# Nonlinear feature extraction for objective classification of complex auditory brainstem responses to diotic…

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**7 authors**, including:

Amir Salar Jafarpisheh
University of Social Welfare and Rehabilitatio…


Amir Homayoun Jafari
Tehran University of Medical Sciences


Mohammadjavad Abolhassani
Tehran University of Medical Sciences


Akram Pourbakht
Iran University of Medical Sciences

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# Nonlinear feature extraction for objective classification of complex auditory brainstem responses to diotic perceptually critical consonant-vowel syllables

Amir Salar Jafarpisheh [a], Amir Homayoun Jafari [a,b,*], Mohammadjavad Abolhassani [a], Mohammad Farhadi [c], Hamed Sadjedi [d], Akram Pourbakht [e,f], Zahra Shirzhiyan [a]

[a] Medical Physics and Biomedical Engineering Department, School of Medicine, Tehran University of Medical Sciences, Tehran, Iran
[b] Research Center for Biomedical Technologies & Robotics (RCBTR), Tehran University of Medical Sciences, Tehran, Iran
[c] Clinical Nanomedicine Laboratory, ENT – Head & Neck Research Center, Hazrate Rasoul Akram Hospital, Iran University of Medical Sciences, Tehran, Iran
[d] Department of Engineering, Shahed University, Tehran, Iran
[e] Department of Audiology, Rehabilitation Research Center, School of Rehabilitation Sciences, Iran University of Medical Sciences, Tehran, Iran
[f] Rehabilitation Research Center, Iran University of Medical Sciences, Tehran, Iran

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ABSTRACT

*Objective:* To examine if nonlinear feature extraction method yields appropriate results in complex brainstem response classification of three different consonant vowels diotically presented in normal Persian speaking adults.
*Methods:* Speech-evoked auditory brainstem responses were obtained in 27 normal hearing young adults by using G.tec EEG recording system. 170 ms synthetic consonant-vowel stimuli /ba/, /da/, /ga/ were presented binaurally and the recurrence quantification analysis was performed on the responses. The recurrence time of second type was proposed as a suitable feature. ANOVA was also used for testing the significance of extracted feature. Post-comparison statistical method was used for showing which means are significantly different from each other.
*Results:* Dimension embedding and state space reconstruction were helpful for visualizing nonlinearity in auditory system. The proposed feature was successful in the objective classification of responses in window time 20.1–35.3 ms, which belonged to formant transition period of stimuli. Also the $p$ value behavior of recurrence time of second type feature as a discriminant feature was close to the nature of the response that includes transient and sustained parts. On the other hand, the /ba/ and /ga/ classification period was wider than the others.
*Conclusion:* The extracted feature shown in this paper is helpful for the objective of distinguishing individuals with auditory processing disorders in the structurally similar voices. On the other hand, differing nonlinear feature is meaningful in a special region of response, equal to formant transition period, and this feature is related to the state space changes of brainstem response. It can be assumed that more information is within this region of signal and it is a sign of processing role of brainstem. The state changes of system are dependent on input stimuli, so the existence of top down feedback from cortex to brainstem forces the system to act differently.



## 1. Introduction

Animal studies have shown that auditory perceptional processing is distributed along the auditory system neurons [1,2]. A number of electrophysiological studies have recorded the complex auditory brainstem response (cABR) elicited by brief acoustic stimuli but most of them used temporal and frequency domain features like latency, amplitude, area and slope for transient peaks and magnitude of frequency following response, fundamental frequency, first formant amplitude and inter-response correlations that are linear approaches for representing differences between recorded responses [1–4]. Finding an insight about brainstem encoding of perceptually critical consonant-vowel stimuli was done through the extraction of important linear features of cABR and its relation to different acoustic stimuli containing /ba/, /da/, /ga/ [1,5].

* Corresponding author at: School of Medicine, Tehran University of Medical Sciences, Poursina Street, Tehran, Iran. Tel.: +98 2166466383.
*E-mail address:* h_jafari@tums.ac.ir (A.H. Jafari).

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In the clinical applications, an objective tool for automatic classification of cABR signals can assist auditory professionals for better diagnosis of auditory possessing disabilities. It can be used for hearing aid fitting or cochlear implant adjustments. There are some sorts of auditory disorders that may have normal ABR or cABR in time domain linear analysis, but the use of a novel approach for the reconstruction of real signal dimension can be a tool for representing these problems. In cochlear implanted persons, this can yield to an adjustment protocol based on what a normal person really hears and what changes in his/her brainstem signal are expected. However, there is limited understanding of the neural responses evoked by various speech sounds [6].

In addition to the contribution of activity in the ascending auditory system to the speech ABR, top-down influences from higher neural centers have been shown to affect the responses. For example, auditory training and experience with a tonal language have been found to enhance responses at F0 [6,7].

Recent studies have shown that children with language based learning problems have abnormal encoding of speech at the brainstem level. Researchers tried to find an appropriate linear feature for objective classification of normal and abnormal cABR data [8]. The source filter model of speech processing showed selective deficiency in the neural encoding of acoustic features associated with the filter characteristics of speech for these subjects [5]. However, linear analysis provides poor information about system real dynamic and its transitions. Therefore, the use of nonlinear analysis may help overcome this limitation.

Using nonlinear methods with applicability to short and noisy data with the aim of representing non-evident changes in physiological behavior of human body system are novel approaches in neurosciences [9]. Detection of weak transition in signal dynamics was done using recurrence time statistics and especially for transitions with very low energy [10]. Recurrence quantification analysis (RQA) is a tool for the representation of similarities and dissimilarities of signals that cannot easily be seen in time domain data. This analysis is based on dimension reconstruction according to Takens' theory. According to this theory, by considering a time series that is sampled from system behavior in one observable dimension, the reconstruction of a scope about multidimensional behavior is possible.

The base of the field of nonlinear dynamics is the representation of trajectories in their phase space [11]. Recurrence plots are new methods based on the nonlinear analysis that have been developed in the last decade. Recurrence plot (RP) represents the times at which states in a phase space recur. It enables us to investigate the *m*-dimensional phase space trajectory through a two dimensional representation of its recurrence [11]. Most of the RP related methods are based on quantifying nearest neighbors in phase space. It has been shown that two types of recurrence points exist: true and sojourn. Therefore two types of the recurrence time can be defined T1 and T2 respectively [10,12]. The use of the sojourn point's concept and its relating recurrence times increased the hope for detecting system's state transition points.

A novel study has shown that the Fuzzy nonlinear model can represent input–output behavior of brainstem in generating cABR to /da/ [13]. Therefore, this can be acceptable to find nonlinear features that can be used for cABR signal classification.

In this paper, we try to use RQA nonlinear method for representing differences between cABR elicited by three different perceptually critical diotic stimuli /ba/, /da/ and /ga/. Exploring this feature can be a tool for the objective classification of these responses and a proof for the hypothesis of processing the role of brainstem.

## 2. Material and methods

### 2.1. Participants

Twenty-seven volunteer students from Tehran University of Medical Sciences (13 women and 14 men), aged from 22 to 29 years (mean ± SD = 24.34 ± 1.95), participated in this study. None of the subjects had a history of auditory, learning or neurologic problems. All students were monolingual Persian speakers by self-report and pure tone hearing thresholds for both ears were equal to or better than 20 dB HL for octave frequencies 250–8000 Hz. Subjects gave written consent to participate intensively in the study. All procedures were approved by the deputy of research review board and ethics community of Tehran University of Medical Sciences.

### 2.2. Stimuli

In this research, three different 170 ms one syllable consonant-vowel synthesized stimuli including /ba/, /da/ and /ga/ were presented to each person at a sampling rate of 20 kHz. These three stimuli were obtained from Kraus and colleagues auditory neuroscience laboratory at Northwestern University and are the same with previous research undertaken by them [1]. Fig. 1 shows time–frequency specifications of these three stimuli schematically.

Stimuli durations are 170 ms with voicing (100 Hz F0) onset at 10 ms. The formant transition durations are 50 ms and comprise a linearly rising F1 (400–720 Hz), flat F4 (3300 Hz), F5 (3750 Hz) and F6 (4900 Hz). Ten milliseconds of initial frication are centered at frequencies around F4 and F5. After the 50 ms formant transition period, F2 and F3 remain constant at their transition end point frequencies of 1240 and 2500 Hz, respectively, for the remainder of the syllable. The stimuli differ only in the starting points of F2 and F3. For [ba], F2 and F3 rise from 900 Hz and 2400 Hz, respectively. For [da], F2 and F3 fall from 1700 and 2580, respectively. For [ga], F2 and F3 decrease from 3000 and 3100, respectively. These synthesized stimuli have an identical and constant F0 throughout their entire duration [1].

The diotic stimuli were delivered with a high precision synchronized stimuli delivery system that was designed and manufactured for simultaneous presentation of the same sound to each ear. The rate of presentation was 4.65/s. Both stimuli polarities (condensation and rarefaction) were presented. The test stimuli were presented to both ears through Etymotic ER-30 earphone (Etymotic Research, Elk Grove Village, IL) at an intensity of 83 dB SPL. To ensure subject cooperation and promote stillness, all subjects watched videotaped programs such as movies or cartoons of their choice. They were instructed to attend to the video rather than to the stimuli.

### 2.3. EEG acquisition and analysis

#### 2.3.1. cABR signal extraction

G.tec EEG recording system was used to record evoked potentials synchronized with auditory stimuli from Cz-to-ipsilateral earlobe, with forehead as ground and digitized at 19,200 Hz.

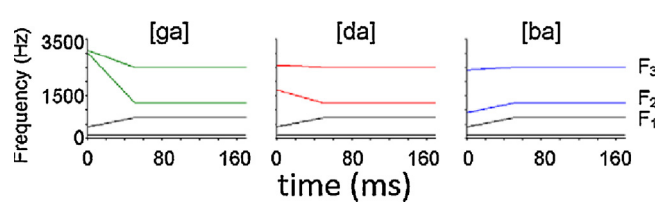


**Fig. 1.** Schematic representations of the spectral composition of [ga] (left), [da] (center), and [ba] (right) stimuli as a function of time (in ms). The first 50 ms are the formant transition period, followed by the steady-state [a] portion [1].

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EEG was processed offline to create averages for each stimulus condition. Each response was band pass filtered from 70 to 2000 Hz to isolate the brainstem response frequencies. To compensate filter phase distortions filtfilt tool was used for Zero-phase forward and reverse digital IIR filtering.

The EEG was then divided into 215 ms epochs (15 ms pre-stimulus and 30 ms post-stimulus according to setting in stimuli delivery system). An artifact criterion of ±35 μV was applied to reject epochs that contained myogenic artifacts. For each stimulus, the processed epochs were separately averaged (according to polarity) and then added together in order to isolate the neural response from that of the cochlear microphonic [1]. The final average waveform for each stimulus contained 4000 sweeps per subject that is cABR signal. This signal was stored for all subjects for three different stimuli as a scalar time series $\{x(i), i = 1, 2, \ldots\}$ for further analysis.

### 2.3.2. Calculating dimension embedding lag

Before implementing RQA algorithm, it is necessary to calculate the dimension reconstruction lag and then the minimum embedding dimension of signal.

The first zero crossing of autocorrelation function is a suitable selection for embedding lag. We find this parameter for all three stimuli and all subjects and then the average of these findings was set as embedding lag for all situations. As we find in this study, the selection of lag is not very critical in embedding results [11]. Therefore, we chose the average lag and can compare and discuss the results of different stimuli. Embedding lag estimation was also performed with mutual information minima method without any significant difference between the results.

### 2.3.3. Calculating minimum embedding dimension

The solution to find minimum reconstruction dimension is False nearest neighbors (FNN) that is proposed by Kennel et al. [14]. This method finds nearest neighbor for each point in any dimension and then seeks to see if these points are near in one higher dimension or not. When the algorithm finds the correct embedding dimension, the ratio of False nearest neighbor algorithm goes toward zero.

We used CRP toolbox developed by Marwan for calculating FNN in this project [15]. According to the results of lag calculation part of this paper, the delay was set to 39 and using MAX norm and maximum dimension equal to 10 and neglecting of existence of FNN below 0.01% for all the cABRs, FNN algorithm was run.

### 2.3.4. Generating recurrence plots and RQA

A recurrence is a time the trajectory returns to a location it has visited before. The recurrence plot depicts the collection of pairs of times at which the trajectory is at the same place. Recurrence plots exhibit characteristic large and small scale patterns that are caused by fundamental dynamic behavior, e.g. short diagonals lines reveal similar local evolution of different parts of the trajectory, while horizontal and vertical black lines appear when a state does not change for some time [9]. After state space reconstruction, we performed Recurrence quantification analysis (RQA) with finding points that are near in the reconstructed state space of cABR using Marwan's CRP toolbox [15]. Using this algorithm does not need any assumption about system stationary [16]. We set the dimension equal to 5 and embedding lag equal to 39 according to the findings in this paper. We first construct vectors of the form $Xi = [x(i), x(i+L), \ldots, x(i+(m-1)L)]$, where $m$ is the embedding dimension and $L$ the delay time. $\{Xi, i = 1, 2, \ldots, N\}$ then represents certain trajectory in a $m$-dimensional space. The threshold value for finding neighbors corresponds to 10% of the maximum phase space diameter and is calculated for each cABR data separately. Normalized cABR data were used and the distance between individual points in the matrix corresponding to a state of the system at a given time was calculated using the option maximum norm fixed recurrence rate that means the number of neighbors in the neighborhood is constant. The sliding window had 420 samples (21.87 ms) and moved with 42 sample (2.18 ms) steps. After the visual inspection of recurrence plots to get an insight about system behavior for each stimulus, RQA was performed in each window to get output parameters of this algorithm for all conditions and stored per subjects for further analysis.

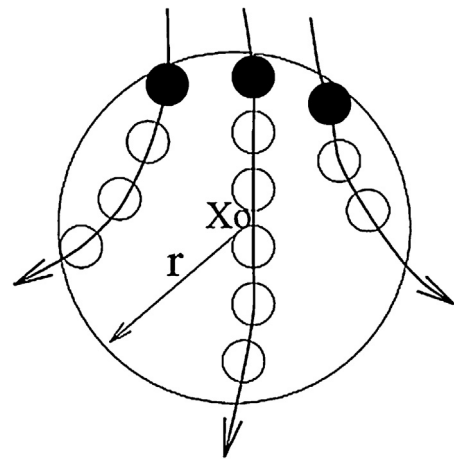


**Fig. 2.** A schematic showing recurrence points of the second type (solid circles) and the sojourn points (open circles) in $B_r(X0)$ [10].

T2 which is the recurrence time of second type was calculated. It is able to detect very weak transitions with high accuracy, both in clean and noisy environments [9,10].

For getting better insight about T2's definition, we arbitrarily chose a reference point $X0$ on the reconstructed trajectory, and considered recurrences to its neighborhood of radius $r$: $B_r(X0) = \{X: ||X - X0|| < r\}$. Then we defined the recurrence points of the 2nd type as the set of points comprised of the first trajectory point getting inside the neighborhood from outside [12]. The trajectory may stay inside the neighborhood for a while, thus generating a sequence of points. These are called sojourn points [10]. Fig. 2 shows a graphical representation of sojourn (open circles) and 2nd type (solid circles) in a neighborhood. It is clear that there will be more such points when the size of the neighborhood gets larger as well as when the trajectory is sampled more densely. Sojourn points form vertical and horizontal lines, and thus square textures, in recurrence plots. The summation of the recurrence points of the second kind and the sojourn points is called the recurrence points of the first kind and so points to a different parameter [10]. The time between successive 2nd type recurrence points is called recurrence time of 2nd type (T2).

Normal distribution of T2 was tested with Kolmogorov–Smirnov goodness-of-fit hypothesis test in each window across the subjects. Using Matlab version 2014, statistical analysis was done. For normal distributed indexes, the mean value of calculated indexes for each window in 3 groups was compared using ANOVA method and $p$ value less than 0.05 was considered statistically significant.

## 3. Results

### 3.1. cABR signal extraction

The cABR signal in response to three stimuli for all subjects was extracted and the grand average of these signals calculated and shown in Fig. 3. According to this figure cABR overall morphology in response to consonant and vowel parts of stimulus and its repeatability can be confirmed in comparison to pervious works.

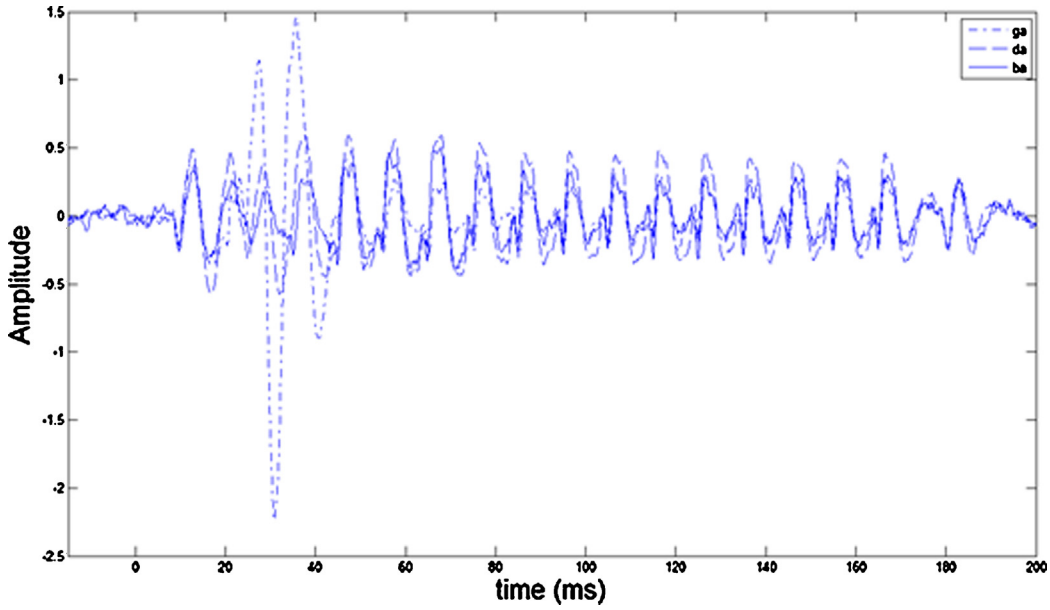


**Fig. 3.** cABR grand average to three 170 ms stimuli including /ba/, /da/, /ga/.

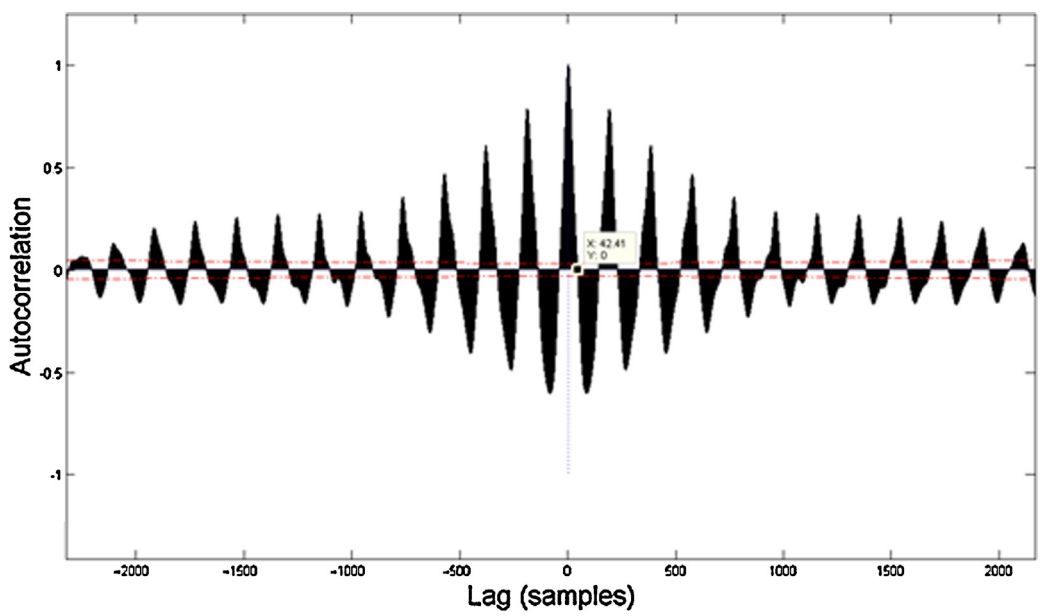


**Fig. 4.** The output of autocorrelation function for grand average signal in response of /ba/.

### 3.2. Calculating dimension embedding lag

By running the autocorrelation algorithm we find the first minimum as described above. Fig. 4 shows the output of the above method that is computed for the grand average of response to /ba/ stimulus as an example. In this figure, the suitable lag should be selected equal to 42.

The results of iterating this algorithm for all situations are represented in Table 1.

**Table 1**
Mean and SD for embedding lag calculation of cABR to /ba/, /da/, /ga/ in all subjects.

| | Mean | Standard deviation |
|---|---|---|
| /ba/ | 37.30 | 7.45 |
| /da/ | 38.22 | 6.56 |
| /ga/ | 40.40 | 5.98 |

The average for all the mentioned states in Table 1 is 38.64, so we set embedding lag to 39 samples that is equal to 2 ms.

### 3.3. Calculating minimum embedding dimension

After running the FNN algorithm, as was described previously, the minimum dimension for embedding cABR of each subject in each condition was calculated.

As you can see in Fig. 5, one instance of this calculation is plotted for /ba/ grand average response. In this figure, the horizontal axis is dimension and vertical axis is the FNN algorithm output in percent and the proper dimension will be 4. The histogram of calculated dimensions was plotted for each stimulus and its results can be seen in Table 2. In this table the percentage of each dimension was calculated in the above manner. It seems that suitable dimension for all future calculations in this paper can be 5.

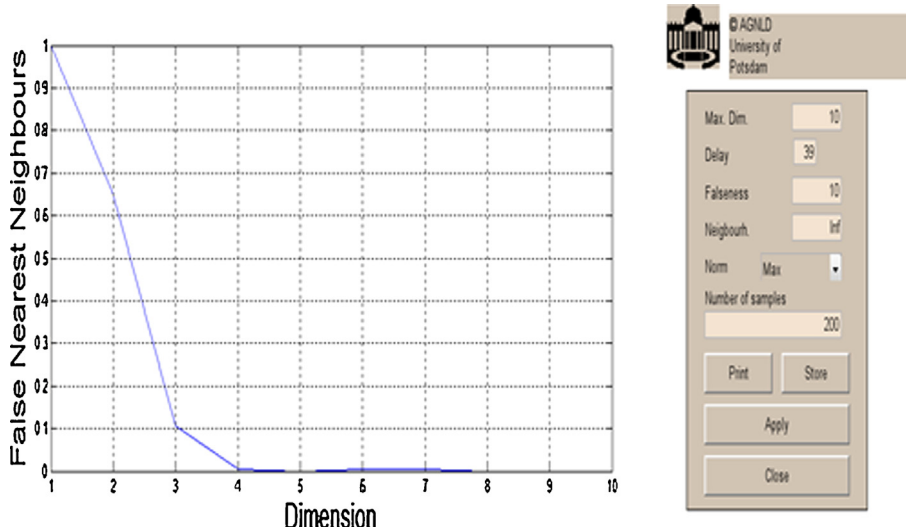


**Fig. 5.** FNN output in response to grand average cABR to /ba/.

**Table 2**
The percentage of calculated dimension for each stimulus.

| | 4 | 5 | 6 |
|---|---|---|---|
| /ba/ | 33.33 | 59.26 | 7.41 |
| /da/ | 0 | 100 | 0 |
| /ga/ | 7.41 | 74.07 | 18.52 |

### 3.4. Generating recurrence plots and RQA

Recurrence plot generation and RQA were performed for all subjects and each stimulus. T2 indexes were calculated as mentioned above. Fig. 6 shows a sample of this calculation for grand average response to /ba/.

For better representation of T2 indexes and their overall behavior across stimuli, the average of each index was calculated and plotted for all three stimuli. Fig. 7 shows recurrence time of 2nd type of cABR for three stimuli.

### 3.5. Statistical analysis

Kolmogorov–Smirnov method was used to approve T2 index coming from normal distribution. Fig. 8 shows recurrence time of 2nd type index $p$ value for each cABR window. There were two successive windows that with post-ANOVA multiple comparison yield three response groups and can be separated automatically according to this feature. Fig. 9 displays multiple comparison method results for one of these two windows. Table 3 shows the

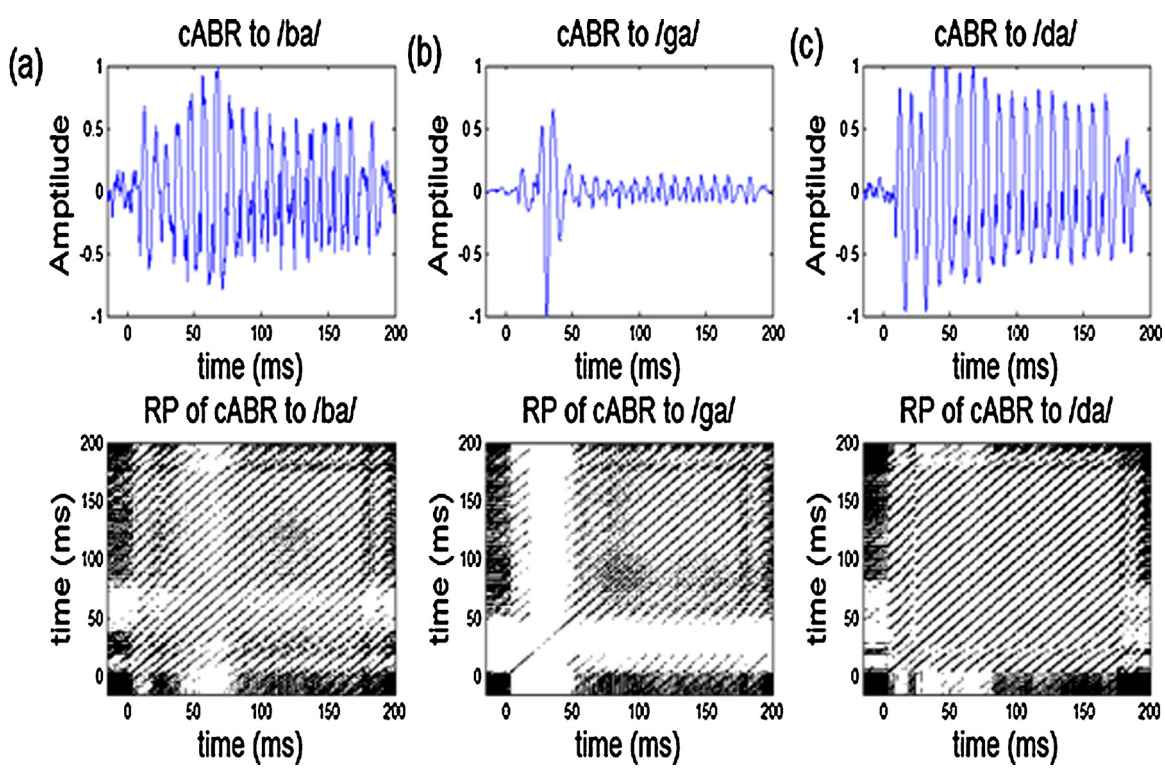


**Fig. 6.** cABR grand average time domain representation (top) and its recurrence plot generated for relating signal (bottom). (a) Response to /ba/, (b) response to /ga/, and (c) response to /da/.

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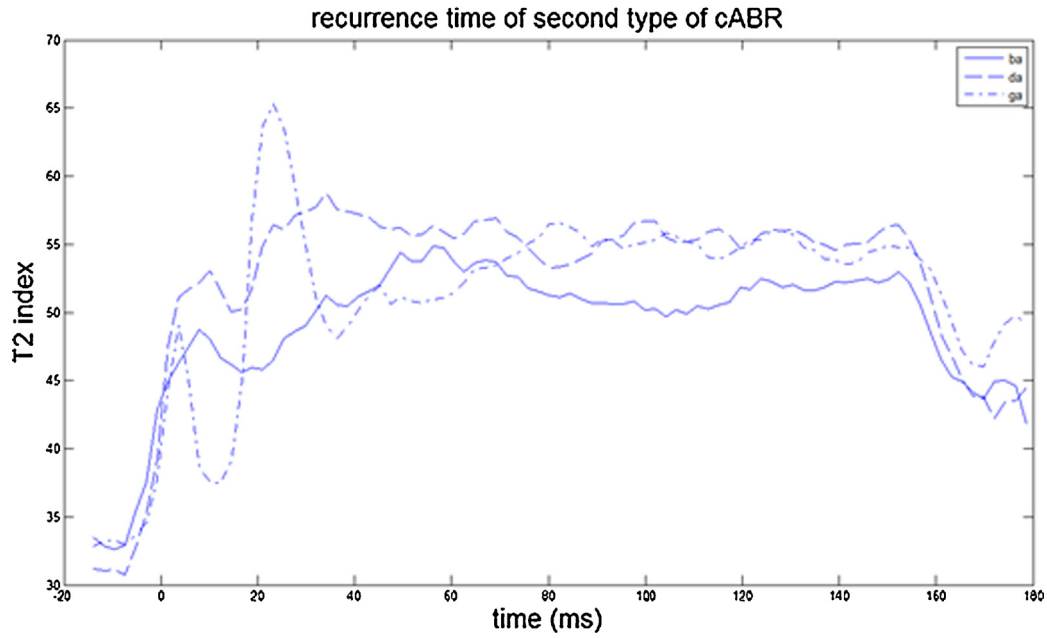


**Fig. 7.** Average recurrence time of 2nd type of cABR for three stimuli.

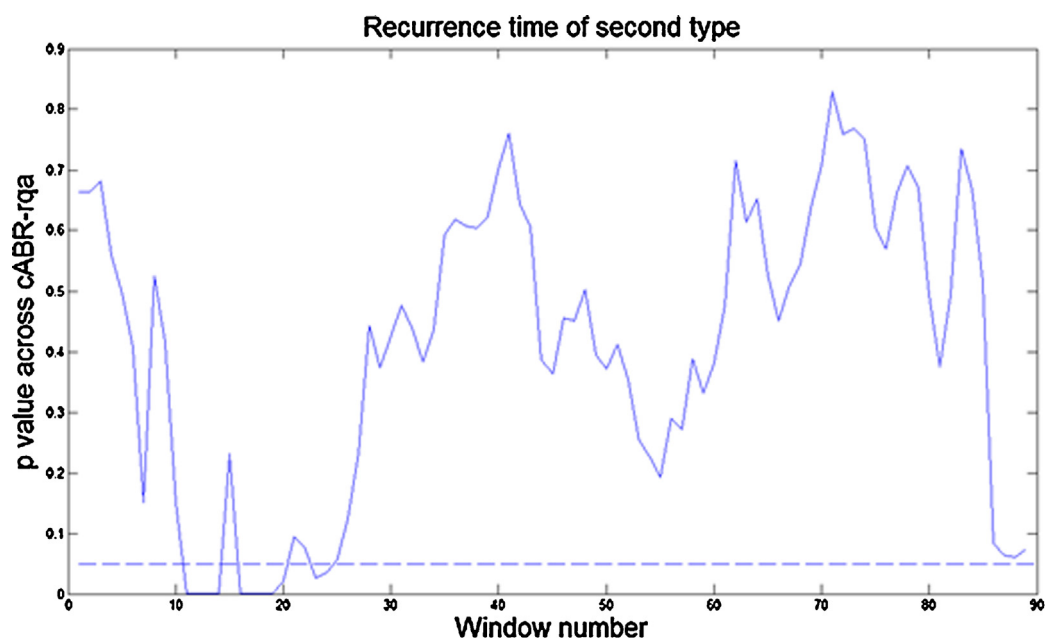


**Fig. 8.** Recurrence time of 2nd type index *p* value for the cABR groups.

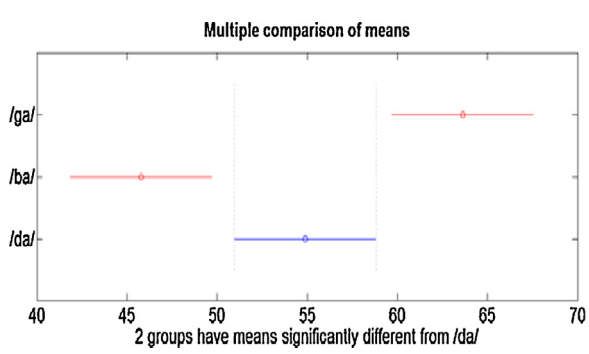


**Fig. 9.** Multiple comparison method shows three separable groups according to recurrence time of 2nd type RQA index.

mean estimates and the standard errors with the corresponding group names relating to Fig. 9.

Comparing these time windows with time domain representation of stimuli shows that windows time is 20.1–35.3 ms and belongs to formant transition period of stimuli. There were also seven other windows that confirmed a significant difference according to *p* value between /ba/ and /ga/ responses.

## 4. Discussion

This research was designed to investigate the possibility of nonlinear feature extraction for the classification of brainstem response to auditory stimuli. According to this study, because feature extraction from brainstem was successful, the hypothesis that auditory processing is distributed along the auditory system

**Table 3**
The mean estimates and the standard errors with the corresponding group names.

| | Mean estimate | Standard error |
|---|---|---|
| /ba/ | 45.7819 | 2.3265 |
| /da/ | 54.8899 | 2.3265 |
| /ga/ | 63.6470 | 2.3265 |

path is approved. Contrary to most previous studies that used simple stimuli like click or tone burst, the used stimuli in this research had a rather similar structure to natural voice of human but with less formants. These stimuli had consonant and vowel parts, so they generate transient and steady state responses of brainstem system. The idea behind the selection of these three stimuli (/ba/, /da/, /ga/) was their similar formant structure, so in children with learning difficulties the possibility of misunderstanding these voices are higher than others [2]. Auditory processing disorders can lead to learning problems and hearing difficulties [2,17].

The selection of nonlinear analysis was based on the scientific principles of these methods that work on the reconstruction of real dimension of signal. Therefore some information can be extracted from this new dimension that may lose in one dimensional projection (time domain) of it or would be features that are very close to other features in this projection so they cannot be used as a classification feature.

It can be mentioned that top down feedback from cortex to brainstem is effective in response to structure formation. If you imagine T2 index that represents the state space points which come from outside to inside of observing radius is a tool for representing firing of neurons that cause system state changes, so it is a flag of top down feedback of auditory processing system.

The extracted feature can classify /ba/, /da/, /ga/ and this classification happens in formant transition period of input stimuli. It means that the information content in the vowel part was the same or has no significant difference. These findings were presented in other forms in previous work with exactly the same auditory stimuli [1]. In that study, the need for peak labeling with expert audiologist exists. But in the proposed method in this paper, a generated algorithm can classify responses objectively. As far as we know, there is no objective method for distinguishing between these three response groups.

The first window of RP where the $p$ value becomes less than 0.05 starts from 6.9 ms of time domain response. It is when the onset response occurs in average. It should be mentioned that by using the windowing concept, the exact detection of onset response time is not possible, but previous linear analysis approved our findings [1]. In Fig. 8, twelve windows showed successfully the classification of /ba/ and /ga/ regarding post-comparison statistical analysis. Considering RP principles these windows are in the range of 6.9–46.1 ms of cABR time domain representation, which belongs to formant transition period. As the sliding window goes forward, the relating formants tend to be more equal (Fig. 1). So it caused no classification feature at the end of format transition period and vowel part of input stimuli.

On the other hand, the /ba/ and /ga/ classification happened more than others. It can be based on their voice frequency specification which is shown in Fig. 1. It represents more differences between these two stimuli than others. It can be according to the tonotopicity nature of cochlea, which explains that the different frequencies are encoded in different regions in it. So the paths /ba/ and /ga/ traveling to the brainstem is more different than others; therefore their T2 index which shows state changes in a state space region is more different than others.

Time interval among 20.1–35.3 ms is where three responses can be classified with this feature according to the statistical significance and post-comparison performed in this project. This time interval is after voicing onset occurs and it can be said that top bottom feedback loop is closed and more firing neurons of those relating to perceptional processing force the cABR nonlinear characteristics to be more different than other regions. With time the formant differences will be less, so the extracted feature (T2) shows no difference as we expected because there is no difference in neural function regarding firing rate or firing performance.

Fig. 9 shows mean estimate and confidence interval for simultaneous comparison of groups. This figure proved the hypothesis that T2 can be assumed as a separating feature. The mean of T2 which is calculated in the proposed window for each response group is significantly different from two other groups. On the other hand, there is a suitable confidence interval to ensure subjects natural variance of this feature, and this do not affect the test results. It can be used as an objective measure for classifying cABR signals for three differing stimuli in normal subjects. This measure may be used as a norm for assessing subjects' auditory processing health in near future.

## 5. Conclusion

This study clearly indicated that reoccurrence quantification analysis can be a valuable tool for the analysis of cABR data. T2 feature successfully classified three diotically presented perceptually critical cABR response and showed acceptable behavior across the time. It is recommended that further research is to be undertaken on other nonlinear features and comprising normal and abnormal data.

## Conflict of interest

None.

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