Research Paper

A Novel Method for Automated Estimation of Effective Parameters of Complex Auditory Brainstem Response: Adaptive Processing Based on the Correntropy Concept

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ABSTRACT

Objectives: Automated Auditory Brainstem Responses (ABR) peak detection is a novel technique to facilitate the measurement of neural synchrony along the auditory pathway through the brainstem. Analyzing the location of the peaks in these signals and the time interval between them may be utilized either for analyzing the hearing process or detecting peripheral and central lesions in the human hearing system.

Methods: In this paper, model-based signal processing is proposed to estimate the effective parameters of ABR signals. In this process, the biological parameters of the signal are assessed by utilizing a Finite Impulse Response (FIR) adaptive filter in which its adaptation procedure is performed based on the correntropy concept. The proposed method is applied on a set of ABR signals recorded in response to three stimuli of /da/, /ba/, and /ga/, and then its performances are compared with an existing state-of-the-art technique.

Results: The results show that the proposed method can significantly increase the accuracy of estimating the parameters in stable stimulations (/da/, /ba/) for major positive and negative peaks. This improvement is more significant (up to 2-3 times) for /ba/ stimulus and especially in major positive peaks. However, in other peaks, the improvements also occurred in smaller amounts. However, for unstable stimuli (/ga/), no significant improvement was achieved.

Discussion: Increasing the accuracy performance of the proposed method for detecting the stable stimuli (while its performance remains unchanged) for detecting unstable stimuli indicates its effectiveness in automated clinical analysis of ABR signals.

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Highlights

- In this paper, a model-based signal processing framework is used to make an appropriate paradigm for distinguishing correct response and noise in ABR signals.

- In the proposed scheme, the locations of peaks in ABR signals are indicated by forming an adaptive Finite Impulse Response (FIR) filter.

- The adaptive filter is adapted by estimating the correntropy of the recorded signals.

- Based on more effective properties of the correntropy concept against second-order statistics, the proposed strategy may have a great potential in detecting correct ABR signals.

Plain Language Summary

This study was conducted in automatic peak detection in complex auditory brainstem responses to /da/, /ba/, and /ga/. This assessment may be performed manually by an audiologist or automatically by the software. Utilizing the correntropy concept may improve parameter estimation accuracy in stable stimuli (i.e., /da/, /ba/) for the main positive or negative peaks. For unstable stimuli (i.e., /ga/), no significant improvement was achieved.

1. Introduction

An acoustic stimulus can provoke the auditory nerve, generating the electrical activity signal in the brainstem [1, 2]. This electrical activity which is a measure of neural synchrony along the auditory pathway through the brainstem, is known as Auditory Brainstem Responses (ABR). An ABR may be recorded by using non-invasive tools and then utilized for some clinical or research purposes such as analyzing the hearing process and, to some extent detecting peripheral and central lesions in the human hearing system [1-3]. ABR contain various waves that occur amid the first 10 ms following stimulus onset, and they are shown by successive Roman numerals [2-4]. For several decades, expert audiologists have done the whole process of detecting this signal visually. So, the reliability of this technique is strongly dependent on the technician's experience, and its effectiveness is hampered by the procedure of measurement and human errors. Likewise, the diagnostic results with this method may be different from one specialist to another, and finally, it is time-consuming. Because of the above problems, in recent years, the automatic analysis of the ABR signal has been substituted [3, 4].

The correct peak detection of the recorded ABR depends on the quality of these signals, which is affected by different factors such as language, music, speech experience, the period of auditory training (short-term vs long-term), and hearing disorders [2, 3]. Furthermore, the differences in age, complex speech stimuli, and the recurrence of boosts may bring out various reactions [4-6]. For example, an age-related hearing deficiency which is to some extent revealed in decreasing speech understanding in noise among the elderly population could be reflected in neural transmission throughout the brainstem and auditory cortex [6, 7].

Despite the multiple effective factors in ABR quality, the two factors of stimulus type in parallel with the amount of noise have the greatest impact on detecting these signals [8, 9]. ABR signals occur in temporal and spectral phases and may be represented as sustained and transient responses according to two types of stimulus, including periodic and non-periodic, respectively [3, 4]. Although brief stimuli may be easily implemented in clinical settings, they do not represent the compound and multipart nature of the neural network activities in the central auditory system during the processing of speech stimuli. The complex sounds comprise both sustained and transient features. Unlike the response to brief stimuli (e.g., click, and tone burst), which is either unstable or unpredictable, the response to a complex sound is predictable and stable. Therefore, auditory neuroscientists prefer to utilize more complex sounds as stimuli [3, 4]. Consonant-Vowel (CV) combinations have a high-frequency occurrence, dynamic physical alterations, and quick spectra-temporal dynamicity because of rapid changes in the channel capacity of the vocal tracts in the source-filter model. To pave the way toward better evok-

ing the brainstem, electrophysiologists highly suggest using a combination of CV compositions [3, 4].

In addition to the type of stimuli, another challenge of the automated ABR detection methods is that the ABR signals possess a considerable amount of noise while recording, which may dramatically lead to unreliable results [5, 6]. So far, some different approaches have been proposed to address this problem.

Some researchers use the zero-crossing concept to extract suitable features that may distinguish between different ABRs. The remarkable advantage of this method is its simplicity and low computational cost, which makes it an attractive choice for practical use. However, zero-crossing-based methods are susceptible to noise as their performances are considerably dropped when the SNR decreases [6, 10]. Some other researchers use adaptive signal enhancement as an attractive solution in digital signal processing. Noise cancellation methods have been studied in the above domain and given impressive consideration. The primary objective of such methods is to update the coefficient estimations of adaptive filters every single iteration until convergence is happening. However, the performance of sub-band adaptive schemes is regularly debased by artifacts introduced by the insertion of filter banks in the signal path [9, 11].

Multi filters are another group of solutions used for nonlinear and non-Gaussian signals. This group of methods tries to estimate the potential being analyzed successively by referring to the past scopes information. By actualizing this procedure, the undesirable signal may be filtered out from each sweep of recorded ABR [8, 12]. Although some types of filters may improve the signal-to-noise ratios, they decrease in response amplitude in parallel with distortion of the ABR waveform at high-pass settings over 65 Hz single-trial covariance analysis [12, 13]. Automatic peak-picking is another method that has been presented so far [12, 14, 15]. Recurrence Quantification Analysis (RQA) is a member of the nonlinear data analysis family to investigate dynamical systems. It quantifies the number and duration of recurrences of a dynamical system presented by its phase space trajectory [16]. Most of these methods use correlation as an effective tool to detect and eliminate noise and identify major and minor peaks, latencies, and amplitudes [14, 17].

In this paper, a model-based signal processing framework is used to make a proper paradigm for correct response and noise in ABR signals produced by CV combinations of stimuli of the auditory system in the nervous system. For this purpose, the recorded signal is modeled as a random process consisting of a component caused by artifacts and noise and a possible transient component caused by the correct response of the auditory nerve. Then, the locations of peaks in ABR signals are indicated by forming an adaptive Finite Impulse Response (FIR) filter [17-19]. This filter is systematically adapted by estimating the correntropy of the aforementioned stochastic processes, which measures the similarity between stochastic sequences across lags based on the entropy of random variables. As the correntropy concept has vastly different properties compared with second-order statistics, our proposed strategy may have a great potential in processing ABR signals which are naturally non-Gaussian [20, 21].

The paper is organized as follows. In section 2, the proposed algorithm is introduced, including detecting peaks via the adaptive filtering scheme in parallel with the estimation of correntropy. In section 3, the performance of the proposed method is evaluated on several ABR signals obtained from experiments on human samples. In section 4, the obtained results are compared to the results obtained from the state-of-the-art methods by using some effective parameters. The conclusion is presented in the last section.

2. Materials and Methods

In this section, first, the details of the proposed method for estimating the peaks of response to auditory stimulation are described, and then the characteristics and conditions of the study data are illustrated.

Proposed method

Consider two signals of g(k) and r(k), the first is the grand average, and the second is the recorded response to one of the stimuli used in this study (/da/, /ba/, and /ga/). Based on the similarity between the recorded responses and the grand average, the above signals may be re-written as the below (Equation 1):

1. $g(k)=s(k)+n_1(k) \quad r(k)=s`(k-k_0)+n_2(k)$

In which the sequences of s (0) and s`(0) consist of those samples which have been initiated from correct nerve response either in a grand average of recorded responses. Because these samples do not necessarily co-occur (i.e., they are not synchronous), they have a delay such as k_0 relative to each other. Based on the above definitions, similarity (i.e., any kind of correlation) between recorded response and grand average may be originated

from these two terms. Furthermore $n_1(k)$ and $n_2(k)$ represent the noise and artifacts in the grand average and recorded response which should be either eliminated or minimized in the proposed process.

To perform the similarity measurement, we apply an adaptive method based on utilizing the finite impulse response (FIR) filter that aims to estimate the sequence r(k) in terms of g(k). Suppose the weight of the mentioned filter as (Equation 2):

2. $w=[w(-\lambda),...w(0),..., w(x)]$

Then the output of the above FIR filter, i.e., the estimation of r(k) may be written as (Equation 3):

3. $\hat{r}(k)=\sum_{m=-\lambda}^{\lambda} w(m)g(k+m)$

The estimation error (the difference between real and estimated values of recorded response) is demonstrated as a vector $\eta=[\eta(1), \eta(2),..., \eta(k),..., \eta(k)]$ whose elements are obtained as below (Equation 4):

4. $\eta(k)=r(k)-\sum_{m=-\lambda}^{\lambda} w(m)g(k+m)$

The more accurate the obtained expression for the filter weights (i.e., w), the less error will be created between the estimated and actual recorded response. In this research, the maximum correntropy criterion is utilized as a cost function for adaptive adjustment of the weights of the FIR filter. As shown in Equation 5, the correntropy of an arbitrary variable , is defined as [18, 19].

5. $C[x]=E\left[\frac{1}{\sqrt{2\pi\sigma}}exp\left(-\frac{x^2}{2\sigma^2}\right)\right]_{(5)}$

, where E and represent mathematical expectation and variance, respectively. Having K pairs of samples belonging to the grand average and recorded response, the correntropy of the error vector η may be estimated as below (Equation 6):

6. $\hat{C}(\eta)=\frac{1}{K-2\lambda}\sum_{m=\lambda+1}^{k-\lambda}\frac{1}{\sqrt{2\pi\sigma}}exp\left(-\frac{\eta^2(m)}{2\sigma^2}\right)$

Substituting the error term from Equation 4 in Equation 6 leads to Equation 7 which illustrates a relationship between the estimated cost function and the weights of the FIR filter:

7. $\hat{C}(w)=\frac{1}{K-2\lambda}\sum_{m=\lambda+1}^{k-\lambda}\frac{1}{\sqrt{2\pi\sigma}}\times exp\left(-\frac{r(m)=r(k)-\sum_{m'=-\lambda}^{\lambda}w(m')g(k+m')}{2\sigma^2}\right)$

Now the weights of the FIR filter may be obtained by maximizing Ĉ(w) using the stochastic gradient method, which leads to:

8. $w_{i+1}=w_i+\alpha\left[\frac{\partial\hat{C}[w]}{\partial w}\right]_i=w_i+2\alpha\frac{1}{\sqrt{2\pi\sigma}}exp\left(-\frac{\eta^2}{2\sigma^2}\right)\eta_i\frac{1}{2\sigma^2}\bar{g}$

, where wi+1 and wi demonstrate estimated weights for FIR filter in successive iterations i and i+1, respectively. Furthermore ηi and ηi denote the error vector and its transpose both in the iteration i. Finally, the term ḡ in Equation 8 may be demonstrated as (Equation 9):

9. $\bar{g}=[i-\lambda),...,g(i),...,g(i+\lambda)]$

Evaluating the value of the cost function in final regulated weights may be used as a similarity measure between the grand average and recorded responses. Next, using the method described in a study [5], all response signals of each subject were marked automatically. As a result, the values of latencies and amplitude were tabulated in different lookup tables for each stimulus and subject.

Description of dataset

To evaluate the performance of the proposed method, we should apply it to real data. Test database included 27 recorded signals in response to the three stimuli: /da/, /ba/, and /ga/. These stimuli were performed separately for 27 adult volunteers, including 13 females and 14 males, in such a way that for each of them, the recording was performed only through electrodes located in the range of CZ to the ipsilateral earlobe. Figure 1 shows how these electrodes were placed in the International 10-20 system: The 10-20 System of Electrode Placement is a method used to describe the location of scalp electrodes. These scalp electrodes are used to record the Electroencephalogram (EEG) using a machine called an electroencephalograph. The volunteers were individually exposed to each stimulus as mentioned above for 170 ms using an Etymotic's ER-3 headphone in a stimulus presentation level of 83 dB SPL. EEG signals were recorded via the electrode mentioned above to collect the response; then, this signal was filtered and digitized in the band range (0.05-3khz).

Important specifications of these tests, including the information about the candidates, stimulations, and recording procedures, are shown in Table 1. The interested reader may also refer to other studies [3-5] for more details.

3. Results

The proposed method was implemented using Matlab 2019a on a PC with a 7-core CPU, a 2.60-GHz processor, 60-GB RAM, and Windows 10 operating system. To perform valid comparisons between the performances of the proposed and alternative methods, all recorded

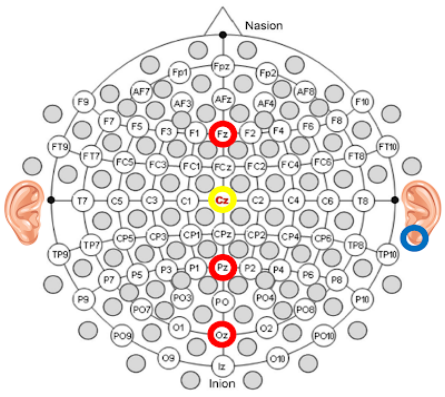

Figure 1. 10-20 System of Electrode Placement

signals were analyzed by two experts, and the main 16 peaks of recorded signals were labeled. The results of each of the proposed and alternative methods were compared by sharing these two types of manual labeling. Then, the similarity of automated recognized peaks to those peaks found by the manual method was considered as an index for the superiority of each method.

Figure 2a shows the grand average signal obtained from /ba/, and Figure 2b shows one of the recorded responses to this stimulus. By comparing these figures, it is observed that neither location nor arrangement of the peaks in the recorded signals is necessarily the same as the corresponding grand average. For example, as indicated by the circle, although the third peak is visible in both grand average and recorded signals, its occurrence time differs by about 7.13 ms between the above signals. Furthermore, its shape is considerably different in these comparative signals. Similar differences may be observed for other peaks. A similar situation may be observed for the other two stimuli. For instance, Figure 3 parts a and b show that such difference has reached a maximum of 17.65 ms, occurring in the fourth peak corresponding to the grand average and recorded response to /da/ stimulus. The worst-case may be observed in the case of /ga/ stimulus (Figure 4a and 4b), where the difference between the time of occurrence of the onset peaks in the grand average and recorded signals have even reached 32.81 ms. It is observed that the above mismatch for the response to stimulation /ga/ has appeared more dramatically than the other two types of response, which is probably related to the noise-wise nature of either this stimulus or its corresponding response.

In the next step, the results of automated methods were compared with expert analysis. In other words, the proximity of the results obtained from each method to expert subjective judgment was used as an indicator of its performance.

For example, Figure 5a shows a signal recorded as a response to the /da/ stimulus. Figure 5b shows the peaks labeled on the above signal by one of the experts. Figure 5, parts c and d show the results obtained from alternative and proposed methods on the same signal, respectively.

The visual comparison of these results clearly shows the superiority of the proposed method against its alternative. In the first major peak (the onset), the peak time estimated by the proposed method differs by 0.653 ms from the manual reference. However, the same difference for the alternative method has reached 0.837 ms. A similar situation is observed in estimating other peaks (Figure 5c and 5d).

Table 1. Descriptive details

Technical Specification			Demographic Specification	
Stimulus	/da/ /ba/ /ga/	Formants Information	Gender composition of volunteers	13 Females 14 Males -All participants were native monolingual speakers of Persian with normal hearing and no neurological disorders.
Number of recorded responses	/da/: 27 /ba/: 27 /ga/: 27	/da/ F2 and F3 falling /ba/ F2 and F3 rising /ga/ F2 and F3 falling		
Hearing thresholds of volunteers	≤20dB at octave frequencies (250–8000 Hz)	Frequency Ranges Range of /da/:1700-2580 Hz Range of /ba/:900-2400 Hz Range of /ga/:3000-3100	The age range of volunteers	22 to 29 years (mean ± SD: 24.34 ±1.95)
Type of recording electrodes	Ag/AgCl	Number of recorded responses		
Impedance of electrodes	≤5kΩ	/da/: 27 /ba/: 27 /ga/: 27	Place of data recording	Students from Tehran University of Medical Sciences
Specification of recording	Continuous EEG (G.Tec EEG) Model: G. USBamp			

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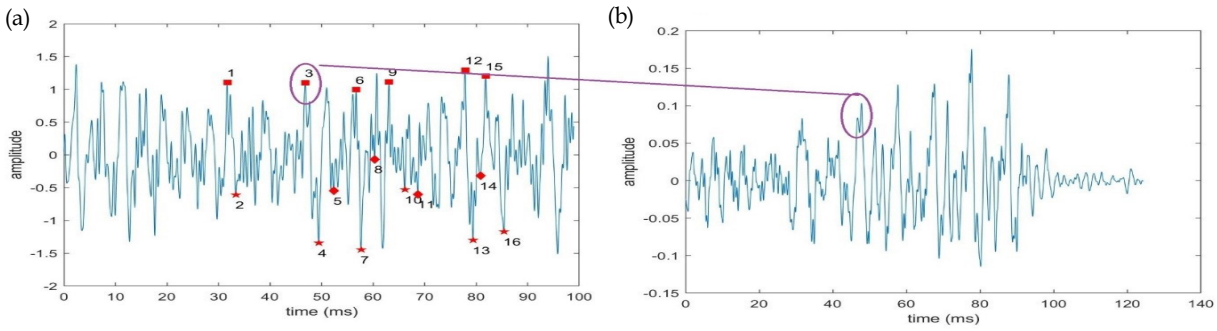

Figure 2. (a) schematic of automatic /ba/ grand average (b), schematic of recorded response to/ba/

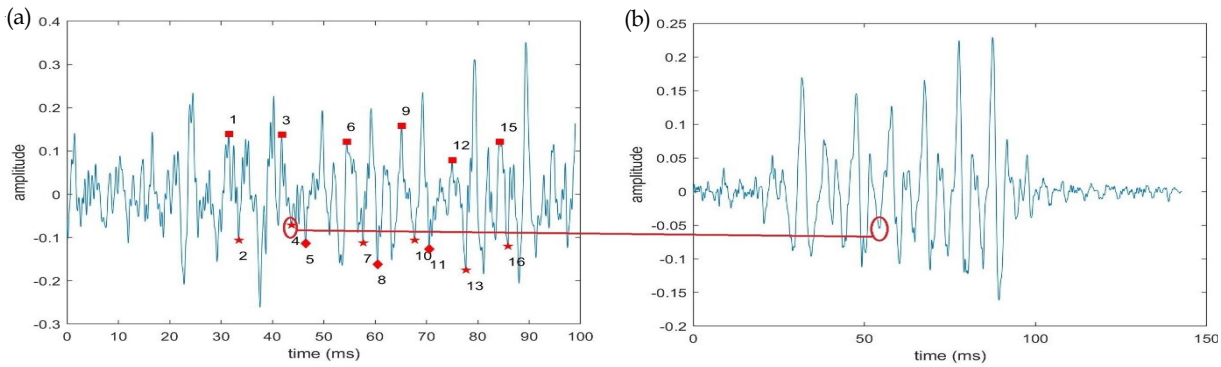

Figure 3. (a) Schematic of automatic /da/ grand average (b), schematic of recorded response to /da/

Figure 6 shows another example of the recorded signals corresponding to the /ba/ stimulus. Figure 6a shows the raw response signal, and Figure 6b shows the peaks labeled by the experts. Figure 6, parts c and d show the results of alternative and proposed methods on the above signal, respectively. Similar to the stimulus /da/, this example demonstrates the superiority of the proposed method against its alternative in such a way that its estimations for peaks 1, 3, 10, and 14 have been, respectively, 0, 0.01, 0.06, and 0.02 ms different from the corresponding peaks extracted by the experts. These values were significantly less than the 4.67 ms error obtained using an alternative method. However, in some peaks (e.g., 9, 11), the difference was not considerable.

Finally, similar investigations have been performed to respond to the /ga/ stimulus. The obtained results, shown in Figure 7, parts a to d, demonstrate that the deviation of the results of either proposed or alternative methods from the experts' results does not show a significant difference. As the marked circles in Figure 7, parts c and d show, in some cases, the peak found by the proposed method had a slight advantage over its alternative (e.g., the peaks 4, 12), and sometimes this advantage was reversed (e.g., peaks 8, 9, 16). Consequently, unlike the

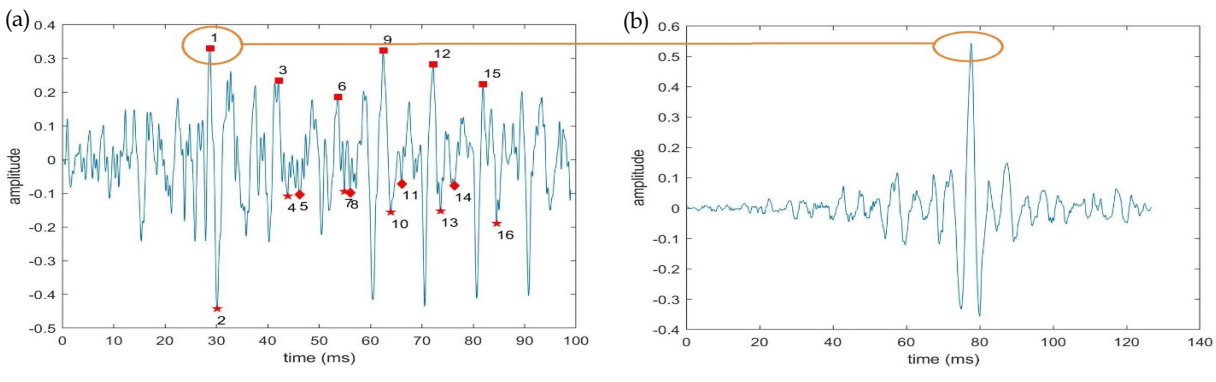

Figure 4. (a) Schematic of Automatic /ga/ Grand Average (b), Schematic of Recorded Response to /ga/

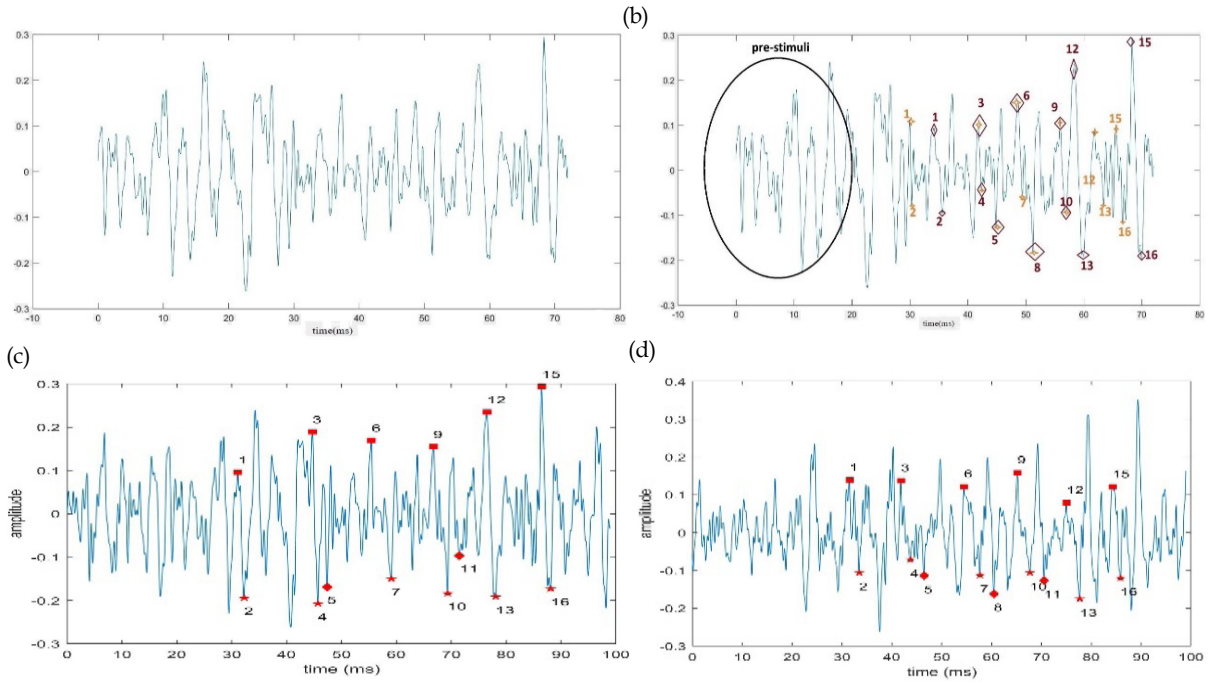

Figure 5. Recorded responses to /da/ (a), responded to /da/ (b), which labeled by two experts of cross-correlation result for /da/ (c). correntropy result for /da (d)

previous two stimuli, regarding the responses related to /ga/ stimulation, it is unclear whether the results of which method are superior.

4. Discussion

In ABR responses, the peaks do not necessarily have the same neuroscience identity. From a biological point of view, these peaks may be divided into major types of positive and negative major peaks (that have different biological origins), onset, and offset. The above classification arises because all stimuli and, of course, the response to them have different energy spectra. As the above stimuli are in burst and noise mode, they enter the nervous system with this much energy and thus produce onset. Offsets, on the other hand, are a continuation of the ABR signal and trigger a neural response at the end of the stimulus. Also, several neurons respond during the presence of a stimulus that has a more stable nature. The main peaks, either positive or negative, indicate the activity of the latter group of neurons so that a significant population of them begins to discharge synchronously, which constructs a peak [4, 22, 23].

The difference between positive and negative peaks arises from different populations of neurons operating in each. As the nature of the stimuli energies is different, they may stimulate two different neuronal populations. Latency and distance between peaks, slope, and length between peaks, and finally, the sharpness and slope are important from a neuroscientific point of view [22-26]. It may be impossible to say that a positive or a negative peak has pathological significance alone. However, their diagnosis, which leads to identifying the latency of other peaks, the time between two consecutive peaks, and the formation of other peaks, may provide valuable pathological information. Some people have problems in the steady part, and others in the onset or offset parts. Thus, it is observed that the accuracy of the results in the detection of several peaks may have different impacts on treating patients with different types of defects. The results obtained in the previous section showed that the proposed method was in good agreement with the results of the experts' analysis. However, the results of the detection of all peaks (16 important peaks) indicated that the proposed method has a slight advantage over the method used in the last previous research [5]. In this section, a comparison of the results of two examined methods in detecting each of the peaks was performed, based on considering the neuroscience nature of each peak. Tables 2-7 show how much each of the proposed and alternative methods can estimate the location of the 16 peaks of the ABR response separately. By investigating these tables, it is observed that each of the implemented methods was more useful for revealing which peaks and, consequently, related disorders may be better analyzed using that method. First, Table 2, parts a and b, shows the results obtained from applying the above methods in

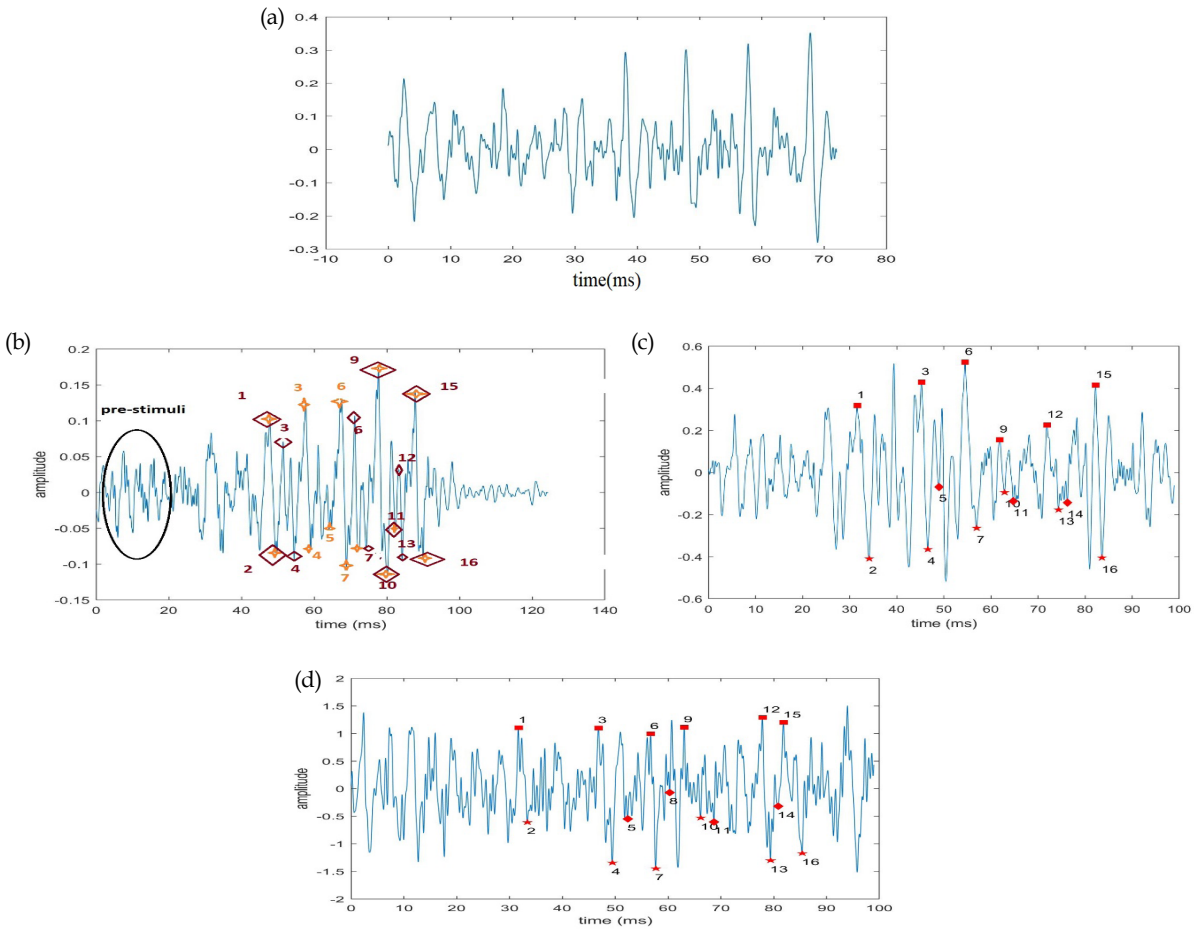

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Figure 6. (a) Signal recorded to respond to /ba/ stimulus (b), responded to /ba/ which labeled by two experts (c), automatic method (cross-correlation) peak detection for /ba/ (d), automatic proposed method (correntropy) peak detection for /da

determining major negative peaks (peaks 5, 8, 11, 14). Such investigation indicated the similarity between the location of the automatically estimated peaks and the peaks recognized by the expert.

The first row of the above tables clearly shows that the proposed method has performed better than its alternative in detecting all the peaks of the responses related to stimulus /da/. These rows demonstrated that this improvement reached a maximum of 0.302 and a minimum of 0.012 for peaks 5 and 8, respectively. The second row of the above tables clearly shows that the proposed method has performed better than its alternative in detecting all the peaks of the responses related to stimulus /ba/. These rows demonstrated that this improvement reached a maximum of 0.63 and a minimum of 0.11 for peaks 5 and 8, respectively. The most considerable advantage was obtained in estimating the time of occurrence of the fifth peak, in which the result of the proposed method was up to 3.5 times better than the estimation of the alternative method. However, in the case of peak 8, this advantage may not be considered so adequate.

Regarding the response to stimulus /ga/ (third rows of two tables) in peaks 8 and 14, we observed the superiority of the alternative method, and in peaks 5 and 11, we observed the superiority of the proposed method. However, except for peak 5, in other cases, the superiority of either method was not so effective. Given these cases, it may be seen that while the proposed method of this paper has made effective improvements over its alternative in detecting major negative peaks in the case of /ba/ and /da/ stimuli. However, in the case of the stimulus /ga/, none of the examined methods had a special advantage.

In the next step, we review Tables 4 and 5, parts a and b, which show the results of the implementation of the proposed and alternative methods in the detection of major positive peaks, i.e., 3,4,6,7, 9, 10, 12, 13 peaks. Similar to what was observed in the case of major negative peaks, the proposed method also performed better

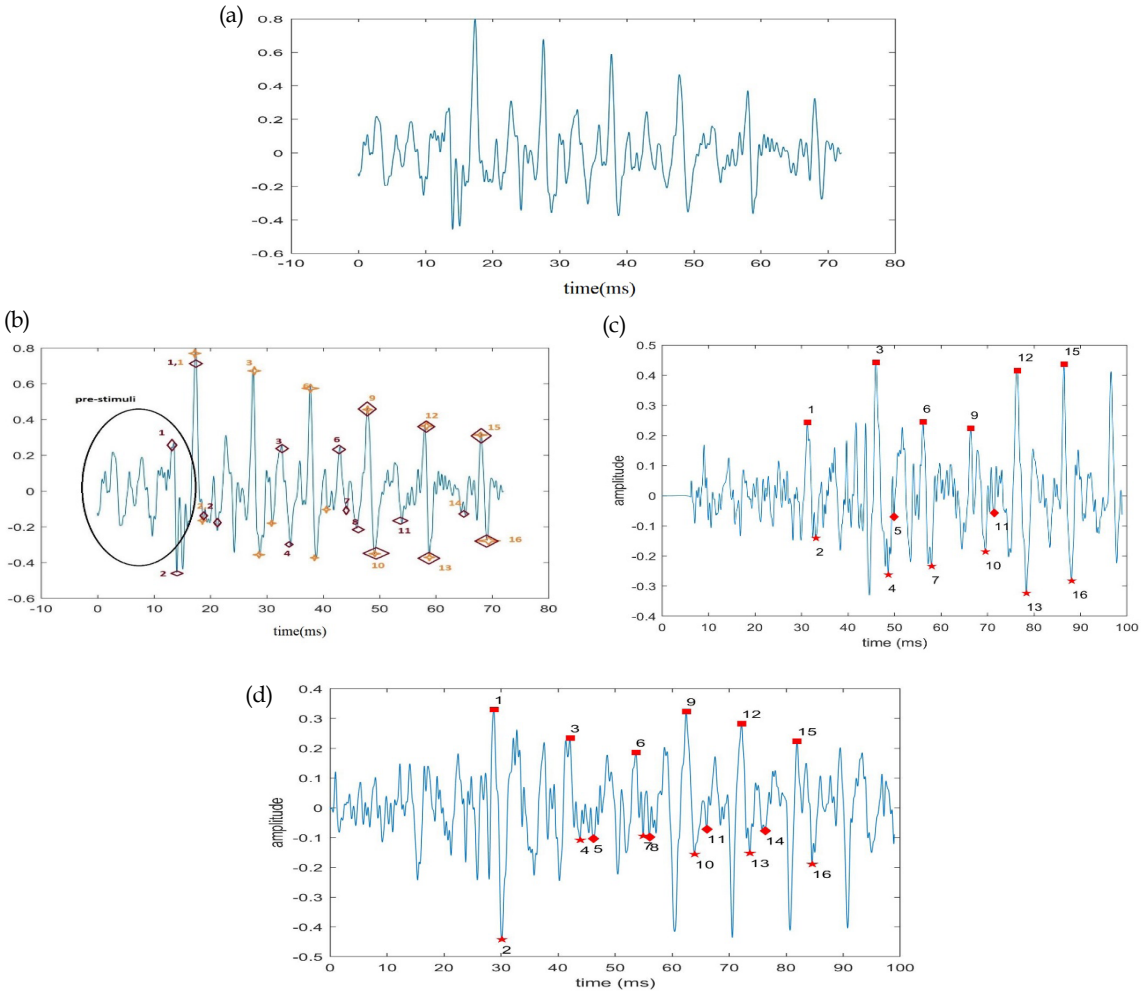

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Figure 7. (a) Signal recorded to respond to /ga/ stimulus recorded (b), responded to /ga/, labeled by two experts (c), automatic method(cross-correlation) peak detection for /ga/(d), the automatic proposed method (correntropy) peak detection for /ga

for the response to stimulus /ba/ than its alternative for positive peaks. The maximum improvement was 0.581, and the minimum improvement was 0.078 for peaks 3 and 7, respectively. It was also observed that the degree of this superiority for the first three peaks (3, 4, and 6) was much more considerable and has reached up to 3 times improvement in recognizing the location of other peaks. Contrary to the response to stimulus /ba/, there is no superiority of the proposed method over its alternative in detecting major positive peaks for the stimulus of /da/ as strongly as we saw in the case of negative peaks. A comparison of the first rows of the two above tables showed that here, although the superiority of the proposed method over its alternative was observed in most peaks, e.g., 6, 7, 12, 9, and 13, in a significant minority of peaks, e.g., 3, 4 and 10, the alternative method performed better. The maximum superiority of the proposed method over the competing method was equal to 0.131, which occurred at peak 7, and the least superiority was equal to the extent of 0.02, which occurred in detecting peak 9. Similarly, the maximum and minimum superiorities of the alternative method over the proposed method occurred by the extents of 0.608 and 0.16 for peaks 4 and 3, respectively. Regarding the stimulus-response to /ga/ (the third row of the two tables), we still did not observe a significant superiority over any of the examined methods in such a way that the difference between the performance and the method at all peaks was about 0.1 or less.

The third category of peaks is known as onset or offset and practically includes the first two peaks and the last two peaks. The biological nature of these peaks was also mentioned at the beginning of this section. Tables 6 and 7 parts a and b show the performance of the methods examined in this study that estimate these two types of peaks. Similar to what was investigated in the case of

Table 2. Comparing the detection of major negative peaks (5, 8, 11, and 14) for the automatic and manual method (expert 1, 2, & correntropy) in each stimulus

Stmuli		P5	P8	P11	P14
/da/		0.469	0.742	0.918	0.760
/ba/	ICC	0.871	0.671	0.655	0.761
/ga/		0.823	0.614	0.478	0.505

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Table 3. Comparing the detection of major negative peaks (5, 8, 11, and 14) for the automatic and manual method (expert 1, 2, & cross-correlation) in each stimulus

Stmuli		P5	P8	P11	P14
/da/		0.167	0. 73	0.782	0.541
/ba/	ICC	0.232	0.559	0.435	0.37
/ga/		0.501	0.721	0.411	0.710

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major peaks (both positive and negative), the proposed method has been significantly better performed than its alternative in detecting peaks of the response corresponding to stimulus /ba/. It is observed that the proposed method could obtain two onset peaks about 2.5 and 3 times, respectively, more accurately than the alternative algorithm.

Regarding offset peaks (i.e., 15 and 16), although the superiority of the proposed method was not so brilliant, the superiority of more than 0.3 in the estimation of peak 16 seems sufficiently acceptable. In examining the response to stimulus /da/, contrary to what we observed in the case of /ba/, the proposed method not only did not perform better than its competitor in onset and offset peaks, but in the first onset peak, the result of the competitor method was more accurate. For the other peaks, the differences between the estimates of the two examined methods did not seem to be significant. Regarding

Table 4. Comparing the detection of major positive peaks (3, 4, 6, 7, 9, 10, 12, 13) for automatic and manual method (expert 1, 2, & correntropy) in each stimulus

Stmuli		P3	P4	P6	P7	P9	P10	P12	P13
/da/		0.384	0.145	0.731	0.708	0.440	0.210	0.495	0.414
/ba/	ICC	0.915	0.941	0.956	0.950	0.985	0.797	0.838	0.834
/ga/		0.352	0.349	0.709	0.399	0.569	0.555	0.772	0.722

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Table 5. Comparing the detection of major positive peaks (3, 4, 6, 7, 9, 10, 12, 13) for automatic and manual method (expert 1, 2, & cross-correlation) in each stimulus

Stmuli		P3	P4	P6	P7	P9	P10	P12	P13
/da/		0.552	0.753	0.661	0.577	0.420	0.399	0.363	0.369
/ba/	ICC	0.334	0.392	0.494	0.872	0.829	0.290	0.612	0.613
/ga/		0.489	0.470	0.729	0.588	0.721	0.388	0.778	0.811

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Table 6. Comparing the detection of onset and offset peaks (1, 2, 15, and 16) for the automatic and manual method (expert 1, 2, & correntropy) in each stimulus

Stmuli		P1	P2	P15	P16
/da/		0.618	0.688	0.519	0.133
/ba/	ICC	0.994	0.983	0.950	0.913
/ga/		0.236	0.453	0.335	0.537

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Table 7. Comparing the detection of onset and offset peaks (1, 2, 15, and 16) for the automatic and manual method (expert 1, 2, & cross-correlation) in each stimulus

Stmuli		P1	P2	P15	P16
/da/		0.986	0.688	0.612	0.046
/ba/	ICC	0.409	0.297	0.825	0.604
/ga/		0.254	0.074	0.855	0.797

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the response to the stimulus /ga/ (the third row of the two tables), we still see the same confusion previously observed for the two types of major peaks. Here, although in peak 2, the proposed method had a significantly better estimate regarding the other peaks, either significant superiority of the alternative method (peak 15) or no effective difference (peaks 1, 16) was observed.

The results described above clearly indicate that the methods examined in this research have shown two different types of performances against the stimuli /ba/ and /da/ and the stimulus /ga/. The results of two stimuli of /ba/ and /da/ showed that the proposed method could significantly improve estimating the types of major positive, major negative, onset, and offset peaks against its alternative. Note that in the case of results corresponding to /da/ stimulus, although the proposed method did not have a significant advantage in positive peaks, it significantly improved the performance of detecting negative peaks. This ability allows the proposed method to estimate the interval between peaks better than its alternative in the case of /da/ stimulus; therefore, the performance of the proposed method is practically improved. However, in the case of the /ga/ stimulus, the situation is quite different, in such a way that neither of the two methods could perform effectively better than another one. The important reason for this difference in behavior may be explained by the difference like the stimulus /ga/ compared to the other two stimuli. The two stimuli of /ba/ and /da/ are inherently stable and stimulate a series of neurons that respond during stimulation stability. Conversely, the /ga/ stimulation has a more noisy nature than the previous two stimuli, and thus the resulting response, unlike the stable responses induced by /ba/ and /da/, has more random properties. Thus, in parallel with more similar behavior to noise, none of the examined methods could achieve effective results. Accordingly, in the presence of more stable stimuli, our proposed method based on the concept of correntropy may replace the existing methods as an effective tool for automatic estimation of major, onset, and offset peaks.

5. Conclusions

In this paper, we used model-based signal processing to recognize ABR signals produced by consonant-vowel (CV) auditory stimuli. The proposed technique tried to estimate the location of peaks in ABR signals by forming an adaptive correntropy-based FIR filter. The performance of the proposed scheme was evaluated on a real dataset, including ABRs initiated from the three stimuli of /da/, /ba/, and /ga/. Then, the results were compared with one of the methods recently proposed in this domain. Comparing the results of the proposed and existing methods with the experts' judgment (i.e., the golden model) indicated two different trends. Although the whole obtained results for all peaks showed a slight gain in the performance of the proposed method against its alternative, the comparison of their results separately in detecting each of the peaks was inspiring. The results demonstrated that the proposed method caused considerable improvement in estimating ABR parameters when stable

stimuli were utilized: /ba/ and /da/. These advantages for the response to the /ba/ stimulus have been observed in all major positive and negative peaks, as well as onsets and offsets, in such a way that for a significant number of peaks, the similarity between automated and manual detections of the proposed methods, has even doubled or tripled compared to its alternative. In the responses due to the /da/ stimulus, such superiority was still observed for negative peaks. Therefore, in both stable cases, the results have ultimately improved the estimation of the interval between major peaks, which is one of the most important parameters in ABR clinical studies.

Based on the tests performed, it seems that the performance of the examined methods has been highly dependent on the stability of the stimulus and its relevant response. Thus, in the case of the/ga/ stimulus that the stimulus itself and its response had a more noisy nature, practically none of the examined methods show effective superiority. Based on the above tests and descriptions, it can be concluded that in the presence of more stable stimuli, the proposed method is a high potential tool for automated estimation of the effective parameters of ABR signal in clinical investigations.

Ethical Considerations

Compliance with ethical guidelines

There were no ethical considerations to be considered in this research.

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Authors' contributions

All authors equally contributed to preparing this article.

Conflict of interest

The authors declared no conflict of interest.

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