Original Article

Nonlinear Analysis of Electroencephalogram Signals while Listening to the Holy Quran

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Abstract

Background: Electrical activity of the brain, resulting from electrochemical signaling between neurons, is recorded by electroencephalogram (EEG). The neural network has complex behavior at different levels that strongly confirms the nonlinear nature of interactions in the human brain. This study has been designed and implemented with the aim of determining the effects of religious beliefs and the effect of listening to Holy Quran on electrical activity of the brain of the Iranian Persian-speaking Muslim volunteers. **Methods:** The brain signals of 47 Persian-speaking Muslim volunteers while listening to the Holy Quran consciously, and while listening to the Holy Quran and the Arabic text unconsciously were used. Therefore, due to the nonlinear nature of EEG signals, these signals are studied using approximate entropy, sample entropy, Hurst exponent, and Detrended Fluctuation Analysis. **Results:** Statistical analysis of the results has shown that listening to the Holy Quran consciously increases approximate entropy and sample entropy, and decreases Hurst Exponent and Detrended Fluctuation Analysis compared to other cases. **Conclusion:** Consciously listening to the Holy Quran decreases self-similarity and correlation of brain signal and instead increases complexity and dynamicity in the brain.

Keywords: *Electroencephalogram, Holy Quran, nonlinear analysis*

Introduction

Electrical activity of the brain which is measurable by the electroencephalogram (EEG) shows complex behavior and nonlinear dynamics. This behavior of the EEG is derived from different patterns with different complexities. EEG signals can provide useful information about the brain's condition. Linear methods that are used in the field of signal processing are not always strong methods for analysis of signals derived from nonlinear live systems such as human brain. In recent years, the analysis of human EEG by means of nonlinear dynamics and chaos theory has become more common and they are known to be very effective in understanding the underlying mechanisms of brain electrical activity.[1] Using nonlinear dynamics to describe the time series which are produced by nonlinear dynamic systems provides a more complete description of the EEG records.[2] Hence, the theory of nonlinear dynamics has opened a new window for understanding the behavior of the EEG signal, and it is used in studies such as investigating different modes of thinking,[3] different phases of sleep,[4] epilepsy,[5] emotions,[6] and schizophrenia.[7]

Much attention has been paid in recent years to the effect of spirituality on human health and well-being. In various religions such as Islam, Christianity, and Judaism also prayer are claimed to positively affect wellbeing of the humankind. Various studies have proved that brain is involved in religious experience; as they demonstrated a bilateral increase of blood flow in the thalamus, frontal cortices, and cingulate gyrus. On the other hand, considering the reciprocal relation of the nervous and immune systems, meditation alters brain function and affects both the immune system and autonomic nervous system to reduce blood pressure, heart rate, and cortisol levels and alleviates anxiety.[8]

Quran is the holy scripture of Islam, and can affect the emotional and physiological states of humans.[9,10] Numerous factors can affect human emotions such as heart rate variability and breathing rate.[11] Listening to Quran can also influence believers'

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emotions, and induce hormonal changes and is known to calm Muslim individuals; such that it can be used to model human emotions.[11,12] Few are those research works that have studied the effect of listening to Quran on EEG; of which we review some; as follows:

Salleh *et al*. showed that the alpha relative power in EEG spectrum of Muslim people increases during prostration compared with mimic prostration.[13] Julianto and Estem showed a significant difference in the short-term memory of human individuals between before and after Quran recitation, as well as a significant increase in relative power of brain waves in P4, Fp2, and Fp1.[14] Kamal *et al*. showed that the power density of alpha band increased when their individuals were reading Quran compared to when they were reading any other book.[15] Alshaikhli *et al*. showed that while listening to Quran, compared to listening to some music, their individuals exhibit more calmness, evident by their EEG frequency spectrum and the smoothness of their ECG curves in time domain.[16] Nasir and Mahmud studied the effect of a wide variety of music genres and also Quran recitations on Muslim individual's ' brain. They showed that Holy Quran, Rock, and Mozart music, as opposed to all other genres they tested (e.g., Jazz and Light music) increased attention.[17] Al-Galal and Alshaikhli claimed to have observed a higher alpha magnitudes in their individuals while listening to Quran rather than listening to a relaxing music.[18] Fattouh used wavelet coherence analysis to study brain signals of healthy controls while listening to Quran.[19] Alsolamy devised an emotional BCI system to study their individual's emotions while listening to Quran. They studied the power spectral density and fractal dimension to discriminate between two types of emotion: Devout and nondevout.[20] Ardabili *et al*. studied the effect of listening to Quran, versus listening to any other arbitrary Arabic text, in Persian speaking subject; and based on changes observed in the frequency spectrum of frontotemporal circuits, suggested some applications of listening to Quran for stress relief in Muslim's lives.[21]

Lindenthal *et al*.[22] and Pfeifer and Waelty[23] showed that anxiety and psychiatric diseases are less prevalent among religious believers than the normal population. A person's beliefs heavily influence their opinions and decisions. Indeed, such beliefs can be considered as the main difference between human individuals.[24] The review of recent studies about changes in the EEG signals in Persian-speaking Muslims showed that they have not investigated the beliefs of volunteers in the Holy Quran. In addition, the signals have been evaluated using linear features in most of these studies. Therefore, in this research, the effects of listening to the Holy Quran verses on the brain of the Iranian Persian-speaking Muslim volunteers were investigated consciously and unconsciously. In these circumstances, the belief of volunteers in the Holy Quran can also be investigated. In addition, given the nonlinear nature of the EEG signal, the nonlinear features were used to better investigate the changes in these signals.

Therefore, we studied EEG signal in three conditions: (1) listening to Quran while the subject was informed in advance that it would be Quran they would be listening to; (2) listening to Quran while the subject received no such information whatsoever in advance that it would be Quran they would be listening to; and (3) listening to another Arabic text without any prior knowledge of what it would be. Forty-seven Iranian Persian-speaking Muslim subjects who were not considered a knowing Arabic (by local standards) and were not professional Quran reciters or memorizers volunteered in our experiment. Their EEG signals were analyzed for several nonlinear features to measure complexity and scaling behavior in the brain; namely sample entropy,[25,26] approximate entropy,[27,28] Hurst Exponent,[29,30] and detrended fluctuation analysis.[31,32]

Materials and Methods

Subjects

During the experimental session, individuals were seated in an acoustically sealed room where the only sound they could be exposed to was our auditory stimuli. There were 47 Persian-speaking Muslim volunteers, 19 females and 28 males, ages range from 16 to 25-year-old, with their mean 21.4 (standard deviation = 2.708). None of the volunteers were familiar with the Arabic language, and they were not Holy Quran Reciters. The recording time of EEG data was 10:30 am for half of the volunteers, and 1:00 pm for the other half. All the individuals were healthy, underwent the experiment on their own free will, and filled questionnaires of personal information and mental health. Just before participating in our experiment, they read and signed the appropriate consent forms.

Electroencephalogram acquisition

The purpose of this research is to study changes in the EEG signals due to listening to the Muslim's holy book, Quran. We used a few verses of Quran taken from Surahs "Al-Fath" and "Al-Furqan," which have positive connotations; as they include promising and supporting statements. The Arabic text, which we asked experts in the Arabic language to devise for the specific use of our experiment, also had positive connotation.

The EEG signal was recorded in the baseline condition (in which the subject of the experiment was listening to no audio file), when listening to the Holy Quran consciously (as the volunteer did not know Arabic and had not memorized the Holy Quran, he has been informed that what he is listening to is the Quran), when listening to the Holy Quran unconsciously (the volunteer was not informed of what he is listening to, and whether it is the Arabic text or the Holy Quran) and when listening to an

Arabic text unconsciously (the volunteer was not informed of what he is listening to, whether it is the Arabic text or the Holy Quran).

In order to generate the auditory stimuli that we needed for our experiment, we asked a Qari who was well versed in Arabic texts and Quran recitation, but whose voice was unknown to our subjects, to record the auditory stimuli.

The playback time for all three conditions, Quran consciously (Q2), Quran unconsciously (Q1) and Arabic text unconsciously (NQ) was 10 min and all the files were read by a Qari in Tartyl and as similarly as possible. Tartyl means reading in a way that all the letters and words are pronounced clearly with no speed and rush. For having no interaction of the phases, a 15-min break was used between the phases. Volunteers listened to these files using headphones. The order of EEG data recording was as follows, Figure 1 shows this process too:

- Stage I: Baseline (Pre): Recording EEG, 2 min with eyes opened, and then 2 min with eyes closed
- Stage II: Unconscious: Recording EEG, 2 min with eyes opened, and 2 min with eyes closed, and then random playing of Q1 or NQ and recording EEG for 10 min, with eyes closed
- Stage III: Unconscious: Recording EEG, 2 min with eyes opened, and 2 min with eyes closed, and then playing the file which was not selected in stage II and recording EEG for 10 min, with eyes closed
- Stage IV: Conscious: Recording EEG, 2 min with eyes opened, and 2 min with eyes closed, and then playing the file Q2 and recording EEG for 10 min, with eyes closed.

Electroencephalogram recordings

The EEG signals were recorded using a 16-channel amplifier (g. USBamp, g. tec, Graz, Austria) from 13 unipolar scalp electrodes positioned on Fp1, Fp2, F3, Fz, F4, C3, Cz, C4, P3, Pz, P4, O1, O2 according to the 10–20 standard system, to have surveyed all lobes of brain. An electrode on the right earlobe served as reference, another electrode did so on Fpz as GND, another one under right eye to record EOG, and two other on the two wrists to monitor HRV. Bandpass filter (0.1–60 Hz) and notch filter (50 Hz) in g. USBamp amplifier was also used, and the sampling frequency was 256 Hz.

The time of events such as the movement of head, neck, hands and legs, moving in the chair, deep respiration, and swallowing, was noted and then marked in the signals. In the first stage, the EEG signal was recorded for 2 min; but in the latter, three stages of the experiment, the recording lasted for 10 min. In all four stages, the subjects closed their eyes as per our instructions. In each of those four stages, the signal was divided by windows of 4-s duration; then those 4-s epochs that did not contain any of the above-mentioned events were selected. Then, the value of the said set of features was calculated in each epoch and averaged among them. Finally, those average values underwent statistical analysis to unveil any possible significant difference between those 4 stages of (Pre, Q1, NQ, Q2) in each single one of those 47 subjects.

Electroencephalogram data analysis

Nonlinearity is a necessary condition for chaotic behavior which exists in many dynamic systems of nature, such as the brain. The assumption of being completely random is rejected about the brain due to its ability in performing difficult and complex cognitive tasks.[33]

In this research work, the most common nonlinear features in the realms of entropy and fractals have been investigated. Fractals can be expressed in terms of self-similarity and fractional dimension;[34] each of which can be calculated by several methods; of which we used Hurst Exponent and detrended fluctuation analysis to estimate long-term correlation and self-similarity of time series. In information theory, uncertainty is measured by entropy, which is a measure of the complexity of systems.[34] There are several methods to estimate entropy; of which we have used the approximate entropy and sample entropy in the present work.

Approximate entropy

Pincus in 1991[35] introduced approximate entropy with the aim of measuring the regularity of the signal to determine similar patterns in time series and so on. Approximate entropy has the ability to analyze several systems that have random noise. This entropy has nonnegative value. The larger values are associated with disordered or random series, and smaller values are associated with regular sequences or series in which there are more recognizable features or patterns. There are two input parameters for the entropy: *m* and *r*. *m* is the length of

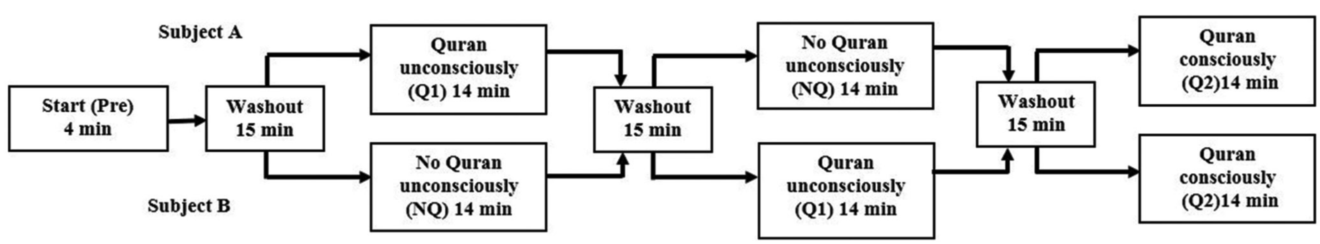

Figure 1: The protocol for EEG recording

the components which should be compared in the time series, and r is the acceptable range of the change for a member of the time series (the value of r is typically considered between 10% and 25% of standard deviation of the time series). Pincus suggested that the embedding dimension (m) is considered 1 or 2, and the value of r is considered a numerical constant between 0.1 and 0.25 times the standard deviation of the original time series. The approximate entropy approximates the logarithmic probability and samples that are close to each other remain to be compared with further samples.[36] The algorithm to compute the approximate entropy of the signal $X = (x_1, x_2, x_3, \quad , x_N)$ is as follows:[35]

1. New vectors of $X^i = (x_i, x_{i+1}, \; x_{i+m-1})$ are defined for $X^j = (x_j, x_{j+1}, \; x_{j+m-1})$. Each of these vectors includes m successive values of X
2. The distance between two vectors X^i and X^j is defined as the absolute maximum difference between the vector components of the two vectors:

$$d\left[X^i, X^j\right] = \max_{k=0,\dots,m-1} \left|X_{i+k} - X_{j+k}\right|$$

3. For every vector X^i, the number of vectors X^j, whose distance with X^i is less than or equal to r, is counted. The $C_i^m(r)$ is abundance of similar patterns with a window length m

$$C_i^m(r) = \frac{\text{number of } d\left[X^i, X^j\right] \le r}{N - m + 1}, \text{ for } 1 \le j \le N - m + 1$$

And for $1 \le i \le N - m + 1$ we have:

$$\varphi^m(r) = \frac{1}{N - m + 1} \sum_{i=1}^{N-m+1} \ln C_i^m(r)$$

4. With an increase of one unit to the dimension (m), $C_i^{(m+1)}(r)$ and $\varphi^m(r)$ is defined
5. Finally, the approximate entropy is $ApEn(m,r) = \lim_{N\to\infty}\left[\varphi^m(r) - \varphi^{m+1}(r)\right]$, that can be estimated with the Eq. 1.

$$ApEn(m,r,N) = \left[\varphi^m(r) - \varphi^{m+1}(r)\right] \quad (1)$$

N is the length of time series, m is the length of sequence that should be compared, and r is the tolerance for the acceptance of matches.

Sample entropy

Richman and Moorman[37] modified the approximate entropy to eliminate imperfections, and introduced Sample Entropy which is always a regularity estimator. The differences which sample entropy has compared to approximate entropy are: (1) Self-matches are not considered. (2) It does not use a template-wise approach to estimate the conditional probabilities. The small amount of sample entropy shows more self-similarity in time series.[38] To calculate the sample entropy from the time series $X = (x_1, x_2, x_3, \quad , x_N)$, the following steps are performed:[37]

1. New vectors of $X_m^i = (x_i, x_{i+1}, \dots, x_{i+m-1})$ are defined for $i = 1, \dots, N - m + 1$
2. The distance between two vectors X_m^i and X_m^j is defined as the absolute maximum difference between the components of the two vectors:

$$d\left[X_m^i, X_m^j\right] = \max_{k=0,\dots,m-1} \left|x_{i+k} - x_{j+k}\right|$$

3. For every vector X_m^i, the number of vectors X_m^j, whose distance with X_m^i is less than or equal to r, is counted. It should be noted that, unlike the approximate entropy, self-matches are not counted here ($j \neq i$)

$$B_i^m(r) = \frac{\text{number of } d\left[X_m^i, X_m^j\right] \le r}{N - m - 1},$$
$$\text{for } 1 \le j \le N - m, j \neq i$$

Then $1 \le i \le N - m$, we have:

$$B^m(r) = \frac{1}{N - m} \sum_{i=1}^{N-m} B_i^m(r)$$

4. For every vector X_{m+1}^i, the number of vectors X_{m+1}^j, whose distance with X_{m+1}^i is less than or equal to r, is counted:

$$A_i^m(r) = \frac{\text{number of } d\left[X_{m+1}^i, X_{m+1}^j\right] \le r}{N - m + 1},$$
$$\text{for } 1 \le j \le N - m, j \neq i$$

$$A^m(r) = \frac{1}{N - m} \sum_{i=1}^{N-m} A_i^m(r), \text{ for } 1 \le i \le N - m$$

Thus, B^m and A^m are two probabilities that specify the total number of direct matches with the length of m and $m + 1$, respectively

5. Sample entropy is defined as $SampEn(m,r) = \lim_{N\to\infty}\left\{-ln\left[\frac{A^m(r)}{B^m(r)}\right]\right\}$ which is estimated statistically with Eq. 2:

$$SampEn(m,r,N) = ln\left[\frac{A^m(r)}{B^m(r)}\right] \quad (2)$$

Hurst exponent

Hurst Exponent was introduced by Hurst in 1951[39] to quantify the self-similarity of time series and provide information about the recurrence rate of similar patterns in time series in different scales.[40] The oldest and the best-known method for estimating the Hurst Exponent is Rescaled Range Analysis (R/S) proposed by Mandelbrot and Wallis[41] according to Hurst Exponent.[39] The time series of length L is divided into d subseries ($Z_{i,m}$) with the length of n and for each subseries, $m = 1, \dots\dots, d$.

1. It is necessary to calculate the mean (E_m) and Standard deviation (S_m) of subseries ($Z_{i,m}$) first
2. Each sub-series data ($Z_{i,m}$) is normalized by subtracting the mean.

$X_{i,m} = Z_{i,m} - E_m$, $i = 1, \dots, n$

3. Integrated time series are made:

$$Y_{i,m} = \sum_{j=1}^{i} X_{j,m}, \; i = 1, \dots, n$$

4. The Range is calculated:
   $$R_m = max\{Y_{1,m},\ldots,Y_{n,m}\} - min\{Y_{1,m},\ldots,Y_{n,m}\}$$
5. The range is converted to a smaller scale (R_m/S_m)
6. The mean $(R/S)_n$ is calculated from the scaled range for all subseries with length n.

It is known that the statistic R/S follows the equation $(R/S)_n \approx cn^H$, in which c is a fixed number. $Ln\ (R/S)_n$ is plotted in a chart with respect to ln n and the regression line is fitted on it. The slope of the regression line shows the value of H for this series. Hurst exponent has a value between 0 and 1. If $0 < H < 0.5$, there is no long-term correlation in time; If $0.5 < H < 1$, series the time series have long-term correlations.

Detrended fluctuation analysis

Peng *et al.*[42] introduced an algorithm called Detrended Fluctuation Analysis, to describe the long-term correlation between nucleotide sequences. This technique was used successfully to describe the correlation structure in nonstationary time series that were extracted from various systems such as social, financial, physical, and biological systems. In practice, the DFA method involves several steps:[43]

1. At first, the time series (x [t]) (i = 1,2,…., N) are integrated. So $y(n)$ is the n-th value of the integrated sum and $<x>$ is the mean value of time series
   $$y(n) = \sum_{i=1}^{n}\left[x(t) - <x>\right], n = 1,2,\ldots,N$$
2. Then y (n) is divided into B windows, in each, there is k = *int* (N/B) time data
3. Within each window (b = 1,…., B), a straight line, (y_b), is fitted to the data of the window using the minimum squares (local orientation data)
4. The variance of fluctuations (y [n]) of the line $y_b(n)$ in the b-th window is defined. So the local trend in the b-th window is measured
   $$F_b^2(k) = \frac{1}{k}\sum_{n=(b-1)k+1}^{bk}\left[\{y(n)\} - y_b(n)\right]^2$$
5. Finally, the root mean $F_b^2(k)$ is calculated in all windows.
   $$F(k) = \sqrt{\frac{1}{B}\sum_{b=1}^{B}F_b^2(k)}$$

This process is repeated for different scales (different sizes of windows) until the power law behavior between F (k) and k is obtained. When the signal follows the power law, the power law behavior is observed for the function F (k), i.e., $F\ (k) \propto k^{\alpha}$. The scaling exponent offers information about the correlation properties of long-lasting power law of the signal. The exponent scaling α has a value >0. So that α = 0.5 corresponds to white noise (noncorrelated signals), α < 0.5 shows that there are long-term anti-correlations in the signal, for 0.5< α <1 there is a long-term correlation between the signal and the signal is permanent. α = 0 shows the uniform power law behavior of the noise 1/*f*, and α = 1.5 represents the Brownian motion,[43] while α > 1.5 indicates that there are long-term correlations in the signal and may be related to the certain or random correlations.[44]

Results

The nonlinear features of approximate entropy, sample entropy, Hurst and DFA exponent for all windows with 4s length and in four stages of Pre, Q1, NQ, Q2 were calculated for all volunteers. Statistical analysis was performed on the mean value of these nonlinear features.

SPSS software was used for the statistical analysis of the results. The normality of data distribution was investigated using Kolmogorov–Smirnov test. If the data are normal, parametric tests and otherwise nonparametric tests are adopted. When several, identical measurements from the same subject or case are obtained, variance analysis test with repeated measurements, which is a parametric test, should be conducted for data analysis and comparing the mean of data. The Friedman test is a nonparametric test equivalent to variance analysis test with repeated measurements. Once the difference between various stages is clear, the position of difference is known using *t*-test of paired samples (*post hoc* test). The Wilcoxon test is a nonparametric test equivalent to the *t*-test of paired samples. The significance level of 0.05 is used for all tests.

Figure 2 shows the mean and mean deviation approximate entropy for 13 electrodes in four stages of Pre, Q1, NQ, and Q2. Table 1 shows the result of Friedman and Wilcoxon nonparametric tests in those electrodes that had significant Friedman test results. The significant results of this feature are:

- For electrodes Fp1 and Fp2: The significant difference was found between the four stages. Moreover, it became clear using *post hoc* test that approximate entropy increased significantly in Q2 stage compared with the three stages of Pre, Q1, and NQ
- For electrodes F3, Fz, F4, C3, Cz, C4, P3, Pz, P4, O1, O2: No significant difference was found between the four stages.

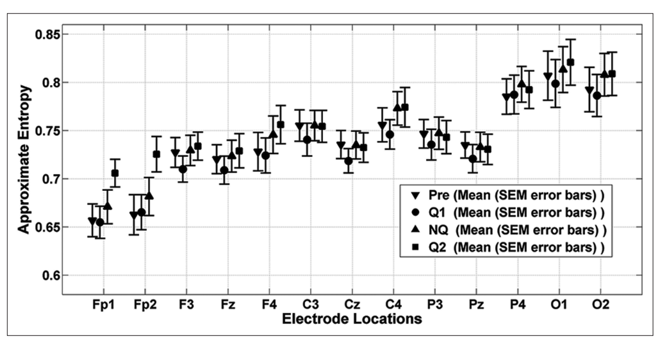

Figure 2: The mean value and the deviation of the mean for approximate entropy in each of the 13 electrodes in 4 stages Pre, Q1, NQ, Q2

Figure 3 shows the mean and mean deviation sample entropy for 13 electrodes in four stages of Pre, Q1, NQ, and Q2. Table 2 shows the result of Friedman and Wilcoxon nonparametric tests in those electrodes that had significant Friedman test results. The significant results of this feature are as follows:

- For electrodes Fp1 and Fp2: The significant difference was found between the four stages. Moreover, it became clear using *post hoc* test that sample entropy increased significantly in Q2 stage compared with the three stages of Pre, Q1, and NQ
- For electrodes F3, Fz, F4, C3, Cz, C4, P3, Pz, P4, O1, O2: No significant difference was found between the four stages.

Self-similarity parameter, Hurst Exponent (H), was calculated for all four phases Pre, Q1, NQ, and Q2. The value of exponent was more than 0.5 in each of the 4 phases. Figure 4 shows the mean and mean deviation Hurst Exponent for 13 electrodes in four stages of Pre, Q1, NQ, and Q2. Table 3 shows the results of repeated measure ANOVA and paired *t*-test in those electrodes that had significant ANOVA. The significant results of this feature are as follows:

- For electrodes Fp1, Fp2, F3, Fz, F4, C3, Cz, C4, P3, Pz, P4, O1, O2: The significant difference was found between the four stages. Moreover, it became clear using *post hoc* test that Hurst Exponent decreased significantly in Q2 stage compared with the three stages of Pre, Q1, and NQ.

DFA Method showed the scaling in EEG signal for each of the four stages of Pre, Q1, NQ, and Q2. The DFA value was larger than 0.5 in all phases and for all electrodes. Figure 5 shows the mean and mean deviation DFA Exponent for 13 electrodes in four stages of Pre, Q1, NQ, and Q2. Table 4 shows the result of Friedman and Wilcoxon nonparametric tests in those electrodes that had significant Friedman test results. The significant results of this feature are as follows:

- For electrodes Fp1, Fp2, F3, Fz, F4, C3, Cz, P3, Pz, P4, O1, O2: The significant difference was found between the four stages. Moreover, it became clear using *post hoc* test that DFA Exponent decreased significantly in Q2 stage compared with the three stages of Pre, Q1, and NQ
- For electrode C4: The results showed that there is significant difference between the four stages. Moreover, it became clear using *post hoc* test that DFA Exponent decreased significantly in Q2 stage compared with the three stages of Pre, Q1, and NQ and in NQ stage compared with Pre stage.

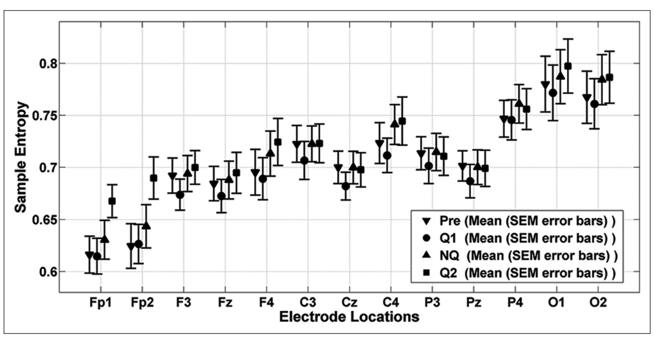

Figure 3: The average and the mean deviation for the sample entropy in each of the 13 electrodes in 4 stages of Pre, Q1, NQ, and Q2

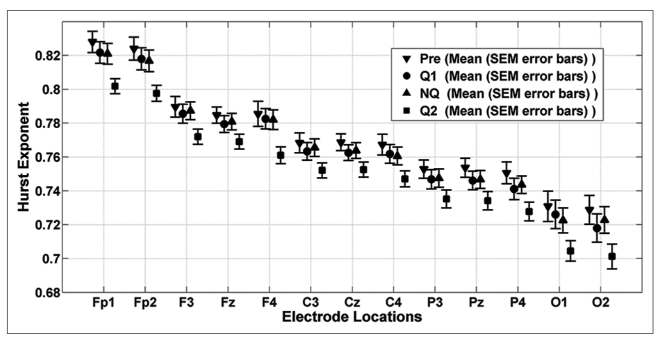

Figure 4: The average and the mean deviation for the Hurst Exponent in each of the 13 electrodes in four stages of Pre, Q1, NQ, and Q2

Table 1: The findings of Friedman test and Wilcoxon test for approximate entropy in 4 stages of baseline, Quran unconsciously, Arabic text unconsciously, Quran consciously

Approximate entropy	Friedman test	Wilcoxon test					
		Pre-Q1	Pre-NQ	Pre-Q2	Q1-NQ	Q1-Q2	NQ-Q2
Fp1	0.002*	0.852	0.453	0.004*	0.843	0.001*	0.005*
Fp2	0.002*	0.546	0.172	0.003*	0.374	<0.001*	0.004*

*P<0.05. Pre – baseline; Q1 – Quran unconsciously; Q2 – Quran consciously; NQ – Arabic text unconsciously

Table 2: The findings of Friedman test and Wilcoxon test for sample entropy in 4 stages of baseline, Quran unconsciously, Arabic text unconsciously, Quran consciously

Sample entropy	Friedman test	Wilcoxon test					
		Pre-Q1	Pre-NQ	Pre-Q2	Q1-NQ	Q1-Q2	NQ-Q2
Fp1	0.001*	0.596	0.302	0.002*	0.682	0.001*	0.002*
Fp2	0.002*	0.525	0.189	0.003*	0.357	<0.001*	0.004*

*P<0.05. Pre – baseline; Q1 – Quran unconsciously; Q2 – Quran consciously; NQ – Arabic text unconsciously

Discussion

Approximate entropy and sample entropy are measures of the dynamic changes of EEG signals in the time domain. Sample entropy was introduced to resolve the shortcomings of approximate entropy.[37] In general, the approximate entropy and sample entropy are very dependent on the parameters (m, r, and N).[45] The findings showed that the approximate entropy and sample entropy for the frontal pole (Fp1, Fp2) had a significant increase in Q2 compared to Pre, Q1, and NQ. Entropy increases indicate less predictability, increase in random behavior, and decrease in the order of the EEG signal. A significant increase in entropy when listening to Quran consciously (Q2) indicated that when the brain is processing Q2, the complexity of EEG activity had an increase in the frontal lobe. These results corresponded to Schmidt and Trainor[46] and Karthick's *et al.* idea[47] based on the relationship between acoustic stimulation and activity of the frontal lobe.

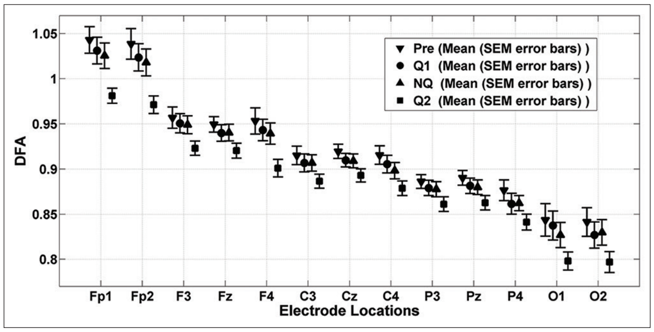

Figure 5: The average and the mean deviation for DFA in each of the 13 electrodes in the four stages of Pre, Q1, NQ, and Q2

There were no significant differences between the entropy values of three phases Pre, Q1, NQ. So when a Persian-speaking Muslim listened to Quran consciously

Table 3: The findings of repeated measure ANOVA and paired *t*-test for Hurst Exponent in 4 stages of baseline, Quran unconsciously, Arabic text unconsciously, Quran consciously

Hurst exponent	Repeated measure ANOVA	paired *t*-test					
		Pre-Q1	Pre-NQ	Pre-Q2	Q1-NQ	Q1-Q2	NQ-Q2
Fp1	<0.001*	0.136	0.051	<0.001*	0.862	<0.001*	<0.001*
Fp2	<0.001*	0.192	0.105	<0.001*	0.796	<0.001*	<0.001*
F3	<0.001*	0.337	0.5137	0.001*	0.608	0.001*	0.001*
Fz	<0.001*	0.161	0.273	<0.001*	0.629	0.002*	0.001*
F4	<0.001*	0.648	0.505	0.001*	0.879	<0.001*	<0.001*
C3	0.014*	0.385	0.561	0.004*	0.496	0.008*	0.001*
Cz	0.001*	0.146	0.222	0.001*	0.637	0.001*	<0.001*
C4	<0.001*	0.227	0.091	<0.001*	0.714	<0.001*	<0.001*
P3	<0.001*	0.188	0.163	<0.001*	0.832	0.003*	0.001*
Pz	<0.001*	0.101	0.108	<0.001*	0.839	0.001*	<0.001*
P4	<0.001*	0.058	0.336	<0.001*	0.291	0.005*	0.002*
O1	0.005*	0.505	0.243	0.006*	0.576	0.010*	0.017*
O2	0.002*	0.148	0.572	0.001*	0.398	0.025*	0.005*

**P*<0.05. Pre – baseline; Q1 – Quran unconsciously; Q2 – Quran consciously; NQ – Arabic text unconsciously

Table 4: The findings of Friedman test and Wilcoxon test for DFA in 4 stages of baseline, Quran unconsciously, Arabic text unconsciously, Quran consciously

DFA	Friedman test	Wilcoxon test					
		Pre-Q1	Pre-NQ	Pre-Q2	Q1-NQ	Q1-Q2	NQ-Q2
Fp1	<0.001*	0.195	0.072	<0.001*	0.987	<0.001*	<0.001*
Fp2	<0.001*	0.247	0.170	<0.001*	0.897	<0.001*	0.001*
F3	0.001*	0.559	0.764	0.002*	0.574	0.006*	0.002*
Fz	<0.001*	0.081	0.076	<0.001*	0.334	0.016*	0.002*
F4	<0.001*	0.200	0.252	<0.001*	0.897	<0.001*	<0.001*
C3	0.002*	0.495	0.635	0.004*	0.891	0.003*	0.003*
Cz	<0.001*	0.148	0.098	<0.001*	0.926	0.001*	<0.001*
C4	<0.001*	0.130	0.017*	<0.001*	0.448	0.001*	0.001*
P3	0.001*	0.245	0.054	<0.001*	0.978	0.003*	0.001*
Pz	<0.001*	0.136	0.105	<0.001*	0.935	0.002*	0.001*
P4	0.001*	0.160	0.081	0.003*	0.596	0.016*	0.010*
O1	0.040*	0.488	0.148	0.012*	0.516	0.030*	0.021*
O2	0.015*	0.287	0.181	0.003*	0.961	0.038*	0.016*

**P*<0.05. Pre – baseline; Q1 – Quran unconsciously; Q2 – Quran consciously; NQ – Arabic text unconsciously

(Q2), Entropy of the EEG signal and thus the complexity of the signal would increase and dynamics of the brain would be improved. However, listening to the Holy Quran or Arabic text unconsciously (Q1, NQ) did not change the complexity of the EEG signal. Karthick *et al*. stated that brain complexity increases during listening to any tone;[47] but in the present work, we showed that such an increase was significant only when subjects were consciously listening to the musical recitation of Quran. In the two conditions of Q1 and NQ, we did not observe the said increase probably because in those two conditions our subjects were not paying any attention to the tone, but they were trying to figure out whether or not it is Quran being played.

For Hurst exponent estimation, there are various methods such as rescaled range analysis and detrended fluctuation analysis. It has also been shown that these two criteria have similar results in long time series.[48] In the present work, we utilized both. Hurst exponent showed the permanent behavior and long-term correlation of EEG signals, which means that there was a correlation between its data, even when there was a large time interval between them. Figure 4 shows the exponent in all four phases had a value of more than 0.5, so the EEG signal in all four phases was permanent. There was a significant reduction in Hurst exponent in all areas of the head in Q2, compared to Pre, Q1, and NQ. The reduction of Hurst exponent represents a reduction in self-similarity. On the other hand, a significant reduction in Hurst exponent represents an increase in chaotic behavior in Q2. There was no significant difference between pairs of phases Pre, Q1, NQ. Hence, listening to the Holy Quran consciously (Q2) caused an increase in Hurst exponent compared to the rest or normal state (Pre). However, listening to the Holy Quran and an Arabic text, if the volunteer had no idea of what he was going to listen to (Q1 and NQ), made no significant change in Hurst exponent compared to the rest or normal state (Pre).

Self-similarity parameter or scaling exponent may be considered as an indicator of neural fluctuation dynamics, whose mean amplitude is strongly dependent on fluctuation activities.[49] Exponent scaling value was >0 and if $\alpha = 0.5$, it indicated that the time series was random, which is dynamically called random noise. Calculating exponent scaling for EEG signal in the four phases indicates that $\alpha > 0.5$. This result showed a correlation and persistence between the EEG signals. On the other hand, the DFA exponent in all lobes of the head had a significant increase in Q2 compared to other phases and signal correlation had a decrease in Q2. So since the DFA exponent shows the degree of correlation between time series and the similarity of this series, it became clear that hearing the Holy Quran consciously, significantly reduced the degree of correlation and self-similarity of EEG signal in all areas of the head. However, if the Arabic text or the Holy Quran was heard unconsciously (Q1, NQ), no significant changes would be found compared to the initial state.

The results derived from the entropy change, Hurst exponent and DFA scaling exponent were consistent with each other when listening to Quran consciously (Q2). Both methods of Hurst exponent and DFA have been utilized to find long-term correlations, which directly corresponds to complexity, and self-similarity of physiologic time series.[50] All of these three nonlinear features showed that the complexity of the brain increases in listening to Quran consciously, and thus, it becomes more dynamic. We observed changes in EEG signal when subject had an explicit knowledge of that it was Quran they were listening to; therefore, the observed effect could, at least in part, be a result of subjects' religious beliefs.

No significant change was observed in the nonlinear features of entropy, Hurst exponent, and DFA exponent when listening to the Arabic text or the Holy Quran unconsciously which could be caused by lack of sufficient knowledge of the volunteers about Arabic language and the Quran. Since all of the volunteers participating in this study were Persian, they were not familiar with Arabic language, and also had not memorized the Holy Quran. When they listened to the file unconsciously, because of the curiosity of their mind, they tried to determine whether the file being played was the Holy Quran or not. However, when they listened to the Holy Quran with a prior notification, this conflict and intellectual curiosity did not exist, and they only listened to the file, and thus entropy and self-similarity exponent were changed.

Therefore, whenever our subjects listened to Quran with knowing in advance that it would be Quran that they would be listening to (the Q2 condition) they exhibited significant changes in self-similarity and complexity of their brain signals. In such case, subjects might even have not understood the meaning of what they were hearing; but since they believed in their religious book, these significant changes occurred. Therefore, listening to Quran, with a prior knowledge that this is Quran they are listening to, can decrease self-similarity, increase complex dynamics in the brains of Muslim believers, which might be indicative a spiritual peace of mind.

The research has shown that in Muslim believers, listening to Quran increases calmness,[51] reduces stress,[52] changes heart rate,[53] improves respiration,[54] and mental health.[55] Fattouh *et al*.,[56] and Alsolamy[20] have both studied nonlinear features such a fractal dimension to model human emotions while listening to Quran, but they have not mentioned any numerical value of those features or their trends (increase or decrease). Thus, we cannot compare our study with those of theirs. Our results contradict those of Rabbani *et al*.[57] who have reported a decrease in entropy while listening to Quran. Various research works on meditation have reported a wide variety of changes, ranging from a decrease to an increase, in entropy.[58,59] The scarcity of research-work in this field has made it difficult to compare the present work with any other.

Conclusion

Forty-seven volunteers who were Persian speaking Muslims and did not speak Arabic and had not memorized the Holy Quran participated in this study. EEG signals of frontal pole (Fp1, Fp2), frontal (F3, Fz, F4), central (C3, Cz, C4), parietal (P3, Pz, P4), and occipital (O1, O2) are recorded at rest condition, listening to Quran consciously, listening to Quran unconsciously and listening to an Arabic text unconsciously.

EEG signals are obtained from brain electrical activity, and considering that the neurons of the central nervous system show a nonlinear behavior, many researchers have used the measure derived from nonlinear dynamics and chaos theory to study EEG signal[60,61] and gained better results compared to the linear analysis methods. Hence, in this paper, nonlinear features such as approximate entropy, sample entropy, Hurst and DFA exponent were used to study EEG signals.

Entropy is known as a measure of the disorder of a time series. If the structural and functional order of a time series decreases, its entropy will increase. Calculating the approximate entropy and sample entropy for EEG signals showed that listening to the Holy Quran consciously caused an increase in the entropy of the frontal pole electrodes. Therefore, the Q2 stimulus caused an increase in the complexity and dynamics of the brain, and in this circumstance more neurons were involved in processing.

Furthermore, Hurst exponent and DFA methods are suitable methods for analyzing self-similarity of the EEG signal and the scaling behavior of the fluctuations observed in it. The results obtained from the changes of these two features showed that the correlation of the EEG signals for all areas of the head decreased when they listened to the Quran consciously and thus the self-similarity would decrease.

Therefore, the resulting significant changes in the brain signal of Persian-speaking Muslim volunteers who were consciously listening to the Quran could be a result of subjects' religious beliefs that in this stage, unlike the other two, the volunteers were listening to the audio file and their focus was on the speech sound. Whereas, in Q1 and NQ stages, subjects probably filtered out the musical aspects of the auditory stimulus, to find out whether its source was Quran or the other Arabic text. Moreover, their religious beliefs when consciously listening to it has led to significant changes in their brain signals.

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Conflicts of interest

There are no conflicts of interest.

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