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Brain-Activity-Filters: Efficient performance of Translation-Invariant (TI) Wavelets approach for Speech-Auditory Brainstem Responses of human subjects

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Abstract- This paper presents the design of different filtering techniques for the Neuro-Biomedical signals in single electrode EEG collected Brainstem Speech Evoked Potentials data of Audiology for the Signal-to-Noise Ratio performance evaluations. We have designed Yule-Walk multiband filter, Cascaded Yule-Walk-Comb-Peak filter; conventional Wavelet transform filters of Daubechies, Symlet, Coiflet Wavelets for these Auditory Brainstem Responses. In addition we have designed a Translation-Invariant (TI) Wavelet estimation filtering technique which is highly useful. In our research the idea of Cascaded Yule-Walk-Comb-Peak filter is giving us a considerable improvement in SNR over Yule-Walk filter; and the conventional wavelets are performing far better that too specifically Daubechies wavelets are performing better than all. The TI wavelets technique is performing exceptionally well and better than conventional wavelets.

Index Terms- Yule-Walk, Comb filter, Brainstem Speech Evoked Potentials, EEG, Wavelets, Translation Invariant wavelets.

I. Introduction

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. To remove the background activity most widely used ensemble averaging process requires a large number of trials, which take more time for data acquisition and is more nuisance for the subjects. In addition to this, averaging process considers that "no variations at all in amplitude, latency or waveform of the evoked potentials across many trials, which is not valid in practice (W. Truccolo et al., 2003). If there is a violation in this consideration, dynamics of the cognitive process is lost.

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 Signal-to-Noise Ratio we have designed various Filtering 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 SNR of a signal. In this research we specifically concentrated are Yule-Walk filter, Cascaded Yule-Walk-Comb-Peak filter; Wavelet filters of Daubechies, Symlet, Coiflet Wavelets; then Translation Invariant Wavelets estimation filtering. In our research on our collected data cascaded Yule-Walk-Comb-Peak filter is giving us a considerable improvement in SNR over Yule-Walk filter; and the wavelets are performing far better that too specifically Daubechies wavelets are performing the best. Ultimately Translation Invariant wavelets are working far better than Conventional Wavelets in suppressing noise for extracting Evoked potentials; and hence a better improvement in SNR.

The paper is organized in the following way: there is discussion in the design of the various filters in Section II, The Result Analysis is made in the Section III, and the section IV concludes the research.

II. FILTERING TECHNIQUES DESIGN

In these filtering techniques our goal is to remove the background noise and recover the signal of interest, by improving SNR by using various methods. In this research we have developed different procedures for SNR performances in the collected Neuro-biomedical Auditory signals from single electrode EEG for Brainstem Speech Evoked Potentials (Dajani et al., 2005; Johnson et al., 2005; Russo et al., 2004., M.S. John et al., 2000). 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. We have considered 1024, 2048 samples from the data for performance evaluation purposes. For these data we have implemented several different filtering techniques such as Comb-Filters, Yule-Walk multiband filters, some cascaded filters such as Cascaded Yule-Walk-Comb-Peak filters; conventional Wavelets filters: Daubechies, Symlet, Coiflet Wavelets and Translation-Invariant (TI) Wavelet estimation filtering procedures.

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:

1. Possesses frequency-dependant windowing, which allows for arbitrary high resolution of the high-frequency signal components; unlike STFT.
2. 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).

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.

As a result out of all we found that conventional wavelets are outperforming and giving excellent SNR performances.

Translation-Invariant (TI) Wavelet 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 5 human subjects. We have calculated local SNRs for each subject, Table 3, at those frequency components of interest where the evoked potentials are strongly found ie> 100 Hz, 200 Hz, and so on. TI is working with better SNR performances. 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.

III. RESULT ANALYSIS

In this research we have done the design of Yule-Walk, Cascaded Yule-Walk-Comb, Wavelet transform filters of Daubechies, Symlet, Coiflets Wavelets and Translation Invariant (TI) Wavelets filtering for these Auditory Brainstem Responses. The results are represented in time domain analysis, spectral analysis. Finally the Signal-to-Noise Ratios performance analysis of the filters for 5 different human subjects is represented in tabular forms Table 1, Table 3 and Table 4.

There is one more table, Table 2 (Ranganadh et al., 2012, Ranganadh et al., 2013), which shows the results of different Voice Activity Detection processes. Our own process of Signal to Noise Ratio Peak Valley Difference Detection Ratio (SNRPVD), proved to be performing excellently well than even the standard statistical techniques and giving a guarantee all the time. In this table we are showing for 12 subjects from Ranganadh et al., 2012; but there are 10 more subjects' results also given in Ranganadh et al., 2013. But here we are giving the results to make sure of the Voice Activity Detection, related and essential to the context of this paper, but not exactly related to this cause of the filters design topic of this paper.

From figures Fig 1 and Fig 2 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 3 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 Fig 1, 2, 3 frequencies are same. In Table 1 it can be seen of the SNR performances.

The Figures Fig 4, 5, 6 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. The Signal-to-Noise Ratios for 5 different human subjects of the wavelets can be seen from the tabular form Table 1. There is one more table Table 3 we have provided SNR values of the Local SNRs using TI wavelets estimator filtering procedure. In table 4 the results of SNR performances for overall SNR using TI Wavelets filtering estimator approach when compared to outperforming conventional Daubechies Wavelets. Here TI wavelets approach is far better performing than the conventional Daubechies wavelets. Fig 7 shows the exact spectral peaks at the frequency harmonics of interest.

Signal-Noise-Ratio:

As per the Table 1 we observed the SNR improvements from "Yule-Walk filter" to "Cascaded Yule-Walk-Comb-Peak" Filter. From the table we can clearly visualize that Yule-Walk filtering technique when it is cascaded with a Comb-Peak Filter, it is performing better than just with Yule-Walk Filtering for all the 5 subjects. Significant improvement in the Signal-to-Noise ratios and the time domain signals for these two techniques are proving that cascading is improving the signal to be freer from noise and showing significant SNR performance. The wavelet methods are clearly showing much more and far extant performance than first two methods in terms of SNR values and hence in terms of noise suppression. Out of the 3 wavelet methods Daubechies wavelets are performing the best. The idea of cascading approach of Yule-Walk and Comb-Peak-Filter providing us a good performance than Yule-Walk filtering approach. From the tables Table 3 and Table 4 it is clear that TI wavelets are working perfectly well at local frequency harmonics of interest and also outperforming than conventional wavelets in its SNR to suppress noise to extract evoked potentials. On a conclusive basis Wavelets are outperforming and that too Daubechies wavelets are performing the best. It is clear that TI wavelets estimator filtering approach is exceptionally well even better than conventional Wavelets.

IV. CONCLUSION

In this research we have done the comparative study for the Signal-to-Noise Ratio performances on our own data of single electrode EEG ABR evoked potentials collected from 5 different human subjects by designing the filters: Yule-Walk multiband filter, Cascaded Yule-Walk-Comb-Peak filter; Wavelet transform filters of Daubechies, Symlet, Coiflets Wavelets; Translation Invariant (TI) Wavelets estimator filtering. We conclude that our idea of Cascaded Yule-Walk-Comb-Peak filter is giving better SNR performance than Yule-Walk multiband filter. It is also proved that cascading of filters basing on their time and frequency domain properties some times can give better performances. We observed that conventional wavelets are performing excellently well and Daubechies wavelets are giving the highest performance in SNR than Symlet, Coiflets wavelets. Ultimately we found in our experiment of our data sets that Translation-Invariant (TI) Wavelet Estimator filtering approach is performing exceptionally well than all conventional wavelet filters family of filtering approaches; for the 5 human subjects. We conclude that conventional wavelets and TI wavelets estimator filtering approaches are highly successful in suppressing the background noise and highly useful in extracting the Evoked Potentials from our data collected from 5 human subjects in Audiology Lab.

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NOTE

The result analysis of filtering methods is made for 5 different Human subjects; who are different from the VAD table Table 2 is for 12 different human subjects. Please make a note of this matter to avoid any confusion. This table is specifically provided is to prove that Voice Activity has been successfully and strongly detected in our experiments of Brainstem Speech Evoked Potentials in University of Ottawa Audiology LAB; and it is surely detected all the time (ie> for all subjects, and one more table for 10 more subjects from the table in Rangandh et. al., 2013) without any discrepancies; unlike the standard technique of Statistical VAD Methods, where it detects some times and some times not.

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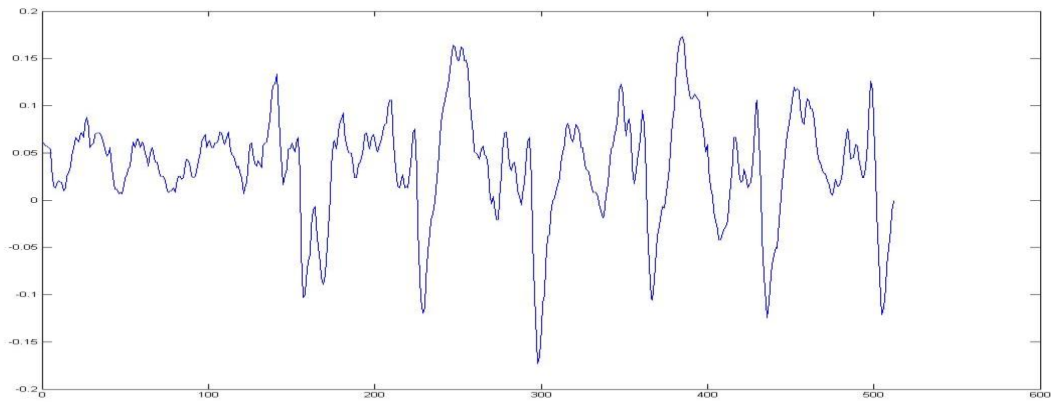

Fig 1 Given data time domain noisy signal, for Subject 1

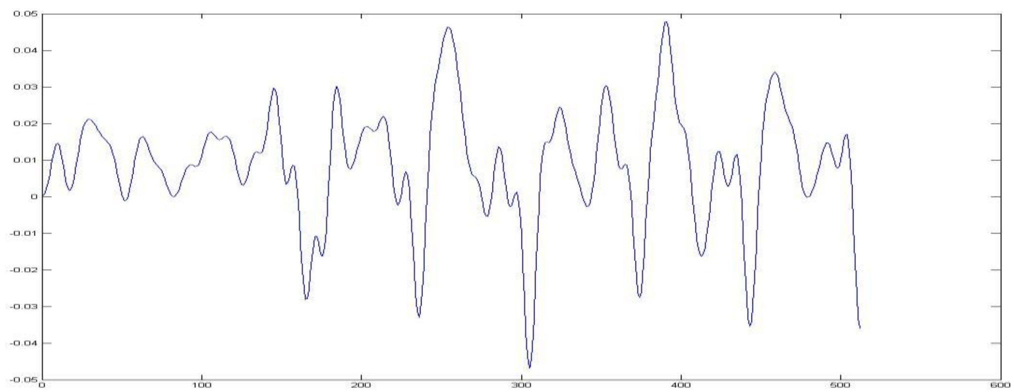

Fig 2 After Yule-Walk filtering time domain signal, for Subject 1

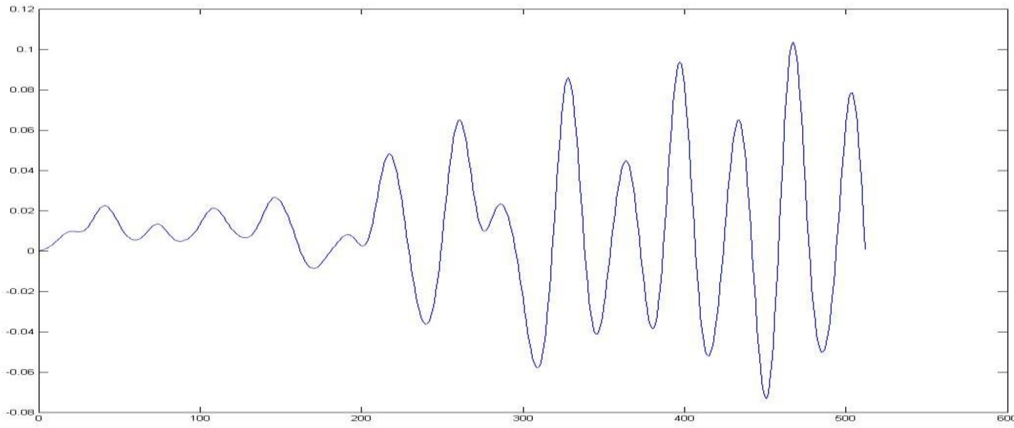

Fig 3 After Yule-walk-comb-peak filtering time domain signal, Subject 1, with better SNR

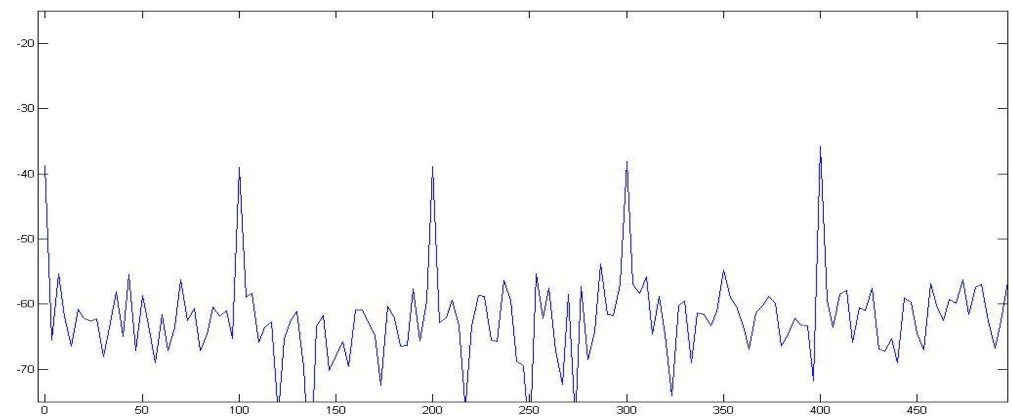

Fig 4 Daubechies Wavelets, Subject 1, spectral peaks

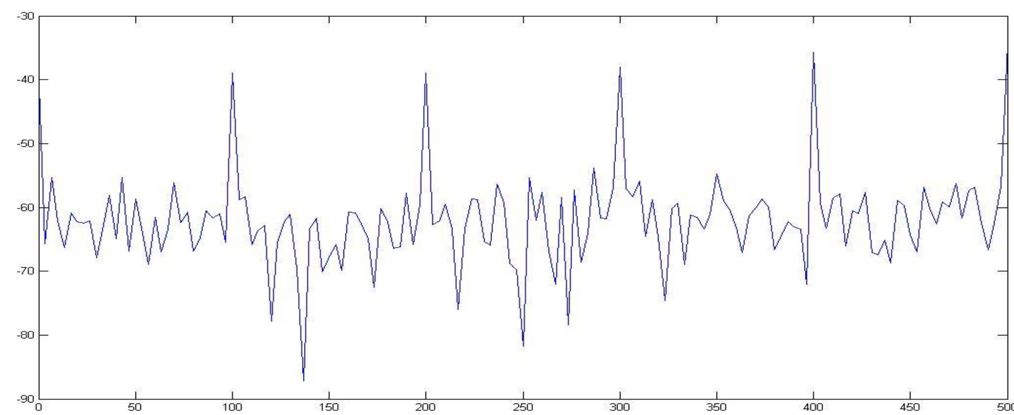

Fig 5 Symlet Wavelets, Subject 1, spectral peaks

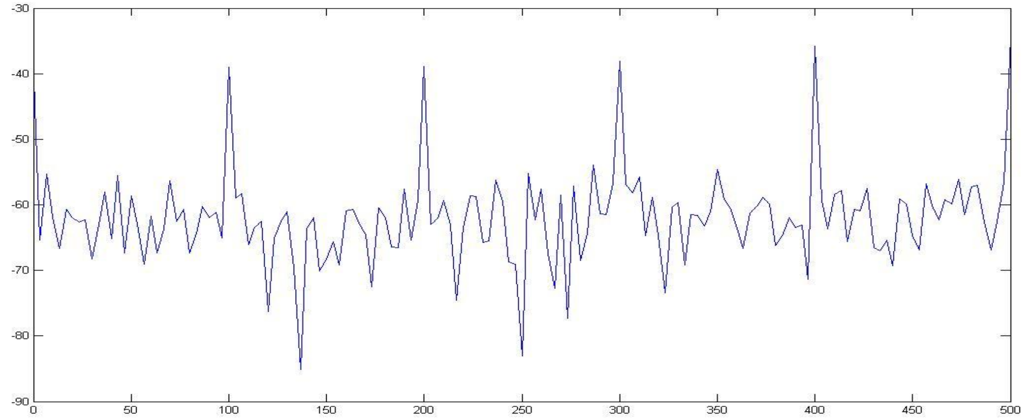

Fig 6 Coiflets Wavelets, Subject 1, spectral peaks

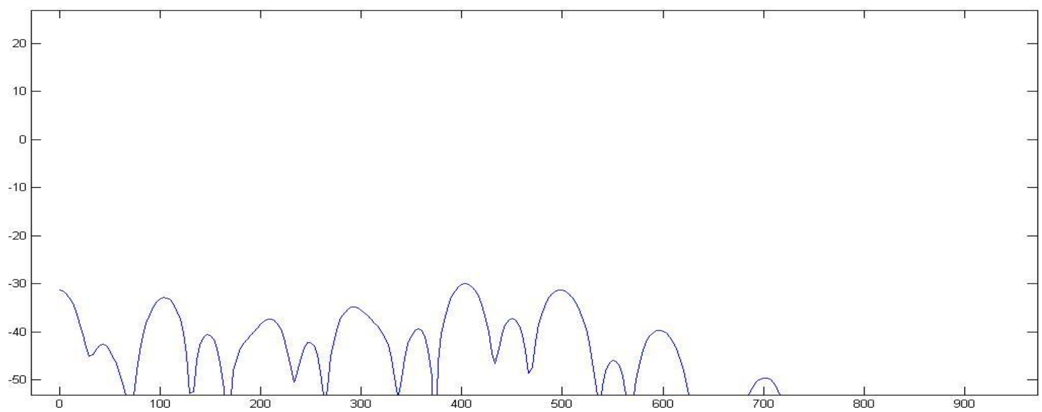

Fig 7 The frequency components in TI wavelets de-noising: the frequency components where the evoked responses concentrate strongly are the 100 Hz, 200 Hz, and so on. Which are our interested components of brainstem speech evoked potentials of our collected data.

Table 1 The SNR performance evaluation of Different filters for single electrode EEG collected Speech ABR for 5 different subjects

Subject S.No.	Signal-to-Noise-Ratio (dB)				
	IIR Yule-Walk Filter	Cascaded IIR "Yule-Walk Filter & Comb-Peak Filter"	Conventional Wavelet Filters		
			Daubechies	Symlet	Coiflets
1	2.6386	7.0123	14.8412	13.9801	13.9512
2	3.1428	8.5241	18.6278	18.0410	17.9801
3	2.8968	6.9842	20.8543	19.9941	19.6427
4	4.8211	8.9128	16.8428	16.1322	16.0329
5	5.2105	7.2129	19.3214	18.7211	18.6028

Table 2 VAD Results 12 different subjects: SNRPVD outperforming and giving surety all the time

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

Table 3 Using Translation-Invariant Wavelets Local SNR performances at the brainstem speech evoked potential strong existence 100 Hz, 200 Hz and so on. It found to be far better performing.

Subject 1	100 Hz	200 Hz	300 Hz	400 Hz	500 Hz	600 Hz	700 Hz	800 Hz
Before Denoising	2.1786	1.3733	1.4964	2.456	0.783	2.2299	1.8593	1.3687
After Denoising	24.0411	23.297	26.8231	24.1522	27.8168	22.8498	28.6662	24.8747
Subject2								
Before	2.3972	1.7961	1.7346	1.3401	1.4194	1.5621	1.8229	2.024
After	25.9627	29.5527	30.1144	32.3335	21.9219	21.8193	24.294	25.2139
Subject3								
Before	1.9656	2.0873	0.5875	1.7476	2.1723	1.2665	1.515	1.3458
After	29.0608	28.4097	34.82	25.3336	29.4272	27.4171	26.0825	25.9617
Subject4								
Before	1.3198	1.6802	1.5015	1.3536	2.0328	1.2059	2.427	1.2451
After	22.7578	32.1224	29.909	39.3063	29.2954	31.2538	30.3914	25.0714
Subject5								
Before	1.74	2.1347	2.4966	2.042	0.959	0.46	1.625	1.0006
After	21.0816	29.7672	29.9777	22.0256	31.5719	23.6533	35.6878	27.548

Table 4 The Overall SNR performances of TI wavelets for the 5 subjects over conventional wavelets of Daubechies. TI is outperforming for our data sets of 5 human subjects.

SNO	SNR after denoising using Conventional Daubechies wavelets	SNR after denoising using TI wavelets
Subject 1	14.8412	28.3456
Subject 2	18.6278	30.4567
Subject 3	20.8543	34.2817
Subject 4	16.8428	32.2345
Subject 5	19.3214	37.06342