Original Article

The Relation between Chaotic Feature of Surface EEG and Muscle Force: Case Study Report

Abstract

Background: Nonlinear dynamics, especially the chaos characteristics, are useful in analyzing bio-potentials with many complexities. In this study, the evaluation of arm-tip force estimation method from the electroencephalography (EEG) signal in the vertical plane has been studied and chaos characteristics, including fractal dimension, Lyapunov exponent, entropy, and correlation dimension characteristics of EEG signals have been measured and analyzed at different levels of forces. **Method:** Electromyography signal was recorded with the help of the BIOPEC device (the Mp-100 model) and from the forearm muscle with surface electrodes, and the EEG signals were recorded from five major motor-related cortical areas according to 10–20 standard three times in a normal healthy 33-year-old male, athlete and right handed simultaneously with importing a force to 10 sinkers weighing from 10 to 100 Newton with step 10 Newton. **Results:** The findings confirm that force estimation through EEG signals is feasible, especially using fractal dimension feature. The R-squared values for Fractal dimension, Lyapunov exponent, and entropy and correlation dimension features for linear trend line were 0.93, 0.7, 0.86, and 0.41, respectively. **Conclusion:** The linear increase of characteristics especially fractal dimension and entropy, together with the results from other EEG and neuroimaging studies, suggests that under normal conditions, brain recruits motor neurons at a linear progress when increasing the force.

Keywords: *Brain, dynamic, electroencephalography, force estimation, motor control, signal complexity*

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Introduction

One of the ways to check the performance of the muscle in the body and also to estimate the amount of force of it is to record and process electromyography (EMG) signals. There are some problems related to EMG signal and recording of it that can be invasive and painful and need for existence physicians specialize in signal recording to prevent damage to the nerve and muscle, as well as the correct selection of the desired muscle, or in a noninvasive manner that is superficial and the deeper muscular signal is not accurately recorded and it can interfere with the signals and noise of adjoining muscles.

In the field of motor control, it is a basic problem to quantify the brain signal that modulates the force in a motor task: One of the few available and powerful is electroencephalography (EEG).[1] In EEG, the strength of the brain signal is typically estimated as the so called movement-related cortical potential (MRCP). It is desirable to find new quantities that can extract more information from the brain signal; one of these quantities can be fractal dimension that is a good candidate because of its intrinsic power in characterizing complexity.

A linear relationship have found between the fractal dimension of EEG and the force of the hand.[1] It is observed that the fractal dimension of EEG is suitable for calculating brain quantities of great complexity. The four factors were evaluated, including force level, physiological period, fractal dimension calculations, and electrode recording. An increase in fractal dimension during the motor activity indicates that the brain increases motor neurons' use and their rate of fire. Therefore, increasing the force will increase the fractal dimension of the EEG signal.[1] It was suggested to assist persons with disabilities by estimating

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force/torque information from the brain activity and estimating the muscle activity by EEG through principal component analysis and recursive least squares methods.[2] The results have shown that the estimation of EMG of EEG is feasible, and this indicates the high potential of EEG to assist in the analysis of muscle activity.[2]

Some research have been done on the relationship between cortical motor activity and voluntary muscular activity and concluded that with increased muscle activity and strength, MRCP range increased, and there is a strong correlation between force and MRCP.[3] The effect of force and movement on the magnitude and increasing of brain signals have been studied and shown that the rate of EEG changing and its correlation with muscle activity depend on the amount of using force and motions of the head or body and have a regular pattern, the result is that EEG signal is directly related to force and movement.[4]

It is stated that nonlinear dynamics has recently been widely used to analyze the biological data.[5] Their results show that systemic variations of EEG signal are significantly correlated with muscle strength and fatigue. A study has been showed that a positive relationship is observed between the strength of EEG signal source and hand compression force at the time of simultaneous EEG signal recording. There is communication over a short period of time.[6] A study has been conducted of hand motion reconstruction using EEG and EMG signals. In this study, the focus is on assistive devices and prosthetics for arm cuts that EEG and EMG signals have been recorded and reconstructed using a noninvasive method, and hand motion reconstruction was performed using the high-precision neural network algorithm.[7] They have shown that synchronization of EEG and EMG signal in the beta range is directly related to varying degrees of subjective consideration, and the amount of contraction and the peak of signals' coordination in the beta range is in high consideration and maximum contraction.[8] A study called multivariate autoregressive modeling has been performed to analyze the interaction between EEG and EMG signals in the human body and showed that the interaction of information from the brain to muscle was delayed in appropriate physiological conditions with little delay.[9] A study of upper limb function estimation using EEG and EMG signals has been done and stated that EMG are widely used in the control of limb-bound robots to estimate individuals' intention to move and perform movement.[10] It is important to use the brain signals to estimate muscle strength, especially when it is not possible to record EMG signal.[11] Reached the existence of chaos phenomena in the Two-Link Arm driven by six muscles model controlled with reinforcement learning that using tools such as bifurcation maps, Lyapunov exponents, phase-plane trajectories, and spectral analysis using fast Fourier transform. The results yield that chaos phenomena may occur in the overall system by changing the some

internal parameters of muscles that have a physiological explanation.[12]

In patients with spinal cord and paralysis in organs, especially neck paralysis, organs are involuntary, and it is not possible to measure and estimate muscle force voluntarily, but if force can be achieved through the noninvasive EEG signal, it can stimulate and move the individual's organs as much as needed by later external stimuli. This method has ambiguous or obscure points, such as whether the correlation between the two signals is such that one can obtain the desired features to calculate the force or whether the specified points are appropriate for recording an EEG signal or what areas of the cerebral cortex are most suitable for testing and whether there is a relationship that leads to the discovery of a precise and generalizable relationship for all individuals between the two signals. In this study, it was tried to overcome the previous problems of methods to estimate muscle force from EMG signal and improve them, the correlation between EMG and EEG signals was evaluated to study the feasibility of muscle force estimation by EEG signal. Chaos features of EEG were extracted in this study. The theory of chaos has been one of the scientific researches of various fields in recent decades, but in fact, its simple concept is rooted in the basic human perceptions of the world. From the point of view of chaos theory, complex systems are merely chaotic in appearance, and as a result, appear irregular and random, while they may be a result of a given function with a definite mathematical formula.[11]

Complex time series, such as received signals from the brain, are assumed to be unpredictable. While these series are likely to be the result of a certain dynamic nonlinear process, or rather chaotic, and therefore, they will be predictable. Many traditional analysis tools analyze these signals assuming it is unpredictable, while in fact, the occurrence of targeted behaviors in biological systems contradicts it.

Methods

Subject and motor task

One healthy 33-year-old right-handed male was participated in this study. The individual was asked to raise each weight 10 times in a 2 min period with a 2 s interval to raise and lower the weights and 1 s rest between each contraction in a vertical direction at an angle of 90° upward by the forearm. He was also asked to relax without distraction and with full focus on avoiding blinking, shaking his head and body, mouth and jaw, talking, squeezing teeth and lips while raising weights. Furthermore, disturbing factors of focus such as driving light and noise were eliminated from the environment. After each contraction, the muscles were rested for 30 min. This was done for ten different weights of 10–100 Newton with step 10 Newton over a day, the

weights have been applied in sequential order from lowest weight to highest and then the same procedure was repeated over the next 2 days. At the end of the 3rd day of the signal recording, another signal recording with the same weights was performed in the form of contraction for each weight as the test signal recording so that after performing the investigation and obtaining the force estimation relation; this signal was used as the test signal. After recording the signals and completing the task, the recorded EMG signal and EEG signal obtained from the beta band were transferred to MATLAB R2017a to perform processing and feature extraction.

Data recording

Electromyogram

Surface signal recording was performed by two electrodes on the forearm and a reference electrode in the wrist area for EMG signal recording. EMG of muscles was obtained from BIOPAC system, Model MP150 (Biopac Systems, 2010). The subject was asked to sit behind a special table. The height of this table is adjustable that the shoulder and the person's body meet a 90° angle. He has no neuromuscular problems. Ag–AgCl surface electrodes were used to record EMGs. For bipolar recording, the electrodes of 8 mmAg–AgCl BIOPAC-EL208S were attached to the subject's skin. The EMG signals were obtained by 5000 gain factor amplifiers (BIOPACEMG100A) with a sampling rate of 1 kHz.

Electroencephalogram

EEG signals were recorded from scalp at five cortical locations. These five locations roughly overlaid major cortical sensory motor regions involved in motor control and exhibited prominent MRCP: The contralateral (C3) and ipsilateral (C4) primary sensorimotor cortices, the supplementary motor area (Cz), the central frontal lobe (Fz), and the central parietal lobe (Pz).The electrodes were placed at these locations according to the international 10–20 positioning method. A reference electrode was also attached to the auricle. The Subject was seated in a comfortable chair suitable for his height and weight in front of the BIOPEC device (the Mp-100 model). The scalp at the recording places was first cleaned using alcohol pads. Conductive gel was then applied to connect the recording surface of the electrodes to the scalp. The impedance of each EEG channel was maintained below 10KΩ, determined by an electrode impedance meter. All the metal tools were out of order. He was provided with the proper weights already prepared.

The time taken for recording the signals for each weight was 2 min. The sampling frequency was 1000 Hz. The image of EMG measurement device and a sample of recorded EMG signal are shown in Figure 1, and the image of EMG measurement device and a sample of recorded EEG signal are shown in Figure 2.

Then, the time from rise to the peak of each muscle contraction was determined by muscle-related signals. Chaos features of EEG were also extracted during the time of the rise range to the peak obtained from EMG signal. For each signal, 10 numbers were extracted as the corresponding features, and the mean of the 10 numbers was obtained, and the result was considered as the desired feature for the specified weights and series. The same procedure was done for each of the three recorded signal series and was performed separately for each channel (every 5 channels). Then, according to the tables based on the results, averaging of three series of signal recordings was done, and the amount of standard deviation was calculated and its Error bar graph was plotted and the polynomial trend lines by order 1, 2, and 3 and linear trend were added. A Polynomial equation is always in the form $Y = A_0 + A_1X + A_{2 \times 2} + \ldots + A_kX^K + C$. The number of coefficients can be from 2 to 8A polynomial of order k-1 can be passed through k points, so that more or fewer curves or "'hills" can be added or taken away for accuracy purposes.[13] R-squared value measures the trend line reliability and the near R^2 is to 1, the better the trend line fits the data. This value was calculated for linear trend line and third-order polynomial trend line.

Results

Figure 3 shows the fractal dimension output values in the Fz, Cz, Pz, C3, and C4 channels in three times of the signal recording, with mean values and standard deviations in terms of the amount of force applied to the muscle. The standard deviations are <0.0121. As it can be seen in Figure 3, the numerical values of fractal feature increase with increasing force, with an almost regular rhythm. The average value of all three series of signal recordings is very close to the fixed values and has a small standard deviation.

Figure 4 shows the Lyapunov exponent output values in the Fz, Cz, Pz, C3, and C4 channels in three times of the signal recording, with mean values and standard deviations in terms of the amount of force applied to the muscle. The standard deviations are <0.0254. In Figure 4, the Lyapunov exponent values increase with a relatively irregular rhythm at most force values as the force increases, but decrease at 30 Newton and 80 Newton. The mean values of all three series of signal recordings are close to the fixed values and have a low standard deviation. However, the values of the standard deviation of the data are somewhat increased compared to the standard deviation of the fractal specificity.

Figure 5 shows the Entropy output values in the Fz, Cz, Pz, C3, and C4 channels in three times of the signal recording with mean values and standard deviations in terms of the amount of force applied to the muscle. The standard deviations are <0.0120. In Figure 5, the values of the entropy feature increase with increasing force with a relatively regular rhythm that increases at most force
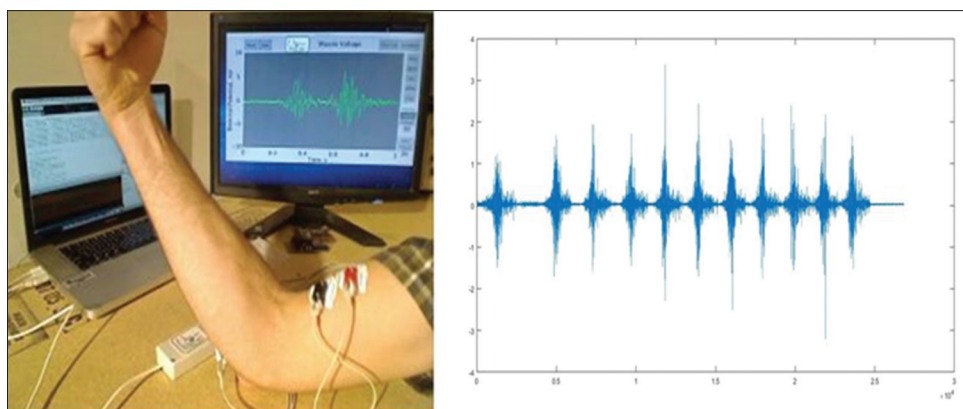
Figure 1: Electromyography measurement device and a sample of recorded electromyography signal
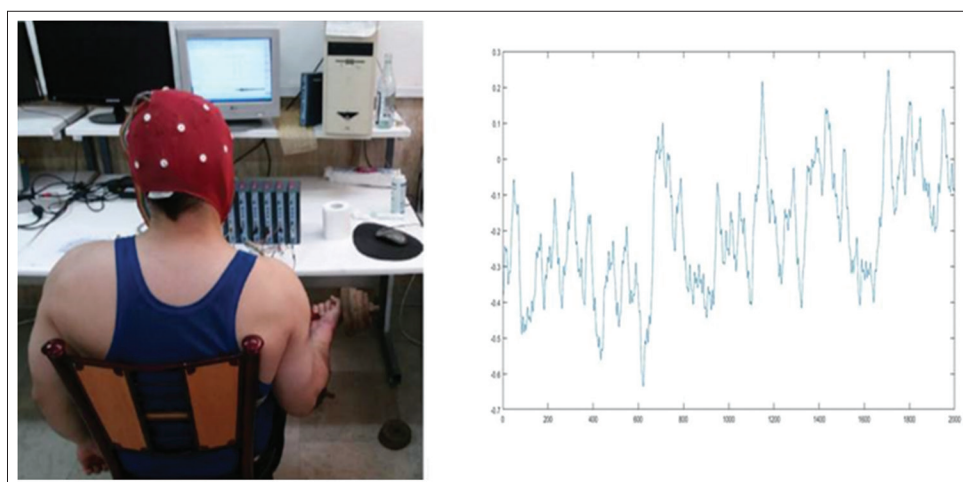

Figure 2: Electroencephalography measurement device and a sample of recorded electroencephalography signal in the beta band

values, but decreases at 70 Newton, but to a large extent can be expressed that in all graphs, as the amount of force exerted on the muscle increases, the entropy increases. The average value of all three series of signal recordings is close to the fixed values and has a small standard deviation. However, the values of the standard deviation of the data are slightly increased compared to the standard deviation of the fractal feature.

Figure 6 shows the correlation output values in the Fz, Cz, Pz, C3, and C4 channels in three times of the signal recording, with mean values and standard deviations in terms of the amount of force applied to the muscle. The standard deviations are <0.0085. In Figure 6, the values of the correlation properties are relatively irregular with increasing force, so that at some values the force is relatively increasing, but decreasing at 50 Newton and 70 Newton, and it cannot be stated that at all curves increase with increasing amount of force applied to the muscle. The average value of all three series of signal recordings is close to the fixed values and has a low standard deviation. However, the standard deviation values of the data are increased compared to the standard deviation values of fractal feature.

Averages were calculated between the five channels for each feature, and the standard deviation was calculated, and then, the error bar graph was plotted to calculate the mean of the different channels for each feature and compare the results. After calculating mean and standard deviation for five channels related to each feature, the polynomial trundling by three orders added to curves in each feature, and the force estimation formula was specified. The different sinkers weights were determined for each feature.

Figure 7 shows the average of fractal dimension, Lyapunov exponent, entropy, correlation dimension values in the Fz, Cz, Pz, C3, and C4 channels, and their standard deviation in terms of the amount of force applied to the muscle and also the polynomial trend lines by order 1, 2, and 3 and linear trend were added. The standard deviations for fractal dimension, Lyapunov exponent, entropy, and correlation dimension are <0.0089, 0.0074, 0.0070, and 0.0035, respectively. In Figure 7, it can be seen that all five cortical locations demonstrated the similar pattern of changes in extracted features. That is, if we examine the results of one of the channels instead of averaging the five channels, the overall result will not be significantly different.
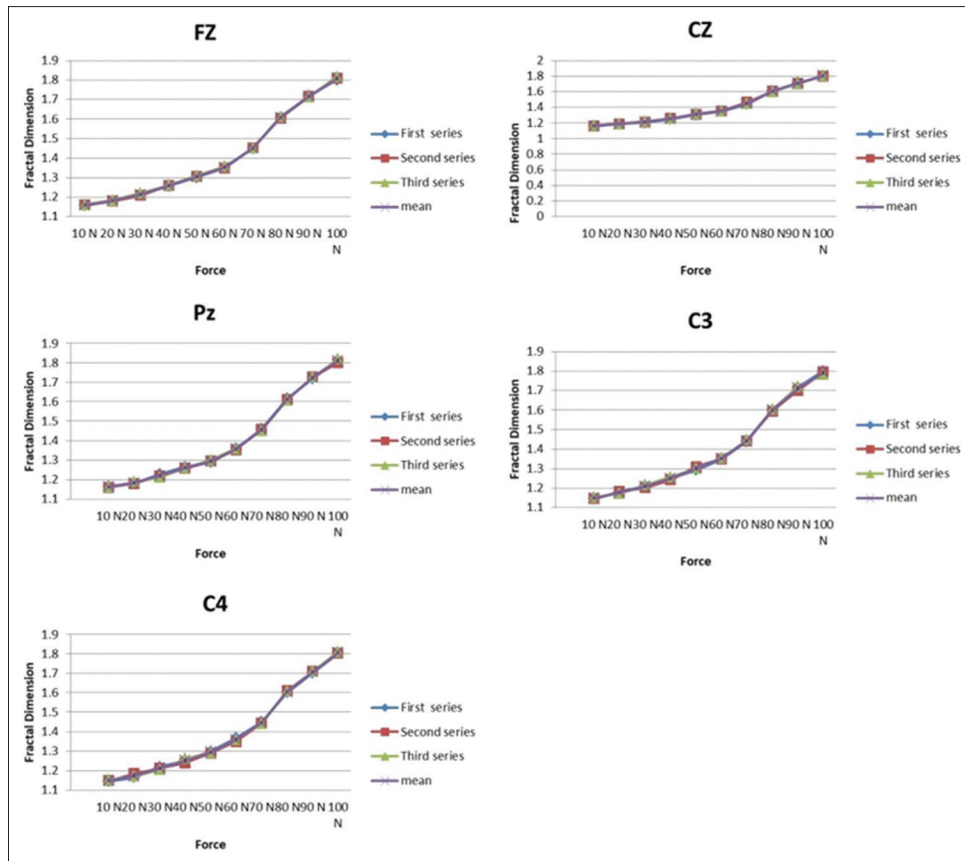
Figure 3: The Fractal dimension output values in the Fz, Cz, Pz, C3, and C4 channels in three times of the signal recording

According to the results obtained by giving the output value of a quadratic feature to the written code with mean data values and weights values, one can estimate a certain amount of force. For a signal recording performed as a test against the device in the laboratory, the fourth series of signal recorded to compare the results of the test series with the previous three series and to verify the results with 10–100 Newton weight at the end of the 3rd day of the signal recording. The output values of the four attributes are shown in Figure 8. As it shown in Figure 8, in comparison with the results of the four extracted properties, the estimation of the force from the fractal feature of EEG signal is more accurate than the other properties and is very close to the original values, indicating a more effective estimation. The force estimation by the entropy feature of EEG signal after the fractal characteristic is also a reasonable estimate. The results of this feature are only somewhat distant from the actual value at 70 N and are almost unacceptable. However, two other properties, correlation and Lyapunov exponent, are relatively acceptable in some estimates, and in others, their estimates are inadequate.

Discussion and Conclusion

The complexity of the EEG signal may be the result of two major parameters including the number of motor neurons that were recruited and their discharge rates. In this study, the values of features derived from the EEG signal including fractal, Lyapunov exponent, entropy and correlation dimension are presented in separate figures. These figures show the values of each feature in each of the five EEG channels in each of the three signal registers, as well as the average graph of the three registrations, along with an Error Bar plot showing the variation of these three registered signals.

Figure 7 suggests that primary sensory motor cortices (C3 and C4) and the higher level association and secondary cortices (Fz, Pz and Cz) modulate a motor task in a highly coordinated manner, which has also been observed in other EEG and neuroimaging studies.[1]

In a study, the chaotic characteristics have been extracted from the brain signal,[1] they only compared the amount of brain activity with increasing force, and a fractal dimension is extracted, they indicated that for the movement and holding periods, the fractal dimension values (in the range of about 1.45–1.75) at all 5 motor-related cortices increased linearly with the handgrip force. The increase are significant under multiple comparisons, the linearity is high (R-squared value ranges from 0.92 to 0.97) but in present study all four chaotic extraction features including fractal, Lyapunov and entropy and correlation are derived for force estimation and obtaining numerical quantification,
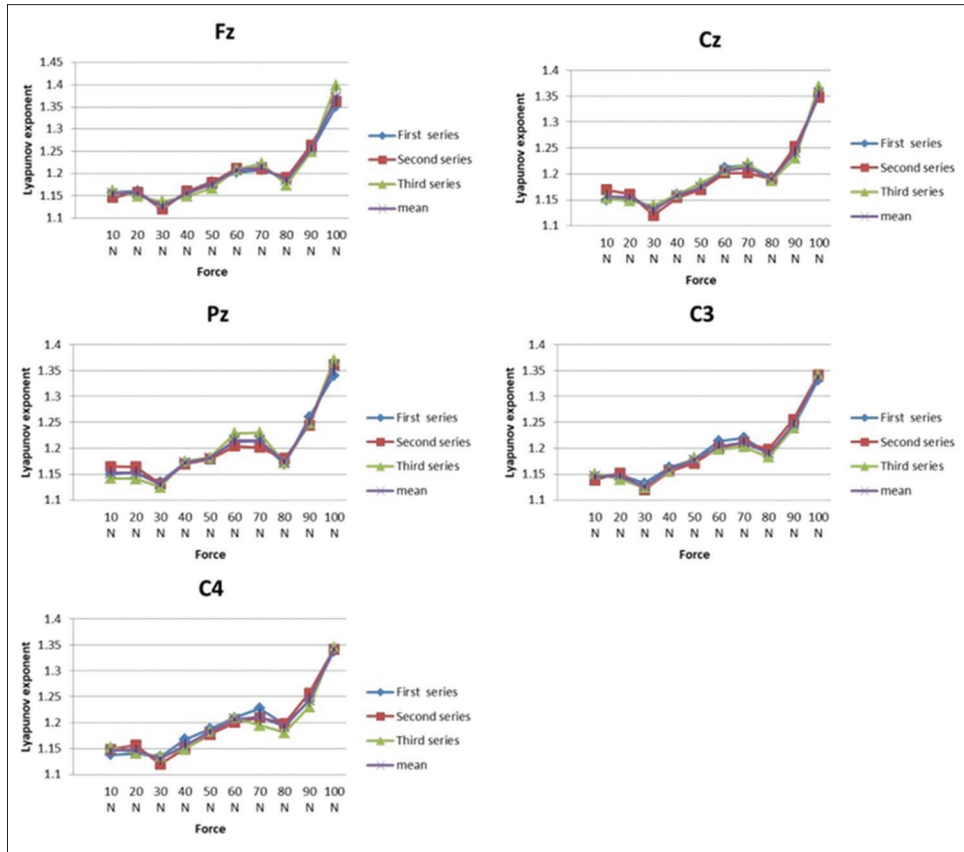
Figure 4: The Lyapunov exponent output values in the Fz, Cz, Pz, C3, and C4 channels in three times of the signal recording
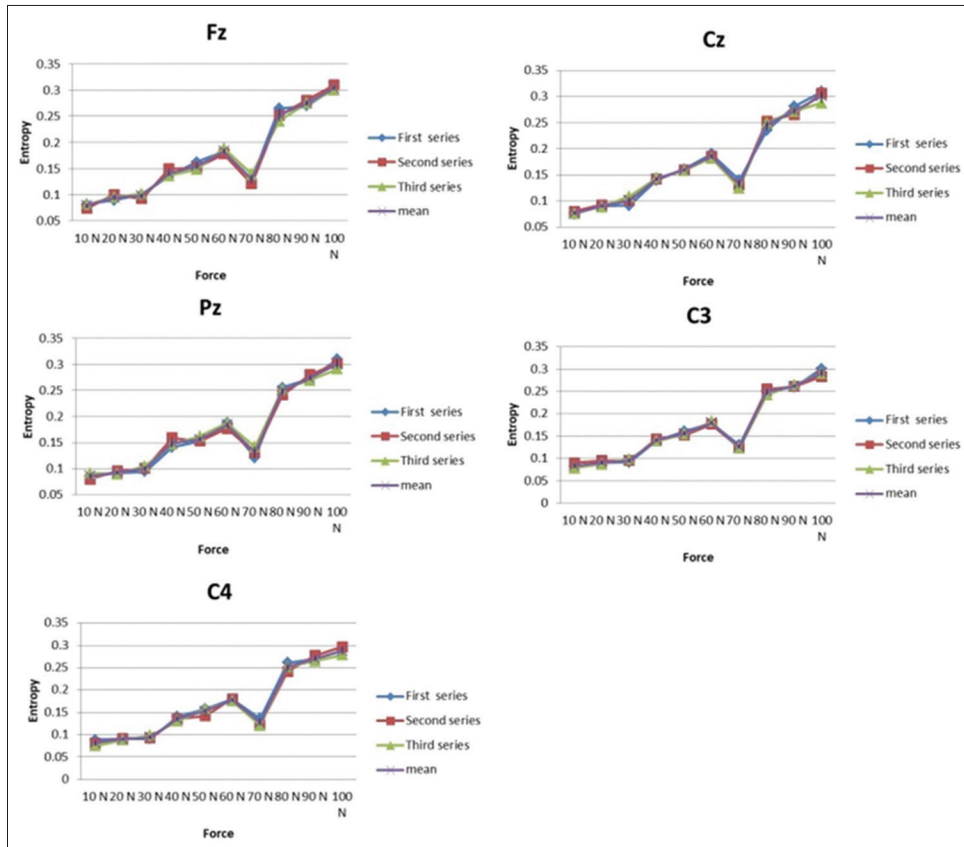

Figure 5: The Entropy output values in the Fz, Cz, Pz, C3 and C4 channels in three times of the signal recording
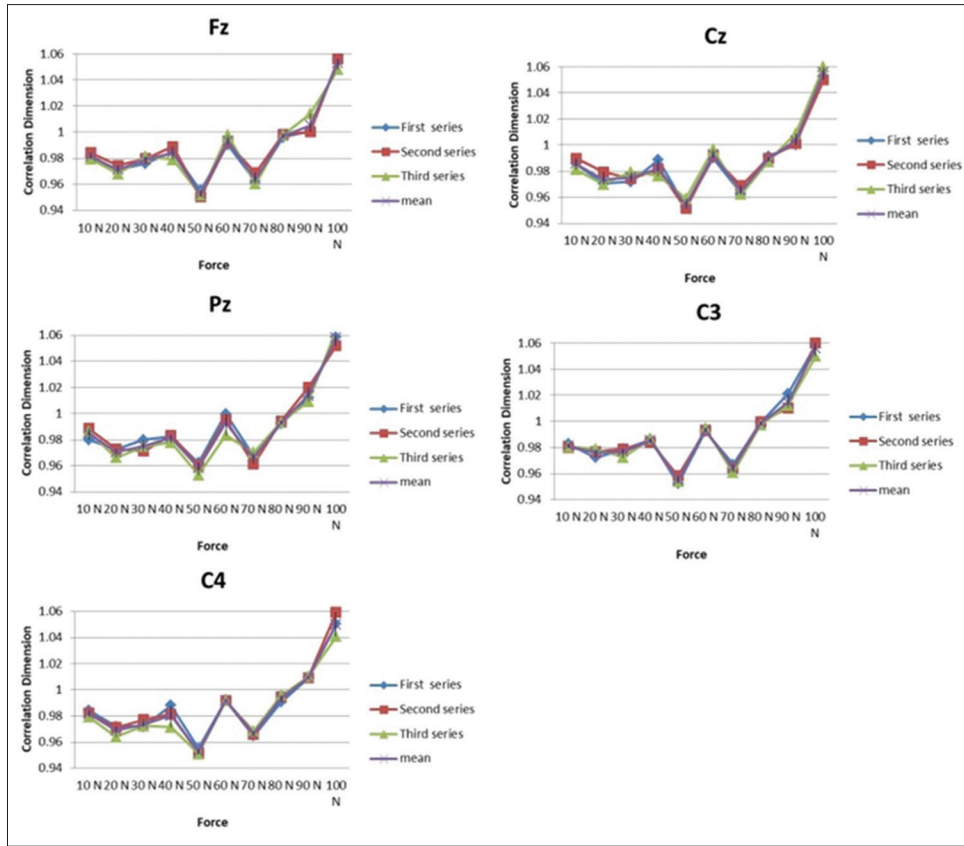
Figure 6: The correlation output values in the Fz, Cz, Pz, C3 and C4 channels in three times of the signal recording
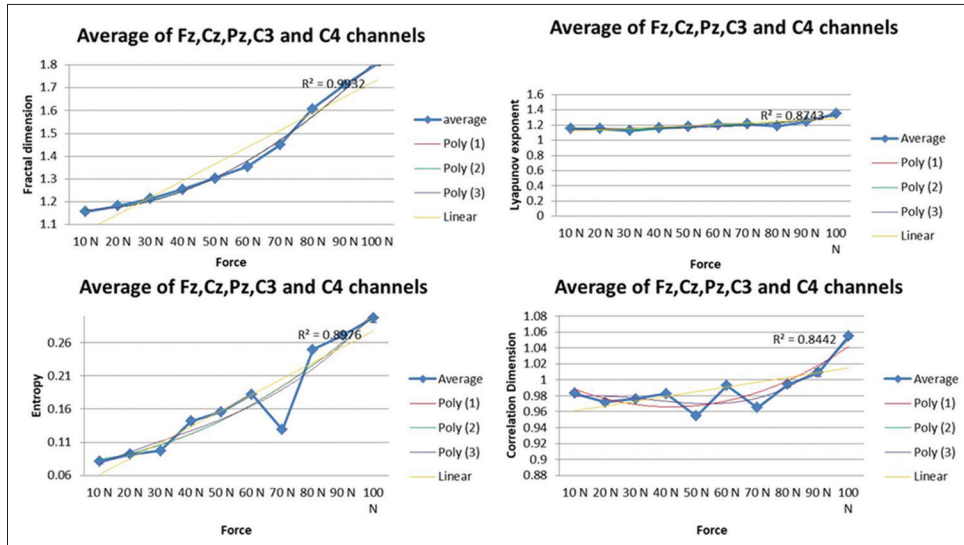

Figure 7: Average of fractal dimension, Lyapunov exponent, entropy, correlation dimension data of FZ, Cz, Pz, C3 and C4 channels and their standard deviation and also the polynomial trend lines by order 1, 2 and 3 and linear trend line. R-squared value is related to third order polynomial trend line

and comparisons were made between feature outputs, and the results were reported as numerical force estimates.

In the present study, EMG signal was used to analyze the brain signal in order to obtain a more accurate estimation, but in the,[2] brain signals were used to estimate and analyze muscle behavior.[4] only compares the relationship

between head and body force in increasing brain activity, and in the present study, a numerical estimation of the force from brain activity has been performed.[6] also states that the relationship between brain activity and muscle strength is quantitatively hypothesized, but this relationship has not been quantitatively investigated. In the present study, EMG signal has been recorded from arm, forearm,
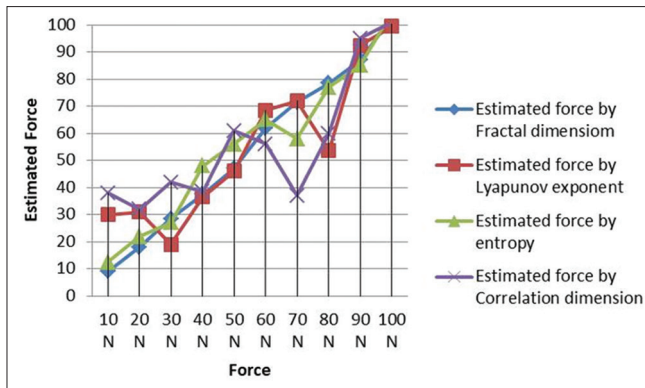
Figure 8: Estimated force by "fractal dimension, Lyapunov exponent, entropy, correlation dimension" of real test force

and fingers at the same time as the force was applied, and the results of[6] were used to record signals of present study. In,[8] it is stated that there is a coordination and coherence between the brain and muscular activities in the beta band with the increase or decrease of the activity. In the present study, the force was estimated by using the Beta-band signal recording with different amount of forces applied to the muscle and the cohesion and coordination of these two fixed signals in the central regions of the head under voluntary contraction.

The R-squared values for Fractal dimension, Lyapunov exponent, and Entropy and Correlation dimension features for linear trend line were 0.93, 0.7, 0.86, and 0.41, respectively. As it shown for fractal dimension and entropy data, the linearity was high.

According to the results of this case study, the Fractal dimension, Lyapunov exponent, and Entropy can serve as a sensitive index for quantifying dynamical changes in EEG signals during the voluntary motor tasks and has a potential to become a useful tool to characterize the patterns of motor-related cortical activities for the purpose of medical research. It is suggested signal recording is done from more people as the target population and include different men and women of different ages and left and right hand people are employed and accurate and comprehensive review of the inaccurate estimation of the correlation and Lyapunov features in some weights are done, as well as the use of other nonlinear dynamics and other properties extracted from the brain signals and compare them with the chaotic features.

Ethical code

IR. IAU. SRB. REC.1396.72.

Conflicts of interest

There are no conflicts of interest.

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