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Research Paper

Effect of Psychoacoustic Annoyance on EEG Signals of Tractor Drivers

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The purpose of this study was to evaluate the psychoacoustic annoyance (PA) that the tractor drivers are exposed to, and investigate its effects on their brain signals during their work activities. To this aim, the sound of a garden tractor was recorded. Each driver's electroencephalogram (EEG) was then recorded at five different engine speeds. The Higuchi method was used to calculate the fractal dimension of the brain signals. To evaluate the amount of acoustic annoyance that the tractor drivers were exposed to, a psychoacoustic annoyance (PA) model was used. The results showed that as the engine speed increased, the values of PA increased as well. The results also indicated that an increase in the Higuchi's fractal dimension (HFD) of alpha and beta bands was due to the increase of the engine speed. The regression results also revealed that there was a high correlation between the HFD of fast wave activities and PA, in that, the coefficients of determination were 0.92 and 0.91 for alpha and beta bands, respectively. Hence, a good correlation between the EEG signals and PA can be used to develop a mathematical model which quantifies the human brain response to the external stimuli.

Keywords: EEG; Higuchi; fractal; tractor; sound.

1. Introduction

Today, it may no longer be possible to imagine a work and life environment without noise, and finding such an environment is one of the human dreams. Although humans are accustomed to the presence of noise around them, its effects on the body and the performance of individuals are not hidden from anyone. So far, a lot of research has been done on the impact of sound on body and mind (Van Kamp, Davies, 2013; Sygna *et al.*, 2014; Basner *et al.*, 2014). People working in various agriculture sectors are exposed to many sound sources, including a variety of agricultural machinery and implements. For this reason, noise effects on people working in this sector have been studied by many researchers (Lalremruata *et al.*, 2019; Ghaderi *et al.*, 2019).

Noise annoyance is another crucial issue in the field of sound. Noise annoyance has nothing to do with the users' health and is merely a measure of a user's comfort. For example, the sound may have a low pressure level and therefore not be dangerous to the user, but qualitatively it can create annoying conditions for the user. Thus, in addition to assessing the sound pressure level, it is necessary to consider the effective factors causing noise annoyance (Fujii *et al.*, 2002). For this purpose, the sound quality criteria are needed to express people's mental feelings. Therefore, psychoacoustics was proposed to study the human mental perception of sounds. In fact, psychoacoustics relates the physical properties of a sound to the sensation and perception that arises from it (Allen, 2000). There are several qualitative criteria for the noise annoyance. The most important criteria are loudness, sharpness, roughness and fluctuation strength (Fastl, Zwicker, 2007).

In recent years, much research has been done to find a model of noise annoyance. Using jury test and regression analysis, some models have been proposed. Meanwhile, a model called psycho-acoustic annoyance was introduced (Fastl, Zwicker, 2007). So far, several studies have been conducted on the effect of sound quality parameters on people's performance, such as cars (Nor *et al.*, 2008), trains (Park *et al.*, 2015), agricultural machines (Lashgari, Maleki, 2016), construction machinery (Carletti *et al.*, 2011), ships (Han, 2012), and aircraft (Janssens *et al.*, 2008). Therefore, it can be seen that the issue of sound quality and noise annoyance is still of interest to researchers.

In recent decades, another important topic that has attracted the attention of ergonomic researchers is the assessment of physiological changes of individuals in the working environment. To measure the physiological changes of individuals, various methods can be used, including the electroencephalography (EEG). The EEG method directly evaluates the electrical activity of the human brain and reflects all the physical and mental activities of individuals. EEG signals are divided into five major frequency bands. These frequency bands are called delta, theta, alpha, beta, and gamma. The delta waves lie within the range of 0.5–4 Hz and are mostly associated with deep sleep. The theta waves lie within the range of 4–8 Hz and are associated with drowsiness or deep meditation. The alpha wave is a fairly regular pattern between 8 and 13 Hz. This wave is associated with relaxed, alert state of consciousness. The beta activity, which is an irregular pattern between 13 and 30 Hz, occurs mostly during alertness and active thinking, active attention and solving problems. The frequencies above 30 Hz correspond to the gamma range. This rhythm can be used for confirmation of certain brain diseases (Dietrich, Kanso, 2010; Sanei, Chambers, 2013; Jiang *et al.*, 2019).

Several studies have been performed on oscillatory brain activity while the participants were exposed to auditory and visual stimuli. So far, different frequency bands were used to measure brain activity in response to auditory stimuli. Studies have indicated that the delta, theta, alpha, beta, and gamma bands are influenced by auditory stimuli (Mazaheri, Picton, 2005; Lippé *et al.*, 2009; Hettich *et al.*, 2016; Mai *et al.*, 2016).

Because the brain has a nonlinear dynamic structure, the brain signals are also complicated and nonlinear in nature (Korn, Faure, 2003). Therefore, one of the most appropriate ways to describe the brain function is to use a nonlinear analysis based on the chaos theory (Khodabakhshi, Saba, 2018). One of the most essential features for evaluating the turbulence of a signal is measuring complexity using the fractal dimension (Mohammadi *et al.*, 2018). When fractal geometry was introduced by a French mathematician named Mandelbrot, it attracted many researchers. It was used to interpret complex natural phenomena in various fields of science and engineering. In fractal geometry, complexity is expressed by a number called the fractal dimension. There are various algorithms for calculating the fractal dimension, such as Katz, Higuchi, Petrosian, and Box Counting.

People react to external stimuli such as sound, vibration, light, and so on. By analyzing the reactions, we can determine the positive or negative effects of stimuli on humans and their behaviour. Since psychoacoustics is the human mental perception of sound, the effect of sound quality parameters on the brain signals is also important. Therefore, the effect of parameters such as loudness, sharpness, roughness, and fluctuation strength on some bands of the EEG has been studied. The results show the correlation between loudness and alpha band (Lee *et al.*, 2013).

Since most garden tractors do not have cabs, the drivers of these vehicles are exposed to the direct sound. Therefore, it is essential to be aware of the effects of sound on them. The purpose of this study was to evaluate the psychoacoustic annoyance that the tractor drivers are exposed to, and investigate its effects on their brain activity during their work activities.

2. Material and methods

2.1. Equipment

In this research, the sound of a garden tractor (Goldoni 341) with a 3-cylinder engine and 41 horsepower was recorded. The tests were carried out at five engine speeds. Recording the sound signals was done at the driver's ear position. For this purpose, the measurement microphone (MP201 model) was placed horizontally on a tripod at an elevation appropriate to the driver's ear position.

2.2. Participants

Sixteen healthy males with an average age of 29 years and right-handed volunteers participated in this study. All participants reported normal hearing and no medical problems. The participants were asked to close their eyes to avoid unwanted activity such as eye blink/movement (Chen *et al.*, 2017). First, the EEG data of each participant was recorded in a quiet room (rest mode). Then, they were asked to sit next to the tractor (to eliminate the effects of other parameters such as seat vibration) and listen to the emitted sound (Fig. 1). At this stage, the participants were exposed to the tractor sound at five different engine speeds. This study was approved by the Ethics Committee of Arak University.

a)

b)

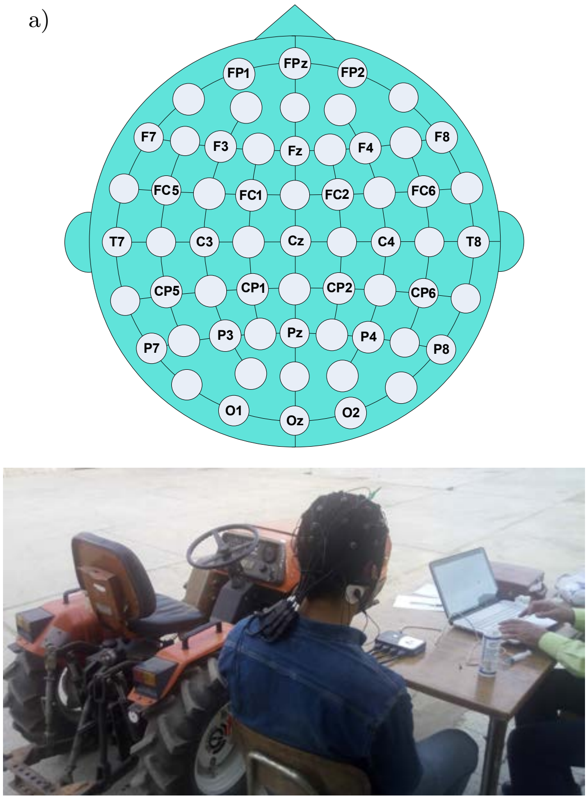

Fig. 1. Electrodes position (a) and experiment setup (b).

2.3. Electroencephalogram

At each stage, the data was stored for 29 electrodes FP1, FPz, FP2, F7, F3, Fz, F4, F8, FC5, FC1, FC2, FC6, T7, C3, Cz, C4, T8, CP5, CP1, CP2, CP6, P7, P3, Pz, P4, P8, O1, Oz, and O2 for 120 seconds (Fig. 1). The reference region was linked at the right earlobe and the ground electrode was placed at AFz. To record the brain signals, the eWave32D was used at a sampling rate of 1 kS/s, 24-bit resolution, with a standard 10–20 hat.

After recording the data, all the intrusive artifacts such as blinking, eyeball movement, facial muscle movement, electrode movement on the scalp, and 50 Hz noise were removed using MATLAB software R2016. In order to noise removing, discrete wavelet transformation (DWT) was used. In this study, each signal is decomposed by DWT to 8 levels using a mother wavelet of Daubechies 8 (db8). The db8 function is widely used for removing artifacts from EEG signal (Nagabushanam *et al.*, 2020; Luo *et al.*, 2016). The 8 level decomposition of EEG signals resulted in one approximation and eight details coefficients. Thresholding functions are then applied to remove noise using noise thresholds. Finally, the EEG denoised signal is reconstructed using inverse discrete wavelet transform. After removing the artifacts, the signals were decomposed into the frequency bands delta, theta, alpha, beta, and gamma.

2.4. Psychoacoustic annoyance

Psychoacoustic annoyance was proposed for the first time by Zwicker and Fastl. The PA's value is calculated from N_5 loudness (the loudness value reached to or exceeded from 5% of the measurement time and was calculated by statistical analysis), sharpness, roughness, and fluctuation strength together. The formula for the psychoacoustic annoyance reads as follows (Zwicker, Fastl 2007):

$$\mathrm{PA} = N_5\left(1 + \sqrt{\omega_S^2 + \omega_{FR}^2}\right), \tag{1}$$

where N_5 is percentile loudness in sone.

$$\begin{aligned} \omega_S &= (S - 1.75)0.25\log(N_5 + 10) \\ &\qquad\qquad \text{for } S > 1.75 \text{ acum}, \\ \omega_S &= 0 \qquad\qquad \text{for } S < 1.75 \text{ acum}, \end{aligned} \tag{2}$$

$$\omega_{FR} = \frac{2.18}{(N_5)^{0.4}}(0.4F + 0.6R), \tag{3}$$

where S is sharpness in acum, R is roughness in asper, and F is fluctuation strength in vacil. All details concerning these metrics are described in other researches (Lee *et al.*, 2013; Lashgari, Maleki, 2015). Based on these equations, specialized software is designed and presented to calculate the mentioned metrics. In this research, LabView software was used.

2.5. Higuchi's fractal dimension

In this work, the HFD method was applied for the EEG analysis. HFD is a fast algorithm to estimate the fractal dimension of time series signals such as EEG. This algorithm also provides a more accurate measure of the signals' complexity compared to other methods (Al-Nuaimi *et al.*, 2017; Mohd Radzi *et al.*, 2019).

The method for calculating the HFD of a signal is presented in detail in other papers and the readers are referred to a review on this method, and its application (Kesić, Spasić, 2016). However, this algorithm is briefly described below.

If $x(1), x(2), ..., x(N)$ is the time series under analysis, the new time series X_k^m is defined as:

$$\begin{aligned} X_k^m :\ & x(m), x(m+k), \\ & x(m+2k), ..., \left(m + \mathrm{int}\left[\frac{(N-m)}{k}\right]k\right), \\ & m = 1, 2, ..., k, \end{aligned} \tag{4}$$

where m and k are initial time and time steps, respectively.

The length $L_m(k)$ of each curve X_k^m is calculated as follows:

$$L_m(k) = \frac{1}{k}\left[\frac{N-1}{\mathrm{int}\left(\frac{N-m}{k}\right)k} \cdot \left(\sum_{i=1}^{\mathrm{int}\left(\frac{N-m}{k}\right)} |x(m+ik) - x(m+(i-1)k)|\right)\right]. \quad (5)$$

Total average length, is computed for all series for each k (ranging from 1 to $k_{\max}$):

$$L(k) = \frac{1}{k}\sum_{m=1}^{k} L_m(k). \quad (6)$$

Then, in the plot of $\ln(L(k))$ versus $\ln(1/k)$, the estimate of HFD is given by the slope of the least-squares linear fit.

Time step is a free parameter and fractal dimension increases as this parameter grows and reaches a constant value for $k > k_{\max}$. The point at which fractal dimension plateaus is considered to be the value of $k_{\max}$ (Zappasodi *et al.*, 2015). In this work, $k_{\max}$ was found to be equal to 70.

3. Results

Table 1 shows sound quality metrics and sound pressure level (SPL) at different engine speed.

The results of the PA are presented in Fig. 2. The ascending trend of PA is visible due to an increase in engine speed. Comparison of means at 5% probability level shows a significant difference between the mean values of PA. The average PA in this tractor is 6.97, with a standard deviation of 1.56. The highest PA value was obtained at speed 5, which is 89.4% higher than speed 1.

To evaluate the HFD changes due to the increase of engine speed, the HFD averaged across all electrodes and all subjects. Therefore the HFD value of all 29 electrodes was calculated for each subject, and finally, the average HFD for all subjects was determined separately for each frequency band.

The mean HFD in different stages for each band is shown in Fig. 3, separately. As can be seen from this figure, in the frequency bands, except for the delta

Table 1. Sound pressure level and sound quality metrics at different engine speed.

	1	2	3	4	5
SPL [dB]	90.32	90.27	90.87	91.43	92.16
Loudness (sone)	3.61	5.00	5.51	5.81	7.00
Sharpness (acum)	1.43	1.67	1.72	1.75	1.84
Roughness (asper)	0.10	0.14	0.20	0.22	0.20
F.Strength (vacil)	0.11	0.09	0.08	0.07	0.07

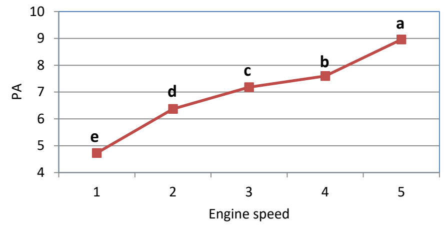

Fig. 2. PA values in different engine speeds.

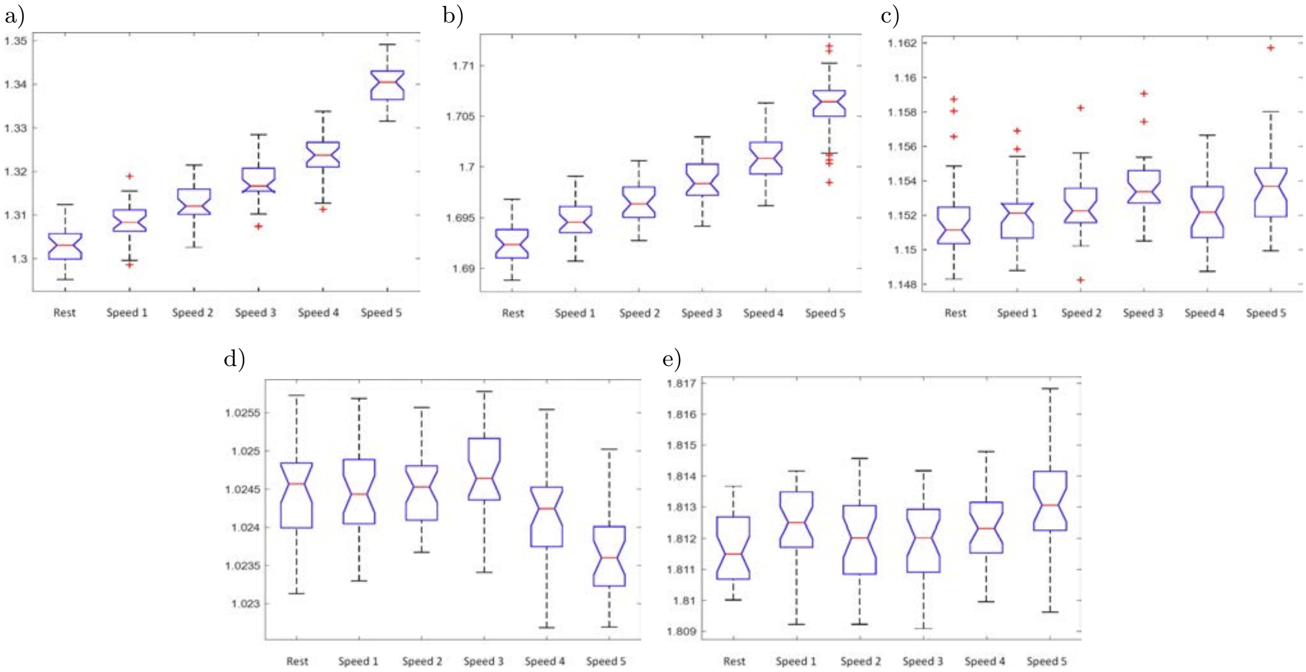

Fig. 3. Mean HFD in different stages for each band: a) alpha; b) beta; c) theta; d) delta; e) gamma.

band, the mean HFD of different engine speeds has increased compared to the rest stage. Although there is no definite trend in theta, delta, and gamma bands, the general trend of the graphs represents the increase of mean HFD of the alpha and beta bandwidth due to an increase in engine speed. For the theta and delta bands, fluctuations are seen in the mean HFD of different engine speeds.

The mean HFD at the first stage (rest) and the last stage (speed 5) is shown in Fig. 4. In this figure, the mean HFD of the last stage also increases compared to the first stage. According to Table 2, the effects of stages were significant at a level of 5%. The last stage, which has the highest PA, shows an increase in mean HFD in most electrodes. In just six electrodes, 3 (FP2), 4 (F7), 8 (F8), 9 (FC5), 10 (FC1), and 12 (FC6), the mean HFD in the last stage is lower than in the first stage. As the figure shows, half of these six electrodes are in the frontal lobe and the other half are in the central lobe of the brain. According to Fig. 1a, it can be seen that these six electrodes are located almost symmetrically in both hemispheres of the brain.

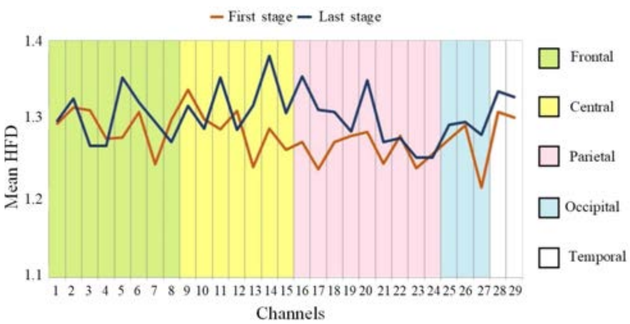

Fig. 4. Mean HFD of 29 electrodes for all subjects at first and last stages.

Table 2. Analysis of variance of data on mean HFD.

Source	SS	df	MS	F	Prob > F
Stages	0.00946	1	0.00946	9.81	0.0028
Error	0.05401	56	0.00096		
Total	0.06347	57			

To compare the results of the first and last stages, the HFD averaged across all frequency ranges. Figure 5 shows the brain map of mean HFD for the first and last stages. Besides, the difference between the two stages is shown. As can be seen from the figure, the fractal dimension of parts of the frontal, central and parietal lobes increased in the last stage compared to the first stage when the PA level reached a maximum. The symmetry seen in the first stage brain map is not seen in the last stage.

To more closely examine the relationship between the sound and brain activity of the subjects, the regression between the PA and different bands was performed separately, and the results are shown in Table 3. As can be seen, there is a high correlation between the alpha and beta bands, and PA. In some studies, in addition to evaluating each band individually, different relative algorithms have been proposed to examine the state of brain activity (Chen *et al.*, 2013; Eoh *et al.*, 2005; Jap *et al.*, 2009). In this study, some algorithms were used and the results of the regression between PA and these algorithms are shown in Table 3. The result indicates that none of these algorithms improved the coefficient of determination.

Table 3. Correlation between PA and different bands and algorithms.

Bands and algorithms	R^2
α	0.92
β	0.91
θ	0.53
δ	0.46
γ	0.26
β/α	0.90
θ/α	0.86
θ/β	0.77
γ/δ	0.39
$(\alpha+\theta)/\beta$	0.77
$(\gamma+\beta)/(\delta+\alpha)$	0.92
$(\alpha+\theta)/(\alpha+\beta)$	0.69

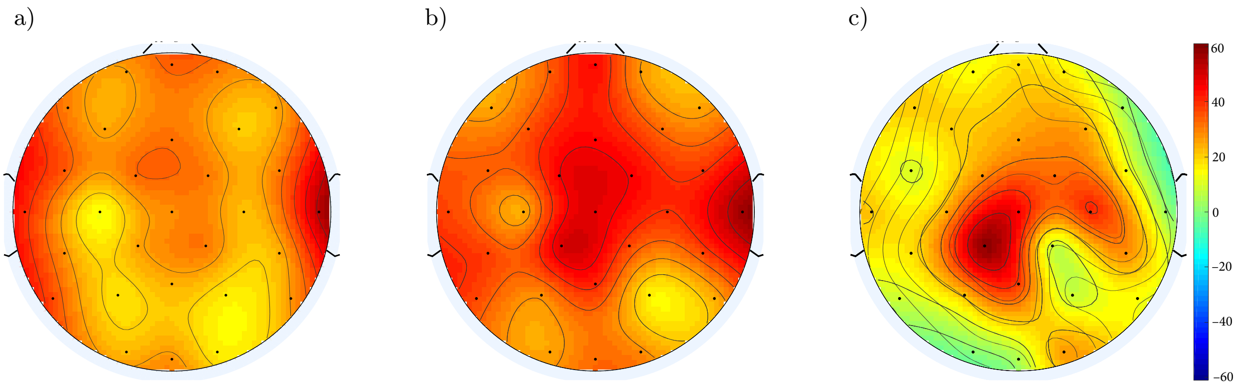

Fig. 5. Brain mapping for the first stage (a), last stage (b) and difference (c).

4. Discussion and conclusion

In this study, a garden tractor whose engine is very close to the driver was used. Since the tractor does not have a cab, the sound of the engine as one of the main sources of sound reaches the driver directly. An increasing trend of PA was observed due to the increase of engine speed. Changing the values of sound metrics due to changes of the engine speed is logical, as reported in other studies (Siano *et al.*, 2015; Liu *et al.*, 2015). Since PA is formed from these criteria, PA's change is due to a change in the engine speed.

In this study, it was decided that the participants were exposed to the sound of the tractor directly. In order to eliminate the effects of other parameters such as seat vibration, the participants were requested to sit next to the tractor. Therefore, lateralization is the limitation of this study.

Since the participants were only exposed to the engine sound, the changes observed in HFD can be attributed to differences in PA. A similar result has been reported for increased HFD of the brain signals when exposed to sound stimuli (Gladun, 2020). However, the effect of sound on human brain activity has also been reported in other studies. Studies have shown that human exposure to pleasant and unpleasant tones affects different areas of the brain (Banerjee *et al.*, 2016). A noisy work environment can also cause changes in brain signals (Bhoria *et al.*, 2012). According to the results, the two alpha and beta bands had the greatest effect in this regard. The effect of the external stimuli on the alpha and beta bands has also been expressed in other studies (Bhoria *et al.*, 2012; Yeo *et al.*, 2009).

According to the results, in most electrodes, the mean HFD of the last stage, which has the highest PA level, is higher than the first stage. In many previous studies, midline scalp sites have been used to record auditory activity (Atli *et al.*, 2019; Neuhaus *et al.*, 2009; Kropotov *et al.*, 2000). Among midline electrodes used in this study, only electrode 22 (Pz) was unchanged in two stages. At the other four electrodes, the mean HFD of the last stage is higher than the first stage.

The maximum difference between the two stages is also related to the electrodes of the two central and parietal lobes. The motor and somatosensory cortexes are located in these areas. These cortexes are significantly more involved in the cognitive information processing and functional control than other regions of the brain (Zhang *et al.*, 2018). The results of other studies have shown that in the drowsiness phase, the activity of neurons in both motor and somatosensory cortex decreases and leads to significant changes in EEG signals (Zhang *et al.*, 2018).

Since increasing the sound level leads to the irregularity of signal, it can be concluded that the disturbance rate of the wave rises for high level sounds. Therefore, the fractal dimension of the sound will increase in proportion to the increase in engine speed (Boroujeni, Maleki, 2019). On the other hand, research has shown that the fractal dimension of the biological signals is correlated with the fractal dimension of the external stimuli. Increasing the fractal dimension of the external stimuli increases the fractal dimension of the biological signals. Research has also been done on the fractal dimension of the sound stimuli on the fractal dimension of the brain signals (Namazi, 2018; Sink *et al.*, 2011). Therefore, the increase in the fractal dimension of the last stage by increasing the engine speed is consistent with the results of the other research.

As other findings confirm, an increase in the fractal dimension is associated with an increase in the complexity of the neural activity (Hinrikus *et al.*, 2011; Pavithra *et al.*, 2014; Vega, Noel, 2015; Kesić, Spasić, 2016). Complexity is assumed to be synonymous with the functioning of the brain system. Complexity in nervous systems is related to the functional benefits such as high flexibility, rapid adaptation to the environment, and system dynamics (Zappasodi *et al.*, 2015). On the other hand, the reduction in brain complexity can be interpreted as a reason for reducing the brain's ability to continue a task. The reduction in brain complexity can be explained by the functional isolation of the neurons with greater independence of the brain components (Xu *et al.*, 2018). This is why decreased EEG complexity has been linked to dysfunction in the neurological injuries such as Alzheimer's disease (Zappasodi *et al.*, 2015).

Other studies have shown that FD in the wakefulness is increased compared to the drowsiness state (Klonowski *et al.*, 2005; Pavithra *et al.*, 2014). Due to the decreased brain activity in drowsiness, sleepy drivers lose the ability to make decisions and cannot respond quickly to external stimuli (Mardi *et al.*, 2011). On the other hand, sound can cause mental stress in people. Research has shown that the alpha and beta bands are related to stress and rapid brain activity such as decision making, analysis, and information processing (Banerjee *et al.*, 2016). Measuring changes in the alpha and beta bands is one way to detect stress through brain signals (Sulaiman *et al.*, 2011). Also, acoustic stimuli are often used as stressors to measure stress (Nishifuji *et al.*, 2010).

Low levels of HFD in the first stage (rest) in Fig. 4 show that participants are in a stress-free and relaxed position. The HFD values increased after sound exposure. This increases the brain activity and alertness. In some studies, a quiet environment has been used to accelerate drivers' drowsiness, because a quiet environment can make people drowsy (Mardi *et al.*, 2011; Samiee *et al.*, 2014; Kong *et al.*, 2011). Therefore, it can be concluded that sound can prevent drivers from falling asleep and increase their focus on their tasks.

The delta and theta bands are regarded as slow wave activities, while the alpha and beta bands are considered the fast wave activities (Jap *et al.*, 2009; Zhang *et al.*, 2018). Results showed that there is a high correlation between the fractal dimension of fast wave activities and PA. However, there is a weak correlation between the fractal dimension of the slow wave activity and PA, and in algorithms that include slow wave activity, this weak correlation is also seen.

However, the research has shown that a small fractal dimension indicates resting state and the environmental sounds increase brain activity and consequently the fractal dimension of brain signals (Bojić *et al.*, 2010). Increasing the fractal dimension is a sign of alertness and will cause the driver to react quickly (Mohd Radzi *et al.*, 2019). Therefore, it can be said that in cases such as driving, the presence of sound can to some extent prevent the driver from falling asleep and increase the driver's concentration, and reaction speed, though the other aspect of sound that causes severe injuries to people should not be ignored. However, in this study, the sound pressure level in the driver's ear position was less than 80 dB, which according to all standards, will allow the driver to work 8 hours a day.

In conclusion, the HFD method may not be the simplest and the most effective method for analyzing the EEG signals; still, the speed, accuracy, and cost of using the HFD method have made it widely useful for medical research and diagnosis. However, the use of HFD combined with other linear and nonlinear methods will lead to better results (Kesić, Spasić, 2016). The results of this research show that the PA model has a high correlation with the alpha and beta bands. The early detection of the driver's fatigue and drowsiness can effectively prevent accidents, so, the use of the PA model in this regard can be useful and further research in this area is suggested. An important result of investigation the correlation between the EEG signals and PA is that the analysis could potentially be used in the development of mathematical models that relate human reaction to external stimuli.

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