Evaluating the Effect of Quran Memorizing on the Event-related Potential Features by Using Graphs Created from the Neural Gas Networks

Abstract

Background: Quran memorizing causes a state of trance, which its result is the changes in the amplitude and time of P300 and N200 components in the event related potential (ERP) signal. Nevertheless, a limited number of studies that have examined the effects of Quran memorizing on brain signals to enhance relaxation and attention, and improve the lives of patients with autism and stroke, generally have not presented any analysis based on comparing structural differences relevant to features extracted from ERP signal obtained from the two groups of Quran memorizer and nonmemorizer by using the hybrid of graph theory and competitive networks. **Methods**: In this study, we investigated structural differences relevant to the graph obtained from the weight of neural gas (NG) and growing NG (GNG) networks trained by features extracted from the ERP signal recorded from two groups during the PRM test. In this analysis, we actually estimated the ERP signal by averaging the brain background data in the recovery phase. Then, we extracted six features related to the power and the complexity of these signals and selected optimal channels in each of the features by using the t test analysis. Then, these features extracted from the optimal channels are applied for developing the NG and GNG networks. Finally, we evaluated different parameters calculated from graphs, in which their connection matrix was obtained from the weight matrix of the networks. **Results:**. The outcomes of this analysis show that increasing the power of low frequency components and the power ratio of low frequency components to high frequency components in the memorizers, which represents patience, concentration, and relaxation, is more than that of the nonmemorizers. These outcomes also show that the optimal channels in different features, which were often in frontal, peritoneal, and occipital regions, had a significant difference ($P < 0.05$). It is remarkable that two parameters of the graphs established based on two competitive networks, i.e. average path length and the average of the weights in the memorizers, were larger than the nonmemorizers, which means more data scattering in this group. **Conclusion:** This condition in the mentioned graphs suggests that the Quran memorizing causes a significant change in ERP signals, so that its features have usually more scattering.

Keywords: *Event-related potential signal, neural gas and growing neural gas networks, Quran memorizer and nonmemorizer, visual memory*

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Introduction

The process of storing and retrieving information stored in the mind is different in various people, and each person does this process according to their dominant memory. Quran memorizing is no exception to this rule. One of the important issues for entering any subject is familiarity with the style and method of working with it. In the Quran memorizing, how to memorize and retrieve Quran verses by using visual memory is an efficient factor in the process of memorization.[1,5] Quran memorizers accordingly create a mental image by paying attention to the position of the Quran words and verses at each page by using visual memory. In other words, the main method for the Quran memorization by memorizers is the use of visual memory. Hence, visual memory is an important issue in the Quran memorizers and its study is of utmost importance. Various researches have been currently done on the processing of brain signals of people who memorize the Quran. These studies have often examined the effects of the Quran memorizing on cognitive behaviors such as attention, relaxation, blood pressure, and diabetes. They have also examined

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these effects on improving the lives of people with stroke and treating disorders caused by autism.[2,4] For example, Hojjati *et al.*[2] in 2014 and Zulkurnaini *et al.*[3] in 2013 examined the effects of listening to the Quran's voice and tone on improving attention, memory, and increasing intelligence and relaxation. In a study conducted by Tumiran *et al.*[4] in 2013, the effects of the Quran listening and memorizing were also introduced as a factor in strengthening the range of electroencephalogram (EEG) alpha components and treating autism disorders. Mahjoob *et al.*[6] in 2016 and Ma'ruf *et al.*[1] in 2019 also discussed the effects of the Quran memorizing on increasing the brain's ability to reorganize interbrain connection in people with stroke. Generally, they showed that the Quran memorizing improved the life level of patients with stroke. Nevertheless, although these studies have provided relatively useful results about the effects of the Quran memorizing, they have not provided information about structural differences that the Quran memorizing creates on features extracted from the event-related potential (ERP) signals, which is usually estimated by competitive models such as neural gas (NG) and growing NG (GNG) networks. On the other hand, research, which have been currently done on the use of growing neural networks to cluster unlabeled and labeled data and to detect the boundary between different clusters ,have often used growing neural networks due to their ability for learning data topology, which lead to structural flexibility in the number of neurons and connections.These self-organized networks for clustering the artificial data, had impressive outcomes. For example, in a study by Maximo *et al.*[7] in 2015, which used a semi-supervised growing neural network based on consensus to classify unlabeled data, their remarkable results also showed an improvement in the performance of supervised classification. In another study by Auwatanamongkol and Jirayusakul[8] in 2007, which is provided as a supervised GNG network based on the initial sample, the algorithm was automatically able to determine the optimal number of clusters based on the similarities between labeled data in different classes for determining the minimum number of clusters. In addition, Qin and Suganthan[9] in 2004 used the Robust growing neural gas (RGNG) network, which automatically determines the optimal number of clusters by seeking the extreme value of the minimum description length measure during the network growing process. They accordingly showed that the resulted center positions of the optimal number of clusters represented by prototype vectors are close to the actual ones irrespective of the existence of outliers. In 2011, Ghaseminezhad and Karami[10] also presented a self-organized neural network with a new structure for multidimensional data analysis and cluster analysis with the feature of maintaining data structure, so that similar input data remain close to each other in the output layer. In this study, a nonsupervised method was used to automatically classify discrete data. The second winning algorithm and

batch training was used to update the weight of the neurons to avoid placing the data in the wrong position between two different clusters. On the other hand, in the study conducted by Yang xu *et al.*[11] in 2015, a new algorithm called the ten-pole organization map itself depends on two variables, radius, and angle, which represent the weight and feature of the data, is used to display differences between different clusters.It not only maintained the data topology and the distance between neurons but well showed the difference between different clusters in terms of data weight and

feature. Nevertheless, although competitive networks such as the NG and GNG networks have provided amazing results for identifying clusters created in the artificial data, these studies show that cluster identification is performed by competitive networks when clusters in data had significantly occurred in the space under analysis. Therefore, since significant separate mass (cluster) does not usually occur in the space of features extracted from the brain activities of the Quran memorizers and nonmemorizers, in this study, due to the inefficiency of competitive networks in clustering features related to the brain activities of the Quran memorizers and nonmemorizers, we have used a different approach to analyze the status of brain activities in the two groups. In other words, we investigated the structure of the NG and GNG neural networks trained by features extracted from ERP signals by using the graph theory to evaluate the structural difference in the features of ERP activity recorded during visual stimulation, which its result is the identification of the scope of brain activity, especially the ERP activity, in two groups of the Quran memorizers and nonmemorizers. The remainder of this paper is set as follows: Section 2 explains data collection during the visual memory test in two groups of the Quran memorizers and nonmemorizers. Section 3 provides the methodology, which includes the feature extraction method and how to process the ERP signals by using graph theory. Section 4 provides experimental results to compare the ERP feature and the graph parameters in two groups of the Quran memorizers and nonmemorizers. Sections 5 and 6 also include discussion and conclusion.

Data collection

Data acquisition

In this study, 30 volunteers among Quran memorizers with an average age of 23.5 ± 9.54 and IQ above 80 participated. The volunteers[12] had no history of any neurological disease. They also used no medicine. They participated in the Ishihara color blind test and the Edinburgh[13] Handedness inventory test before the PRM test.[14] According to the results of these tests, all volunteers were right handed and normal in terms of the sense of sight and color blindness.

The PRM test had been also done by using the Cambridge Neuropsychological Test Automated Battery software, which

is usually employed for measuring the visual recognition memory.[15] This test generally includes two phases (encoding and retrieval), which is shown 48 various images to subjects in these phases. These patterns are designed so that participants cannot allocate a verbal label to each pattern. In this process, we also asked subjects to memorize the images, which are randomly displayed on the monitor located across from the subjects. Then, in the retrieval phase, 24 image pairs were shown to subjects, which were a combination of new images unseen in the encoding phase. In this phase, the subjects must actually select the image that they had seen in the encoding phase. The images in the mentioned phase were shown in the time duration of about 2700 ms, and the time duration of screen blanking after showing the images was considered between 300 and 500 ms. In the retrieval phase, the showtime of each image pair was 2700 ms. In this time, the subject actually selected the image, which he had seen in the encoding phase. In addition, the guideline of performing test was first explained to the subjects in 9 s, and a 5-s gap was considered between this step and the test. Figure 1 and Table 1 explain the protocol of the performing of PRM test. In this test, two parameters, i.e. the speed of responding and the number of correct answers, are evaluated, which the results of this evaluation in Table 2 are presented. According to the results presented in this table, the group of memorizers responded to stimulants with more delay comparing to that of nonmemorizers. However, the number of incorrect responses in the group of memorizers was lesser than the group of non- memorizers, which indicates the more precision of this group to selecting the right image.

Event-related potential extraction

Block diagram shown in Figure 2 also indicated the process of processing the ERP signals recorded during the visual memory test in the retrieval phase for two groups of the Quran memorizers and nonmemorizers by using the information contained in the structure of growing neural networks. As seen in this block diagram, this process includes recording brain data, preprocessing,
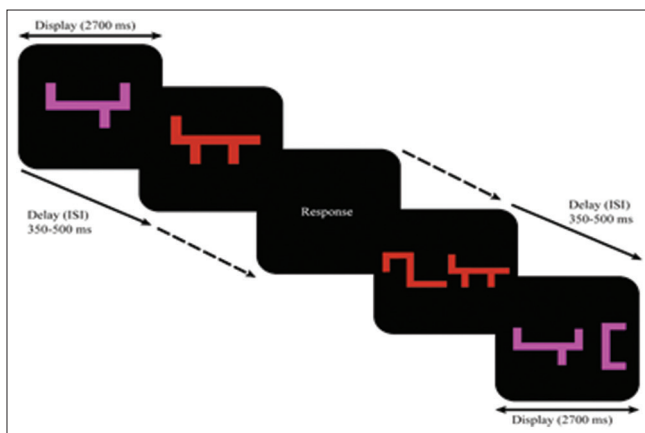

Figure 1: Cambridge Neuropsychological Test Automated Battery PRM test designed in PSYTASK software for evaluating the visual memory

segmentation of brain background signals, ERP extraction, feature extraction, optimal channel selection, training the NG and GNG networks for the two groups, generating connection matrices from the weight matrixes of the networks, extracting graph parameters, and investigating the differences between these parameters in two groups of the Quran memorizers and nonmemorizers.

According to this block diagram, a Mitsar-202 recorder along with WinEEG information management software was used to collect EEG data. The signals were recorded according to the system standard 10–20. Two Ag AgCl electrodes, which were attached to the ears, their average was considered as reference. The impedance in all channels was below 5Ω during recording the EEG signals. The sampling frequency and A/D converter of the recorder were 250 Hz and 24 bits, respectively. The band-pass filter in this recorder was also set to DC-70 Hz.

In the preprocessing phase, the high-frequency and power noises were first removed in 19 EEG channels by using a fifth-order band-pass filter with a cutoff frequency of 0.1–40 Hz. Then, the EEG signal was cut into 2-s segments according to the start time of the stimuli. In the next step, the average taken from five consecutive EEG segments with an overlapping 80% was used for estimating the ERP resulted from the activity of brain neurons related to the stimulus applied in two phases of encoding and retrieval to both groups of the Quran memorizers and nonmemorizers. We have also performed the PRM test twice for each of the Quran memorizers and nonmemorizers. In each PRM test, we applied 24 visual stimuli in the retrieval phase, in which 48 segments of brain background signals (EEG signal) were generally collected for each group. Therefore, given the number of subjects, 660 ERP signals were generally extracted in each group for the retrieval phase. Finally, we use these ERP segments obtained from five EEG segments after feature extraction and selection of optimal channels from each feature to develop a competitive network.[16]

Figure 3 typically shows the ERP signal relevant to O1 channel in two phases of encoding and retrieval for both groups, which we have extracted it from averaging all EEG segments. As can be seen in these diagrams, the ERP amplitude in the encoding phase was higher than that of the retrieval phase for the period of 100–500 ms. The P300 component for the ERP segments taken from the group of the Quran memorizers had also a more time delay than that of the Quran nonmemorizers. The amplitude and time of occurrence of the N200 component had also a significant difference in both the encoding and retrieval phases, which had been probably influenced by factors such as stimulus classification, cognitive processing aspects of stimulus identification, and stimulus differentiation in visual stimulation.

According to the results reported in Table 2, which indicates more delay in the responding of the memorizers

Table 1: The timing of the PRM test designed in the PSYTASK software

Task	Number of trials in each block	Stimulus duration	ISI	Response choice
PRM	48 stimulus (24 presentation + 24 response) (1 instruction and 1 response alarm also added)	2700 ms instruction=9 s wait time=5 s	350-500 months	Left/right

ISI – Intersymbol interference; PRM – Pattern recognition memory.

Table 2: The results of PRM test in two groups of the Quran memorizers and nonmemorizers based on WINEEEG software

Parameter	Mean±SD		t	P
	Memorizers (*n*=15)	Nonmemorizers (*n*=15)		
Age	26.5±6.5	25.8±5.9		
IQ	92.8±9.8	86.5±8.4		
Visual memory				
PRM reaction time	1366.279±8379.704	1300.885±10903.8	1.941626	0.044831
PRM percent errors	10.52557±34.83437	18.36063±196.4905	2.124004	0.033051

SD – Standard deviation; PRM – Pattern recognition memory; IQ – Intelligence quotient.
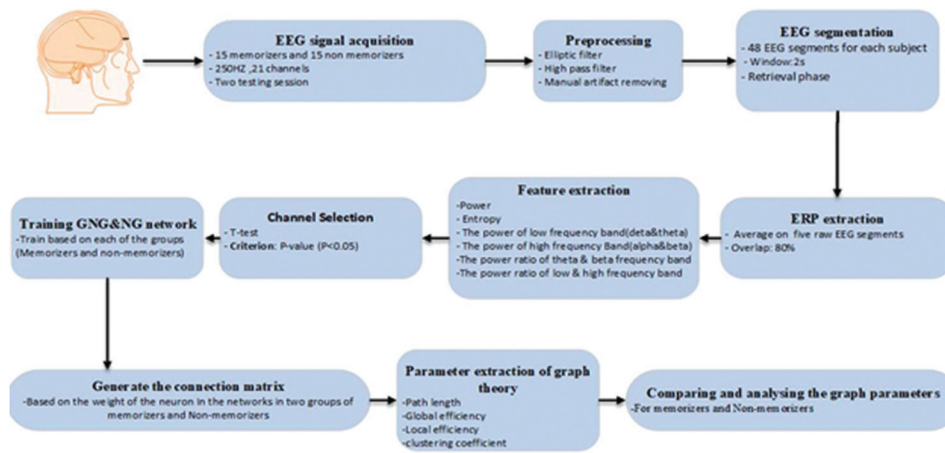

Figure 2: The process of processing the event-related potential signals using graph theory
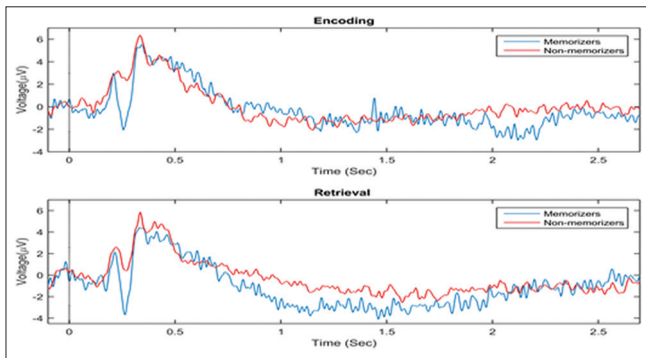

Figure 3: The event-related potential signal relevant to O1 channel in two phases of encoding and retrieval for both groups of the Quran memorizers and nonmemorizers

during the retrieval phase of the PRM test and also indicates a higher percentage of selecting the correct answers in this group than the nonmemorizers, it is interesting that the delay observed during the P300 component in the memorizers also represents that this group tried to recognize the correct images more accurately. Therefore, this is the origin of delay in the response time and the P300 component as well as the increase in the percentage of correct responses.

Methodology

Evaluating the effect of Quran memorizing as a protocol such as meditation, neurofeedback, and game therapy is clinically important, because if this method has an effect on human activities, especially the electrical activity of the brain, it can be used to improve and treat human psychological activities. Therefore, since clustering networks such as the NG networks can evaluate and reveal the changes made by memorizing the Quran on the data structure, evaluating variations created in the structure of these networks can detect the effects of the Quran memorizing on the brain activity, especially activity related to brain function in the face of external stimuli. For this purpose, in this study, we evaluated the effect of Quran memorizing on the structure of the clustering networks developed by the feature extracted. The next sections, respectively, provided feature extraction method and how to evaluate the structure of the clustering networks by using the graph theory

Feature extraction

Some researchers believe that useful information can be obtained through processing the ERP signals in the frequency domain.[17] Some, including Bashar, believe that ERP, like EEG, is the result of a series of activities performed in different frequency bands (delta, theta, alpha, beta, and gamma), each of which is related to a specific part of brain activity, and they actually make up the functional components of the ERP signals.[16,18] Accordingly, in this research, the following six features have been extracted:

1. Power of the ERP segment
2. Entropy of the ERP segment
3. Power of low-frequency components (delta and theta band components) of the ERP segment
4. Power of high-frequency components (alpha, beta, and gamma) of the ERP segment
5. Power ratio of low-frequency components to high ERP components
6. Power ratio of theta band to beta ERP components.

In the set of this feature, feature 2 measures the complexity of the ERP signals recorded in both of the Quran memorizers and nonmemorizers during the PRM test and other features measure the power distribution of the ERP signal and the frequency bands defined on the ERP signal. After extracting the above features from the ERP signal, as shown in the block diagram in Figure 2, we used the *t*-test for selecting optimal channels. In other words, channels, which had $P < 0.05$, are used to develop the NG and GNG networks. The parameter values of the NG and GNG networks are used in this research.

Neural gas network and growing neural gas network

NG is an artificial neural network, inspired by the self-organizing map and introduced in 1991 by Ma'ruf *et al*.[1] NG is a simple algorithm for finding optimal data representations based on feature vectors. The algorithm was coined "NG" because of the dynamics of the feature vectors during the adaptation process, which distribute themselves like a gas within the data space.

The NG algorithm[19] arranges the network units for each input signal according to the distance of their reference vectors. Based on this "ranking order," a number of units are matched. The number of adapted units and the power of adaptation are decreased according to a schedule.

In contrast, GNG[20] is an incremental neural model able to learn the topological relations of a given set of input patterns by means of competitive Hebbian learning. Unlike other methods, the incremental character of this model avoids the necessity to previously specify the network size. On the contrary, from a minimal network size, a growth process takes place, where new neurons are inserted successively using a particular type of vector quantization.[21] A GNG for inserting new neurons measures local error during the adaptation process and each new unit

inserts to near the neuron that has the highest accumulated error. At each adaptation step, a connection between the winner and the second-nearest neuron is created as dictated by the competitive Hebbian learning algorithm. This is continued until an ending condition is fulfilled. In addition, in the GNG network, the learning parameters are constant in time, in contrast to other methods whose learning is based on decaying parameters. Table 3 provides the parameter values of the NG and GNG networks used in this research.

Connection matrix and graph parameters

As stated in the previous section, we first trained a neural network (NG or GNG) with each of the features after selecting the optimal channels (N channels) by using the *t*-test analysis based on the *P* value ($P < 0.05$) for each group (memorizers and nonmemorizers). Then, we created a connection matrix based on the weight matrix of the neural network, which includes the position of the neurons in the N-dimensional space. In other words, for creating the connection matrix, we calculate the distance of each neuron from the other neurons and consider the obtained value as an array of the connection matrix. Finally, we computed the graph parameters based on the connection matrix for the two groups of memorizers and nonmemorizers. The extracted graph parameters included three parameters: shortest path length, global efficiency, and local efficiency. Given that the initial weight of the networks is randomly generated, we for reducing the effect of initial weight in the neural network on the graph parameters presented the average graph parameters after developing the neural networks 10 times by using each feature.

Path length

Since the connection matrix calculated in this study creates a weighted graph. This value is obtained from paths that have the least sum of the weight in vertices between the two nodes. In other words, the average of the shortest paths between the pairs of nodes is called the characteristic path length. This parameter is a criterion for the measures of functional integration in the graph. In networks with shorter path lengths, the exchange between nodes is faster. If L is the path length, we have:

$$L = \frac{1}{n(n-1)} \Sigma_{i \neq j} \, d(i,j) \tag{1}$$

Another criterion for measuring the functional integration in a graph is efficiency, which is the inverse of the path length and shows the efficiency of the graph in transmitting information between different areas. For each vertex i, let G_i is the subgraph of G which is induced by the neighbors of i, and let Gi' is the subgraph of G which is induced by vertex i and the neighbors of i. In 2001, Cahill ND[21] defined the global efficiency of a graph to be:

$$E_{global}(G) = \frac{1}{n(n-1)} \Sigma_{i \neq j} \frac{1}{d(i,j)} \tag{2}$$

Table 3: The parameter values of the neural gas and growing neural gas networks used in this research

Network parameter	Maximum number of neurons	Maximum iteration	t_{max}						
NG	1000	40	10,000	0.5	0.01	5	0.5	5	10

Network parameter	Maximum number of neurons	Maximum iteration	L					
Growing NG	1000	30	50	0.2	0.005	0.5	0.995	20

NG – Neural gas

The local efficiency is defined to be:

$$E_{local} = \frac{1}{n}\Sigma E_{glob}(Gi) \tag{3}$$

where the local efficiency is the average of the global efficiencies of the subgraph G_i.[21]

Average amount of weights

This criterion is calculated by averaging the weight of trained networks with the selected channel for each group.

Clustering coefficient

In graph theory, a clustering coefficient is a measure of the degree to which nodes in a graph tend to cluster together.

Experimental Results

The statistical analysis of features

Table 4 shows the results of the *t*-test analysis for separating the ERP data of the Quran memorizers and nonmemorizers by using six features extracted from 19 channels. Generally, as shown in this table, the number of channels, which had a significant difference ($P < 0.05$ for each feature), was more than one channel. Nevertheless, these results indicate that channels located on the frontal, parietal, and occipital lobes in most features, which are involved with the attentional networks and visual memory, had significantly different in both groups. In Figure 4, the box plot of the six features for channels with the lowest *P* value has been typically shown. As shown in this figure, features such as power, the power of low-frequency components, and the power ratio of low-frequency components to high-frequency components in the group of Quran memorizers had also larger values, which indicate more patience, concentration, and relaxation in memorizers than nonmemorizers. A significant increase in the power of theta/beta frequency band is another reason for this issue. The result of this increase is a decrease in the power of high-frequency bands, which is also seen in the distribution of PH feature.

Results of the neural gas and growing neural gas networks by using graph theory

As shown in Tables 5 and 6, all ERP channels had not significant information to distinguish the memorizers and the nonmemorizers. Hence, in this study, we have only used optimal channels with $P < 0.05$ to develop the GNG and NG networks by using each feature. Then, after the development of the mentioned networks, as previously described, based on the weights of the network, we created a graph with M nodes, which M is the number of network neurons. In other words, we created a connection matrix for the graph by using grid weights. As mentioned earlier, we have also considered a validation technique to reduce the effect of initial weight (random weight) on the developed networks, so that each of the developed networks is trained 10 times with optimal feature channels. Tables 5 and 6 present the results obtained from the analysis of graphs generated from the weights of the GNG and NG networks by using five graph parameters (L, EG, EL, clustering coefficient, and average network weight). According to the values obtained in these tables, the parameters of average path length and average weights in the group of memorizers had larger values, which represent more scattering in the data of this group. In contrast, two parameters EG and EL were less in the group of memorizers, which indicates the better integration and the higher efficiency of the networks in transmitting data in this group. This was also true in all the selected features in the two groups of the Quran memorizers and nonmemorizers, and the difference between these parameters in the two groups indicates the difference in the structure of the GNG and NG networks trained with the features of the optimal channels extracted from the ERP data of each group. According to Table 6, the number of neurons in the GNG networks trained with the features of the optimal channels extracted from the ERP data relevant to the group of the memorizers was more than that of the nonmemorizers, which means more scattering in the data of the mentioned group.

Discussion

As mentioned in the introduction, a significant part of research on the effect of the Quran memorizing and listening has reported an increase in the range of the alpha components of the brain processes as well as the degree of relaxation in different individuals, which usually increases the delay in selecting the appropriate image, especially in recovering the visual memory. Its results are also a delay in the occurrence of the P300 component. In a study conducted by Ramchurn *et al*.[22,23] in 2014, a positive correlation occurred between the time of the P300 component of the ERP signal and the reaction time has been reported, which reflects a significant relationship between these two components. In this study, the dependence between the time and amplitude of the P300 component with the speed of the subject's responsiveness for selecting the target stimulus has been observed, which indicates an increase in the occurrence time of the P300 component and more delay in selecting the target stimulus during the visual test. Interestingly, these results, similar to previous studies, have shown that the P300 component in the ERP signals appeared in the memorizers has a longer time delay than that of the nonmemorizers. The amplitude and occurrence time of N200

Table 4: The *t*-test results for separating the event-related potential data of memorizers and nonmemorizers by using six features extracted from 19 channels

Feature	Channel									
	Fp1	Fp2	F7	F3	FZ	F4	F8	T3	C3	CZ
Variance	0.027904	2.14E-07	0.00719	0.266718	0.000853	0.246616	1.29E-10	0.055862	0.369976	0.286621
Entropy	0.019415	0.001706	0.374379	0.09066	0.248752	0.390027	0.385644	0.01219	0.057015	0.002629
PL	0.395418	0.000109	4.62E-09	0.381451	0.106494	0.396748	9.77E-14	3.97E-05	0.041582	0.036101
PH	4.41E-12	0.032328	0.210158	1.15E-19	1.31E-27	4E-19	0.241176	4.07E-05	2.56E-14	1.33E-31
PL/PH	0.009463	2.15E-05	2.6E-07	4.64E-05	1.21E-08	0.003396	4.2E-10	0.017868	4.25E-06	2.1E-06
PT/PB	0.340704	0.213858	0.09644	0.237696	0.015332	0.327018	0.005035	0.198908	0.143552	0.202081

Feature	Channel								
	C4	T4	T5	P3	PZ	P4	T6	O1	O2
Variance	0.395446	0.340956	0.053299	0.392826	0.385637	0.090345	0.016139	0.153481	0.098135
Entropy	0.38793	0.388446	0.027157	0.23213	0.000794	0.354989	0.017275	0.00028	0.381192
PL	0.344572	0.002224	0.004269	0.147615	0.13015	0.134401	0.354502	0.00068	0.040406
PH	7.14E-15	2.39E-14	0.000112	2.19E-26	1.33E-33	1.06E-27	1.44E-22	0.392173	4.77E-09
PL/PH	7.25E-05	1.8E-15	0.003849	1.61E-06	1.34E-15	3.67E-11	7.42E-13	0.000104	0.003047
PT/PB	0.099393	8.47E-05	0.001494	0.377703	0.193119	0.384936	2.19E-05	0.009941	0.321392

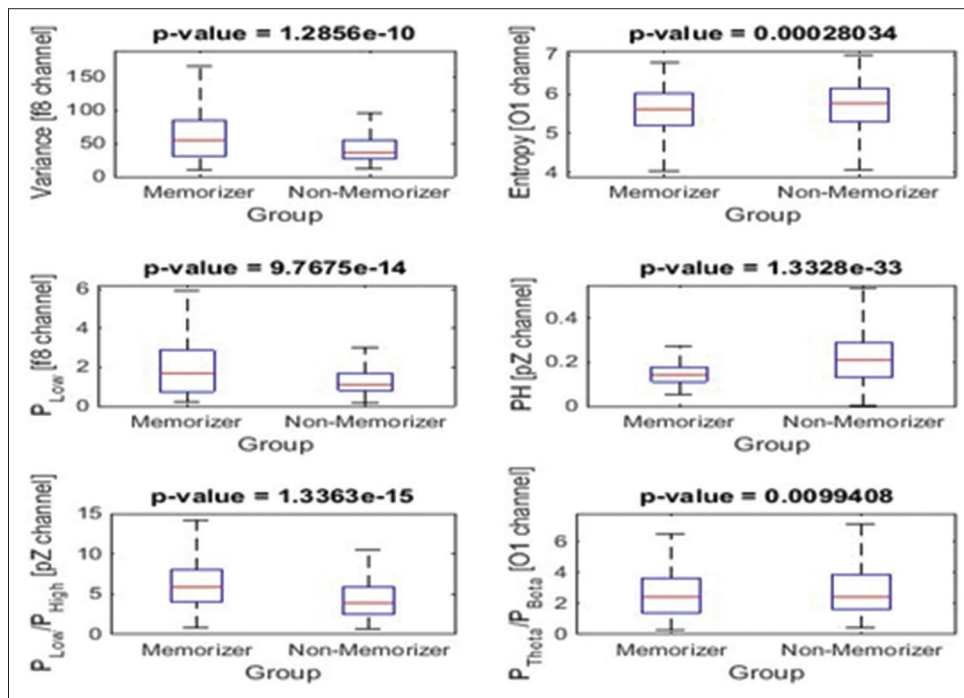PL – Power$_{low}$; PH – Power$_{high}$; PT – Power$_{theta}$; PB – Power$_{beta}$

Figure 4: Box plot related to six features for the most optimal channels selected by *t*-test analysis for distinguishing two groups of memorizers and nonmemorizers

component had also significant differences in both encoding and retrieval phases, which had been probably influenced by factors such as stimulus classification, cognitive processing aspects of stimulus identification, and stimulus differentiation in visual stimulation.[23] Given that the results reported in this study, which shows a greater delay in the answering of memorizers in the retrieval phase of the PRM test and a higher percentage of selecting the correct answers in this group compared to nonmemorizers, the delay observed at the time of P300 component in the group is also proof of that memorizers try to have to recognize the correct image more accurately. Therefore, this leads to delaying the response time, increasing

the percentage of correct responses, and delaying the P300 component. Nevertheless, although this change in ERP waves causes a scattering in the features extracted from the brain activity of the memorizers and nonmemorizers, especially the brain activities stored in the ERP signals, none of the previous researches has provided information about this scattering in features. Furthermore, although artificial data clustering by the NG and GNG networks has provided specific results for identifying clusters caused by data scattering, these studies show that cluster identification is performed by competitive networks when clusters had occurred in the space under analysis. Therefore, since there is not usually such clusters in

Table 5: The values of graph parameters for the graphs generated from the growing neural gas networks in two groups of Quran memorizers and nonmemorizers

Feature	Parameter graph					
	L	EG	Clustering	EL	WMean	n
Variance (nonmemorizer)	228.44	0.0050	228.44	0.0093	70.13	273
Variance (memorizer)	294.36	0.0046	294.36	0.0100	84.92	343
Entropy (nonmemorizer)	145.42	0.0065	145.42	0.0131	35.52	274
Entropy (memorizer)	298.16	0.0047	298.16	0.0094	61.12	344
PL (nonmemorizer)	200.38	0.0047	200.38	0.0094	39.78	273
PL (memorizer)	354.33	0.0042	354.33	0.0085	63.90	343
PH (nonmemorizer)	152.66	0.0054	152.66	0.0108	27.31	274
PH (memorizer)	349.29	0.0043	349.29	0.0086	44.00	342
PL/PH (nonmemorizer)	222.88	0.0039	222.88	0.0078	32.84	273
PL/PH (memorizer)	392.05	0.0035	392.05	0.0071	47.83	343
PT/PB (nonmemorizer)	191.32	0.0049	191.32	0.0099	60.97	274
PT/PB (memorizer)	262.69	0.0048	262.69	0.0096	75.68	344

$EG - E_{global}$; $PL - Power_{low}$; $PH - Power_{high}$; $PT - Power_{theta}$; $PB - Power_{beta}$; $EL - E_{local}$

Table 6: The values of graph parameters for the graphs generated from the neural gas networks in two groups of Quran memorizers and nonmemorizers

Feature	Parameter graph					
	L	Eglobal	Cclosed	Elocal	Wmean	n
Variance (nonmemorizer)	285.69	0.0034	285.69	0.0068	88.29	200
Variance (memorizer)	358.22	0.0027	358.22	0.0054	103.26	200
Entropy (nonmemorizer)	199.53	0.0046	199.53	0.0093	47.36	200
Entropy (memorizer)	360.10	0.0026	360.10	0.0053	77.10	200
PL (nonmemorizer)	247.92	0.0036	247.92	0.0073	49.90	200
PL (memorizer)	432.57	0.0020	432.57	0.0040	84.56	200
PH (nonmemorizer)	220.42	0.0035	220.42	0.0071	37.63	200
PH (memorizer)	459.42	0.0018	459.42	0.0037	62.93	200
PL/PH (nonmemorizer)	313.733	0.0025	313.73	0.0051	44.30	200
PL/PH (memorizer)	521.69	0.0015	521.69	0.0031	68.12	200
PT/PB (nonmemorizer)	241.06	0.0038	241.06	0.0076	78.29	200
PT/PB (memorizer)	348.40	0.0026	348.40	0.0052	106.89	200

$PL - Power_{low}$; $PH - Power_{high}$; $PT - Power_{theta}$; $PB - Power_{beta}$

the features extracted from the brain activities of memorizers and nonmemorizers, and is only occurred a significant change in the distribution of data, competitive networks are practically inefficient in clustering the features related to the brain activities of memorizers and nonmemorizers and are required a different approach to analyze the status of brain activities in the two groups. In other words, as shown in this research, evaluating the graphs constructed based on the NG and GNG neural networks trained by features extracted from the ERP signals of a group for measuring the difference in the scattering of ERP activity recorded during visual stimulation can provide important information about the structural difference of each data in the two groups. The analysis of six features extracted from the ERP data of the Quran memorizers and nonmemorizers in this research has accordingly shown that the channels of the frontal, peritoneal, and occipital lobes generally have a more significant difference in the distribution of features, which its reason is probably that they are involved with the attentional networks and video memory. Furthermore, there was an increase in the power of the low-frequency components

in the group of memorizers, which indicates more patience, concentration, and relaxation of this group when they select the correct images in the retrieval phase of the visual memory. These results are also consistent with the amplitude and time results of the various components of the ERP signal reported in this study. On the other hand, increasing the two parameters of average path length and weights of GNG and NG networks in the group of memorizers proved more scattering in the data of this group, and decreasing parameters EG and EL in the graph in the group of memorizers also indicated more integration and higher efficiency in transmitting the data in this group. In general, these differences in graph parameters for two groups of memorizers and nonmemorizers also show this issue that there are significant differences in the structure of the NG and GNG networks trained by the features of the optimal channels extracted from the ERP data of these groups.

Conclusion

In this paper, investigating structural differences relevant to the graph obtained from the weight of NG and GNG

networks trained by features extracted from the ERP signal recorded from two groups during the PRM test represented that Quran memorizing had a significant effect on the brain activities of the Quran memorizers. Therefore, this finding shows the Quran memorizing can be employed as a protocol to improve brain activity, especially for relaxation. Of course, there are limitations to this research. One of the limitations of this study is the low number of statistical populations, which reduces the observed differences in the parameters of the graphs, which are obtained from the matrix of weights of the GNG and NG networks trained by data from memorizers and nonmemorizers. Therefore, the evaluation of the ERP signals in the memorizers by using a larger database can be a new starting point for future studies. According to the results reported in this study and previous research, a more comprehensive study according to the effects and the manner of the Quran memorizing on the dynamics of brain waves and the connections between different parts of the brain during the Quran memorizing can help to improve neurofeedback-based methods. Furthermore, the study of interbrain connection through the graphs based on clustering networks can be another starting point for future work and its output can provide appropriate solutions to strengthen the visual memory of ordinary people during memorizing long texts.

Ethical approval and informed consent

The EEG signals used in this study were noninvasive, so that we recorded the EEG signal by using electrodes located on the scalp. We also used a Mitsar-EEG-202 recorder, which its company has received IEC 60601-1 for it. On the other hand, we had provided comprehensive information to Quran memorizers and nonmemorizers (subjects) about recording the noninvasive EEG signal (method and recorder) and had obtained written informed consent from the Quran memorizers and nonmemorizers (subjects) before recording the EEG signal. Therefore, all procedures performed in studies involving human participants were in accordance with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards.

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Conflicts of interest

There are no conflicts of interest.

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