ISSN: 2277-9655
Scientific Journal Impact Factor: 3.449
(ISRA), Impact Factor: 2.114

IJESRT

INTERNATIONAL JOURNAL OF ENGINEERING SCIENCES & RESEARCH TECHNOLOGY

EFFICIENT DE-NOISING PERFORMANCE OF A COMBINED ALGORITHM OF "TRANSLATION INVARIANT (TI) WAVELETS AND INDEPENDENT COMPONENT ANALYSIS" OVER "TI WAVELETS" FOR SPEECH-AUDITORY BRAINSTEM RESPONSES

Ranganadh Narayanam*

[*] Assistant Professor, ECE department, Faculty of Science and Technology, Institute of Chartered Financial Analysts of India Foundation for Higher Education Deemed University (IFHE) – Hyderabad, India

ABSTRACT

In this paper we have presented a research for de-noising the EEG collected Brainstem Speech Evoked Potentials data collected in an audiology lab in University of Ottawa, from 10 different human subjects. Here the de-noising techniques we have considered are Yule-Walker Multiband Filter, Cascaded Yule-Walker-Comb Filter, Conventional Wavelet Transform estimation filters: Daubechies, Symlet, Coiflet Wavelet families, Translation Invariant (TI) Wavelet Transform estimation filter, FAST Independent Component Analysis (FASTICA) De-noising Technique, Combined algorithm of "Translation Invariant (TI) Wavelets and Independent Component Analysis" De-noising technique. The performance measures we have considered are Mean Square Error (MSE) and Signal-to-Noise-Ratio (SNR) values. Out of these techniques we found that cascading of Yule-Walker filter and Comb-Peak filter gave better De-noising performance than Yule-Walker Multiband Filter. Then conventional Wavelets performed far better than the cascaded filter, in those Daubechies family of wavelets worked better than all. Then FASTICA Algorithm worked near to the performance of Conventional Wavelets but far better than cascaded filter. Then we have utilized Translation Invariant (TI) wavelet algorithm which provided the excellent performance than above all. Then we have utilized combined Algorithm of "Translation Invariant (TI) Wavelets and Independent Component Analysis - CSTIICA" algorithm which found to be, it may perform better than TI wavelets algorithm. Ultimately TI and CSTIICA algorithms are found to be may be the best auditory artifact removal techniques and can be highly useful in auditory EEG data analysis to the best.

KEYWORDS: ICA, Wavelets, Translation Invariance, MSE, SNR, FASTICA, EEG

INTRODUCTION

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

ISSN: 2277-9655
Scientific Journal Impact Factor: 3.449
(ISRA), Impact Factor: 2.114

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 Guassian 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.

Basing on the most recent (may be 1.5/2 decades) 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, 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). 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. 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). 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. Some times 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

ISSN: 2277-9655
Scientific Journal Impact Factor: 3.449
(ISRA), Impact Factor: 2.114

(TI) wavelets, FASTICA, 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 SNR, 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.

The paper has been organized in this fashion: Section II gives the introduction to the designed filters; Section III discusses different results evaluating the performances of all the implemented de-noising techniques. Section IV discusses the Conclusion of the research.

INTRODUCTION TO DESIGNED FILTERS

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. 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 main concentration is to de-noise the EEG collected Auditory Brainstem Responses. For this purpose we have done the de-noising process by using the Yule-Walker filter, Cascaded Yule-Walker-Comb Peak filter (Ranganadh et al., 2014), Conventional Wavelets (Ranganadh et al., 2014): Daubechies, Symlet, Coiflet Wavelet family, Translation-Invariant (TI) wavelets (Ranganadh et al., 2014), Fixed point ICA: FASTICA, Combination of "Cycle Spin TI wavelets and FASTICA - CSTIICA" filters. The performance measures considered are SNR (dB), MSE.

IIR Filters and Conventional Wavelets (Ranganadh et al., 2014): IIR filters such as Yule-Walk Multiband Filters and Comb filters are some of the filters which work for EEG audio-logical signals for de-noising the signals as that work well on multiband signals. We considered here both these filters and evaluated their de-noising performances and evaluated by individual filters and cascaded Yule-Walk and Comb-Peak filters to get better performance. The cascading process has given interesting results by providing considerable improvement in the de-noising process (Ranganadh et al., 2014). 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.

ISSN: 2277-9655
Scientific Journal Impact Factor: 3.449
(ISRA), Impact Factor: 2.114

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).

Translation-Invariant (TI) wavelets Filtering Estimator (Ranganadh et al., 2014): 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) (S. Julier et al., 1997; S. Julier et al., 2004): UKF is a Bayesian filter which uses minimum mean square error as the criterion to measure the optimality. UKF involves Unscented Transformation 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:

$$x_{k+1} = A\,x_k + B\,u_k + v_k$$
$$y_k = H\,x_k + w_k$$

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:

$$\hat{s} = \frac{1}{k_1 k_2} \sum_{i=1,\, j=1}^{k_1 k_2} S_{-i,-j}\left(T^{-1}\left(\theta\left[T\left(S_{i,j}(x)\right)\right]\right)\right)$$

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

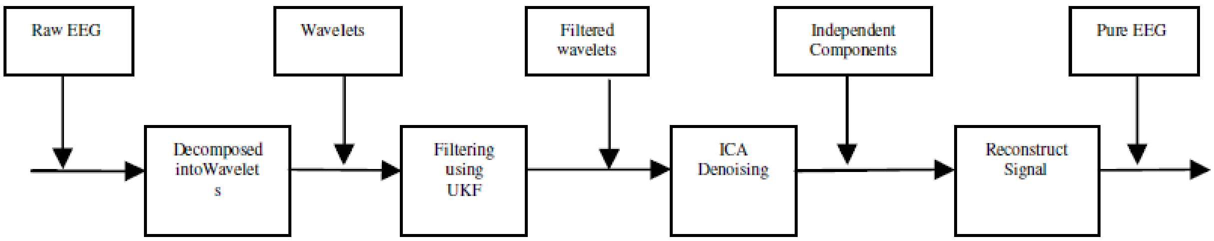

Fig 1. Combined (CSTIICA) – Artifacts removal system. The blocks in the order from left to right: Raw EEG, Decomposed into Wavelets, Wavelets, Filtering using UKG, Filtered wavelets, ICA de-noising, Independent components, Reconstruct signal, pure EEG.

filtering of noisy wavelet coefficients. The combination of WT and Kalman filter (KF) (S. Julier et al., 2004) 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 can not 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.

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 Fig 1.

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.

$$S_h(f(n)) = f((n+h) \bmod N)$$

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:

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

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

6. **Apply ICA algorithm:** Signals and noise may have nearly the same frequency

ISSN: 2277-9655
Scientific Journal Impact Factor: 3.449
(ISRA), Impact Factor: 2.114

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 (U.E. Emuir et. al, 2003). 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.

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

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 1 and Table 2. 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 1 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 3 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 4 shows that % reduction in MSE values of CSTIICA filter over TI filter represents the % performance of CSTIICA over TI.

The Table 2 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 2 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 5 shows the % improvement in SNR values of TI wavelets filters over Daubechies wavelets filtering. Table 6 shows the % improvement in SNR values of all 10 subjects of CSTIICA over TI wavelets filtering.

CONCLUSIONS

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) Yule-Walker Multiband filter; b) Cascaded Yule-Walker-Comb-Peak filter; c) Conventional Wavelets of Daubechies, Symlet, Coiflet family wavelets; d) FASTICA algorithm, e) TI wavelets Estimation Filter, f) CSTI-ICA 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 and also comparable to the performance of conventional Wavelets. 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 CSTI-ICA algorithm found to be performing better than TI by having smallest MSE values and highest SNR values. We found that TI and CSTI-ICA have done exceptional performances of auditory artifact removal from Speech ABR out of all the techniques

ISSN: 2277-9655
Scientific Journal Impact Factor: 3.449
(ISRA), Impact Factor: 2.114

we have considered. 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.

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 1 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 2 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.

ISSN: 2277-9655
Scientific Journal Impact Factor: 3.449
(ISRA), Impact Factor: 2.114

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 3 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 4 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 5 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 6 shows the performance of CSTIICA over TI in terms of % improvement in SNR values.

ISSN: 2277-9655
Scientific Journal Impact Factor: 3.449
(ISRA), Impact Factor: 2.114

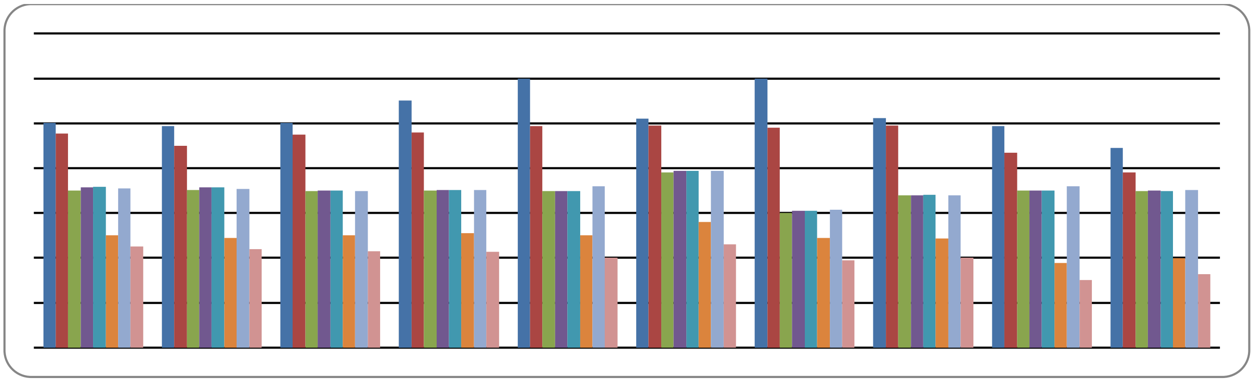

***Figure 1.** MSE Bar Graph: Bar graph showing MSE performance of all the de-noising techniques. On the X-axis it is subject number (1 to 10). On the Y-axis the values of Mean Square Error (MSE). For each subject 1st bar is Yule-Walker, 2nd bar is Cascaded-Yule-Walker-Comb, 3rd bar is Daubechies, 4th 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.*

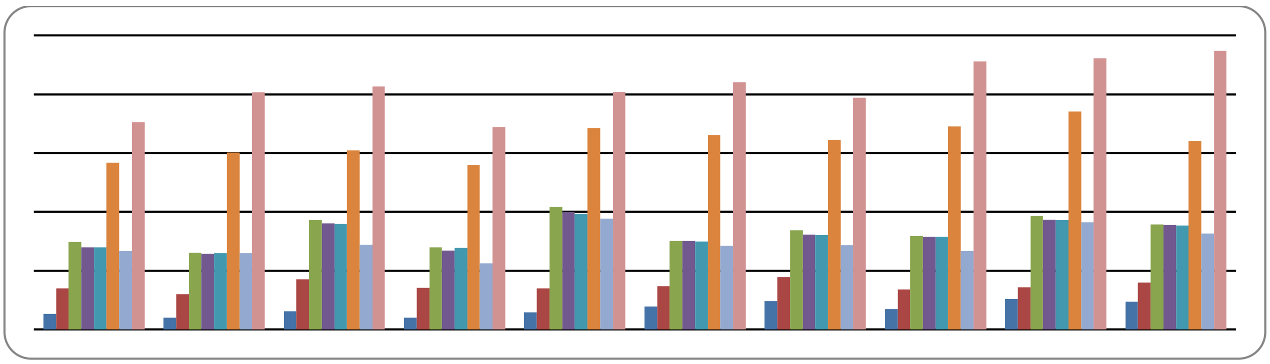

***Figure 2.** SNR Bar Graph: Bar graph showing SNR (dB) performance of all the de-noising techniques. On the X-axis it is subject number (1 to 10). On the Y-axis the values of SNR (dB). For each subject 1st bar is Yule-Walker, 2nd bar is Cascaded-Yule-Walker-Comb, 3rd bar is Daubechies, 4th bar is Symlet, 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.*

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. CSTI-ICA 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.

REFERENCES

1. Ranganadh Narayanam, 2013 "An efficient Peak valley detection based VAD algorithm for Robust Detection of speech auditory brainstem responses", Proceedings of AIRCC-international Conference on Computer Science and Information Technology (CCSIT-2013).
2. Dajani, R.H., Purcell, D., Wong, W., Kunov, H., Picton, T.W. 2005. Recording Human Evoked Potentials That Follow the Pitch Contour of a Natural Vowel. IEEE Transactions on Biomedical Engineering 52, 1614-1618.
3. Ranganadh Narayanam, 2012 "Robust detection of speech auditory brainstem responses using Voice Activity Detection (VAD) algorithms", IEEE CAMAN international conference – 2012.

ISSN: 2277-9655
Scientific Journal Impact Factor: 3.449
(ISRA), Impact Factor: 2.114

4. Johnson, K.L., Nicol, G.T., Kraus, N. 2005. Brain Stem Response to Speech: A Biological Marker of Auditory Processing. Ear & Hearing 26, 424-434.
5. Russo, N., Nicol, T., Musacchia, G., Kraus, N. 2004. Brainstem responses to speech syllables. Clinical Neurophysiology 115, 2021-2030.
6. Galbraith GC, Arbagey PW, Branski R. Intelligible speech encoded in the human brain stem frequency-following response. NeuroReport 1995; 6:2363-2367.
7. M.S. John, T.W. Picton, MASTER: a Windows program for recording multipleauditory steady-state response. Computer Methods and Programs in Biomedicine 61 (2000) 125–150, Elsevier.
8. JOHN L. Semmlow, 2004 "Biomedical Signal and Image Processing; Signal Processing and communications series"; Dekker Media
9. Mikel Gainza; gugne covle, Bob laulor 2005 "ONSET detection using combfilters", IEEE workshop on applications of signal processing to audio and accostics.
10. Aileen Kelleher, Derry Fitzgerald, Mikel Gainza, Eugene Coyle, and Bob Lawlor, "Onset Detection using coming, Music Transcription and Ornament Detection for the Traditional Irish Fiddle", Audio engineering society convention paper, Barcelona, Spain. Onset detection using combing. 2005.
11. Robert W. B auml and Wolfgang S orgel, "UNIFORM POLYPHASE FILTER BANKS FOR USE IN HEARING AIDS: DESIGN AND CONSTRAINTS" Siemens Audiological Engineering Group germany, 16th European Signal Processing Conference (EUSIPCO 2008), Lausanne, Switzerland, August 25-29, 2008
12. W. Truccolo, K.H. Knuth, A.S. Shah, S.L. Bressler, C.E. Schroeder, M. Ding, Estimation of single-trial multi-component ERPs: differentially variable component analysis (dVCA), Biol. Cybern. 89 (2003) 426–438.
13. E.A. Bartnik, K.J. Blinowska, P.J. Durka, Single evoked potential reconstruction by means of wavelet transform, Biol. Cybern. 67 (2) (1992) 175–181.
14. O. Bertrand, J. Bohorquez, J. Pernier, Time-frequency digital filtering based on an invertible wavelet transform: an application to evoked potentials, IEEE Trans. Biomed. Eng. 41 (1) (1994) 77–88.
15. R.Q. Quiroga, M. Schürmann, Functions and sources of evoked EEG alpha oscillations studied with the wavelet transform, Clin. Neurophysiol. 110 (1999) 643–654.
16. R.Q. Quiroga, H. Garcia, Single-trial event-related potentials with wavelet denoising, Clin. Neurophysiol. 114 (2003) 376–390.
17. R.R. Coifman, D.L. Donoho, Translation-Invariant De-Noising, in: A. Antoniadis, G. Oppenheim (Eds.), Wavelets and Statistics, Lecture Notes in Statistics, Springer, New York, 1995.
18. I.M. Johnstone, B.W. Silverman, Wavelet threshold estimators for data with correlated noise, J. R. Statist. Soc. Ser. B (Statist. Methodol.) 59 (1997) 319–351.
19. R.R. Coifman, D.L. Donoho, Translation-Invariant De-Noising, in: A. Antoniadis, G. Oppenheim (Eds.), Wavelets and Statistics, Lecture Notes in Statistics, Springer, New York, 1995.
20. M. Akin, "Comparison of Wavelet Transform and FFT Methods in the Analysis of EEG Signals", Journal of Medical Systems 26(3), 241-247, 2002.
21. M. Alfaouri and K. Daqrouq, "ECGSignal Denoising By Wavelet Transform Thresholding", American Journal of Applied Sciences 5 (3), 276-281, 2008.
22. M.I. Bhatti, A. Pervaiz and M.H. Baig, "EEG Signal Decomposition and Improved Spectral Analysis Using Wavelet Transform", In Proceedings of the 23rd Engineering in Medicine and Biology Society 2, 2001, 1862-1864.
23. Z. Chen, "Bayesian Filtering: From Kalman Filters to Particle Filters, and Beyond", Adaptive Systems Lab., McMaster University., Hamilton, Ontario, Canada, 2003, Retrieved June 20, 2009, from: http://users.isr.ist.utl.pt/~jpg/tfc0607/chen_bayesian.pdf.
24. J. Chien; H. Hsin-Lung and S. Furui, "A new mutual information measure for independent component analysis", In the Proceedings of the IEEE International Conference on Acoustics, Speech and Signal Processing, 2008 (ICASSP 2008), 2008, 1817 – 1820
25. S. Choi, A. Cichocki, L. Zhang, and S. Amari, "Approximate Maximum Likelihood Source Separation Using the Natural

ISSN: 2277-9655
Scientific Journal Impact Factor: 3.449
(ISRA), Impact Factor: 2.114

Gradient",In the Proceedings of theIEICE Transaction Fundamental E84A(12), 2002.
26. R.R. Coifman, and D.L. Donoho, "Translation Invariant Denoising",Lecture Notes in Statistics: Wavelets and Statistics, 125-150, 1995.
27. P. Comon, "Independent Component Analysis, a new concept?", Signal Processing, Elsevier, 36(3), 287-314, 1994.
28. D.L. Donoho and I. Johnstone, "Adapting to unknown smoothness via wavelet shrinkage", Journal of American Statistical Association, 90,1200—1224, 1995.
29. U.E. Emuir, A. Akin, A. Ertuzun, B. Sankur and K. Harmanci, "Wavelet Denoising vs ICA Denoising for Functional Optical Imaging", In the Proceedings of the 1st International IEEE EMBS Conference on Neural Engineering, 2003, 384-387.
30. B. Ferguson, D. Abbott, "Denoising Techniques for Terahertz Response of Biological Samples", Microelectronics Journal 32, 943-953, 2001.
31. N. Gadhok, and W. Kinsner, "Robust ICA for Cognitive Informatics". International Journal of Cognitive Informatics and Natural Intelligence (IJCINI) 2(4),86-92, 2008.
32. S. P. Ghael, A. M. Sayeed and R. G. Baraniuk, "Improved Wavelet Denoising via Empirical Wiener Filtering", In the Proceedings of theSPIEvol. 3169, 389-399, 1997.
33. A. Graps, An Introduction to Wavelets. IEEE Journal of Computational Science and Engineering 2(2),1-17, 1995.
34. Y.M. Hawwar, A.M. Reza, and R.D. Turney, Filtering(Denoising) in the Wavelet Transform Domain,, Unpublished, Department of Electrical Engineering And Computer Science, University of Wisconsin-Milwaukee, 2002.
35. C.S. Herrmann, M. Grigutsch and N.A. Busch, (2005). EEG oscillations and wavelet analysis. Event-related potentials: A methods handbook,MIT Press, 229-259, 2005.
36. G.G. Herrero, and K. Egiazarian, "Independent Component Analysis by a Resampling Strategy", Technical Report 2005, Retrieved September 18, 2009, fromhttp://www.cs.tut.fi/~gomezher/projects/bss/rica/rica.pdf
37. S. Hoffman, and M. Falkenstien , "The Correction of Eye Blink Artefacts in the EEG: A Comparison of a Two Prominent Methods", PLoS One 3(8):e3004, 2008
38. A. Hyvärinen and E. Oja, "A Fast Fixed-Point Algorithm for Independent Component Analysis" , Neural Computation,9(7), 1483-1492, 1997
39. A. Hyvarinen, J. Karhunen and E. Oja , Independent Component Analysis, eds. Wiley & Sons, 2001
40. G. Inuso, F. La Foresta, N. Mammone, and F.C. Morabito, "Wavelet-ICA methodology for efficient artifact removal from Electroencephalographic recordings", In the Proceedings of the International Conference on Neural Networks,1524-1529
41. N. Jacob, and A. Martin, "Image Denoising in the Wavelet Domain Using Wiener Filtering", Unpublished course project, University of Wisconsin, Madison, Wisconsin, USA, 2004.
42. S. Julier, and J.K. Uhlmann, "Unscented Filtering and Nonlinear Estimation",Proceedings of the. IEEE 92(3), 401-421, 2004.
43. S. Julier, and J.K. Uhlmann, "A New Extension of the Kalman Filter to Nonlinear Systems" In the Proceedingd of AeroSense: 11th Int. Symp. Aerospace/Defense Sensing, Simulation and Controls,182-193, 1997.
44. A. Kallapur, S. Anavatti, and M. Garratt, "Extended and Unscented Kalman Filters for Attitude Estimation of an Unmanned Aerial Vehicle,In the Proceedings of the 27th IASTED Int. Conf. Modelling, Identification, and Control (MIC 2008) , 2008
45. J. Karvanen, J.,Eriksson, and K.V. Pearson, "System Based Method for Blind Separation", In the Proceedings of Second International Workshop on Independent Component Analysis and Blind Signal Separation, Helsinki 2000, 585—590, 2000.
46. L. Kaur, S. Gupta, and R.C. Chauhan, "Image Denoising using Wavelet Thresholding", In the Proceedings of the 3rd Indian Conf. Computer Vision, Graphics & Image Processing (ICVGIP 2002), 22(14), 2002.
47. Z. Koldovský and P. Tichavský, P., "Time-Domain Blind Audio Source Separation Using Advanced ICA Methods", In the Proceedings of the 8th Annual Conference of the International Speech Communication Association (Interspeech 2007), pp. 846-849, 2007. [29] V. Krishnaveni, S. Jayaraman, A. Gunasekaran, and K. Ramadoss, Automatic

ISSN: 2277-9655
Scientific Journal Impact Factor: 3.449
(ISRA), Impact Factor: 2.114

Removal of Ocular Artifacts using JADE Algorithm and Neural Network, International Journal of Intelligent Systems and Technologies 1(4), 322-333, 2006.

48. V. Krishnaveni, S. Jayaraman, S. Aravind, V. Hariharasudhan, and K. Ramadoss, "Automatic Identification and Removal of Ocular Artifacts from EEG using Wavelet Transform",Measurement Science Review 6(2, 4), 45-57, 2006.
49. S. Makeig, J. Anthony, A. J. Bell, T. Jung, and T.J. Sejnowski,. "Independent Component Analysis of Electroencephalographic data", Advances in Neural Information Processing Systems 8, 1996.
50. M. Mastriani, and A.E. Giraldez, "Kalman's Shrinkage for Wavelet-Based Despeckling of SAR Images", International Journal of Intelligent Systems and Technologies 1(3),190-196, 2006.
51. N. Nikolaev, A. Gotchev, "ECG Signal Denoising using Wavelet Domain Wiener Filtering" In the Proceedings of the 10thEuropean Signal Processing Conference (EUSIPCO 2000), 2000
52. S. Postalcioglu, K. Erkan, E.D. Bolat, "Comparison of Kalman Filter and Wavelet Filter for Denoising", In the Proceedings of the International Conference onNeural Networks and Brain 2005 Vol. 2, 951 – 954, 13-15 Oct. 2005
53. V.V.K.D.V. Prasad, P. Siddaiah, and B. Prabhaksrs Rao, "A New Wavelet Based Method for Denoising of Biological Signals", International Journal of Computer Science and Network Security 8(1), 2008, 238-244, 2008.
54. R. Romo-Vazquez, R., Ranta, V. Louis-Dorr, and D. Maquin, "Ocular Artifacts Removal in Scalp EEG: Combining ICA and Wavelet Denoising", In the Proceedings of Physics in Signal and Image Processing (PSISP 07), 2007
55. R. Sameni, M.B. Shamsollahi, and C. Jutten, "Filtering Electrocardiogram Signals using the Extended Kalman Filter", In the Proceedings of the 27th IEEE Engineering in Medicine and Biology (EMBS) Annual Conference, 5639-5642, 2005.
56. P. Senthil Kumar, R. Arumuganathan, K. Sivakumar, and C. Vimal, "A Wavelet based Statistical Method for De-noising of Ocular Artifacts in EEG Signals",IJCSNS International Journal of Computer Science and Network Security. 8(9), 87-92, 2008.
57. P. Senthil Kumar, R. Arumuganathan, K. Sivakumar, and C. Vimal, "Removal of Ocular Artifacts in the EEG through Wavelet Transform without using an EOG Reference Channel", International Journal of Open Problems in Computer Science & Mathematics 1(3). 2008
58. P. Shui, and Y. Zhao, Image Denoising Algorithm using Doubling Local Wiener Filtering with Block Adaptive Windows in Wavelet Domain, Signal Processing 87(7), 1721-1734, 2007.
59. L. SuWen, L, WenQing, X. PinHua, Z. YuJui, "Application of Kalman Filtering and Wavelet Transform in DOAS", In the Proceedings of the 2006 IEEE International Conference on Information Acquisition, 748-753, 2006.
60. M. Unser, and A. Aldroubi, "A Review of Wavelets in Biomedical Applications", In the Proceedings of the IEEE 84(4), 626-638, 1996.
61. Ranganadh Narayanam, " Brain-Activity-Filters: Efficient performance of Translation-Invariant (TI) Wavelets approach for Speech-Auditory Brainstem Responses of human subjects", International Journal of Scientific and Research Publications, volume 4, issue 9, September 2014.