead of red ink), naming the color of the word takes longer and is more prone to errors than when the color of the ink matches the name of the color.

Randall W. Sencaj and Jorge I. Aunon (1982) worked on Dipole Localization of average and single visual evoked potentials and demonstrated a relationship between dipole parameters and polarity inversions in the average evoked potentials [8]. A relationship was demonstrated between the dipole parameters and polarity inversions in the average evoked potentials.

Osamu Katsumi, Eli Peli, Yoshihisa Oguchi, Tetsuo Kawaras (1985) showed that when both eyes are stimulated with the same checkerboard but at different pattern reversal rates a fusional visual evoked potential component appears at a frequency intermediate between the two stimulus frequencies [9]. The power of this intermediate
frequency component will be constant despite of the changes in the magnitude of the stimuli.

M. Kutas and A. Dale (1997) analyzed electric and magnetic readings of mental functions. They examined the nature of the mapping between perception, movement and cognition on the one hand and electrical and magnetic activity at various scalp locations on the other [10].


2.2 MEAN AND MEDIAN

G. D. Dawson proposed a summation technique for detecting small signals in a large irregular background and applied this technique for the detection of small evoked potentials [2].

R. P. Borda and J. D. Frost (1968) proved that error can be reduced in small sample averaging through the use of the median rather than the mean. Median distance is large for abnormal samples when compared with the normal ones [5].

2.3 EXTRACTION AND ANALYSIS OF EVOKED POTENTIALS

R. J. Sclabassi and H. A. Risch (1977) studied multiple sclerosis using complex pattern evoked somatosensory responses. Three approaches are described for investigation of human somatosensory evoked responses in normal subjects and in multiple sclerosis patients [12]. To median-nerve stimulation, the cortical evoked
response reveals components whose shapes and latencies may be altered as a consequence of the disease. The use of periodic trains of stimuli demonstrates that the oscillatory response of the nervous system deteriorates with advancing disease. Finally, the use of functional power series to characterize the somatosensory modality shows that responses to temporally interactive stimuli are nonlinear, decrease with increasing rate, and degenerate in the advanced state of the disease.

Kenneth S. M. Fung, Francis H. Y. Chan, F. K. Lam and Paul W. F. Poon (1997) proposed an algorithm based on adaptive radial basis function (RBF) neural network model for evoked potential estimation and tracking EP waveform variations [13]. A method for evoked potential estimation based on an adaptive RBF neural network model is presented in this paper. During training, the number of hidden nodes (number of RBFs) and model parameters are adjusted to fit the target signal which is obtained by averaging. In order to reduce computational complexity and the influence of noise in estimating single-trial evoked potential (EP), the number of hidden nodes is also minimized in training. After training, both peak latency and amplitude, being distinctive features of an EP, are characterized by center and height of the corresponding RBF respectively. In EP estimation, an adaptive algorithm is employed to track the peaks from trial to trial by adapting the center and height of RBFs directly.

Joseph A. Sgro, Ronald G. Emerson and Paul C. Stanton (1998) used back propagation neural networks for the automated analysis of evoked potentials [14]. They used two separate networks: a “classification network” classifies evoked potential waveforms as absent, interpretable or uninterpretable; and a “latency measurement network” determines the latency of interpretable waveforms. Each network is a feed forward back propagation network with two hidden layers. Network
performance was evaluated using single channels from 279 visual evoked potential recordings and 137 median nerve somatosensory evoked potential recordings. For each modality, data were randomly divided into two data sets, one for training and the other for testing. The system correctly classified 90% of VEPs and 93% of SEPs. For EP waveforms correctly classified as interpretable, the system determined the peak latency within ±3 msec for VEPs and ±0.5 msec for SEPs in all cases.

J. Kremlacek and M. Kuba (1999) applied independent component analysis to multichannel visual evoked potentials, elicited by high component pattern reversal and motion onset [15]. Three overlapping independent components with different topographical distribution over the scalp were described. The first component displayed similar timing in response to all three stimuli (40-200 ms) but was a different in shape and scalp projection. This activation component is considered to reflect the stimulus properties. The second component (100-227 ms), related to negativity at about 160ms, can be referred to visual processing of motion. The last component, attributed to positivity at 230 ms dominates in the fronto-central area and might represent a cognitive process.

S. Makeig, S. Debener, J. Onton, and A. Delorme (2004) developed an approach combining independent component analysis (ICA), time/frequency analysis, and trial-by-trial visualization that measures EEG source dynamics without requiring an explicit head model [16].

L. Gupta, B. Chung, M.D. Srinath, D.L. Molfese and H. Kook (2005) applied multichannel fusion models for the parametric classification of differential brain activity [17]. They introduced parametric multichannel fusion models to exploit the different but complementary brain activity information recorded from multiple channels in order to accurately classify differential brain activity into their respective
categories. A parametric weighted decision fusion model and two parametric weighted data fusion models are introduced for the classification of averaged multichannel evoked potentials (EPs). The decision fusion model combines the independent decisions of each channel classifier into a decision fusion vector and a parametric classifier is designed to determine the EP class from the discrete decision fusion vector. The data fusion models include the weighted EP-sum model in which the fusion vector is a linear combination of the multichannel EPs and the EP-concatenation model in which the fusion vector is a vector-concatenation of the multichannel EPs. Multivariate parametric classifiers are developed for each fusion strategy and the performances of the different strategies are compared by classifying 14-channel EPs collected from five subjects involved in making explicit match/mismatch comparisons between sequentially presented stimuli. It is shown that the performance improves by incorporating weights in the fusion rules and that the best performance is obtained using multichannel EP concatenation. It is also noted that the fusion strategies introduced are also applicable to other problems involving the classification of multiclass multivariate signals generated from multiple sources.

Srinivas Kota, Lalit Gupta, Dennis Molfese, Ravi Vidyanathan (2009) introduced a dynamic channel selection strategy for dense array ERP classification [18]. To exploit the enhanced spatial information offered by dense arrays while overcoming the significant increase in the dimensionality problem introduced by the large increase in the number of channels they introduced a spatiotemporal-array model to observe the dense-array ERP amplitude variations across channels and time, simultaneously. Selecting spatiotemporal elements that fit the assumed model and also statistically differ across the ERP categories not only ensures high classification
accuracies but also decreases the dimensionality significantly. The selection is
dynamic in the sense that selecting spatiotemporal-array elements corresponds to
selecting ERP samples of different channels at different time instants. Each selected
array element is classified using a univariate Gaussian classifier, and the resulting
decisions are fused into a decision fusion vector that is classified using a discrete
Bayes classifier.

H. Cecotti (2010) used visual stimuli duty cycle for the classification of
steady-state visual evoked potentials (SSVEP). To produce an SSVEP response, a
visual stimulus must be presented to the user [19]. This stimulus can be a light that
flickers at a particular frequency. Classical SSVEP-BCIs consider a frequency for
each BCI command. One problem for an SSVEP based BCI can be the number of
simultaneous flickering stimuli. It is difficult to render many flashing boxes with as
many frequencies as boxes, due to hardware constraint like the vertical refresh rate of
a screen. As an alternative to the common paradigm that assigns one command to
each frequency, we propose to classify different type of SSVEP responses based on
the duty cycle of the flickering lights, the frequency being the same for evoking
SSVEP responses. Three paradigms based on different duty cycles over six subjects
are compared. The offline classification of the obtained SSVEP responses is
performed with spatial filters combined with a Bayesian linear discriminant analysis
classifier. The results show that it is possible to efficiently discriminate SSVEP
responses given by visual stimuli at the same frequency but with different duty cycles.

Zhiguo Zhang, Keith D. K. Luk, and Yong Hu (2010) developed a high-
resolution time-frequency analysis (TFA) algorithm for the identification of detailed
time-frequency components in somatosensory evoked potentials. Somatosensory
evoked potential (SEP) usually contains a set of detailed temporal components
measured and identified in time domain, providing meaningful information on physiological mechanisms of the nervous system [20]. The purpose of this study is to reveal complex and fine time-frequency features of SEP in time-frequency domain using advanced time-frequency analysis (TFA) and pattern classification methods.

Ruben Gaitan-Ortiz, Oscar Yanez-Suarez, and Juan M Cornejo-Cruz (2011) applied PCA and genetic algorithms for maximizing signal-to-noise ratio of evoked potentials [21]. Middle Latency Auditory Evoked Potentials are bioelectrical signals that constitute a key technique for the assessment and diagnosis of various clinical conditions, nonetheless background electrical activity and artifacts prevent clinically relevant information to be revealed. A technique based on the iterative evaluation and combination of the available EEG trials is presented and performance is evaluated by comparing the results obtained from processing data from normo-hearing and clinically deaf patients.

H. Nezamfar, U. Orhan1, D. Erdogmus, K.E. Hild, S. Purwar1, B. Oken and M.Fried-Oken (2011) discussed about visual evoked potentials in EEG induced by multiple pseudorandom binary sequences for brain computer interface design. Visually evoked potentials have attracted great attention in the last two decades for the purpose of brain computer interface design [22]. Visually evoked P300 response is a major signal of interest that has been widely studied. Steady state visual evoked potentials (SSVEP) that occur in response to periodically flickering visual stimuli have been primarily investigated as an alternative. The use of multiple m-sequences for intent discrimination in the brain interface, as opposed to a single m-sequence whose shifted versions are to be discriminated from each other was studied.

Gary Garcia-Molina, and Danhua Zhu (2011) used optimal spatial filtering for extracting the steady state visual evoked potential [23]. Their attention was focused
on a repetitive visual stimulation (RVS) at a constant frequency, elicits the so called steady-state visual evoked potential (SSVEP). This effect can be advantageously utilized in brain-computer interfaces (BCIs). SSVEP based BCIs can offer higher bitrates and require shorter training time as compared to other BCI modalities. Detection of the SSVEP from the EEG can be facilitated through spatial filtering.

2.4 NOISE CANCELLATION

D. S. Ruchkin (1965) analyzed average response computations for the study of evoked potentials recorded from the central nervous system [24]. A mathematical analysis of the mean and variance of the average response computation is based upon aperiodic stimuli.

Madhavan, G. P., de Bruin, H. and Upton, A. R. M. (1984) proposed adaptive noise cancellation for estimating the evoked potential without repetitive application of stimulus [25]. A new weighted least squares lattice algorithm was derived for this purpose. Pattern recognition of evoked potentials was achieved by syntactic methods.

J. R. Boston (1985) used noise cancellation filter function for Brainstem Auditory Evoked Potentials to remove background noise [26]. Since sensory evoked potentials are generally much smaller than the background noise, a large number of individual responses must be averaged to cancel this noise.

B. Lutkenhoner and C. Pantev (1985) discussed about the statistical analysis of weighted averaging and its limitations for the estimation of small signals buried in noise [27]. The weighting factor used by this method is in inverse proportion to the variance estimated for the noise. It is shown that, compared to conventional averaging weighted averaging can improve the signal-to-noise ratio to a high extent if the variance of the noise changes as a function of time. On the other hand, uncritical application of the method involves the danger that the signal amplitude is
underestimated. How serious this effect is depends on the number of degrees of freedom available for the estimation of the weighting factor. The effect can be neglected, if this number is sufficiently increased by means of an appropriate preprocessing.

C. Davilla and M. Mobin (1992) discussed about the cancellation of background EEG noise by weighted averaging of evoked potentials. Weighted averages of brain evoked potentials (EP's) are obtained by weighting each single EP sweep prior to averaging [28]. These weights are shown to maximize the signal-to-noise ratio (SNR) of the resulting average if they satisfy a generalized eigenvalue problem involving the correlation matrices of the underlying signal and noise components. The signal and noise correlation matrices are difficult to estimate and the solution of the generalized eigenvalue problem is often computationally impractical for real-time processing. Correspondingly, a number of simplifying assumptions about the signal and noise correlation matrices are made which allow an efficient method of approximating the maximum SNR weights. Experimental results are given using actual auditory EP data which demonstrate that the resulting weighted average has estimated SNR's that are up to 21% greater than the conventional ensemble average SNR.

L. Gupta, D. L. Molfese, R. Tammana and P. G. Simos (1996) focused on estimating the evoked potentials from noisy background EEG by non-linear alignment and averaging [29]. The problems associated with averaging brain responses evoked through a repetitive application of an external stimulus were addressed. In order to improve the estimate of the evoked potential (EP) through signal averaging, a method which incorporates nonlinear alignment of the EPs into the averaging operation is developed. They designed the nonlinear alignment procedure to generate optimally
aligned EPs by backtracking along the optimal alignment path. The nonlinear alignment and averaging operations are systematically combined to develop methods to estimate the EP. Results from a series of experiments conducted on simulated and real sets of responses show that, through nonlinear alignment and averaging, the events in the EPs are preserved and the estimates of the EP are quite robust.

Mehmet Engin, Kadir Erkan, Melih Inal, Mehmet Yıldırım (1999) discussed about the detection of visual evoked potentials in electroencephalogram using a nonlinear operator [30]. Localization of VEPs have been determined with respect to ensemble averaged VEP coming from data base segments.

Lalit Gupta, Jim Phegley, and Dennis L. Molfese (2002) used the estimation of the mean and the covariance matrix of the feature vectors for parametric classification of multichannel averaged event-related potentials [31]. It is shown that the parameters of the averaged ERP ensemble can be estimated directly from the parameters of the single-trial ensemble, thus, making it possible to design a class of parametric classifiers without having to collect a prohibitively large number of single-trial ERPs. An approach based on random sampling without replacement is developed to generate a large number of averaged ERP ensembles in order to evaluate the performance of a classifier. A two-class ERP classification problem is considered and the parameter estimation methods are applied to independently design a Gaussian likelihood ratio classifier for each channel. A fusion rule is formulated to classify an ERP using the classification results from all the channels. Experiments using real and simulated ERPs are designed to show that, through the approach developed, parametric classifiers can be designed and evaluated even when the number of averaged ERPs does not exceed the dimension of the ERP vector. Additionally, it is
shown that the performance of a majority rule fusion classifier is consistently superior to the rule that selects a single best channel.

Kevin H. Knuth, Wilson A. Truccolo, Steven L. Bressler, and Mingzhou Ding (2002) applied Bayesian methodology for the separation of multiple evoked responses using differential amplitude and latency variability [32]. In neurophysiology one records electric potentials or magnetic fields generated by ensembles of synchronously active neurons in response to externally presented stimuli. These evoked responses are often produced by multiple generators in the presence of ongoing background activity. While source localization techniques or current source density estimation are usually used to identify generators, application of blind source separation techniques to obtain independent components has become more popular. They utilized the differential amplitude and latency variability of the evoked potentials to identify cortical components.

### 2.5 FILTERING

D. G. Wastell (1979) attained filtering without phase distortion through the application of low-pass linear filters to evoked potential data [33]. A linear filter, whose weights are based on the binomial coefficients, is described. It is shown that the phase distortion introduced by the filter is zero and the filter is used to smoothen evoked potentials.

J. R. Boston and P. J. Ainslie (1980) observed the effects of analog and digital filtering on brain stem auditory evoked potentials. Compared the effects of different upper and lower cutoff frequencies for both analog and zero-phase shift digital filters [34]. For given cutoff frequencies, analog filtering causes more distortion of the response than digital filtering, due primarily to phase distortion introduced by the analog filter. It is likely that differences in filter cutoff frequencies, especially lower
cut-off frequencies, are a significant source of variability in results reported by different investigators.

Ken Nakayama and Manfred Mackeben (1982) observed that the steady state visual evoked potentials (SSVEP) can show either broad or narrow spatial frequency tuning, depending on electrode location, temporal frequency, contrast and method of analysis [35]. These findings suggest that the SSVEP can reflect the activity of two distinct neural mechanisms responsive to pattern stimulation. The degree to which either mechanism is evident determines the spatial and temporal frequency tuning of the VEP.

J. R. Wolpaw and C. C. Wood (1982) studied the distribution of auditory evoked potentials on the human scalp using non-cephalic reference recordings [36]. AEPs to binaural click stimuli were recorded simultaneously from 20 scalp locations over the right hemisphere in 11 subjects. For potentials between 20 and 60 msec, the results demonstrate a stable scalp distribution of dipolar form that is consistent with sources in primary auditory cortex. For potentials between 60 and 250 msec, the results demonstrate changes in AEP morphology across electrode locations and changes in scalp distribution over time that lead to two major conclusions. First, AEPs in this latency period are generated by multiple sources which partially overlap in time. Second, one or more regions of auditory cortex contribute significantly to AEPs in this period. This work had raised the problem of exact positioning of electrodes on the scalp for a particular class of stimuli. Here is the need for detecting non responsive channels and trials.

John J. Westerkamp (1987) designed an optimum linear multielectrode filter for estimating the evoked potential contained in a single scalp-recorded brain response to a visual stimulus [37]. The filter is derived under the criterion of
minimum mean-square error and is time varying to allow for the nonstationarity of the brain response. Single- and two-channel filters are designed for simulated and human visual evoked potential data.

Owe Svensson, Bengt Almqvist and Karl Erik Jonsson (1987) showed that the shape of the auditory brainstem response (ABR) is changed by the non-linear phase response of analog filter (350–1700 Hz). Peaks IV and V are particularly affected [38]. This is because the low-frequency part of the ABR interferes with peaks IV and V. The latencies of peaks I to V obtained from ABRs after digital and analog filtering have been compared. This showed small but significant differences.

**Discrete signals** and **discrete mathematical tools** are used in this research work to avoid the effects of nonlinear phase that arise in analog systems.

Ilkay Ulusoy, Ugur Halici1, Erhan Nalcaci, Ilker Anac, Kemal Leblebicioglu, Canan Basar-Eroglu (2004) used Time-frequency analysis of visual evoked potentials for interhemispheric transfer time and proportion in callosal fibers of different diameters [39]. Pattern reversal of checkerboard was used as stimuli in the right visual field and left visual field to record EEG at O1, O2, P3, and P4. They applied the chosen band pass filters (4-8, 8-15, 15-20, 20-32 Hz) to the VEPs of subjects and obtained four different components for each VEP. By using frequency dependent shifts in time and maximizing the cross correlation of direct VEP (DVEP-VEP obtained from contralateral hemisphere) and indirect VEP (IVEP-VEP obtained from ipsilateral hemisphere) pairs in the time-frequency domain, they examined the delay not only at peaks but along a meaningful time interval as well. Furthermore, by shifting back the IVEP according to the delay estimated at each time window, both the amplitudes and energies of the synchronized DVEP-IVEP pairs were compared at the chosen frequency bands.
2.6 WAVELET TRANSFORMS

John B. Siegfried and Jefrey Lukas (1981) used early wavelets in the processing of visual evoked cortical potentials [40]. With the use of a Maxwellian view optical system to present light flashes to the right eye, electroretinograms (ERGs) and visual evoked cortical potentials (VECPs) were recorded from normal subjects. The VECP wavelets probably represent initial arrival of visual information at the cortex, or subcortical activity.

W. Q. Liu, W. Qiu, F.H.Y. Chan, F. K. Lam and P.W.F. Poon (1997) used Wavelet Transform Based Time-Frequency Adaptive Filtering for the estimation of evoked potentials [41]. A time-frequency domain adaptive filtering method is presented to estimate evoked potentials. The wavelet transform is used to represent the original responses in the time-frequency domain with a discrete set of wavelet coefficients. Each wavelet coefficient, which is related to the time extent and the frequency extent in the time-frequency plane, is processed by adaptive signal enhancer (ASE) to enhance signal components of the coefficient. The processed coefficients are then used to reconstruct the evoked potential signals with the inverse wavelet transform. Visual evoked potentials (VEPs) from human subjects are estimated, and good results are obtained by this method.

Ahmet Ademoglu and Evangelia Micheli-Tzanakou (1997) used quadratic spline wavelets for the analysis of pattern reversal visual evoked potentials [42]. The pattern-reversal visual evoked potentials (PRVEP's) collected from normal and demented subjects are investigated by applying the quadratic spline wavelet analysis. They decomposed data into six octave frequency bands. The wavelet coefficients in the residual waveform representing the delta-theta band activity (0-8 Hz) were explored to characterize the (N70-P100-N130) complex. Specifically, the coefficients
corresponding to the location of N70, P100, and N130 peaks are investigated for their sign in order to test whether they represent a consistent (N70-P100-N130) complex in the averaged waveform. Waveforms with normal latency (N70-P100-N130) complex are observed to have positive second, negative third and positive fourth coefficients in amplitude in their residual scale standing for the delta-theta (0-8 Hz) band activity. The method allows for the analysis of oscillatory-phase behavior of the normal and pathological PRVEP’s in their delta-theta band based on a few quantitative measures consistent with the time-frequency occurrence of the major components of the evoked potential.

Arnaud Jacquin, Elvir Causevic, Roy John, and Jelena Kovacevic (2005) used Adaptive complex wavelet-based filtering of EEG for extraction of evoked potential responses [43]. They compared the algorithm to two previously developed methods: The first simply consists of band pass filtering the input EEG signal followed by linear averaging. The second method uses signal-adaptive filtering in the Fourier domain based on phase variance computed at each spectral component of the FFT. The wavelet-based method consistently outperformed the other two methods for ABR signals with an signal-to-noise ratio of less than -20 dB.

M. Fatourechi, S.G. Mason, G.E. Birch and R.K. Ward (2004) introduced a wavelet-based approach for the extraction of event related potentials from EEG. ERPs are low-frequency events that are usually obscured in single trial analysis [44]. To visualize these signals; most of the reliable solutions at the present time use the ensemble averages of many single trials. In this paper, a wavelet-based method called statistical coefficient selection (SCS) is used for the extraction of ERPs from EEG signals. Unlike other wavelet-based denoising methods, the current method does not focus on the wavelet coefficients of the signal itself. Instead, it selects the coefficients
based on the statistical study of trials from training data sets. Simulation results show the superiority of the proposed SCS method in extracting ERPs in comparison with other filtering approaches.

2.7 ARTIFACT DETECTION

R. Veerleger et al. (1982) evaluated regression approach in terms of reliability and validity for the correction of EOG artifacts [45]. Transmission rates are estimated for eight EEG channels in 67 subjects. The trimmed group means of these rates are shown to provide reliable measures. Eye artifact correction based on these group means is superior to the conventional rejection in terms of reducing correlation between EOG and EEG.

G. Gratton, M. G. H. Coles, and E. Donchin (1983) described a new method for off-line removal of ocular artifact [46]. The procedure (EMCP) uses EOG and EEG records for individual trials in an experimental session to estimate a propagation factor which describes the relationship between the EOG and EEG traces. The propagation factor is computed after stimulus-linked variability in both traces has been removed. Different propagation factors are computed for blinks and eye movements. Tests are presented which demonstrate the validity and reliability of the procedure. ERPs derived from trials corrected by EMCP are more similar to a 'true' ERP than are ERPs derived from either uncorrected or randomly corrected trials. The procedure also reduces the difference between ERPs which are based on trials with different degrees of EOG variance. Furthermore, variability at each time point, across trials, is reduced following correction. The propagation factor decreases from frontal to parietal electrodes, and is larger for saccades than blinks. It is more consistent within experimental sessions than between sessions. The major advantage of the procedure is that it permits retention of all trials in an ERP experiment, irrespective of
ocular artifact. Thus, studies of populations characterized by a high degree of artifact, and those requiring eye movements as part of the experimental task, are made possible. Furthermore, there is no need to require subjects to restrict eye movement activity. In comparison to procedures suggested by others, EMCP also has the advantage that separate correction factors are computed for blinks and movements and that these factors are based on data from the experimental session itself rather than from a separate calibration session.

H. V. Semlitsch, P. Anderer, P. Schuster, and O. Presslich (1986) proposed a solution for reliable and valid reduction of ocular artifacts, applied to the P300 ERP [47]. The correction procedure relies on regression analysis. To reduce coherence between eye blink activity and ongoing EEG, visual electro oculogram (VEOG) and EEG are averaged on eye blinks. This yields a high reliability and validity of regression factors, determined per day, subject, and lead. In addition, this correction procedure allows for an estimation of the maximal error that must be taken into account. The efficiency of the procedure is demonstrated for single trials and averaged potentials.

T. D. Lagerlund, F. W. Sharbrough, and N. E. Buseacker (1997) used principal component analysis (PCA) by singular value decomposition (SVD) to analyze an epoch of a multichannel electroencephalogram (EEG) into multiple linearly independent (temporally and spatially noncorrelated) components, or features; the original epoch of the EEG may be reconstructed as a linear combination of the components [48]. The result of SVD includes the components, expressible as time series waveforms, and the factors that determine how much each component waveform contributes to each EEG channel. By omission of some component waveforms from the linear combination, a new EEG can be reconstructed, differing
from the original in useful ways. For example, artifacts can be removed and features such as ictal or interictal discharges can be enhanced by suppressing the remainder of the EEG.

They developed a variation of this technique in which the factors that reconstruct the modified EEG from the original are stored as a matrix. This matrix is applied to multichannel EEG at successive times to create a new EEG continuously in real time, without redoing the time-consuming SVD. This matrix acts as a spatial filter with useful properties. They applied this method to remove artifacts, including ocular movement and electrocardiographic artifacts. Removal of myogenic artifacts was much less complete, but there was significant improvement in the ability to visualize underlying activity in the presence of myogenic artifacts. The major limitations of the method are its inability to completely separate some artifacts from cerebral activity, especially when both have similar amplitudes, and the possibility that a spatial filter may distort the distribution of activities that overlap with the artifacts being removed.

Yong Hee Lee, Sun I. Kim and Doo Soo Lee (1997) used wavelet analysis for the removal of artifacts in the estimation of evoked potentials [49]. For the effective removal of artifacts and the extraction of an improved evoked potential response, we propose the method using the shrinkage of wavelet coefficients. The wavelet analysis decomposes the measured evoked potentials into scale coefficients with low frequency components and wavelet coefficients with high frequency components as a resolution level, respectively. In the wavelet domain, artifacts are dispersed mainly at the wavelet coefficients rather than the scaling coefficients. Thus, in the course of synthesis evoked potentials, this method shrinks the wavelet coefficients to reduce the effects of artifacts in the wavelet domain and then reproduces the evoked potentials
with the constricted coefficients, and lastly averages them. They collected visual evoked responses to simulate the method using the shrinkage of wavelet coefficients and obtained VEP after reproducing evoked responses using the wavelet analysis, and compared it with averaged signal. As a result of simulations, they got VEP with improved SNR in comparison with the averaging method at Daubechies wavelet in the resolution level four. They estimated that the 32 times of averaging was enough to get normal VEPs.

S. Casarotto, A.M. Bianchi, S. Cerutti, G.A. Chiarenza (2004) used Principal component analysis to reduce ocular artifacts in single trial event-related potentials (ERPs) recorded in normal and in dyslexic children [50]. Dyslexia is a condition that makes it very difficult for children to read, write and/or spell. It is unrelated to person’s intelligence.

C.A. Joyce, I.F. Gorodnitsky, M. Kutas (2004) used blind component separation based on Independent Component Analysis (ICA) and Recursive Least Squares (RLS) for automatic removal of eye movement and blink artifacts from EEG data [51]. They proposed an algorithm combining the effective ICA capacity of separating artifacts from brain waves, together with the online interference cancellation achieved by adaptive filtering.

In 2008 Hyunseok Kook, Lalit Gupta, Srinivas Kota, Dennis Molfese, H. Lyytinen, utilized standard deviation test and multichannel median distance test for artifact rejection to improve the classification of multi-channel evoked potentials [6]. To improve the classification of multi-channel evoked potentials (EPs) they introduced a temporal domain artifact detection strategy. Using this strategy they (a) evaluated how the performance of classifiers is affected by artifacts and (b) showed how the performance can be improved by detecting and rejecting artifacts in offline
and real-time classification experiments. Using a pattern recognition approach, an artifact is defined in this study as any signal that may lead to inaccurate classifier parameter estimation and inaccurate testing.

The temporal domain artifact detection tests include: a within-channel standard deviation (STD) test that can detect signals with little or abnormal variations in each channel and also detect faulty channels, a within-channel clipping (CL) test to detect amplitude clipped EPs in each channel, and a multi-channel EP median distance (MC-MED) test to detect atypical signals not identified by the STD and CL tests. It was shown that the improvement in classification accuracy through the incorporation of the artifact detection strategy can be quite significant in real-time classification trials. Furthermore, the generalized formulation of the artifact rejection classification strategy makes it adaptable to various other problems involving the multi-class classification of multivariate signals of multiple sensors.

Carlos Guerrero-Mosquera, Angel Navia Vazquez (2009) applied adaptive filtering and independent component analysis for automatic removal of ocular artifacts from EEG data [52]. They proposed an algorithm combining the effective independent component analysis (ICA) capacity of separating artifacts from brain waves, together with the online interference cancellation achieved by adaptive filtering. The method uses separate electrodes localized close to the eyes that register vertical and horizontal eye movements, to extract a reference signal. Each reference input is first projected into ICA domain and then the interference is estimated using the RLS algorithm. This interference estimation is subtracted from the EEG components in the ICA domain. Results from experimental data demonstrate that this approach is suitable for eliminating artifacts caused by eye movements, and the
principles of this method can be extended to certain other sources of artifacts as well. The method is easy to implement, stable, and presents a low computational cost.

In the present research work *kurtosis* is applied to detect type-A artifacts that could not be detected by standard deviation test and multichannel median distance test. This is because of the fact that since kurtosis is the fourth order moment, small disturbances occurring in some samples a signal will affect more the kurtosis than the standard deviation and the median. Also multichannel median distance can only detect type-B artifacts, little raise in amplitude levels of majority number of samples, that cannot be detected either by direct vision, by standard deviation.