Review Article: Various Methods of Analysis on ABRs

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***Abstract*-The analysis and recognition of auditory brainstem response (ABR) signals is a medical problem of great importance, since it is the best known technique of the auditory organs evaluation. The task of construction of fully automatic method of ABR recognition present considerable technical difficulties, because the signals are in general hardly readable, and in particular the evaluation of the data part obtained for low intensities of the audio stimulus is especially difficult. It can be assumed that the methods of analysis and recognition of ABR signals can be of some interest to other investigators, not necessarily directly interested in audiology, but trying to cope with the difficulties of interpretation and recognition of totally different signals. The survey of the different methods of Analysis of ABRs is presented.**

Keywords: Auditory Brainstem Responses (ABR), Auditory Evoked Potentials (AEP)

I. BACKGROUND

The first description of the human ABR was made by Jewett and Williston in 1971[1]. Auditory Evoked Potentials (AEPs) are scalp-recorded electrical responses of the brain elicited by acoustical stimuli. Auditory brainstem responses (ABRs) comprise the early portion (0-12 msec) of auditory EPs are composed of several waves or peaks. The ABR waves or peaks, labelled using Roman numerals I-VII as shown in the **Fig 1**, are typically 1 msec apart and have amplitudes of about 100-500 nanovolts. Waves I, III and V are generally considered major peaks, generated by the synchronous electrical activity of the auditory nerve, caudal and rostral auditory brainstem structures, respectively, in response to onset of auditory stimuli. The ABR is a far-field, differentially averaged, electro-physiologically recorded signal. It represents the summed and averaged responses of thousands of nerve fibres to repeated acoustic stimulation. The ABR is one of the best recognised electrophysiological tools used by Audiologists, having numerous applications including: hearing threshold estimation (especially for neonatal hearing screening), monitoring traumatic brain injury (TBI) patients and intraoperative monitoring (IOM) for skull base surgery.

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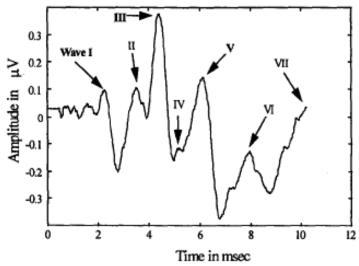

Fig 1: ABRs in the time domain showing seven waves.

The task of construction of fully automatic method of ABR recognition seems to present considerable technical difficulties. The shapes of the ABR recordings obtained for various patients can be considerably different, and even in consecutive studies of ABR signals for the same patient certain differences are observed, because in spite of application of highly sophisticated signal revealing techniques the ABR signals are highly distorted by influence of various interference signals, in particular heterogeneous bio potentials. Particularly difficult is the elimination of influence of other EEG signal(i.e. not invoked by the audio stimulus). The above mentioned difficulties particularly concentrates in that part of the study which regards the border zone between hearing and lack of hearing between presence and absence of hearing, and is of particular interest for the examining physician. It follows from the fact that in the course of presentation the fluctuations and deformations of the ABR signals resulting from presence of external signals intensify, introduce considerable difficulties to the process of proper signal interpretation and its automated recognition. This is also the reason that makes the problem of automated ABR signal recognition more interesting from the scientific point of view, because a similar task of revealing and interpretation of subliminal signals, objectively placed below the noise level is encountered in many tasks of biomedical engineering.

II. LITERATURE

There have been numerous attempts over the past thirty years at automating the analysis of ABR waveforms. Over the last two decades, three major clinical applications of the ABR have been recognized. First are neurological applications, where ABR is used for the diagnosis and localization of pathologies affecting auditory brainstem pathways. The second involves the use of ABRs to estimate hearing thresholds. In recent years, the use of ABRs has gained popularity as one of the methods of choice in determining hearing thresholds of newborns, infants, and multiplies handicapped patients who are not able to provide consistent or reliable behavioural responses to sound stimulation. However the ABR ability to test peripheral auditory function directly has made it an invaluable tool in infant hearing screening. The third is the use of intraoperative or long-term monitoring. Here ABRs are continuously recorded at selected time intervals while the patient is undergoing procedures that may affect the peripheral hearing organ and brainstem pathways. Acoustic neuroma surgery and cornahrain death are some of such conditions in which ABRs have been found to be extremely helpful. In this paper around 20 publications are summarized.

The search for Biomedical Engineering in IEEE explore produced 175 references, which reduced to 150 when the search was limited to Auditory Evoked Potentials, Further restricting the search to methods of analysis on ABRs produced 75 references. Few references with methods of analysis on ABR are summarized in this review.

III. FINDINGS

A. *The Detection of Auditory Evoked Responses Using a Matched Filter.*

The matched filter is used to detect a signal buried in noise where the signal is known and the noise is a stationary random process. The filter is designed to maximize output signal-to-noise ratio (SNR) at a particular time t_k. It was shown that, if the noise is white, the impulse response of the matched filter takes on the form of the signal. That is h (t) = S (t_k - t) u (t), where h (t) is the impulse response, s (t) is the signal, and u (t) is the unit step function. The desired impulse response is simply the signal waveform reversed in time and delayed by t_k seconds. The impulse response of the matched filter was determined by averaging 2000 individual time windows containing both background EEG and individual ABR's. It was assumed that there was no variation in the form of the individual ABR from stimulus to stimulus, which was tested by recording the ABR's for four different volunteers. It was seen that the EEG provides more correlation with the impulse response at 10 ms than the signal containing both EEG and ABR. After analyzing many different input signals, it was evident that the shape of the input signal was the overriding factor in determining the amount of correlation with the impulse response at 10 ms. therefore, the output waveform of the matched filter had a significant peak at 10 ms. If output signal at 10 ms is to be the only factor in determining the presence of an ABR, it can be concluded that the matched filter system cannot detect individual ABR's in background EEG. It is known that averaging a series of time windows containing individual ABR's will help remove the background EEG and increase the signal-to-noise ratio. With this in mind, output SNR of the matched filter could be improved by first averaging the input signal. A threshold level is used as a detection criterion. The threshold level is determined by averaging background EEG and then applying this averaged EEG signal to the input of the matched filter. The maximum output amplitude is then used as the threshold level. For click intensities greater than 25 dB SL above threshold, 400 averages were required. At lower click intensities, this number increased significantly and it is of little value to use a matched filter in place of the conventional averaging technique [2].

B. *Noise Cancellation for Brainstem Auditory Evoked Potentials*

This method described the communication is a form of adaptive noise cancellation, in which a second channel that estimates the noise without the signal is obtained. The second channel is used to cancel the noise in the signal-plus-noise channel. The acoustic stimulus was delivered in the middle of the data window. The control interval, the part of the data window that precedes the stimulus, shows the background noise in both the signal and the noise channels. In the signal channel, the response occurs in the interval following the stimulus. For a BAEP, 1000 or more of these individual responses would be combined to form the final average. The cancellation technique is based on the assumptions that the noise components in the signal and noise channels are correlated and that the correlation is constant throughout a given individual response. That is, the correlation observed in the control interval is the same as that observed in the response interval. The correlation can change completely between two individual responses. The correlation between channels is modelled by the system with impulse response h (t) as shown in **Fig 2**.

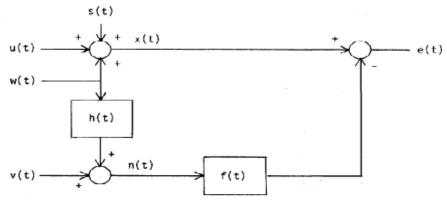

Fig 2: Block diagram of cancellation technique. x(t) is the waveform measured in the signal channel, n(t) is the waveform measured in the noise channel, and e(t) is the output. w(t) represents the correlated noise component. s (t) is the evoked signal and u(t) and v(t) represent uncorrelated noises in the signal and noise channels.

The output signal e (t) is given by

$$e(t) = x(t) - f(t) * n(t) \qquad (1)$$

Where x (t) and n (t) are the electrode potentials recorded from the signal and noise channels, respectively, f (t) is the filter function. The algebraic cancellation technique described here offers an effective method of reducing external electrical interference in evoked potential recordings. Applying the method directly to a complete average provides a substantial improvement, but applying it to each of the individual responses may provide even further improvement if the noise is intermittent or variable in time. The complete filter technique also provides a substantial cancellation effect, but it is not as effective as the algebraic technique. It appears that, for the type of noise studied here, the filter function is approximately constant in frequency [3].

C. *An Autoregressive Model of the BAEP Signal for Hearing-Threshold Testing*

The autoregressive (AR) model which is used in hearing level research is a linear system H (Z) having an all-pole transforms

$$H(Z) = 1/\ 1 + {}^{p}\textstyle\sum_{i=1} a_i z^{-i} \qquad (2)$$

where a_i are model parameters, and p is the order of the model.It is supposed that averaged BAEP signal s(n) is the output of the system excited by white noise w(n). Once the model has been established, the forward prediction error e(n) will be determined as follows:

$$e(n) = s(n) - \hat{s}(n) = s(n) - \left[-\sum_{i=1}^{p} a_i s(n-i)\right] = w(n) \quad (3)$$

where $\hat{s}(n) = -\sum_{i=1}^{p} a_i s(n-i)$ is the estimated output.

The modelling algorithm which was used was the least squares method, which chose the parameters a_i so that the total sum of forward and backward prediction error energy e would be minimized.To determine the hearing threshold, the AR model parameters are estimated for the truncated averaged BAEP signal at different stimulus levels; also the ac signal energy e_o and the normalized prediction error e_{nor} are calculated. They are defined, respectively, as follows:

$$e_o = \sum [s(n) - \overline{s(n)}]^2$$

$$e_{nor} = e/e_o \quad (4)$$

Where $\overline{s}(n)$ is the mean value of the signal and e is the total prediction error energy.

Table I: below shows the mean values and the standard deviations of e_o, e_{nor} and a_1

Stimulus Intensity (HL)	e_0	e_{nor}	a_1
0 dB	7.6/2.5	0.245/0.061	−1.212/0.135
20 dB	61.1/29.1	0.044/0.018	−1.476/0.077
35 dB	159.3/75.5	0.020/0.012	−1.601/0.112
55 dB	278.4/116.6	0.011/0.004	−1.783/0.120

The hearing threshold is successfully estimated by the normalized prediction error e_{nor}. The model parameters effectively characterize the different structures of the signal; it appears promising to use the modelling technique not only in hearing level testing but also in other wide clinical practice [4].

D. *BAEP Enhancement by Weighted Ensemble Averaging*

The method proposed here in has been found to enhance the lower frequency components of the BAEP, including wave V. The scheme averages sweeps having a positive correlation with the current ensemble average to form ensemble average X_1. Those sweeps having a negative correlation with the ensemble average are averaged together to form a second ensemble average X_2. The method can be implemented on-line and correlations are computed with the current ensemble average. The results suggest the possibility that some single sweep signal components have polarities that are opposite to the ensemble average polarity [5].

E. *Auditory Evoked Potential Classification by Unsupervised Art 2-A and Supervised Fuzzy Artmap Networks*

The basic architecture in an ART system is an unsupervised, self-organizing pattern clustering module. Clustering is based on template matching where the prototype template vectors are created from all the available patterns presented to the module. In Predictive ART or ARTMAP architecture two clustering ART modules are linked by a third ART module which forms predictive associations between the categories formed by 2 clustering modules. When the 2 clustering ART modules are Fuzzy ART modules, the resulting Fuzzy ARTMAP architecture can classify analog as well as binary patterns. During teaching a clustering module receives a pattern from the training set and the other clustering module receives its correct class. The linking module forms predictive associations between the categories established by the two clustering modules. The ART 2-A and Fuzzy ARTMAP networks are applied to the classification of Brainstem Auditory Evoked Potential (BAEP) signals into two classes, Response (R) or No Response (NR), corresponding to the presence or absence of a sound evoked waveform following an auditory stimulus. In ART 2-A higher generalization was obtained at high values of p* with a large number of fine categories most of which representing one or two input patterns. The constant α, which determines the initial values of the weight vectors, had no effect on the number of categories at this high p*. However, it affected generalization, because when the test set was presented with large α, new F2 nodes were chosen in favour of those F2 nodes which represent the training set patterns [6].

F. *Estimation of Single Brainstem Auditory Evoked Potential using Time-Sequenced Adaptive Filtering*

The TSAF uses multiple filters and each filter is adapted for filtering a particular portion of the interval between regeneration times, and is suitable for tracking signals whose statistical properties recur at various points in time. The filters are trained and the filter weights are obtained via an adaptive algorithm. **Fig 3** shows the conceptual realization of TSAF. The averaged TSAF is shown in **Fig 4** together the EA using 2000 trials. TSAF and EA are very similar and their correlation coefficient is 0.983, and the measurement time greatly reduced using TSAF. The tracking ability of TSAF makes it possible for the clinician to observe the signal variation trace in every single ensemble [7].

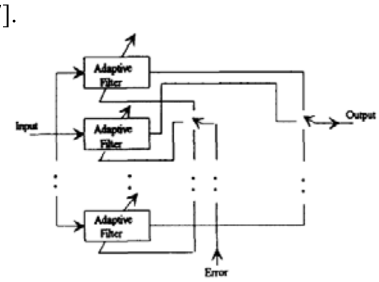

Fig 3: The time-sequences adaptive filter

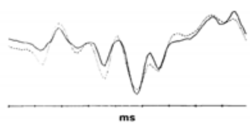

Fig 4: A comparison of averaged TSAF (solid line) and EA (dotted line)

G. *An Adaptive RBF Neural Network Model for Evoked Potential Estimation*

The RBFNN (radial basis Function neural network) model consists of *N*. RBFs arranged in a hidden layer and a linear output node. Its output at time instant *k* is expressed as

$$y(k) = \sum_{i=1}^{N} w_i e^{-\left(\frac{k-\mu_i}{\sigma_i}\right)^2} = \sum_{i=1}^{N} w_i \varphi_i \quad (5)$$

In the i^{th} node w_i, μ_i and σ_i represent the height, center and width of the RBF. The peaks which being the main components of an EP, are modelled by RBFs in the

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network. Simulation results confirm the successful operation of the approach, **Fig 5** & **Fig 6**, where λ is an empirical parameter determining the rate of convergence.

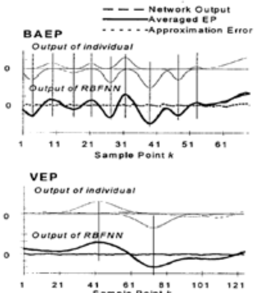

Fig 5: The averaged AEP and VEP (Visual evoked potentials) clearly show their peak components. The numbers of RBFs used are 11 and 7 for AEP and VEP resp. The parameters required in training are $\lambda = 0.01$, $\eta = 0.05$, $\varepsilon = 0.01$ and error threshold= 0.005.

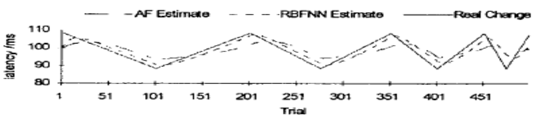

Fig 6: The performance of RBFNN and AF (Adaptive Filter) in tracking of change in P100 latency. Convergence of RBF" and AF are 0.001 and 0.05 resp.

The results also show that the performance of adaptive RBFNN is superior to the AF**,** this may be accounted for by the powerful modelling characteristic of RBFNN,permitting accurate estimation of single-trial EP [8].

H. *On Optimal Aperiodic Stimulation for Brainstem Auditory Evoked Potentials Estimation*

A method with pseudo Gaussian probability density (PGPD). The frequency band occupied by the late EP fractions in each trial should be known, and this is easily accessible when the stimulation frequency is fixed. This technique seems to give better results compared to the uniform probability density stimulation. The results obtained with the optimal probability density when the late EP covariance matrix is well estimated [9].

I. *Multiresolution Adaptive Filter for Estimating Brainstem Auditory Evoked Potentials*

Multiresolution Adaptive Filter' (MAF) is implemented by the orthonormal wavelet transforming (WT) the reference and primary signals, adaptive filtering of each independent, frequency channel separately, and then inverse wavelet transforming (IWT). This is analogous to the frequency domain adaptive filter. There is a stack of time invariant adaptive filters (TIAF's). The filters are connected in parallel. The filters are fed separately with wavelet transform components. **Fig 7** shows the basic structure of multiresolution adaptive filter of order j=2 with Wiener-like TIAF used for average estimation.

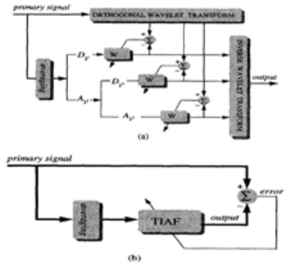

Fig 7: Average estimation using: (a) MAF and (b) Wiener-like TIAF.

An autoregressive process driven by a Gaussian white noise simulated the ongoing EEG as follows

$n_i(t) = 1.5084 n_i(t\text{-}1) - 0.1587 n_i(t\text{-}2) - 0.3109 n_i(t\text{-}3) - 0.0510 n_i(t\text{-}4) + w(t)$ (6)

The simulated BAEP's were generated, which consist of peak components with fixed amplitudes but randomly varied latencies satisfying a Gaussian distribution with zero mean and a covariance equal to 0.2 ms. **Fig 10** clearly illustrates the feasibility of obtaining BAEP's using the multiresolution adaptive filter**.** I observed that a significant improvement in waveform estimation, compared with the ensemble averaging (**Fig 8**) and TIAF (**Fig 9**) can be achieved by multiresolution adaptive processing. The most interesting result of the proposed scheme is that five peak components are clearly detected and significantly enhanced even with a small number of response trials [10].

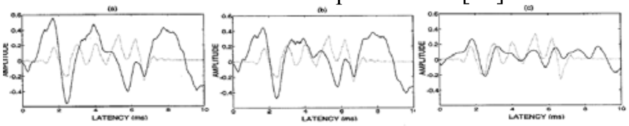

Fig 8: Results for simulated data. Waveform estimates given by ensemble averaging (a), TIAF (b), and MAF ***(c).***

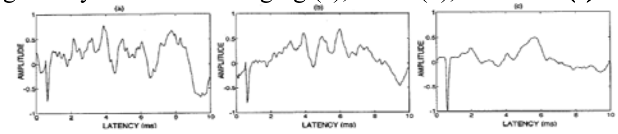

Fig 9: The human BAEP waveform estimated by ensemble averaging with the different number of trials: (a) 50, (b) 150, and (c) 500.

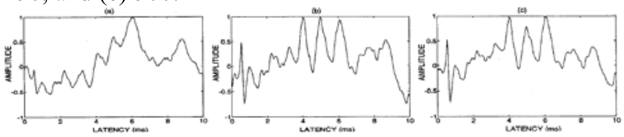

Fig 10: The human BAEP waveform estimated by MAF with the different number of trials: (a) 50 trials, (b) 150 trials, and (c) *250* trials.

J. *Latency Change Estimation for Evoked Potentials via Frequency Selective Adaptive Phase Spectrum Analyzer*

To formulate the EP latency change estimation problem in the context of Time delay estimation (TDE), the following signal model was considered

$$x_1(k) = s(k) + v_1(k)$$
$$x_2(k) = \lambda s(k - D_k) + v_2(k) \qquad (7)$$

where k is the time index, $s(k)$ denotes the noise free signal, $s(k\text{-}D_k)$ is a delayed version of $s(k)$, and D_k is the time delay to be estimated. The time delay D_k can be either time-invariant or slowly varying with time. And $v_1(k)$ and

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v_2 *(k)* are additive noises uncorrelated with each other and with *s (k).*The time delay or latency change between two time sequences can be obtained via their cross correlation function as follows:

$Rx_1x_2\ (T, n) = E\ [x_{1n}\ (k)\ x_{2n}\ (k+T)] = R_{ss}\ (T - D_n)$ (8)

In which R_{ss} *(.)* is the auto-correlation function of *s(k)*. The reference signal is obtained by averaging the first 500 preimpact acceleration sweeps. The Somatic EP's are assumed to have minimum variations at these sweeps because the impact acceleration was applied at the 601st sweep. This proposed a method for tracking and estimating the latency changes in EP's by using the phase spectrum via an adaptive filter in frequency domain. Theoretical analysis and computer simulation as in **Fig 11** shows that the latency change estimation results are better than those provided by existing methods [11].

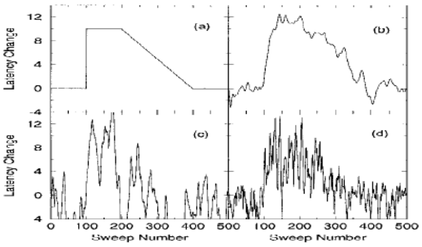

Fig 11: The latency change estimation results based on computer generated data (SNR = -5 dB and SIR = -5 dB). (a) The actual latency changes introduced in the simulated data; (b) the estimated latency changes given by the adaptive phase spectrum analyzer; (c) the estimated latency changes given by direct adaptive time delay estimator; and (d) the estimated latency changes given by the correlation-based method.

K. *A new approach for BAEP analysis simulated annealing method*

This method is based on an optimal correction of random delays. A non convex criterion is then minimized using simulated annealing algorithm, the optimal vector is then used to analyse the dynamic of the cochlea. This method allows the estimated BAEP that are easily identified and interpreted. The enhancement is related to the non stationarity hypothesis. the BAEP are still smoothed or distorted even using the time delay correction, showing that the hypothesis made about the non stationarity are not verified. This calls for developing others models for improving the averaged BAEP [12].

L. *Estimation of the Auditory Brainstem Response's wave V by means of Wavelet Transform*

The performance of different wavelets basis for approximation of the morphology of ABR's wave V was evaluated. The wavelet functions Meyer, Daubechies 10, Symlet 10, and Biorthogonal 6.8 are used, resulting the last one,the most appropriate to fulfill the specific requirement., the performance of the Biorthogonal 6.8 wavelet function to approximate the morphology of wave V for averaged 1000, 750, 500 and 250 epochs, was analyzed as shown in **Fig 12**. The results were promising and address the future study in the use of the wavelet transform to approximate wave V of ABR using a few epochs, with the consequent advantage of reducing the total time of recording [13].

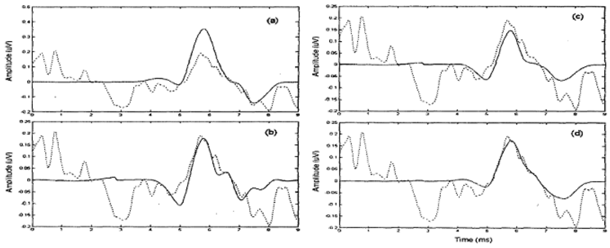

Fig 12: The pattern (dashed line) and the reconstructed wave V using Biorthogonal 6.8 wavelet function for (a) 250, (b) 500, (c) 750 and (d) 1000 epochs (d) (solid line).

M. *Automated Analysis of the Auditory Brainstem Response*

This algorithm is for automatically labelling all seven waves in an ABR waveform based on first and second order derivatives. On a large dataset of normative ABR waveforms, accuracy on the primary waves of clinical interest (peaks I, III and V) was 96-98%to within 0.2ms of human expert [14].

N. *Adaptive Complex Wavelet-based Filtering of EEG for extraction of Evoked Potential Responses*

The method is based on adaptive filtering of signals in the wavelet domain, where the transform used is a nearly shift-invariant Complex Wavelet Transform (CWT). The algorithm is compared with other existing methods: The first simply consists of band pass filtering the input EEG signal followed by linear averaging. The second, uses signal-adaptive filtering in the Fourier domain based on phase variance computed at each spectral component of the FFT. Realistic models of EEG and ABR are generated for the comparison. Results show that the wavelet-based method consistently outperforms the other two methods for ABR signals with an initial signal-to-noise ratio less than -20 dB.

Table II: below gives the comparison of SNR results for 3 EP extraction algorithms; SNR values in dB are given as: average (standard deviation) of a collection of SNR values over a time span of 1 minute (4000 epochs). [15].

pc04ABR	512	750	1024
BP + AVG	6.5 (3.2)	7.8 (3.6)	8.8 (3.9)
BP + AFF	7.4 (3.5)	8.3 (3.7)	9.2 (3.9)
BP + AFW	8.4 (3.2)	9.1 (3.4)	10.1 (3.8)

(A)

(A) Signal: "pc04ABR" (input SNR: - 23.2 dB; sampling: 10 kHz); band pass filter: 30-3000 Hz

pc07ABR	512	750	1024
BP + AVG	1.2 (3.1)	2.7 (3.4)	3.6 (3.5)
BP + AFF	3.5 (2.9)	4.2 (3.0)	4.1 (3.0)
BP + AFW	4.6 (2.8)	4.7 (2.8)	5.5 (2.9)

(B)

(B) Signal "pc07ABR" (input SNR: -26.6dB)

O. *Chaotic Dynamics in Tracing BAEP and its Application on Investigating Brainstem Malfunction*

The chaotic dynamics of tracing BAEP were analyzed using phase projection and correlation dimension techniques. The results demonstrated: there is a much stronger determination in BAEP than in noisy BAEP shown by more deterministic phase projections and lower correlation dimensions D2 in BAEP; trajectories of BAEP never repeat and the value of correlation dimension is fractal; the phase projection of BAEP for brainstem malfunction group shows more chaotic and has higher D2 than those for the tester group. The conclusions suggests that BAEP is chaotic not deterministic and there is rich dynamics in BAEP [16].

P. *Fast Extraction Method of Auditory Brainstem Response Based on Wavelet Transformation*

The extraction of auditory brainstem potential by wavelet transformation is discussed. The wavelet filter obtained from correlation analysis between results of wavelet transformation and traditional superposing and averaging method, the auditory brainstem response signal can be extracted from the signal containing spontaneous brain wave interference based on only a single measurement of the signal. The comparison of waves processed by different methods gives comparison to traditional superposing and averaging method, the wavelet transformation analysis method provides much more distinct waveforms and shortens the time of whole detection by considerably reducing the number of tests [17].

Q. *Gabor Frame Phase Stability Analysis of Chirp Evoked Auditory Brainstem Responses*

This paper proposes for the first time Gabor frame operators as an efficient feature extraction technique for ABR single sweeps. In particular, the decomposition technique to derive the Gabor frame phase stability (GFPS) of sweep sequences of click and chirp evoked ABRs is used. It is shown that the GFPS represents a robust feature of ABRs and that GFPS of chirp evoked ABRs provide a stable discrimination of the spontaneous activity from stimulations above the hearing threshold with a minimum number of sweeps, even at low stimulation intensities[18].

IV. CONCLUSIONS

The system for characterization of the human auditory system simulating the auditory brainstem response discussed can be found useful in many applications.

The main important purpose of the work presented here is to incorporate an automated system and develop them into an improved analysis System.

V. FUTURE RESEARCH

The Nervous System plays a vital role in the well being of the subject**.** The purpose of most studies of the average evoked potential is to determine the extent to which the complex waveform of the auditory evoked potentials varies with the parameters of the stimulation, the state of the subject, or the recording site. Abnormalities can be in the form of slow impulse propagation velocities or an irregular wave shape measured on the scalp. Based on the analysis of sensory evoked potentials, a trained physician determines the presence of a variety of disorders including multiple sclerosis, metabolic disorders, nutritional deficiencies, degenerative diseases, spinal trauma, tumors, infarctions, hemorrhages, and exposure to toxic chemicals. There is definitely a need for a robust and accurate system for monitoring ABRs.

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