[Narayanam* *et al.*, 5(6): June, 2016]
IC™ Value: 3.00

ISSN: 2277-9655
Impact Factor: 4.116

IJESRT

INTERNATIONAL JOURNAL OF ENGINEERING SCIENCES & RESEARCH TECHNOLOGY

DEVELOPING 'STANDARD NOVEL 'VAD' TECHNIQUE' AND 'NOISE FREE SIGNALS' FOR SPEECH AUDITORY BRAINSTEM RESPONSES FOR HUMAN SUBJECTS

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DOI: 10.5281/zenodo.54772

ABSTRACT

In this research as a first step we have concentrated on collecting non-intra cortical EEG data of Brainstem Speech Evoked Potentials from human subjects in an Audiology Lab in University of Ottawa. The problems we have considered are the most advanced and most essential problems of interest in Auditory Neural Signal Processing area in the world: The first problem is the Voice Activity Detection (VAD) in Speech Auditory Brainstem Responses (ABR); The second problem is to identify the best De-noising technique for Auditory Artifact removal in Speech ABR of Brainstem Speech Evoked Potentials. In VAD problem we have implemented Zero-Crossing Detection VAD, statistical algorithms (two algorithms) which are already a standard in Speech Processing VAD problems, and then a third VAD we have presented is based on spectral subtraction method in which we have developed our own mathematical formula for the peak valley difference detection of the frequency spectra to detect the voice activity (we named it as SNRPVD VAD). These algorithms we applied on our data sets of EEG collected Brainstem Speech Evoked Potentials and compared their performances. VAD is verified and we found that SNRPVD VAD algorithm is working better than the Statistical VAD techniques and found to be it is detecting Voice even in more noisy data where statistical method could not detect. The second problem we considered is to de-noise the data from auditory artifacts and improve its SNR. We developed various De-noising techniques specifically: Yule-Walker Multiband filter; Cascaded "Yule-Walker and Comb" filter; Conventional Wavelets: Daubechies, Symlet, Coiflet Wavelet filtering; FAST Independent Component Analysis (FASTICA) filtering; Translation-Invariant (TI) Estimation filtering; Cycle Spin Translation Invariant Wavelets Independent Component Analysis (CSTIICA) Filtering approaches. We found the Wavelets are working better and TI wavelets are working far better than all; and then CSTIICA is working even better than TI wavelets. The performance measures considered are Signal to Noise Ratio (SNR) and Mean Square Error (MSE). Ultimately we observed that Wavelets are working surely as one of the best tools for de-noising neurological signals specifically Speech ABR signals. With these Novel observations in VAD and De-noising for Speech ABR, as both are relatively new and advanced areas in Audiology and as they gained wide interest in the last about a decade in scientific community of audiology scientists and engineers, Novel techniques are essentially emergency and hence with our research we are contributing some advanced working ideas to the community of Auditory Neural Signal Processing.

KEYWORDS: EEG, Translation Invariance, ICA, FASTICA, CS, Yule-Walker Multiband Filter, Comb filter, Wavelets, VAD

RESEARCH OBJECTIVE

The brainstem speech evoked potentials real time data was collected using EEG from different human subjects for synthesized vowel sounds. The data of this Auditory Brainstem Responses (ABR) was collected using EEG from up-to 20 human subjects non-intracortically in an audiology lab in University of Ottawa, Canada. The goals of the research are to

A. Doing Voice Activity Detection (VAD) in Speech ABR (Section I),
B. De-noising and improving SNR in Speech ABR (Section II)

In fact, collecting right data of Auditory Evoked Potentials of Speech ABR from human subjects it-self is relatively a new and most advanced area and a challenging task.

INTRODUCTION

VOICE ACTIVITY DETECTION (VAD) IN SPEECH AUDITORY BRAINSTEM RESPONSES

The first section of the chapter is dedicated to Voice Activity Detection (VAD) in EEG collected Speech ABR. In our experiment (Dajani et al., 2005; Johnson et al., 2005; Russo et al., 2004) EEG Electrode recordings are made from brain stem in response to complex, speech-like, sound stimuli. The data is collected in an audiology lab in University of Ottawa, Canada. An important drawback affecting the EEG collected Neurological data is the noise from various sources and its harmful effect on system performance. Various noise reduction techniques have been developed to relieve the effect of the noise on the system performance and often require an estimate of the noise statistics obtained by means of a precise voice activity detector. Speech/non-speech detection is an unsolved problem in speech processing and effects numerous applications including robust speech recognition. The speech/non-speech classification task is not as trivial as it appears, and most of the VAD algorithms fail when the level of background noise increases. For the last 1-2 decades numerous researchers have developed different strategies for detecting speech on a noisy signal and have evaluated the influence of the VAD effectiveness on the performance of speech processing systems (Yanna Ma et.al, 2013, Jasmina Catic et.al, 2010). Especially for Auditory Speech processing effects of VAD is about a decade research specifically. ABRs provide a window into how behaviorally relevant sounds such as speech and music are processed in the brain. Because temporal and spectral characteristics of sounds are preserved in this Subcortical response, ABRs can be used to assess specific impairments and enhancements in auditory processing. Subcortical function dynamically interacts with higher-level cognitive processes to refine how sounds are transcribed into neural code. By being an objective and non-invasive means for examining cognitive function and experience-dependent processes in sensory activity, ABRs have considerable utility in the study of populations where auditory function is of interest (persons with hearing loss, auditory processing and language disorders). Voice Activity is one of the difficult tasks in ABR as it is highly unobservable. In speech processing there are certain VAD methods are developed based on energy thresholds, zero-crossing detection, higher order statistical methods. There are applications of VAD in speech processing: speech coding, speech enhancement, robust speech recognition systems, noise reduction for digital hearing aid devices. The study of auditory brain stem responses in a variety of neurological disorders has been found to be of assistance in evaluating the mechanisms of coma, the localization of midbrain and brain stem tumors, the localization of demyelization of the brain stem, and the presence of diminished brain stem circulation. The ABR is considered an exogenous response because it is dependent upon external factors. The ABR is used for newborn hearing screening, auditory threshold estimation, intra-operative monitoring, determining hearing loss type and degree, and auditory nerve and brainstem lesion detection. ABR thresholds can be used for hearing aid fittings. Advantages of hearing aid selection by brainstem speech evoked potentials of ABR include the following applications: evaluation of loudness perception in the dynamic range of hearing, determination of basic hearing aid properties (gain, compression factor, compression onset level), cases with middle ear impairment (contrary to acoustic reflex methods), non-cooperative subjects even in sleep, sedation or anesthesia without influence of age and vigilance (contrary to cortical evoked responses). Auditory Brainstem Response (ABR) important for the early diagnosis of hearing impairment in infants. Keeping all these essentialities of ABR collection, and their application and the essential need for Detection of Voice in ABR in audiology, in this research we specifically concerned about VAD in Auditory Brainstem Responses for Speech Stimuli. Voice activity detection in speech ABR is a highly difficult task as it is a highly noisy environment with plenty of auditory artifacts including unknown sources. Considering the essentiality for collecting ABR and Detecting Voice Activity in Brainstem Speech Evoked potentials, in the most recent years there is increasing interest in recording auditory brainstem responses to speech stimuli (speech ABR) as there is evidence that they are useful in the diagnosis of central auditory processing disorders, and in particular in some children with learning disabilities (Johnson et al., 2005). However, the frequency content of natural speech is neither concentrated in frequency nor in time, the recording of speech ABR of sufficient quality may require tens of minutes (Dajani et al., 2005). Even with a synthetic consonant-vowel stimulus, a recording time of several minutes was required (Russo et al., 2004). Speech ABR is believed to originate in neural activity that is phase-locked to the envelope or harmonics of the stimulus. As a result, the recorded responses are remarkably speech-like (Dajani et al., 2005). In fact, speech ABR is quite intelligible if played back as a sound (Galbraith et al., 1995). As a result, methods used for Voice Activity Detection (VAD) may be useful for the detection of speech ABR (Ranganadh et al., 2012, 2013).

An important problem in many areas of speech processing, especially in our case of auditory neural speech signal processing, is the determination of presence of speech periods in a given signal. The purpose is the determination to which class a given signal belongs. The classification is not a trivial task since the increasing level background noise caused by electrical power supply, earth magnetism, heartbeat, breathing, eye movements and blinking, the machinery that are used to record signals and the brain activity which we are not interested are all cause noise in the EEG collected data. EEG signals are therefore a combination of the signals pure EEG and artifacts. The presence of these noises introduces spikes and results in signal distortion and degrades the classifier effectiveness, thus leading to numerous detection errors. When the level of background noise increases and the noise completely masks the speech. The selection of an adequate feature extraction vector for signal detection and a robust decision rule is a challenging task. The objective of feature extraction process is to compute discriminative speech features suitable for detection. Among many of the approaches, the main approaches we are considering in this research of VAD in Speech ABR are: a) Zero Cross Detection Ratio b) Statistical Analysis algorithms c) A spectral subtraction based Peak Valley Difference Detection Ratio based VAD (which is our own VAD algorithm and we named it as SNRPVD). In the third method we have developed our own formula and it is working better than the existing standard of statistical analysis VAD algorithms (first order and second order) and it is detecting even in highly noisy conditions where Statistical could not detect VAD. As part of the first section of the chapter we are considering these VAD techniques for Detecting Voice Activity in the Speech Auditory Brainstem Responses.

VAD Algorithms

In this research we are presenting three algorithms for the purpose of the Voice activity detection in EEG collected brain stem speech evoked potentials. Once the response is detected, then other noise suppression algorithms could in principle be applied to improve the signal-to-noise ratio (SNR). For the purpose of VAD we implemented three algorithms in this research (a) Linear-interpolation zero-crossing rate algorithm (GBrson Eduardo Mog et al., 2007) explained in the section 1.2.1, specifically for our application. (b) A new proposed VAD algorithm that is based on a binary weighting of the spectral components of the signal under test (In-Chul Yoo et al., 2009). This algorithm essentially based on our own developed formula, explained in the section 1.2.2, is based on the property that vowels have distinctive spectral peaks. These are likely to remain higher than their surroundings even after severe corruption. Therefore, by developing a method of detecting the spectral peaks of vowel sounds in corrupted signal voice activity can be detected as well even in low signal-to-noise ratio (SNR) conditions. (c) Two more statistical algorithms are also implemented, based on a statistical approach that has become the standard for detecting harmonic components in a related evoked response, the auditory steady-state response (ASSR). We provided the results in section 1.3. Finally we found the peak valley detection based SNRPVD algorithm performing better than the remaining two. Statistical algorithms (Two), accumulated from different statistical algorithmic procedures (M.S. John et al., 2000;J. Sohn et al, 1999; R. Nicole et al, 1999; Y.D. Cho et al, 2001; K. Woo et al, 2000; E. Vemer et al, 2001; C. Nikolas et al, 1993; T.S. Rao et al, 1982) highlighted as part of the result analysis.

Zero Crossing Rate Usage For The Purpose Of Voice Activity Detection In Speech Abr

First, in this paper we have implemented the Voice Activity Detection for the collected EEG brain stem speech evoked potentials using the “linear interpolation Zero crossing rate algorithm” (Gbrson eduardo mog et al., 2007). In this algorithm the shape of the signal is very close to the straight line near the zero crossing. Near the zero crossing the samples are described as points in straight line defined by the angular parameter a, and a linear parameter b. The two consecutive samples on the X-axis can be expressed as

$$x_n = a \times n + b$$
$$x_{n+1} = a \times (n+1) + b \qquad (1)$$

The parameters a and b can be expressed in terms of the samples.

$$a = x_{n+1} - x_n$$
$$b = (n+1) \times x_n - n \times x_{n+1} \tag{2}$$

The raising zero crossing must be in between two consecutive samples which must satisfy the condition.

$$x_n \leq 0 < x_{n+1} \tag{3}$$

Sample displacement for interpolation parameter d, is defined when interpolated sample n+d is given by

$$x_{n+d} = a \times (n+d) + b \tag{4}$$

By making the interpolated value equal to zero we can calculate the desired instant n+d of the zero crossing.

$$n + d = \frac{b}{-a} = \frac{(n \times x_{n+1}) - (n+1) \times x_n}{(x_{n+1}) - (x_n)} \tag{5}$$

The displacement d is given by

$$d = \frac{-x_n}{(x_{n+1}) - (x_n)} \tag{6}$$

d is a fractional number as of the equation 6, which is the zero crossing instant in sample numbers n+d. The samples x_n and x_{n+1} are trailing and leading samples from the zero cross instant.

Peak Valley Detection Algorithm For The Voice Activity Detection: Signal To Noise Ratio Peak Valley Detection Ratio

This method (In-Chul Yoo et al., 2007) uses spectral peaks of vowel sounds to detect Voice activity in this particular experiment of EEG collected brain stem speech evoked potentials. Using this method we reduce the problem of detecting the voice activity to the problem of detecting the presence of vowels. In this the assumption is that the vowel sounds are nearly unique to speech. Why this vowel sound detection is the reason that consonant sounds are always accompanied by vowel sounds and their duration is short so presence of vowel sounds can be directly related to the presence of speech. Vowel sounds are having distinctive spectral peaks of energy at specific spectral bands. Even though there is severe noise corruption the peaks remain higher than their surroundings. We assume that the positions of major spectral peaks are the most important factor in recognizing the vowel sounds rather than the relative sizes of peaks or the shapes in spectral valleys, which are vulnerable to noise. Using this concept we propose the Signal to noise Ratio peak valley difference (SNRPVD) which calculates the similarity between the peak signature vector S of a registered vowel sound and the spectrum X of the input signal. In this by using one conventional existing peak valley detection formula (In-Chul Yoo et al., 2007) and applying it on several of our data sets and for our application we have concluded and modified the formula to this following formula.

$$A = \sum_{k=0}^{n-1} (X[k] \times S[k]) \tag{7}$$

$$B = \sum_{k=0}^{n-1} S[k] \tag{8}$$

$$C = \sum_{k=0}^{n-1} (X[k] \times (1 - S[k])) \tag{9}$$

$$D = \sum_{k=0}^{n-1} (1 - S[k]) \tag{10}$$

$$SNRPVD(X, S) = (A/B)/ (C/D) \quad (11)$$

S Vector

The peak signature vector S contains the peak position information for a vowel sound. It is a binary vector designed by us for this type of data collection. We already know that the locations of the places where these vowel sounds peaks occur i.e.> for example at 400 Hz, 500 Hz, 700 Hz, 800 Hz, 1000 Hz. So after we locate which frequencies of vowel peaks we need to select then we have to use the following formula for the detection of the locations of the frequencies in the given vector size of 1024 and for the frequency sampling rate of 3202 Hz. Then put "1" in those calculated locations and put zeros in the remaining locations which gives the "S" vector for that particular data set. Then we can apply the above SNRPVD formula for the voice activity detection. There are several ways to design this S vector depending on the application and the data collection.

S vector frequency location calculation formula.

Frequency location = [(Sampling Frequency / Number of Samples)×(frequency for which we need to find the location)] + 2. (12)

Result Analysis

In this section the results of the three algorithms are presented in the form of bar graphs which are useful for the analysis of the performance of the three algorithms. In this we observed the SNRPVD (In-Chul Yoo et al., 2007) algorithm is far better than the ZCR (GBrson Eduardo Mog et al., 2007; Galbraith GC et al., 1995) and Statistical analysis algorithm (M.S. John et al., 2000; J. Sohn et al, 1999; R. Nicole et al, 1999; Y.D. Cho et al, 2001; K. Woo et al, 2000; E. Vemer et al, 2001; C. Nikolas et al, 1993; T.S. Rao et al, 1982). The results are given in the tabular form Table 1. We have 22 different subjects for analysis but we have presented here graphical results of one subject (subject 11) for example purposes for all the three algorithms in Figure 1 (a), (b), (c), (d).

The results are given in the Tabular form Table 1 for all the three algorithms under evaluation. In this we have taken into consideration the EEG pure noise data which we have collected during the data collection. The ZCR (GBrson Eduardo Mog et al., 2007, Russo et al., 2004) and SNRPVD (In-Chul Yoo et al., 2007) values as reference for evaluation which are 120 and 1.8596 respectively for this EEG noise data. On these for precise evaluation purpose we have taken some additional percentage of 5% more on these values which are 126 and 1.95258 respectively to form as a threshold. So this is the 100% surety reference threshold from the ZCR (Russo et al., 2004) and SNRPVD (In-Chul Yoo et al., 2007). So for the statistical analysis purposes we will take as low p-value as possible for the reference threshold value to make it as close as possible for the 100% surety. In our case we have taken 0.01 is the threshold p-value we have taken. Form this we have 1% error i.e. 99% surety. For ZCR (Russo et al., 2004) and SNRPVD (In-Chul Yoo et al., 2007) values of all 22 subjects if the values are more than the taken threshold then it is considered as voice detection. For statistical analysis algorithm if it is less than the given threshold then it is considered as the voice detection. So in this case we started the experiment as adding the noise from 10 db to -40 db and also 1000db to the EEG pure noise signal and then adding this noised signal to the original data signal and then we did put into application this ZCR and SNRPVD and also statistical algorithmic procedures.

Conclusion and Future Research

After as of the observed results from the table 1 it is clear that we can do better in the case of Signal to Noise Ratio Peak Valley Detection (SNRPVD) algorithm than Zero Cross Rating and Statistical analysis algorithms. As SNRPVD is detecting Voice even in very noisy conditions where the existing standard statistical VAD could not detect, SNRPVD VAD can be one of the first VADs in the world which can be the best and better than Statistical VAD techniques. As a future scope of this research we are planning to design these algorithms on hardware using Xilinx FPGAs and CMOS Custom Design Tools. Then we would like to see their hardware feasibility, resource utilization and their efficiency in terms of speed, area, power utilization and resource utilization and compare to find out which is having ease of design in hardware, which is the best out of these with respect to efficiency parameters, and which platform is best (FPGAs or CMOS Custom Design).

Subject number	SNRPVD SNR cutoff (db)	ZCR SNR cutoff (db)	P-values Column 2 SNR cutoff (db)	P-values column 4 SNR cutoff (db)
1	-16	-1	nothing	-6
2	-18	-2	nothing	-6
3	-21	-1	-15	-14
4	-22	-21	-12	-10
5	-22	-10	-14	-12
6	-23	-21	-13	-12
7	-23	-21	-12	-11
8	-23	-2	-16	-15
9	-24	-11	-15	-12
10	-24	-21	-12	-11
11	-26	-21	-14	-13
12	-26	-20	-12	-11
13	-27	-12	-17	-16
14	-30	1000	-18	-17
15	-30	-18	2	-15
16	-30	-18	2	-15
17	-31	-11	-13	-12
18	-31	-11	-14	-13
19	-32	-11	-14	-12
20	-32	1000	-19	-16
21	-35	-14	-13	-16
22	-36	-15	13	-16

Table 1 showing SNR performance comparison for 22 different subjects for the VAD algorithms under evaluation for Brainstem Speech Evoked Potentials

(Note: column 2 is for: For fundamental frequency of 100 Hz. Column 4 is for: For the frequency tone 100 Hz + 200 Hz.)

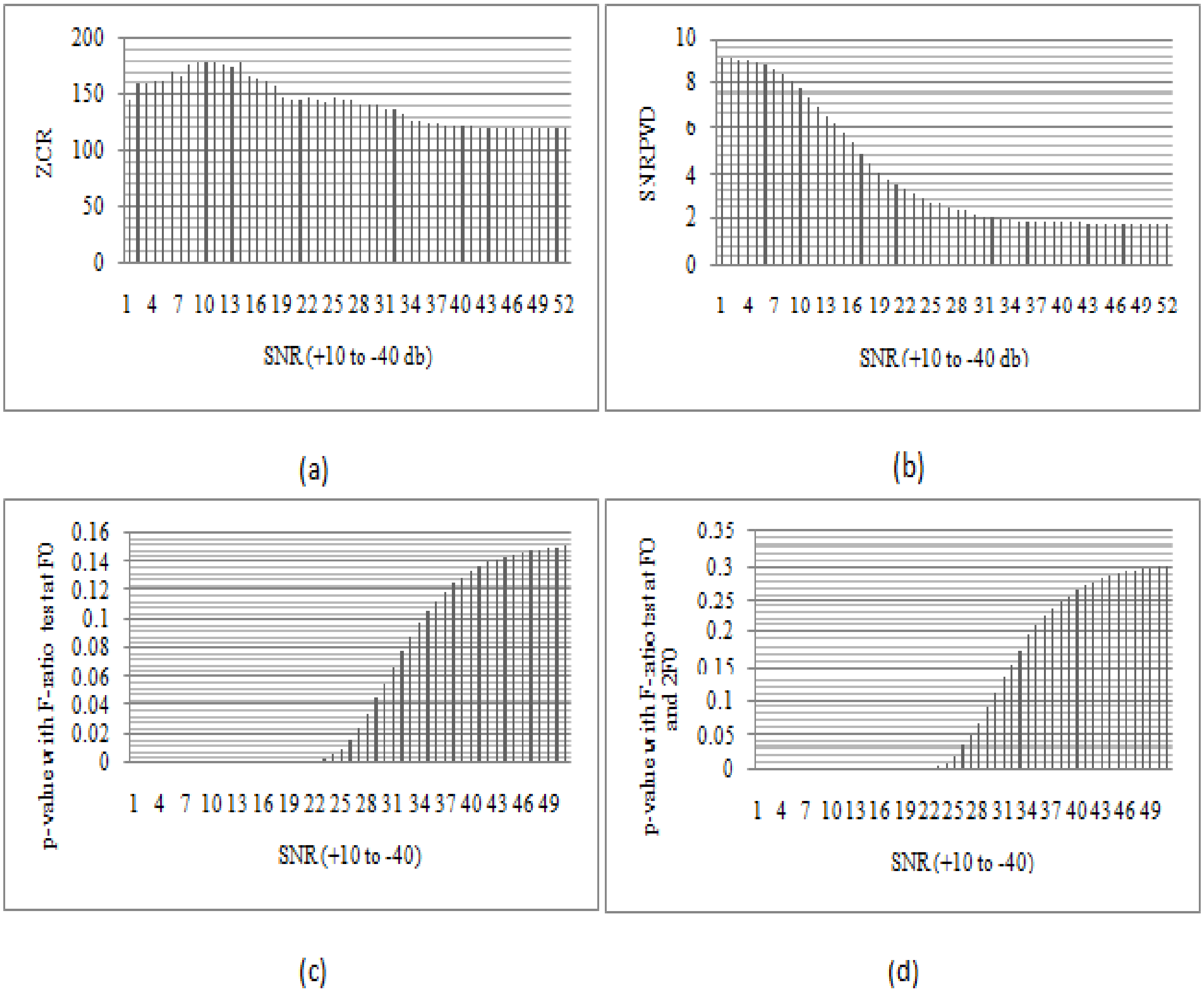

Figure 1. For figures (a), (b), (c) & (d) on the X-axis SNR values in db from 10 dB to -40 dB in the steps of 1, and on the Y-axis ZCR, SNRPVD, Statistical algorithm: For fundamental frequency of 100 Hz, Statistical algorithm: For the frequency tone 100 Hz + 200 Hz respectively.

SECTION – II
DESIGN OF EFFICIENT DE-NOISING TECHNIQUES FOR SPEECH AUDITORY BRAINSTEM RESPONSES

Introduction

The main objective of this section is to find the best approach for getting a best SNR improvement technique for EEG collected Speech Auditory Brainstem Responses. In this we have designed various filtering techniques including Yule-Walker Multiband Filter; Comb filter; Cascaded Yule-Walker and Comb filter; and Conventional Wavelets filters: Daubechies, Symlet, Coifflet; Translation Invariant (TI) Wavelets Filtering, FASTICA Filtering; Cascaded Cycle Spin TI&FASTICA (CSTIICA) filtering approaches. Out of these TI wavelets De-noising and CSTIICA De-noising Approaches are working the best of all approaches. The two performance measures we considered are Signal to Noise Ratio (SNR) values, Mean Square Error (MSE) Values.

EEG measures the brain activity. Major categories of noise in EEG signals are artifacts: electrical power supply, earth magnetism, heartbeat, breathing, eye movements and blinking, the machinery that are used to record signals and the brain activity which we are not interested are all cause noise in the EEG collected data. EEG signals are therefore a combination of the signals pure EEG and artifacts. The presence of these noises introduces spikes and results in signal distortion. So, correct analysis is impossible. This results in misdiagnosis for some patients. Noise must be eliminated or attenuated. The attenuation of noise can lead to considerable information loss. The most recent methods of de-noising techniques are Independent Component Analysis and Wavelet Transform, which have found to be useful tools for de-noising biomedical signals in the last just more than a decade and have become an active research of interest (M. Akin et al., 2002, M.I. Bhatti et al., 2008). Independent Component Analysis is an advanced and recent technique for data analysis such as EEG. In the recent 15 years ICA has been extensively studied upon its attractive potential applications into medical signal processing such as EEG, speech recognition etc (U.E. Emuir et al.,2003). In most of the neurological data, there is a large amount of noise, and the number of independent components is unknown which gives difficulties for many ICA algorithms. So ICA so does work on decomposing a signal (random vector) into statistically independent components. The classical definition of ICA is suppose there are m independently and identically distributed non Gaussian sources, called Independent Components (ICs), with at most one Gaussian source. All of them are statistically independent to each other (S. Hoffman et al., 2008). Independent component analysis originated from the field of blind source separation (BSS). In BSS problem in the given set of observations the inherent signal information is hidden, the mixing weights of the individual signals are unknown. BSS identifies the source signals and/or the mixing weights and separates these sources (A. Hyvarinen et al., 2001). ICA is useful in separation of the EEG signals into its constituent independent components (ICs) and then eliminating the ICs which contribute to the noise. Like ICA, Wavelet transform (WT) has been used to study EEG signals successfully because of its good localization properties in time and frequency domain. EEG signals pass through two complementary fitters and emerge as two signals, approximation and details. This is called decomposition or analysis. The components can be assembled back into the original signal without loss of information. This process is called reconstruction or synthesis. The mathematical manipulation which implies analysis and synthesis is called discrete wavelet transform (DWT) and inverse of it is discrete wavelet transform (IDWT) (B. Ferguson et al., 2001). There have been many approaches to de-noising using WT where the EEG signals are decomposed into wavelets and noise removal done using thresholding and shrinkage. In this we particularly concentrate on thresholding. The wavelet transform is a mathematical tool capable of decomposing a signal into its component frequencies (scales), and then detailing how each scale evolves over time. This provides simultaneous access to time, amplitude, and scale information, and therefore the ability to conduct efficient multi-resolution analysis (MRA). Because of its MRA abilities, WT is a valuable tool for the analysis of many electrophysiological potentials. In the recent 1-2 decades there is reasonable number of literature (Subrata Saha et al., 1999; Wilson, 2013) has come providing the reason for fundamental requirement of applicability of Wavelets for EEG Evoked Potentials. This gave strong interest in the applications of Wavelets to Brainstem Speech Evoked Potentials in the last around a decade, and little literature is for successful advanced algorithms for Speech ABR. As par the essential usefulness of recording Speech ABR has given increasing interest in collecting Speech ABR (Johnson et al., 2005) in the last decade, and hence increasing interest in providing algorithms for De-noising of biomedical signals especially for Speech ABR. There are certain properties of Speech ABR which have to be addressed, which makes the use of wavelet analysis for speech ABR. The Auditory Evoked Potential (AEP) signals frequency spectrum often contains more than one primary frequency component that is of clinical interest; AEP signals are non-stationary in nature and present with variable peak morphology; AEP signals are often sampled with far higher frequency than the Nyquist rate for increased time resolution, for improved SNR while doing A-D conversion process; AEP signals are smooth in appearance. Wavelets properties such as integration to zero and various degrees of compact support, smoothness, and symmetry these features make wavelets ideal for analyzing transient signals such as AEP. Wavelet analysis can be thought of as applying multiple matched filters that are looking for shifted and scaled versions of themselves within the input signal.

Basing on the most recent advancements and applicability of ICA and Wavelets for de-noising Biomedical Signals such as EEG neurological signals we considered their application for de-noising on EEG collected Brainstem speech evoked potentials signals, collected in an audiology lab in University of Ottawa, and collected from 10 human subjects. There is increasing interest in recording auditory brainstem responses to speech stimuli (speech ABR) as there is evidence that they are useful in the diagnosis of central auditory processing disorders, and in particular in some children with learning disabilities (Johnson et al., 2005). As discussed in Section I, as the recorded potentials are remarkably speech like, methods used for Voice Activity Detection (VAD) may be useful for the detection of speech ABR (Ranganadh et al., 2012, 2013). Once the response is detected, then other noise suppression algorithms could in principle be applied to improve the Signal-to-Noise Ratio (SNR). We found the speech like response in these brainstem speech evoked potentials collected from single electrode EEG and also we detected Voice by using VAD algorithms including our own methodology of Signal-to-Noise Ratio Peak Valley Difference Detection Ratio, which confirmedly detected Voice amazingly all the times with higher SNRs (Ranganadh et al., 2012, Ranganadh et al., 2013). Collecting data and Noise reduction in biomedical signals collected from single electrode EEG for Brainstem Speech evoked potentials of Audiology is a highly advanced, huge and interesting area of research and relatively new. In our research we have collected data (Dajani et al., 2005; Johnson et al., 2005; Russo et al., 2004) from single electrode EEG signals, collected in an audiology lab of University of Ottawa. The major component evoked potential, reflects coordinated neural ensemble activity associated with an external event. Evoked potentials offer important information to study the neural basis of perception and behavior. In these signals in addition to evoked potential, potentials caused by background activity are also present. This background activity unrelated to any specific event "noise" to be suppressed and evoked potentials have to be extracted. In clinical and cognitive researches the extraction of evoked potentials is an essential task. So there are plenty of methods have come up to extract the evoked potentials, basing on the application, they work in their limitations to an extant with some tradeoffs. In our research to improve the de-noising performance we have designed various techniques for the Auditory Brainstem Responses of Brainstem speech evoked potentials, which successfully improved Signal-to-Noise Ratio for extracting evoked potentials. Sometimes cascading of filters basing on their frequency and time domain properties can develop a filter which can improve the de-noising performance of a signal. In this research cascading Yule-walker and comb filter gave us better performance than without cascading. In this research we have concentrated on de-noising techniques using Yulewalker filter, Cascaded YuleWalk-Comb filter, Conventional Wavelets: Daubechies, Symlet and Coiflet, Translation-Invariant (TI) wavelets, FASTICA (Bingham E et. al 2000), and an improved technique of " 'Cycle Spinning (CS) based TI wavelets' and 'ICA' " combination algorithm: "CSTIICA". We evaluated all these techniques in terms of the performance measurements of Signal to Noise Ratio (SNR), Mean Square Error (MSE). We found that Cascaded YuleWalk-Comb filter is working better than Yule-walker filter, then conventional wavelets are performing far better than cascaded Yule-comb filter and that too specifically Daubechies wavelets are working best. TI wavelets are working far better than Conventional Wavelets. Among FASTICA and conventional wavelets, Daubechies wavelets are working nearly better than FASTICA, but both are having nearby performances. " 'Cycle Spinning (CS) based TI wavelets' and 'ICA' " combination algorithm: "CSTIICA" is working with far higher performance than TI wavelets and best performed among all the techniques. TI wavelets de-noising technique, and CSTI-ICA de-noising technique are providing highly innovative observational results with better performances in suppressing noise for extracting Evoked potentials; and hence a better improvement in de-noising.

Filtering Techniques

The EEG collected Auditory Brainstem Responses of Brainstem Stem speech evoked potentials data was collected (Dajani et al., 2005; Johnson et al., 2005; Russo et al., 2004) from 10 different human subjects from an audiology lab in University of Ottawa with corresponding hardware and software experimental setups of the audiology lab. For the experimental data analysis purposes for this research it has been sampled for 1024, 2048 samples. We have concentrated at the frequencies of 100Hz, 200Hz up-to a maximum of 1000 Hz for the frequency components and harmonics as at higher frequency components the speech like tones are almost rare. The research performed on MATLAB 7.8 R2009a installed on windows XP professional OS based computer system with Intel E5200, 2.5 GHz processor in University Of Ottawa; and MATLAB 8.3 R2014a installed on windows 7 OS based computer system with Intel Core I5 3.30 GHz processor in ICFAI Foundation for Higher Education, Hyderabad, India. The experiment's goal is to de-noise the EEG collected Auditory Brainstem Responses from auditory artifacts. For this purpose we have done the de-noising process by using the Yule-Walker filter, Cascaded Yule-Walker-Comb Peak filter, Conventional Wavelets: Daubechies, Symlet, Coiflet Wavelet family, Translation-Invariant (TI) wavelets, Fixed point ICA: FASTICA (Bingham E et. al., 2000), Combination of "Cycle Spin TI wavelets and FASTICA- CSTIICA" filters. The performance measures considered are SNR (dB), MSE.

Iir Yule-Walk Multiband Filter

Yule-Walk (John L Semmlow et al., 2004) is an IIR filter with arbitrary magnitude specifications, and this IIR filter approximates an arbitrary magnitude response, it minimizes the error between the desired magnitude represented by a vector and the magnitude of the IIR filter in the least-squares sense. This filter can be highly useful for biomedical signals such as Audiological Biomedical signals (John L Semmlow et al., 2004). We can use different orders for the better approximation of the results.

Iir Comb Filter

A comb filter can be used for increasing the energy of a signal at particular frequencies basing on notch or peak; and hence possibility of improving signals amplitudes in the time domain of the signal (Mikel et Gainza et al., 2005; Aileen Kelleher et al., 2005., Robert W. et al., 2008). Basing on their time domain and frequency domain properties Cascading of filters basing on the type of application some times gives plenty of innovative results. We first implemented Comb filtering Comb-notch and also Comb-peak filters; Yule-Walk multiband filters. Here we implemented Cascading of Yule-Walk multiband filter with few more filters. But after Yule-Walk Filter we found that amplitude of the signal was suppressed keeping frequency same of the signal. To get a good response and to improve the signal amplitude, we would like to extend this IIR Yule-Walk filter design to cascade it with a filter which can improve the amplitude of the signal and also to improve the signal to Noise Ratio. We selected IIR Comb-filter. For this we would like to utilize the properties of Comb filtering process to enhance its time-domain for the nearest approximation. So we cascaded Yule-Walk multiband filter with Comb-Peak filter which approximated the amplitude of signal in its time domain to the simulated original signal keeping the frequency. Then we observed the Signal-to-Noise Ratio for both cases of Yule-Walk multiband filter and the cascaded filter of Yule-Walk-Comb-Peak filter. It found to be there is a significant improvement in the SNR values in Cascaded filter. It's a good success. We found better improvements with different orders of the filters. We found that Yule-Walk-Comb-Peak filter is better smoothening and making the signal to the nearest approximation to the original simulated signal.

Conventional Wavelets

Wavelet transform produces wavelet coefficients of the noiseless signal and the coefficients of the noise. Researchers found that wavelet de-noising is performed by taking the wavelet transform of the noise-corrupted and passing the detail coefficients, of the wavelet transform, through a threshold filter where the details, if small enough, might be omitted without substantially affecting the main signals. There are two main threshold filters – soft and hard. Research has shown that soft-thresholding has better mathematical characteristics and provides smoother results. Wavelets Possesses frequency-dependant windowing, which allows for arbitrary high resolution of the high-frequency signal components; unlike STFT. A key advantage of wavelet techniques is the variety of wavelet functions available. So it allows us to choose the most appropriate one for the signal under investigation. For the above reasons the wavelet transform has emerged over recent years as a powerful time-frequency analysis and signal-coding tool suitable for use in manipulation of complex non-stationary signals in biomedical signal processing such as in human auditory signal processing. Around 2 decades back Wavelet transforms were introduced for Evoked Potentials analysis of EEG (E.A. Bartnik et. al., 1992; O. Bertrand et. al., 1994; R.Q. Quiroga et. al., 1999). Recently, the wavelet transform was applied for EEG evoked potential extraction by choosing a few wavelet coefficients (R.Q. Quiroga et. al., 2003), requiring a priori knowledge of the time and frequency ranges of the Evoked Potential. But such knowledge is abundant in EEG. Wavelets offer higher temporal resolution at lower frequencies, so it suits well the 1/f spectral profile of evoked potentials. Wavelets filtering process includes three steps: 1. Wavelet decomposition 2. Nonlinear thresholding 3. Inverse wavelet reconstruction. Nonliner thresholding (I.M. Johnstone et. al., 1997) is used in the thresholding step for separating the signal from noise. The evoked potential will be wavelet decomposed with large wavelet coefficient, where as the ongoing background activity will be decomposed with small coefficients. So thresholding the wavelets coefficients can estimate the evoked potentials. Here we studied temporally correlated white Gaussian noise model, and we proposed level-dependant thresholding (R.R. Coifman et. al., 1995). Here we have utilized Daubechies, Symlet and Coiflet conventional wavelets. We proved that wavelets are performing far better than cascaded filters (Ranganadh et al., 2014). We have designed wavelet filters of different orders for these brainstem speech evoked potentials collected from single electrode EEG by using different functions of Daubechies, Symlet, Coiflet Wavelets. We found reasonably similar results for all the three wavelet functions even while observing the frequency spectra and also at the SNR performances of these wavelets. It means that the results are almost insensitive to which wavelet family we choose out of the three. But we found better results with Daubechies wavelets than Symlet and Coiflet wavelet functions. In addition to conventional wavelets, we have developed the three steps of the algorithm using wavelet packets. Wavelet packet decomposition, thresholding and reconstruction found to be having more precision than wavelets.

Translation-Invariant (Ti) Wavelets Filtering Estimator

In addition to the conventional wavelet based filtering estimators we are considering the TI wavelet based estimator filtering technique. Here we are choosing translation invariant wavelet evoked potential estimator, in addition to conventional wavelets. In this filtering technique problems such as pseudo-Gibbs phenomenon near the discontinuities (R.R. Coifman et. al., 1995) can be overcome.

To do the process with TI wavelets evoked-potential estimation filtering the steps are
1. We shift the data.
2. Threshold the shifted data.
3. Unshift the thresholded data.
4. Then average the results for all shifting.

We did this process for each individual data sets. We considered shifting and unshifting the signal in the frequency domain and we did 1,2,3,4,5 shifts for each individual data set and averaged the results. We utilized two popular thresholding techniques: hard thresholding, soft thresholding. Soft thresholding sets the wavelet coefficients with the magnitude less than the threshold to zero, but it reduces the remaining coefficients in magnitude by the threshold also when compared to hard thresholding, soft thresholding does not contain noisy spikes, so we strongly considered soft thresholding and it provides smooth estimates. We have implemented this TI wavelets algorithm on our brainstem speech evoked potential data for 10 human subjects. Then we calculated overall SNR values for each subject and compared it with conventional wavelets. TI wavelets estimation filtering method is outperforming the conventional wavelet filters (Ranganadh et al., 2014).

Unscented Kalman Filter (Ukf)

UKF is a Bayesian filter which uses minimum mean square error as the criterion to measure the optimality. UKF involves Unscented Transformation (S. Julier et al., 1997; S. Julier et al., 2004) a method used to calculate the first and second order statistics of the outputs of nonlinear systems with Gaussian. UKF addresses the flaws in Kalman Filters (Extended Kalman Filter). UKF uses the intuition (S. Julier et al., 2004) that it is easier to approximate a probability distribution function rather than to approximate an arbitrary nonlinear function or transformation. Following this intuition, a set of sample points, called sigma points, are generated around the mean, which are then propagated through the nonlinear map to get a more accurate estimation of the mean and covariance of the mapping results. The nonlinear stochastic system used for the algorithm is:

$$\begin{aligned} x_{k+1} &= A\, x_k + B\, u_k + v_k \\ y_k &= H\, x_k + w_k \end{aligned} \tag{13}$$

where A and H are the known and constant matrices respectively, x_k is the unobserved state of the system, u_k is a known exogenous input, y_k is the observed measurement signal, v_k is the process noise and w_k is the measurement noise. UKF uses the intuition that it is easier to approximate a probability distribution function rather than to approximate an arbitrary nonlinear function or transformation.

Application Of Combined Algorithm Of "Translation Invariant Wavelets And Independent Component Analysis" (Cstiica) Filter

Recently there has been research comparing the de-noising techniques of both ICA and WT. Research shows that ICA and wavelets complement each other, removing the limitations of each (V.V.K.D.V. Prasad et. al, 2008). So an algorithm which combines ICA and WT with ICA as post or pre processing tool has been developed (G. Inuso et. al, 2007). They found this to be outperforming. In this cycle spinning (CS), proposed by Coifman and Donoho (R.R. Coifman et al, 1995), introduced as a single yet efficient method which utilizes periodic Time-Invariant of WT in fixing the noise found in wavelet coefficients and defined as:

$$\hat{s} = \frac{1}{k1\,k2} \sum_{i=1,j=1}^{k1\,k2} \mathrm{S}_{-\mathrm{i},-\mathrm{j}} \left(\mathrm{T}^{-1}\left(\theta\left[\mathrm{T}\left(\mathrm{S}_{\mathrm{i,j}}(\mathrm{x})\right)\right]\right)\right) \tag{14}$$

Where k1, k2 are maximum no. of shifts, T shift invariant transform, $S_{i,j}$ is the circulant shift, and Θ threshold operator. CS calls for the suppression of these noises by shifting the signals in time and computing the estimate. Using different shifts produce different estimates which are not completely independent; consequently averaging these estimates results in a reduction in the noise generated in each shift. This result in the de-noising of all possible unique circularly shifted version of the signal and the creation of the translation invariant wavelet transform (TIWT) method. Research shows that this technique has superior performance over plenty of the de-noising algorithms using thresholding or shrinkage of wavelet coefficients and has motivated the analysis of many de-noising algorithms in terms of optimal filtering of noisy wavelet coefficients. The combination of WT and Kalman filter (KF) was a new idea in the year 2006. Research shows that combination effectively correct overlapped spectra and reduces noise (p. senthil et al., 2008). The use of KF and WT combination improved de-noising techniques. Each method aims at improving the other.

(i) WT removes overlapping of noise signals that ICA cannot filter out; (ii) ICA can distinguish between noise and signals that are nearly the same or higher amplitude, which WT has difficulty with; (iii) WT exhibits serious problems such as Pseudo-Gibbs phenomenon which CS eliminates and; (iv) Combination of filters and WT effectively correct overlapped spectra.

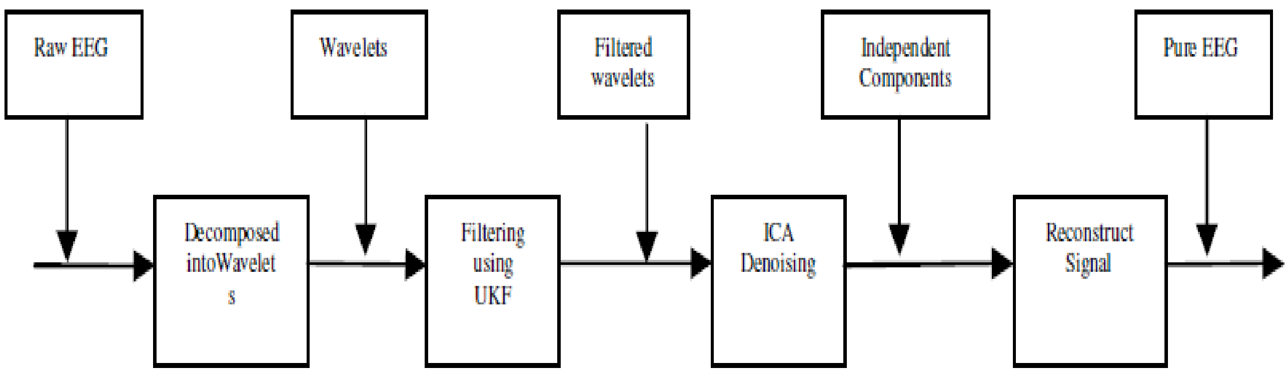

Figure 2. Combined (CSTIICA) – Artifacts removal system. The blocks in the order from left to right: Raw EEG, Decomposed into Wavelets, Wavelets, Filtering using UKG, Filtered wavelets, ICA de-noising, Independent components, Reconstruct signal, pure EEG.

The main difference of CSTI-ICA and TI Algorithm is that of introduction of Cycle Spinning and merging of WT and ICA. This CSTI-ICA algorithm's block diagram is given in the above figure Figure 2. Algorithm is having the following steps:

1. Collection of EEG data of Brainstem Speech Evoked Potentials signals from an Audiology Lab. Here we collected the data from an audiology Lab of University of Ottawa, in which the data had been collected from 10 different healthy subjects in real-time.
2. Apply Cycle Spin to the signal: The number of time shifts is determined; in so doing signals are forcibly shifted so that their features change positions removing the undesirable oscillations which result in pseudo-Gibbs phenomena.

   $$S_h(f(n)) = f((n+h) \bmod N) \tag{15}$$

   f (n) is the signal, S_h is the shift operator, N is the number of signals.
3. Decomposition of signal: Signals are decomposed using DWT separating noise and true signals; using the Daubechies family as the overall performance of De-noising is done best in the case of Daubechies wavelet family among all the three Daubechies, Symlet, Coieflet wavelets family of conventional wavelets (Ranganadh et al., 2014).
4. Filter Coefficients: Perform UKF on the coefficients to filter out some noise.
5. Denoise using the soft-thresholding method discarding all coefficients below the threshold value based on the universal threshold defined by Donoho & Johnstone et. al, 1995 given as:

$$T = \sqrt{2\sigma^2 \log N} \tag{16}$$

N number of samples, σ^2 is the noise power.

6. **Apply ICA algorithm:** Signals and noise may have nearly the same frequency characteristics and overlap in time thus producing noisy coefficients that WT has not been able to distinguish and remove. ICA is able to take care of the inherent distributions hence distinguish noise and remove them. Research shows that ICA is a robust denoising method where its performance is not affected by the severity of the mixing signals. We implemented here a fixed point ICA algorithm FASTICA (G.G. Herrman et al., 2005). Which by itself also we have compared along with conventional wavelets de-noising and also TI wavelets de-noising.
7. Reconstruction of EEG signals of Auditory Brainstem Responses (ABR): Reconstructed using inverse DWT.
8. Apply CS: Revert signals to their original time shift and average the results obtained to produce the de-noised EEG signals. The proposed algorithm can be expressed as Avg [Shift – Denoise -Unshift].

Result Analysis

From figures Figure 3 and Figure 4 it can be seen that the smoothening of the signal is better but amplitude of the signal has been suppressed to an extent. In figure 5 after designing cascaded Yule-Walk-Comb-Peak filter, it reduces the amplitude suppression in the time domain of the signal; and improves the closeness towards the original simulated signal in its amplitude; of-course in Figure 3, 4, 5 frequencies are same. In Table 2 and Table 3 it can be seen of the SNR and MSE performances. The Figures Figure 6, 7, 8 are the frequency spectra of the signal after de-noising using wavelets Daubechies, Coieflets and Symlet wavlelets; up-to the lower frequencies of 500 Hz for the purpose of the space limitations and clarity of the picture at those corresponding frequency peaks of interest, where we are having the interest of Voice Activity Detection frequency harmonics ie> 100 Hz, 200 Hz, 300 Hz etc. They look similar but some differences in the Signal-to-Noise Ratios but similar SNR values, which represents that whichever is the wavelet family out of the three, filtering is almost insensitive. As per the spectral analysis given in Figure 9 (Ranganadh et al., 2014); the wide lobe spectrum for TI wavelets clearly shows that TI wavelets de-noising technique is separating the noise from the Signal. But it is clear that TI wavelets method is giving sharp spectral lobes at some of the frequencies of our interest but not at all frequencies but a lot of improvement in the SNR values than conventional Daubechies wavelets. It is giving sharp edges at 100 Hz, 400 Hz, 500 Hz, 600 Hz and 700 Hz. But not sharp lobes at 200 Hz, and 300 Hz. But showing clearly all the frequencies of our interest. But SNR has been improved to a greatest level when compared to conventional wavelets. As per the spectrum we will have to further refine by doing few more shifts in the TI wavelets, which may further refine the TI wavelets and may give further SNR improvements. But as per the requirements of research it is more than sufficient if we can get clear and sharp peaks identification at one or two or three harmonics of the spectra. The same for SNR improvements case also, if it improves the SNR at one or two or three harmonics of our interest it is sufficient. From this research it is clearly be observed that Translation-Invariant Wavelets are working exceptionally well in terms of de-noising the ABR signals. It's a good sign for proceeding into the research and to develop some reference signals and spectra. Basing on application and requirement we may need to do more shifts or fewer shifts while doing TI algorithm. But it works very well. FASTICA; and CSTIICA wavelets based method are also implemented as part of the research. CSTIICA is implemented as per the algorithm explained in the section 2.2.6. It is found that conventional Wavelets are working better than FASTICA de-noising technique (Ranganadh et.al, 2015). Then CSTIICA Wavelets based FASTICA method is working better than TI wavelets method (Ranganadh et. al, 2015). But it is clear that because of the wavelets combination to FASTICA is working better than ICA itself. It is proved when conventional wavelets worked better than FASTICA; so it is confirmedly assures that CSTIICA is better than TI is mainly because of the Wavelets than ICA. When we see the Table 2,3,4, 5,6,7 it is clear that conventional wavelets working far better than Yule-Walker, Cascaded Comb filters; and Daubechies found to be better than all; and it is working better than FASTICA. TI and CSTIICA are the best de-noising techniques among all. From the bar graph figures Figure 12, 13 also it is clear that both wavelets techniques CSTIICA and TI are working best among all. The better performance of CSTIICA over TI de-nosing technique is discussed in section 2.3.1 by using Time Domain waveforms and phase lag.

Cstiica And Ti In Time Domain

After doing the De-noising the original signal by using the two techniques the time domain analysis of both the results can be seen in the Figure 10. It is clearly observed that the signal de-noised using CSTIICA method (the dark black signal) is highly correlated to the original simulated expected signal (the lightly black signal) when compared to the TI de-noised signal (the dashed signal). This shows clearly CSTIICA De-noising technique is better than TI de-noising technique. It can also be observed from the phase lag graph given in Figure 11 that CSTIICA De-noised signal (the dark black curve) is much in phase to the original expected simulated time domain waveform (the lightly black curve) when compared to TI de-noised signal (the dashed curve). But as per overall result analysis TI wavelets is also one of the best wavelet based de-noising tools for biomedical neural signals as CSTIICA wavelets based De-nosing Tool.

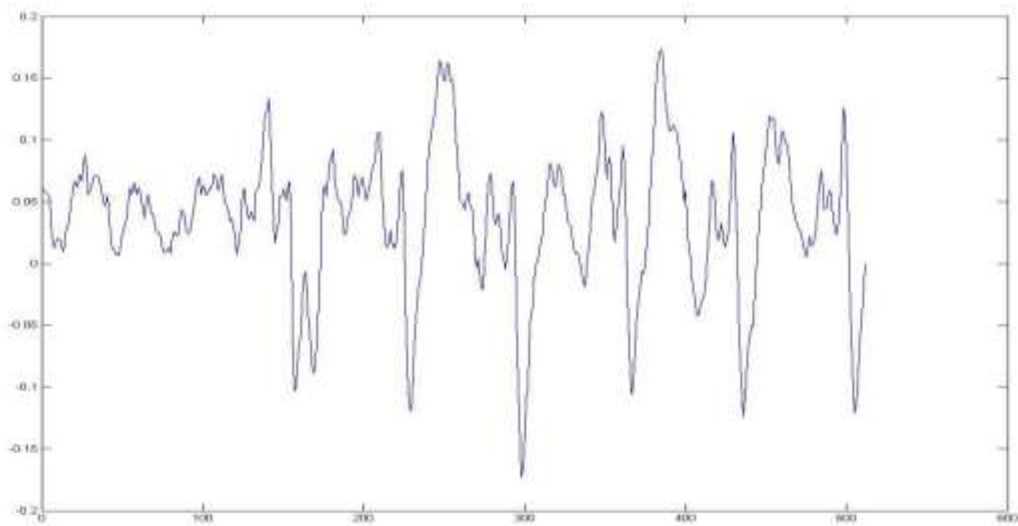

Figure 3 Given data time domain noisy signal, for Subject 1

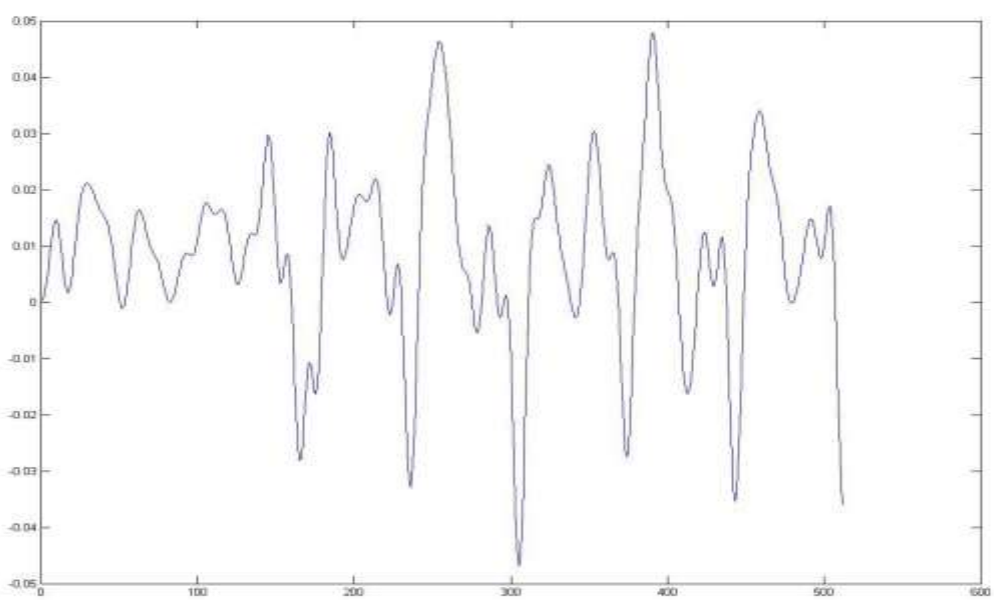

Figure 4 After Yule-Walk filtering time domain signal, for Subject 1

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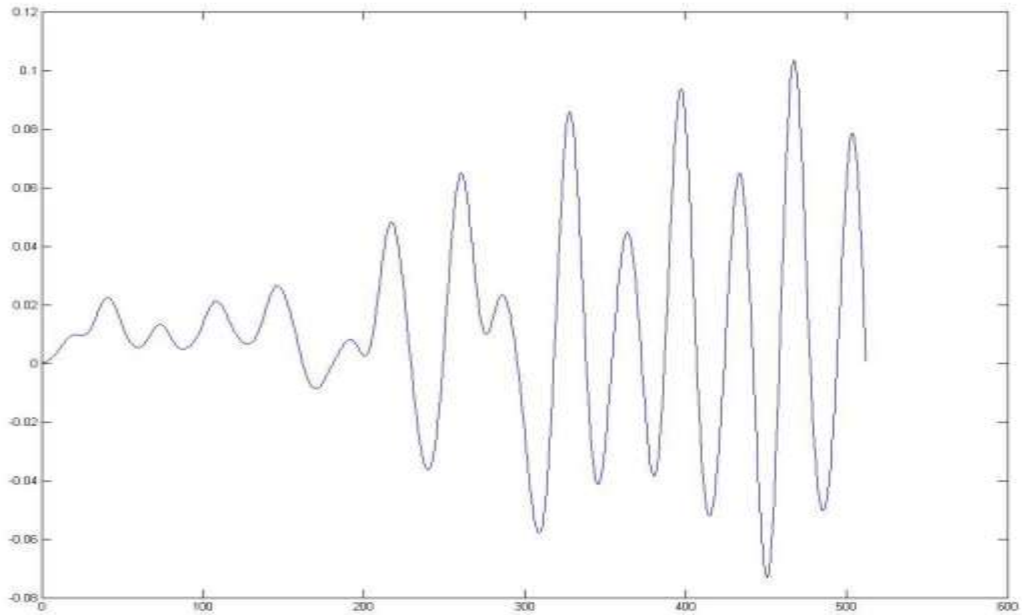

Figure 5 After Yule-walk-comb-peak filtering time domain signal, Subject 1, with better SNR

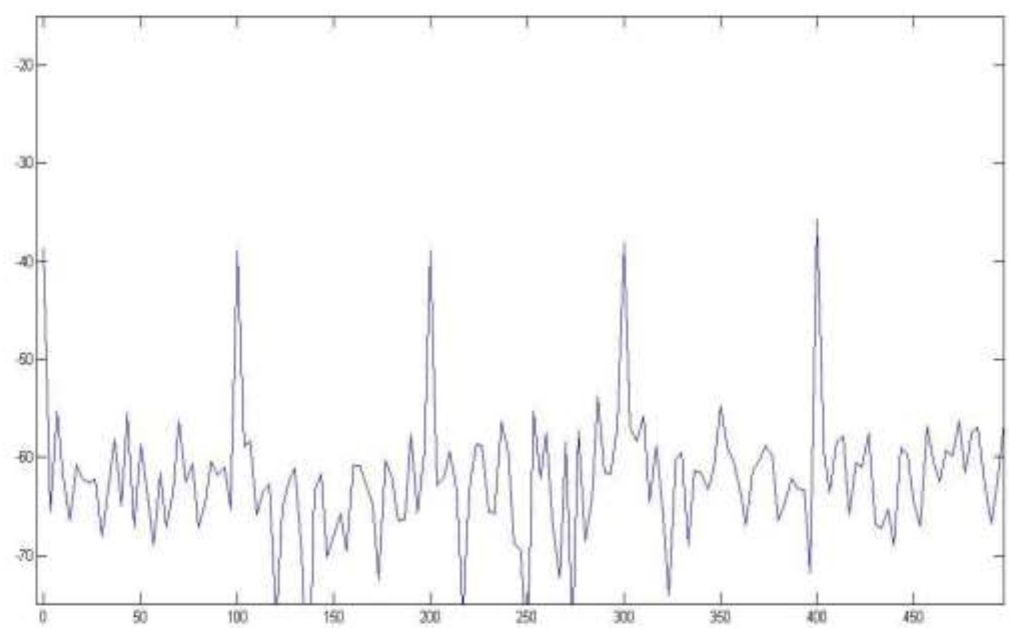

Figure 6 Daubechies Wavelets, Subject 1, spectral peaks

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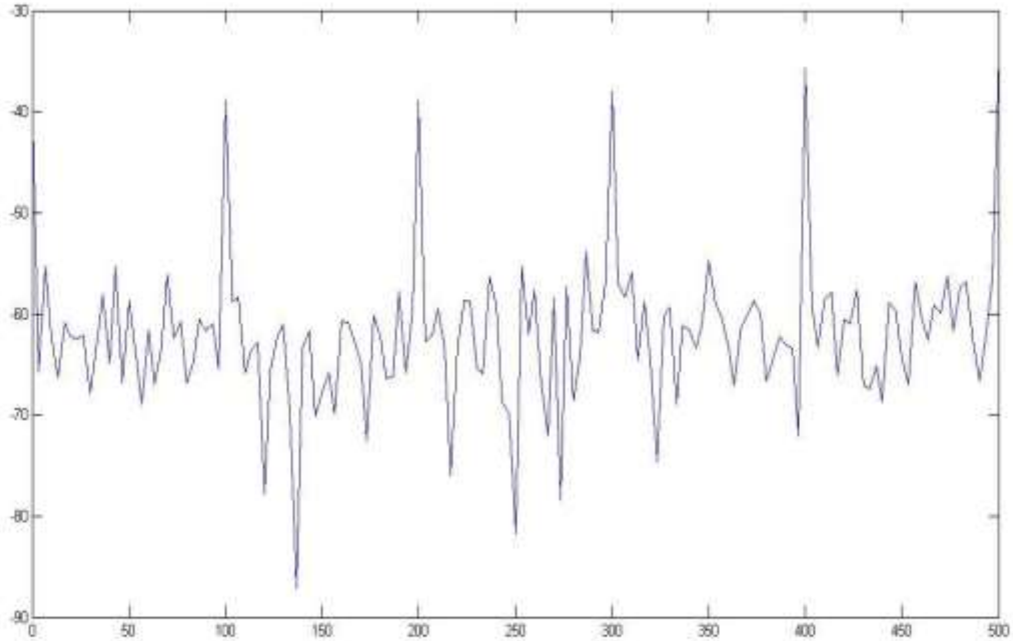

Figure 7 Symlet Wavelets, Subject 1, spectral peaks

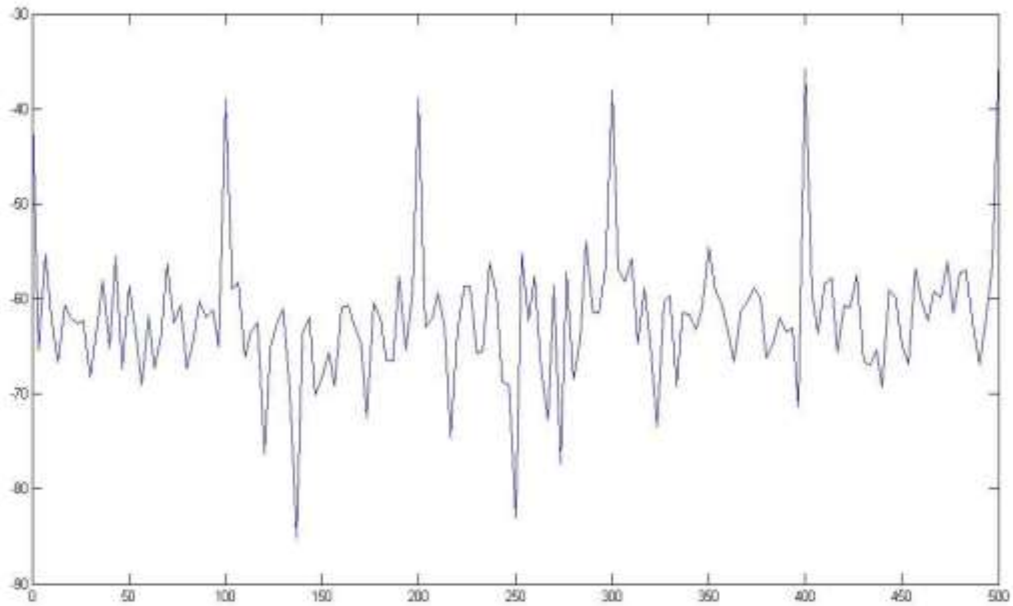

Figure 8 Coiflets Wavelets, Subject 1, spectral peaks

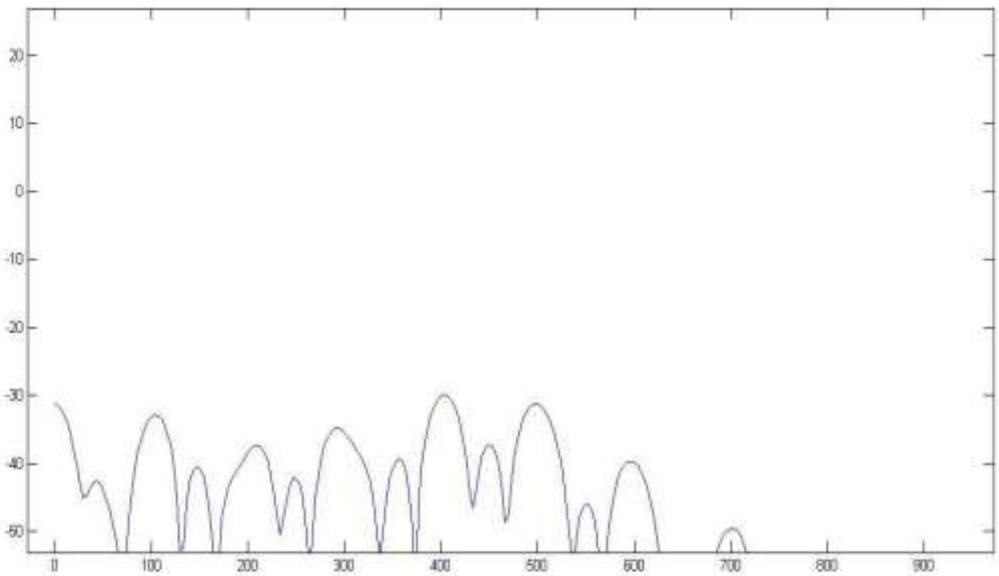

Figure 9 the frequency components in TI wavelets de-noising: the frequency components where the evoked responses concentrate strongly are the 100 Hz, 200 Hz, and so on. Which are our interested components of brainstem speech evoked potentials of our collected data.

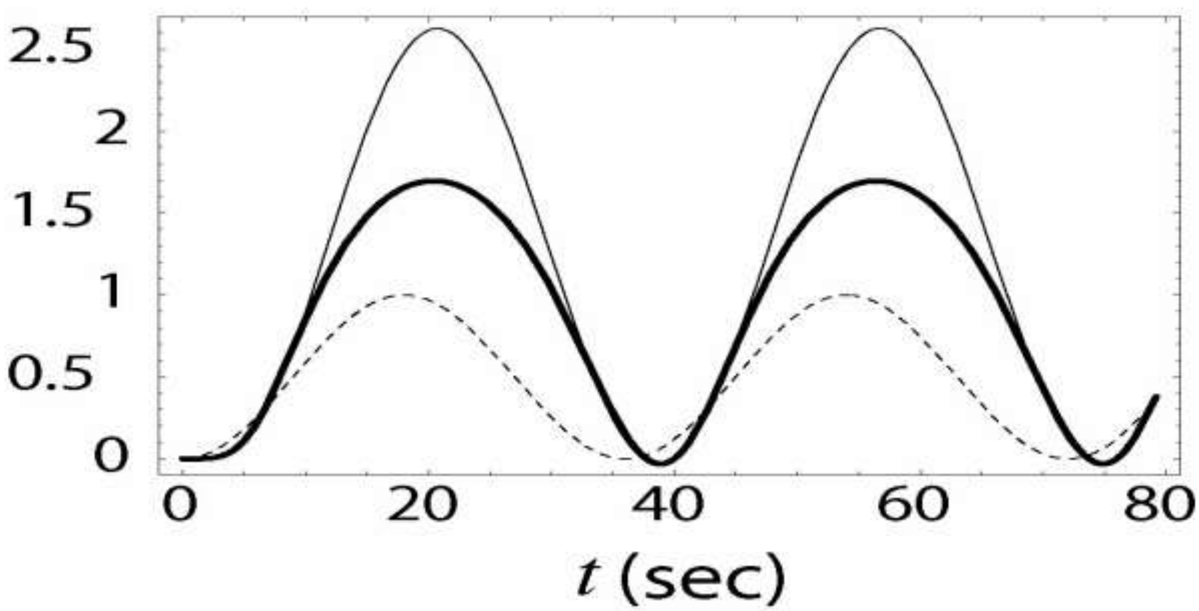

Figure 10 Time domain representation of the De-noised waveforms with original expected simulated signal for subject 10. The light dark signal is original expected simulated waveform. The second dark waveform is using CSTIICA de-noising. The dashed line is using TI de-noising. It is clear CSTIICA obtained better De-noised signal with high correlation than TI wavelets.

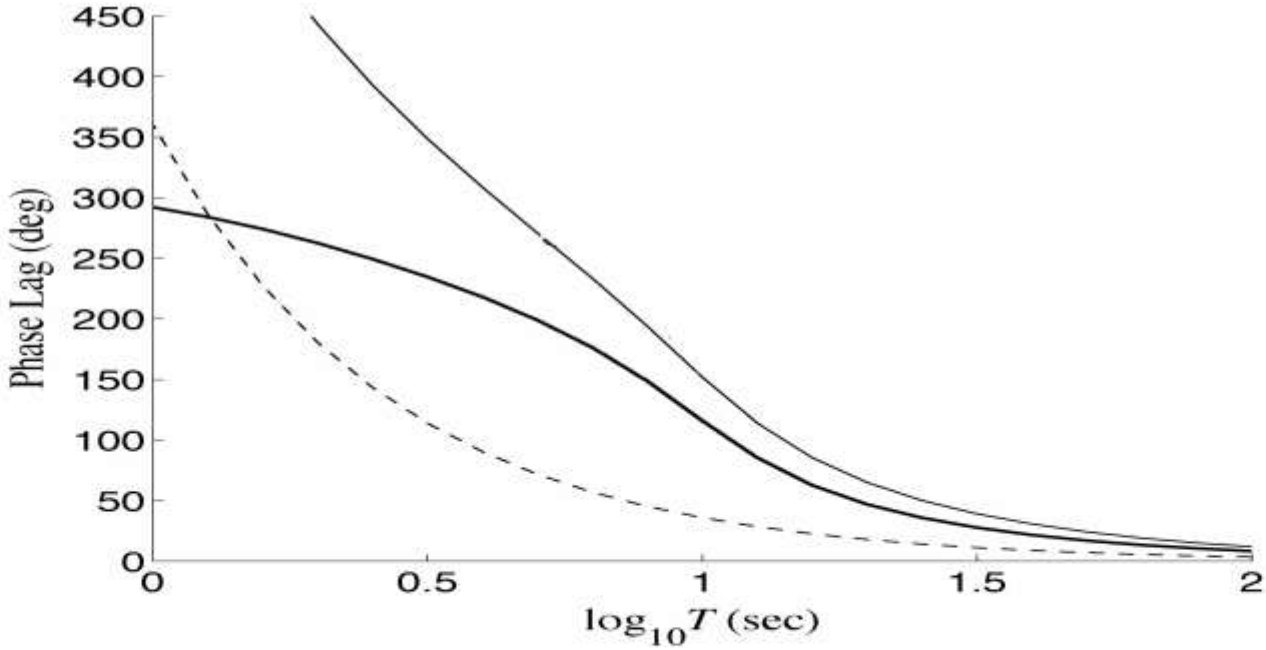

Figure 11. The Phase lag between the original simulated waveform and de-noised signal using CSTIICA and TI wavelets de-noising estimation filtering techniques. The light dark signal is original expected simulated waveform. The second dark waveform is using CSTIICA de-noising. The dashed line is using TI de-noising. It is clear that the CSTIICA de-noising technique is giving the best correlated signal with much in phase with less phase difference.

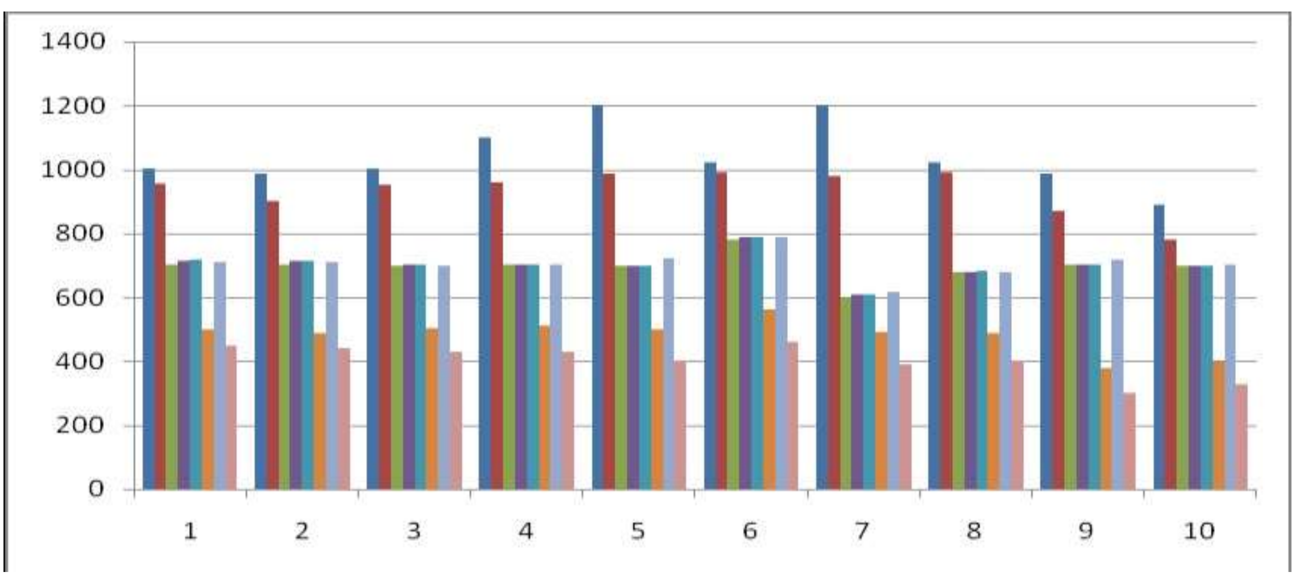

Figure 12. MSE Bar Graph: Bar graph showing MSE performance of all the de-noising techniques. On the X-axis it is subject number (1 to 10). On the Y-axis the values of Mean Square Error (MSE). For each subject 1st bar is Yule-Walker, 2nd bar is Cascaded-Yule-Walker-Comb, 3rd bar is Daubechies, 4th bar is Symlet, 5th bar is Coiflet,6th bar is TI, 7th bar is FASTICA, 8th bar is CSTIICA. It clearly shows TI and CSTIICA are the best and CSTIICA is the smallest MSE.

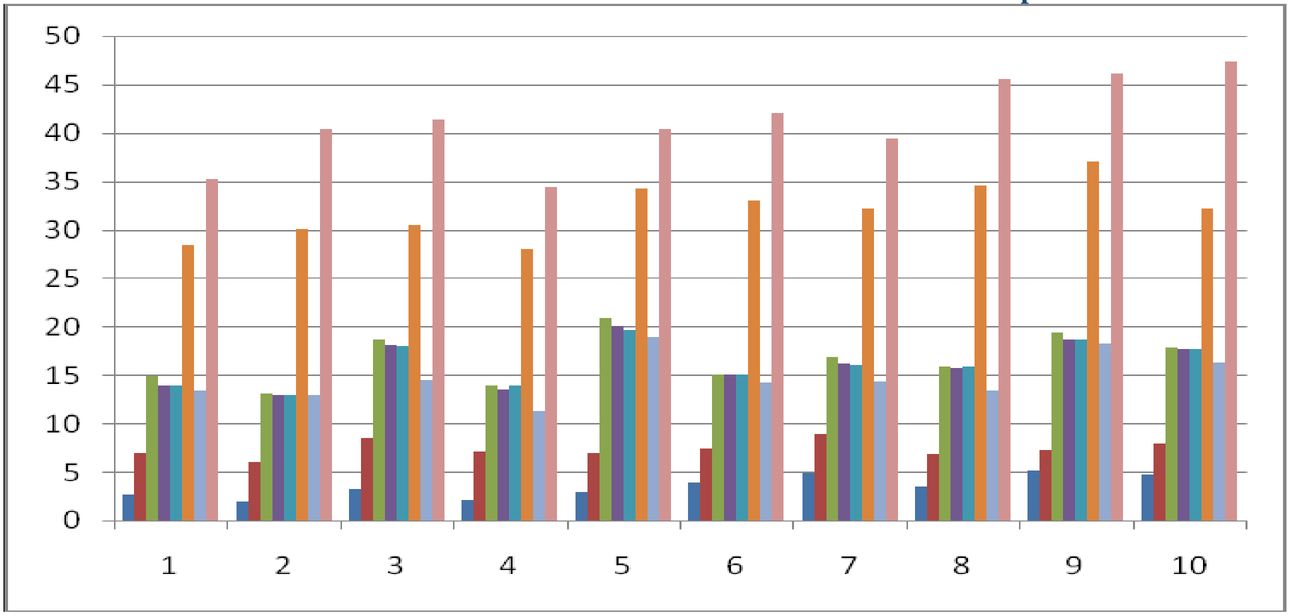

Figure 13. SNR Bar Graph: Bar graph showing SNR (dB) performance of all the de-noising techniques. On the X-axis it is subject number (1 to 10). On the Y-axis the values of SNR (dB). For each subject 1st bar is Yule-Walker, 2nd bar is Cascaded-Yule-Walker-Comb, 3rd bar is Daubechies, 4th bar is Symlet, 5th bar is Coiflet, 6th bar is TI, 7th bar is FASTICA, 8th bar is CSTIICA. It clearly shows TI and CSTIICA are the best and CSTIICA is the highest SNR.

Performance Measures Using Snr And Mse: (Explain Also The Bar Graphs At The End Of This Paragraph)
Here in this research we have done the application of different de-noising filters on the EEG collected Brainstem Speech Evoked Potentials of Auditory Brainstem Responses collected in an audiology lab of University of Ottawa. We have done the de-noising performances by using the performance measures of Mean Square Error (MSE) and; Signal-to-Noise Ratio (SNR) in dB. Here the results are given in the tabular forms Table 2 and Table 3. It is clear that MSE values are less in the case of Cascaded filter than Yule-walk filter showing that it is better in de-noising. Then Daubechies wavelets are having far smaller values of MSE showing far better performance than cascaded filter. Then FASTICA is also having far better performance than the cascaded filter and comparatively near performance of the conventional wavelets. Then TI wavelets are having far smaller MSE values than conventional wavelets and performing best. Then CSTI-ICA filter is working far better than TI, having far smaller values of MSE. In this research CSTI-ICA is performing the best of all. TI and CSTI-ICA are highly useful showing best of all methods. The bar graph Figure 12 shows clearly of this performance of all these techniques in graphical form which gives us much clarity on the result analysis and makes it easier to exactly identify the performance. The table 4 shows the performance of TI wavelets filter over Daubechies wavelets filter in terms of % reduction of MSE values, which represents the performance of TI wavelets estimator for all the 10 subjects. The Table 5 shows that % reduction in MSE values of CSTIICA filter over TI filter represents the % performance of CSTIICA over TI.

The Table 3 shows the performance of all the implemented filters in terms of improvement in the Signal-to-Noise Ratio. Here also the performance of the Cascaded filter is higher. Then Daubechies wavelets are performing excellent than Cascaded filter, and TI wavelets are performing far better than Daubechies. Then FASTICA also performing far better than cascaded filter, but comparatively near (but less) performance to Daubechies wavelets. Then CSTIICA filter is working better than TI filter and is the highest performance than all filters. TI and CSTIICA are best of all filters having highest SNR values and are highly useful for EEG auditory data analysis and auditory artifact removal. The bar graph Figure 13 shows the SNR performances of all auditory filtering techniques, which makes easy to analyze the SNR results and ease of analysis, makes clear that TI and CSTIICA are performing best of all filters. Table 6 shows the % improvement in SNR values of TI wavelets filters over Daubechies wavelets filtering. Table 7 shows the % improvement in SNR values of all 10 subjects of CSTIICA over TI wavelets filtering.

Subject No.	Yule-Walker	Cascaded-Yule-Walker-Comb	Daubechies	Symlet	Coiflet	TI	FASTICA	CSTIICA
1	1003.13	955.24	700.23	715.14	716.25	500.13	710.23	450.14
2	988.14	900.08	703.16	714.15	715.16	489.16	708.14	440.15
3	1001.18	950.14	697.15	700.18	701.18	501.18	699.18	430.13
4	1101.16	960.15	701.12	703.18	703.16	510.16	702.13	428.15
5	1200.18	987.14	698.15	699.14	699.15	500.15	720.16	400.16
6	1020.16	990.34	780.45	787.45	788.56	560.15	788.16	460.17
7	1200.17	980.14	600.16	610.15	609.16	490.15	615.13	390.14
8	1023.19	990.15	678.16	679.15	681.17	487.15	680.15	401.01
9	987.16	870.15	700.16	700.18	700.45	378.56	718.78	300.89
10	890.78	780.56	698.16	699.89	698.78	398.67	701.67	327.67

Table 2 Mean Square Error Values of all the de-noising techniques of all 10 human subjects. It clearly shows TI and CSTIICA are the best and CSTIICA is the smallest.

Subject No.	Yule-Walker	Cascaded-Yule-Walker-Comb	Daubechies	Symlet	Coiflet	TI	FASTICA	CSTIICA
1	2.6386	7.0123	14.8412	13.9801	13.9512	28.3456	13.3456	35.2345
2	1.9987	6.0098	13.0987	12.9087	12.9798	30.1245	12.9878	40.3456
3	3.1428	8.5241	18.6278	18.0410	17.9801	30.4567	14.4567	41.3456
4	2.0345	7.1243	13.9543	13.4535	13.8901	28.0245	11.2345	34.4576
5	2.8968	6.9842	20.8543	19.9941	19.6427	34.2817	18.9087	40.4523
6	3.9098	7.3459	15.0897	15.0587	14.9807	33.0678	14.2345	42.0345
7	4.8211	8.9128	16.8428	16.1322	16.0329	32.2345	14.3456	39.4567
8	3.4532	6.7891	15.8956	15.7658	15.8098	34.5678	13.3456	45.5678
9	5.2105	7.2129	19.3214	18.7211	18.6028	37.06342	18.2345	46.0987
10	4.7612	7.9876	17.8765	17.7567	17.6789	32.1234	16.3456	47.3456

Table 3 SNR (dB) values of all the de-noising techniques of all 10 human subjects. It clearly shows TI and CSTIICA are the best and CSTIICA is the highest.

Daubechies	TI	%reduction in MSE in TI over Daubechies
700.23	500.13	28.576325
703.16	489.16	30.434041
697.15	501.18	28.110163
701.12	510.16	27.236422
698.15	500.15	28.360667
780.45	560.15	28.227305
600.16	490.15	18.330112
678.16	487.15	28.16592
700.16	378.56	45.932358
698.16	398.67	42.897044

Table 4 shows the performance of TI over Daubechies wavelets in terms of % reduction in MSE values

TI	CSTIICA	%reduction in MSE of CSTIICA over TI
500.13	450.14	9.995401
489.16	440.15	10.01922
501.18	430.13	14.17654
510.16	428.15	16.07535
500.15	400.16	19.992
560.15	460.17	17.84879
490.15	390.14	20.40396
487.15	401.01	17.68244
378.56	300.89	20.51722
398.67	327.67	17.80922

Table 5 Shows the performance of CSTIICA over TI in terms of % reduction in MSE values

Daubechies	TI	%improvement Of SNR of TI
14.8412	28.3456	90.99264
13.0987	30.1245	129.9808
18.6278	30.4567	63.50133
13.9543	28.0245	100.8306
20.8543	34.2817	64.38672
15.0897	33.0678	119.1415
16.8428	32.2345	91.38445
15.8956	34.5678	117.4677
19.3214	37.06342	91.82575
17.8765	32.1234	79.69625

Table 6 Shows the performance of TI over Daubechies Wavelets in terms of % improvement in SNR values

TI	CSTIICA	%improvement Of CSTIICA
28.3456	35.2345	24.30324
30.1245	40.3456	33.92953
30.4567	41.3456	35.75207
28.0245	34.4576	22.95527
34.2817	40.4523	17.99969
33.0678	42.0345	27.11611
32.2345	39.4567	22.40519
34.5678	45.5678	31.82152
37.06342	46.0987	24.37789
32.1234	47.3456	47.38664

Table 7 Shows the performance of CSTIICA over TI in terms of % improvement in SNR values

CONCLUSION AND FURTHER RESEARCH

In this research we have done research on De-noising Neurological Biomedical Signals from the EEG collected brainstem speech evoked potentials data from 10 different human subjects using a) YuleWalker Multiband filter; b) Cascaded Yule-WalkerComb-Peak filter; c) Conventional Wavelets of Daubechies, Symlet, Coiflet family wavelets; d) FASTICA algorithm, e) TI wavelets Estimation Filter, f) CSTIICA algorithm filter. Performance measurements are done by using MSE and SNR (dB). We found that MSE value of Conventional wavelets is far less and SNR is far higher than a), b). FASTICA is also performing near to the performance of c) but Daubechies conventional wavelets family is performing better in auditory artifact removal. In our research we found that FASTICA is also one of the best De-noising techniques for Auditory Brainstem Responses but conventional Wavelets are working better. Then we have found that TI wavelets are having highly small values of MSE and highly large values of SNR and performing excellent than conventional Wavelets filtering approach. Then CSTIICA algorithm found to be performing better than TI by having smallest MSE values and highest SNR values. We found that TI and CSTIICA have done exceptional performances of auditory artifact removal from Speech ABR out of all the techniques we have considered. As it is found that conventional Wavelets are working better than FASTICA de-noising technique, then CSTIICA Wavelets based FASTICA method is working better than TI wavelets method; hence it is clear that because of the wavelets combination to FASTICA is working better than ICA itself. It is proved when conventional wavelets worked better than FASTICA; so it is confirmedly assures that CSTIICA is better than TI is mainly because of the Wavelets than ICA. We found one of the most identifiable result that wavelets is an excellent tool for artifact removal from EEG neural signals, even in our specific case of Auditory Artifact removal from speech Auditory Brainstem Responses - which is relatively new area and just more than a decade research. As a future scope of the research we would like to implement the Gabor filter and would like to compare its performance.

ACKNOWLEDGEMENT

It is to acknowledge my research adviser Dr. Hilmi Dajani, who trained me in the area of Audiology while I was a biomedical engineering research student under his instruction in University of Ottawa, Canada. CSTIICA research is completely done in IFHE Deemed University Hyderabad on the data collected in University of Ottawa Audiology Lab. The remaining and first part of the research half happened in University of Ottawa, and half continued and extended in India and a critical part also happened in IFHE – Hyderabad. It is highly appreciated of the support given by ECE department Faculty coordinator Professor K. Kishore Kumar, Faculty of Science and Technology, IFHE.

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