A Novel Approach for Extracting Important Cues in Complex Auditory Brainstem Response to /da/ Using Fuzzy Model

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A B S T R A C T

Purpose: Gathering an insight into brainstem task in generating auditory response to complex stimuli and its nonlinear behavior can be an important base in auditory system modelling, but no study has been done to demonstrate the nonlinear dynamic behavior of auditory systems considering cABR. This study attends the dynamic modeling of auditory brainstem response to consonant-vowel syllable /da/ using fuzzy logic as nonlinear mapping of the input and output of the system.

Methods: We recorded cABR to /da/ from 40 normal Farsi speaking subjects in response to /da/ with 40ms duration. This data set was divided to train and validation sets. We implemented a fuzzy logic based model for the dynamic extraction of cABR to /da/ for data set. This model includes singltone fuzzifier, product inference engine and weighted center of average defuzzifier. Rule base representing dynamic of signal was generated and, then, firing rate of each rule was calculated and a histogram of rule firing rate was plotted. We selected the important regions of the histogram regarding to firing pattern of the rule. By choosing an appropriate threshold, a secondary rule reduction was done to generate a simplified model; remaining rules were best rules related to important cues of cABR.

Results: This model represents the input-output behavior of the brainstem in generating cABR to consonant-vowel /da/. The total error achieved by cross-validation of the model after an important rule selection is 0.1329 with a variance of 7.08×10^{-4}.

Conclusion: Nonlinear fuzzy based dynamic extraction of cABR signal is a valid approach for generating important features of cABR and a remarkable evidence of these signals can be represented by some spatial rules.

Keywords:

Brainstem, Nonlinear,
Fuzzy Logic,
Dynamic Model,
Auditory Cue,
cABR.

1. Introduction

Auditory brainstem responses (ABRs) are biopotentials recorded from the scalp evoked by external stimuli like clicks, mono tones, etc. Neural encoding of sounds relies on central auditory system function which begins in the auditory nerve and reaches to brainstem [1]. ABRs are considered as an important tool to access the information about the neural encoding of sound in auditory systems, but they don not provide comprehensive information about what really happens in encoding of speech. Therefore, studies have been ubdertaken in the last decade to see how the temporal modulations of sounds are represented in the response.

Evoked potential to basic stimuli, like transients, tone bursts and tones are considered more than complex sounds with a contamination of amplitude and frequency modulations[2]. In clinical applications, brainstem responses to clicks or tones are commonly used to distinguish and evaluate the auditory pathway

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integrity [3]. However, a non-speech stimulus such as a click or a tone burst doses not give sufficient information about the real process of encoding of speech, it is necessary to consider encoding of speech at the brainstem level because of the time varying complex nature of speech [4].

Natural complex sounds encompass transient, periodic and quasi periodic features. There is insufficient knowledge about the neurophysiological processing of natural sounds along the auditory pathway. The response to a complex sound is not necessarily predictable from clicks and tones evoked potentials [5, 6]. Because of these, auditory Neuroscientists try to use complex stimulus (e. g. speech, music and other natural sounds like a baby cry) to record ABR[7].

Melcher andKiang (1996) used a convolution method to describe the generation of ABR in cat [8]. Dau developed a model for the generation of ABRs to common transient stimuli like clicks and frequencies following responses to tones (FFR). These AEPs are the results of summed activities by neurons in the auditory nerves (AN) [9]. Cochlear processing such as the filtering of basilar membrane with compressive feedback loop, inner hair-cell function, adaptation of auditory nerves and inner hair-cell synapse are considered in the mentioned model. The output of AN model, instantaneous discharge rate, was convolved with an elementary unit waveform obtained to simulate AEPS. Harte extended Dau's model with current changes in AN modeling [10] and humanized the model. Brainstem responses to complex sounds like speech, music and natural sounds, reveals the temporal and spectral specification of acoustic stimulus [7]. Therefore, the modeling of auditory brainstem response, considering these responses, gives accurate information about the encoding of the natural sound cues in the auditory pathway. Roone and Dau present a model for brainstem responses to transient stimulus based on previous studies [2]. Thenthe ABR model was developed based purely on a bottom-up afferent processing to speech stimulus [11].

The experimental analyses help the mathematical models to develop by means of input-output pairs. However, these dynamical models do not describe the exact internal structure of the system, but are an approximation of the system input and output nonlinear mapping. Although speech evoked potentials is relatively high replicable [12, 13], there are differences in the latencies, almost the fraction of milliseconds which are important in clinical applications [14]. These are because of systematic differences between observed dynamics of everybody auditory pathways. Consonant-vowel stimulus /da/ have been utilized more than other stimulus for studding auditory brain stem response because of its complex nature including both transient and sustained features and its research potential in hearing and learning disorders. It's also the only popular stimuli existing in cABR recording instruments.

Having collected all these, no study has been done to demonstrate the nonlinear dynamic behavior of auditory system in generating cABR signals until now. This study attends a dynamic modeling of auditory brainstem response to consonant-vowel syllable /da/ using fuzzy logic as nonlinear mapping of input-output pairs of system. This model tries to extract the dynamics of these differences in each responseand, then, find common rules that exist in cABRs describing the pattern of major and substantial dynamics of the responses.

2. Method

2.1. Subjects

Forty volunteer students from School of Rehabilitation, Iran University of Medical Sciences (18 women and 22 men), aged 20–28 years (mean ± SD = 22.77 ± 2.05) were registered to initiate the experiment. None of the subjects had a history of auditory, learning or neurologic problems. All students were right handed and monolingual Persian speakers by self-report. All had normal middle ear function (supported by immittance findings) and performed within the normal limits on pure tone audiometry (air conduction thresholds ≤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, Iran University of Medical sciences.

2.2. Stimuli

The 40-ms speech syllable /da/ (Fig. 1) was presented through Biologic Navigator Pro (Natus Medical Inc.). The fundamental frequency (F0) increased linearly from 103 to 125 Hz. During the formant transition period, F1 linearly increases from 220 to 720 Hz, whereas the second formant frequency (F2) decreases from 1700 to 1240 Hz, and the third formant frequency (F3) decreases slightly from 2580 to 2500 Hz, whereas the fourth (F4) and fifth (F5) formant frequencies remain constant at 3600 and 4500 Hz, respectively.

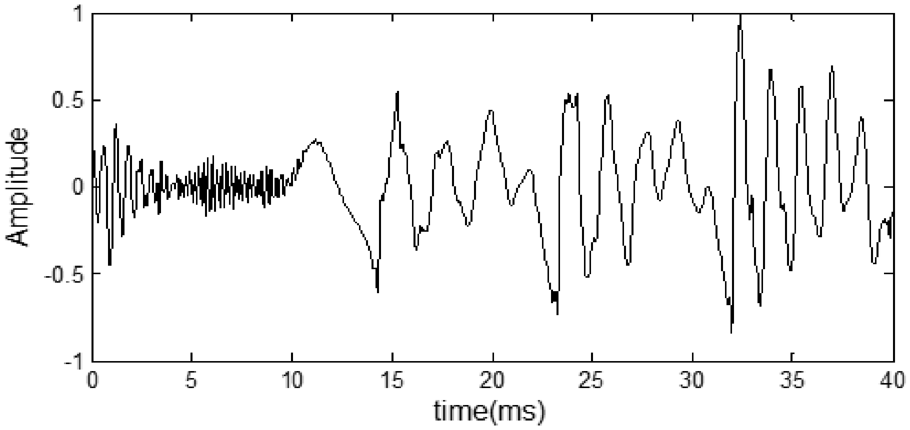

Figure 1. Time based representation of 40-ms speech syllable /da/.

2.3. Recording Procedure

The speech syllable /da/ was presented binaurally through insert ear phones (Biologic 580-SINSER) in alternating polarities at 80 dB SPL with an inter stimulus interval of 70.33-ms. ABRs to the /da/ sound in the quiet conditions were collected with four Ag-AgCl scalp electrodes using Biologic Navigator Pro (Natus Medical Inc.) with sampling frequency of 12 kHz. Brainstem responses were collected with a vertical montage (active electrode at Cz, linked reference electrodes on both earlobes, ground electrode at Fpz). An online filter (100-2000 Hz) selected to pass the brain stem potentials. Electrode impedances were maintained below 5 kΩ.

2.4. Data Processing

Any sweep exceeding 23.8 mV was considered artifact and excluded. After artifact rejection, the average of 3000-sweep separately was recorded in two memories according to their stimulus polarities presentation. Then, two memories were added offline to minimize the stimulus artifact and cochlear microphonic response [7].

Due to low pass nature of brainstem which emphasizes the energy of fundamental frequency of stimulus (F0) and bypasses the high frequencies [7], a low pass filter with cut off frequency 2 kHz was applied to stimuli.

For finding the best model order, a lag embedding of cABR signal was used. Lag embedding is the fundamental technique in nonlinear time series analysis. We used an embedding lag equal to 1 and maximum embedding dimension equal to 30. We calculated the correlation integral for different embedded dimensions and, then, zoomed in the correlation integral representation to find the best scaling region for finding correlation dimensions. After the representation of correlation dimension diagram, we expected correlation dimensions to vary with dimensions until embedded dimensions was equal to or became greater than about twice the dimensions of the state space attractor for the system. After this saturation value, correlation dimensions becomes independent of embedding dimensions.

Then, we implemented the simplest discrete-time model based on correlation dimension method (shown in Fig. 2) to obtain the relationship between the input-output pairs and find the transfer function of the system which was considered as black box without the knowledge of its internal characteristics. The structure of model was followed as (1).

$$\overline{cABR}(n) = a_1 cABR(n-1) + a_2 cABR(n-2) + a_3 cABR(n-3) + a_4 cABR(n-4) + b_1 stimuli(n-n_k) + e(n) \quad (1)$$

Where e(n) is white-noise term and nk is the appropriate delay which is set to the maximum fitness point of model. This point is highlighted in Fig. 3. The ARX model was fitted to train set and the estimated parameters for each data were obtained. Then all corresponding coefficients of regressors were averaged.

Correlation analyses are used for calculating the time delay between stimulus and response and can be used to compare the overall morphology and timing of stimulus and response [15]. The cross correlation between response and stimulus is a function of time shift which measures the degree of their similarity. This quantity can also be used for determining the onset of response which is known as the time delay between stimulus and response [16]. Pearson correlation between response and stimulus with two polarities was calculated. Maxi-

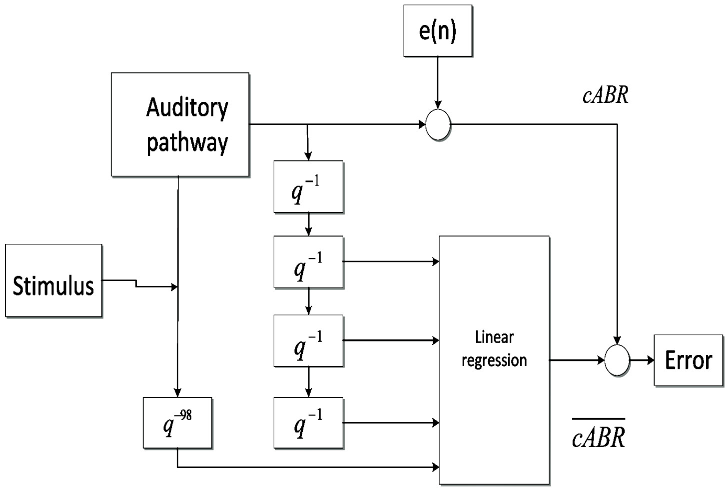

Figure 2. The schematic of suggested linear model.

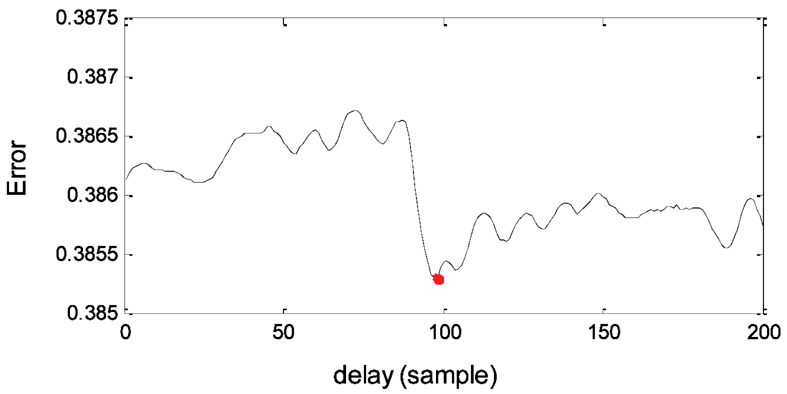

Figure 3. ARX model error versus varying system delay. Minimum error of fitted model was in 98th sample delay of stimuli

mum correlation considering positive polarity was 6.45-ms and negative polarity was 8.23 ms. The suggested delay by ARX model was 8.16-ms (98 sample) which is comparable with Pearson correlation results (with negative polarity) which is 8.23ms.

For creating nonlinear mapping between the input and output of the system, the fuzzy based model was suggested as shown in Fig. 4. One step ahead prediction was done by fuzzy mapping between the input and output of the system. Equations 2 and 3 represent the nonlinear relation between the input and output of the model. Where nk is the system delay which is obtained from ARX model.

$$\overline{cABR}(n+1\,|\,\varphi(n)) = f(\varphi(n)). \tag{2}$$

$$\begin{aligned}\overline{cABR}(n) = f\,(&stimuli\,(n-n_k),cABR\,(n-1),\\ &cABR\,(n-2),cABR\,(n-3),cABR\,(n-4)).\end{aligned} \tag{3}$$

2.6. Fuzzy System Generation

Our objective was to design a Fuzzy system based on existing N=1024 input-output pairs in the form of equation $(x_0^p; y_0^p)$, p=1,2,…,N according to the look up table scheme.

Where x_0^p $U = [\alpha_1, \beta_1]$ *...* $[\alpha_n, \beta_n] \subset R^n$ *and* y_o^p $U = [\alpha_y, \beta_y]$

we selected $[\alpha_y,\beta_y]=[\alpha_i,\beta_i]=[-1$ و$1]$ for $i=1,2,\ldots,5$

Step 1: Define fuzzy sets to cover input and output spaces.

We defined $N_i=N_y=21$ fuzzy sets A^i_j (j=1,2,…,N_i) on each dimention of input space $[\alpha_i,\beta_i]$ μ_{Ai}^j (xi) and $\mu_{Ai}^j(xi)$ to be triangular membership functions whichdefined on input stimuli (/da/) samples and the feedbacks of cABR values (shown in Fig. 5).

We also defined $N_y=21$ fuzzy sets B^j (j=1,2,…,N_y) and $\mu_{Bj}(y)$ to be triangular membership functions.

Step 2: Generate one rule from one input-output pair.

For each input output pair ($x_{01}^p,\ldots,x_{0n}^p;y_{01}^p$), the membership value of x_{0i}^p (i=1,2,…,n) in fuzzy sets A_i^j (j=1,2,…,N_i) and the membership value of y_0^p in fuzzy sets B^j (j=1,2,…,N_y) was determined. Then, for each input variable x_i, the fuzzy set in which x_{0i}^p has the largest membership value (A_i^l) was determined. This action was done for output variable similarly and B^l was calculated, so the fuzzy if-then rule were defined as bellow:

IF *stimuli (n-98)* is A_1^l and *cABR(n-1)* is A_2^l and *cABR(n-2)* is A_3^l and *cABR(n-3)* is A_4^l and *cABR(n-4)* is A_5^l and THEN *cABR(n)* is B^l .

In the above rule A_i^l and B^l are, respectively, input and output fuzzy sets. So we generate 30600 rules for train set.

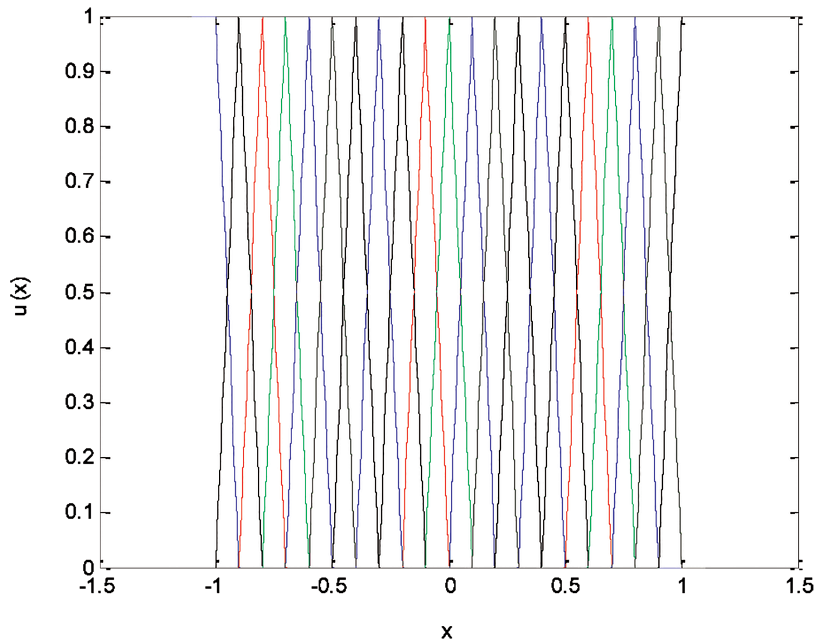

Figure 5. Membership functions consist of 21 triangular functions that covers input (output) space.

Step 3: Assign a degree to each rule generated in step 2 and perform rule reduction.

Since the number of input-output pairs was large and the probability of conflicting rules that have the same IF parts but different THEN parts, we assigned a degree (equation 4) to each generated rule in step 2 and keep only one rule from a conflicting group that has the maximum degree. So the number of rules reduced to around 2000 rule (depending on random selection of train set).

$$D_l(rule)=\prod_{i=1}^{n}\mu_{A^l}(x_i)*\mu_{B^l}(y) \qquad (4)$$

Step 4: Construct the Fuzzy system.

After rule reduction, the fuzzy rule base was created based on look up table and the fuzzy system consisting fuzzifier, inference engine and dufuzzifier, based on the fuzzy rule base was constructed.

Fuzzifier: The singleton fuzzifier was chosen as is defined in (5). In which *x* is input variable and $\mu_A(x)$ are input membership function values.

$$\mu_A(x)=\begin{cases}1\, if x=x^*.\\ 0 \quad ow\end{cases} \qquad (5)$$

Inference Engine: Our experimental data give only local information about the system; because of this the product inference engine was chosen which is defined as (6).

$$\mu_{B^l}(y) = \max[\sup(\mu_{A'}(x).\prod_{i=1}^{n}\mu_{A_i^l}(x)\mu_{B^l}(y))]. \quad (6)$$

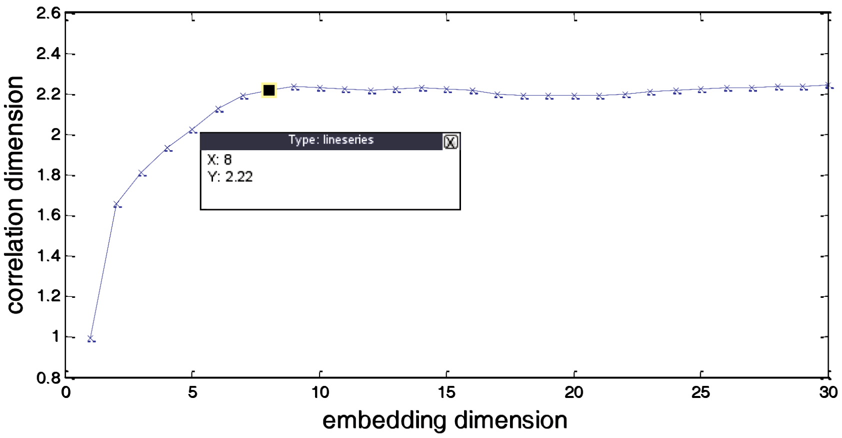

Figure 6. Correlation dimension plotted as a function of the embedding dimension for cABR data. The model order was selected equal to 4.

Defuzzfier: The output of fuzzy system is weighted an average of output membership function centers, where the weights (w_l) are membership function values in the IF part of rules (7). If the input vector of system is matched with IF part of rule, then that rule gets a larger weight.

$$y^* = \frac{\sum_{l=1}^{L}\bar{y}^l w_l}{\sum_{l=1}^{L} w_l}. \quad (7)$$

The nonlinear mapping created by proposed FIS is determined by (8).

$$f(x) = y = \frac{\sum_{l=1}^{L}\bar{y}^l.(\prod_{i=1}^{n}\mu_{A_i^l}(x_i))}{\sum_{l=1}^{L}(\prod_{i=1}^{n}\mu_{A_i^l}(x_i))}. \quad (8)$$

After devolving proposed model by generating fuzzy systems as mentioned above, the model was validated using validation data set.

3. Results

3.1. Model Order Calculation

Fig. 6 shows the saturation value that obtained from lag embedding method and is about 8 for the grand average of dataset, and the correlation dimension of the attractor is about 4. So the model order was selected equal to 4.

3.2. Validating the Model

The data set was divided into two sets, 30 data for train set and 10 for the validation set. The repeated random sub-sampling validation method used for cross-validation of model. This method randomly splits up dataset into train and test sets. Ten random train and validation sets were chosen to validate the model.

Obtained transfer function from the proposed ARX model is as follow:

$$H(z) = \frac{-0.002z^{-98}}{z^4 - 2.4610z^3 + 2.341z^2 - 1.1492 + 0.2795}. \quad (9)$$

Table 1. Arx Model Parameters.

Statistic Moments of Parameters	Estimated Parameters				
	a_1	a_2	a_3	a_4	b_{98}
Mean	-2.46	2.3410	-1.1492	-0.2795	-0.0020
Variance	0.016	0.1281	0.1583	0.0248	4.6×10^{-6}

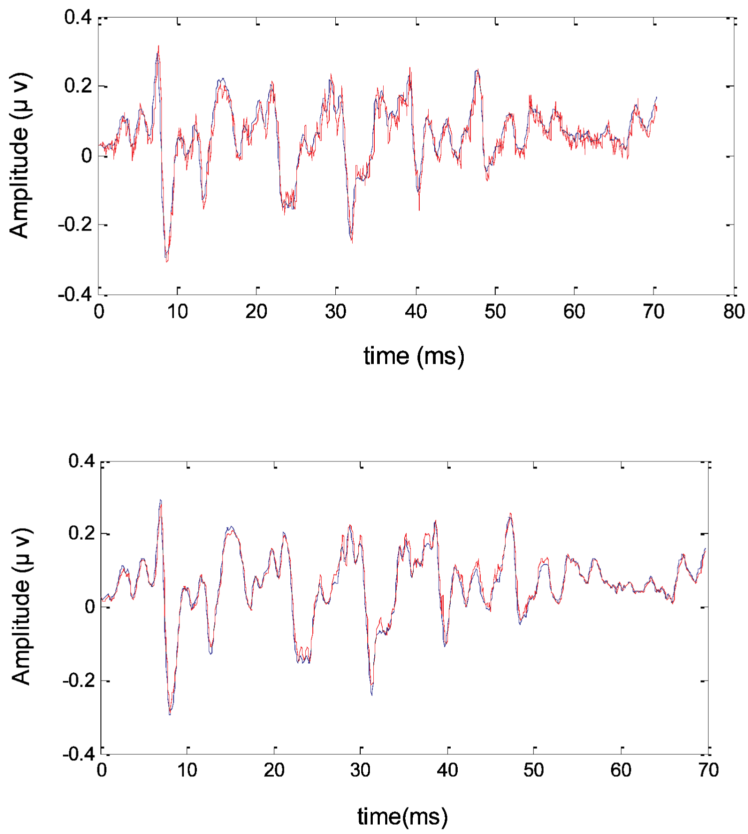

Figure 7. The plot on the top shows the output of model for linear model and the down plot shows the output of fuzzy based model (blue:original signal and red:predicted one).

Outputs for the ARX model and nonlinear ARX was shown in the Fig. 7 which shows nonlinear ARX model acts better than the linear one. The mean and variance of estimated parameters for proposed ARX model is available in table 1. Table 2 shows the mean and variance values of one step ahead prediction error defined by (10) for both linear ARX and nonlinear one, where N is sample size of signal.

$$E = \frac{\sum_{n=1}^{N} |cABR(n) - \overline{cABR(n)}|}{\sum_{n=1}^{N} |cABR(n)|}. \tag{10}$$

The cABR to /da/ includes transient and sustained features corresponding with stimulus acoustic cues. This consonant-vowel syllable /da/ evokes seven major peaks that have been named V, A, C, D, E, F, and O,

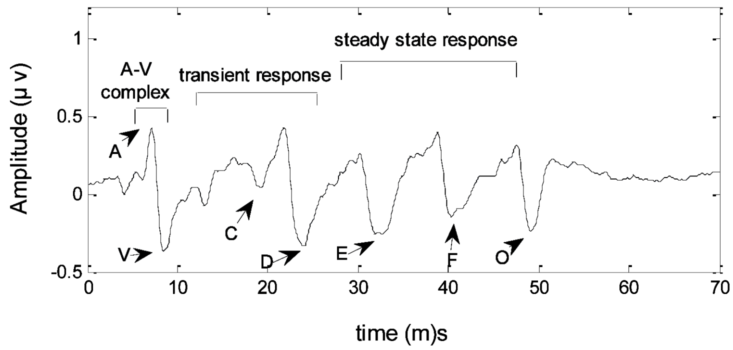

Figure 8. The grand average of cABR signals, consonant-vowel syllable /da/ evokes seven major peaks that have been named V, A, C, D, E, F, and O.

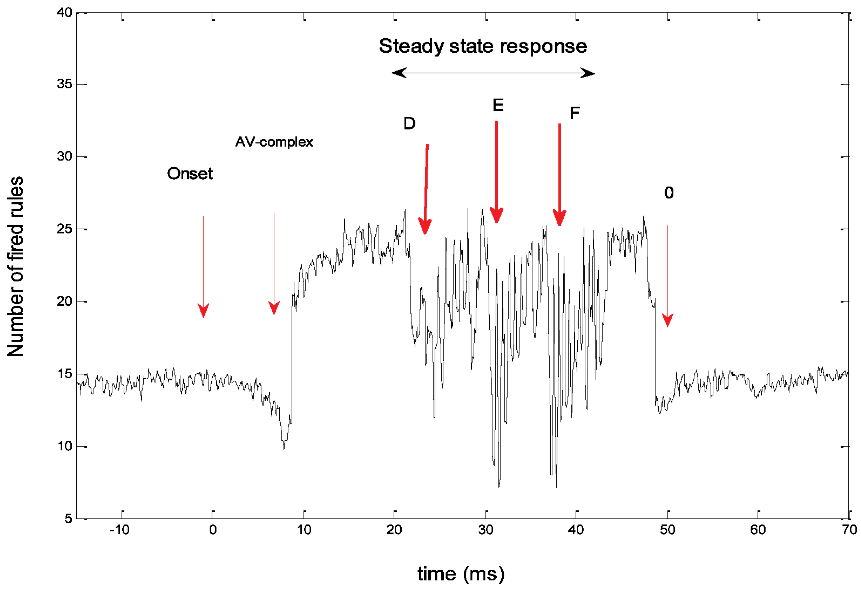

Figure 9. The grand average of the histogram of fired rules for 10 times of model validation in terms of cABR signal time.

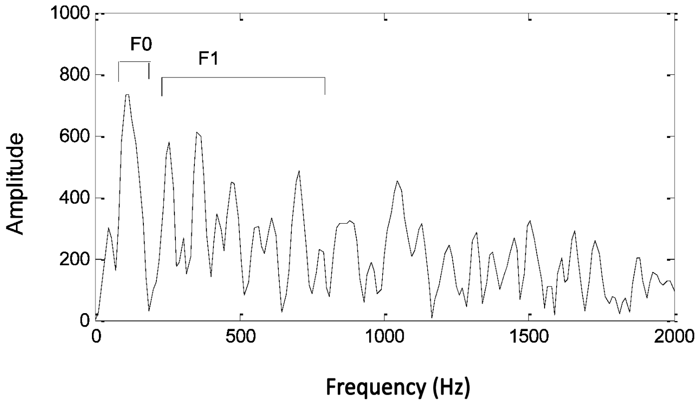

Figure 10. Fourier transform of steady state part of histogram. The pattern of fired rules following the main dominant frequency of stimulus likes F0 and F1 where F0 lineally increases from 103 to 125 Hz in the stimulus and F1 of stimulus increased from 220 to 729 Hz.

as can be seen in Fig. 8. These peaks relate to major acoustic landmarks in the stimulus. These major peaks appear approximately 6 to 9 ms after the corresponding stimulus landmark, which is related to transmission time between the cochlea and rostral brain stem.[7]. Fig. 9 shows the firing number across the cABR time. In this figure a 0.33 ms runnig window from test data was used to distinguish which rule was fired in each window. The Fourier transform of steady state part of firing number pattern is shown in Fig. 10. This figure shows that the pattern of fired rules follow the main dominant frequency of stimulus i.e. F0 and F1 etc. Where F0 linearly increases from 103 to 125 Hz in the stimulus and F1 of stimulus increased from 220 to 729 Hz.

3.3. Simplified Model

Fig. 11 shows the histogram of fired rules for validation set. In this figure, some rules that show high firing rate can be assumed as important rules in generating cABR. Therefore, by chosing an appropriate threshold, the Rule base size can be reduced more than before. The threshold was chosed above minimum firing rate of histogram and the rules that their firing rate is lower than

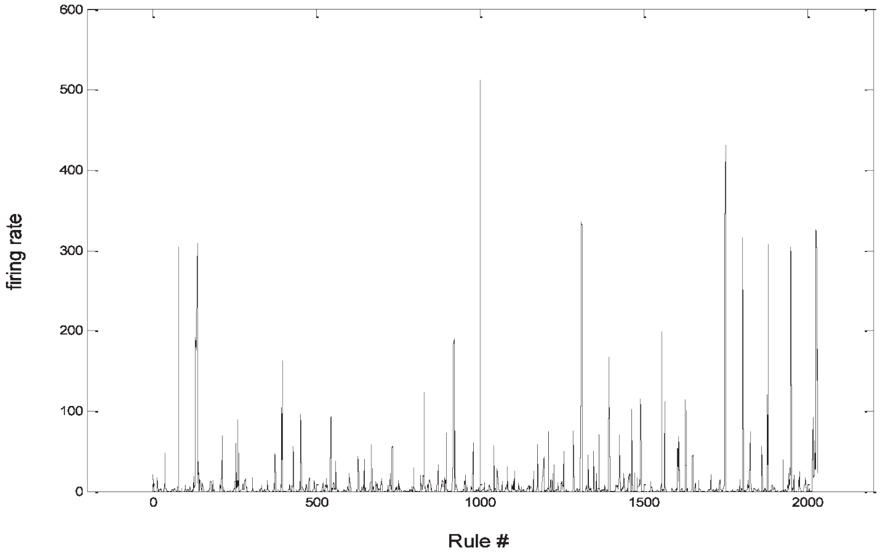

Figure 11. Histogram of fired rules for validation data set. some rules that show high firing rate can be assumed as important rules in generating cABR.

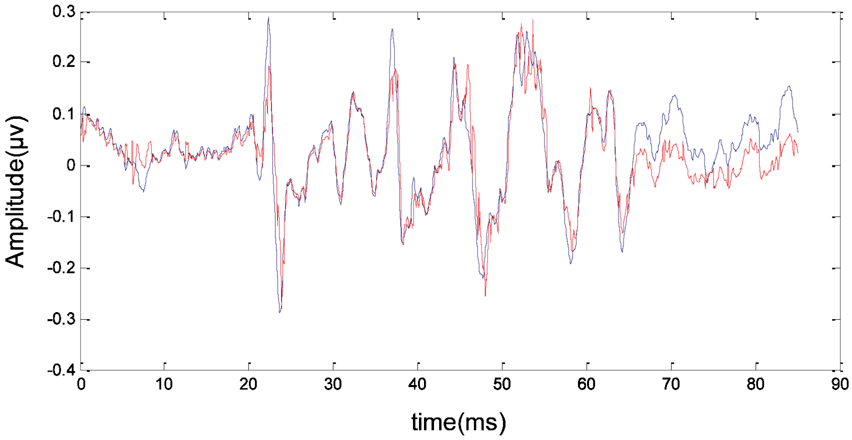

Figure 12. The output of model for a cABR from validation set after constructing simplified model using selecting the rules by their firing rate (blue:original signal and red:predicted one). It can be seen that the model was successful in predicting a whole component of signal but failed in predicting baseline

this value was eliminated. So around 200 rules (depending on random selection of train and test set) remained from the primary rule base. After rule reduction by this approach, the model was revalidated and the output of model for a signal from validation set was shown in Fig. 12. It can be seen that the model was successful

Table 2. The Mean And Variance Values Of Model's Error Resulted From Validation Step.

Models	Error Parameters	
	Mean	Variance
ARX model	0.3187	0.0046
Fuzzy model	0.1419	7.08×10^{-4}
Fuzzy model after histogram based rule reduction (simplified model)	0.2533	0.0048

in predicting a whole component of signal but failed in predicting baseline.

The mean and variance of error from cross-validation were reported in table 2. The error after generating simplified model is a bit higher than before, but the complexity of model was reduced. So the cost is minimized versus a slight increase in error.

4. Discussion

This paper represents a dynamic model for the generation of auditory brainstem responses to syllable /da/ using fuzzy logic as a nonlinear mapping between input (stimulus) and outputs (cABRs) of the auditory system. The proposed model proved that there is special Fuzzy rules that are corresponded to important evidences and dynamics of cABR signal. In Fig. 9 there exist some regions that show less repetition of rules. These regions can be assumed to be in relation to specific dynamics of cABR data, because the rules that is fired in this region does not fire in other times. Some remarkable similarities between the overall morphology of grand average of cABR data (Fig. 8) and the firing number of rules versus time (Fig. 9) can be seen. In Fig. 9 the important acoustic cues like onset, consonant part and vowel in the response can be observed. The first part of Fig. 9 is represented as onset of response and the rules that fired in this region is describing A-V complex dynamic, second part is related to transient part of response and the third part of the histogram, begin from wave D until wave F, is related to vowel part that show periodicity manner of vowel. The last part that specified in Fig. 9 is related to the final transient response witch is named O wave. On the other hand, as it can be seen in Fig. 10, a strong similarity between the frequency content of speech stimuli as input of system and firing number as a sign of system output was proved in this work. This similarity shows that the model could extract the existing nonlinear mapping between input and output of system and the above time and frequency domain results show this fuzzy logic model can represent the behavior of brainstem in generating signals. In fact, this work presents dynamics of cABRs to /da/ for a normal subject, so this rule base can be considered for normal subjects and can be the base of approach to identify abnormalities. In other words, a poor representation of acoustic cues like F0, F1 in the model's output and histograms of fired rules for new cABR signal can be a sign of some abnormalities of brainstem behavior. On the other hand, the histogram of fired rules shows that acoustic cues were mapped with separable rules in cABR signals which can be remarkable rules for normal subjects and can be compared with other pathological subjects. Variations from this normal features can be a sign of an auditory disease. Although a number of studies in neurosciences have used fuzzy logic, it is still largely employable in more applications; the aim is changing the medical diagnosis and management, incorporating fuzzy interpretation in medical diagnostic and clinical applications. This work improved the insight into the real behavior of auditory system and proved that nonlinear behavior exists in auditory pathways. Due to nonlinearity of the auditory pathway in encoding of acoustic cues, nonlinear mapping was successful in predicting cABR signals.

The limitation of this study was the inaccessibility to cABR signals to other speech stimulus and cABR signal to pathological subjects. This limitation is according to popular instrument's only stimulus that is /da/. The ability to generate and combine other stimulus have been reached in this research group and developing this study for other stimulus is the topic of our future works. It is proved that the brainstem encoding of speech depends on various experiences [17] such as language [17-19] and music training [20]. Further studies need to focus on comparing the efficient rules in each case and lead to distinguish more about the function of learning abilities on the auditory processing.

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