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Zainah Md. Zain · Zool Hilmi Ismail ·
Huiping Li · Xianbo Xiang ·
Rama Rao Karri *Editors*

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Contents

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Fractal Dimension Analysis Demonstrates Overestimation and Underestimation of Time in EEG Signal

Maryam Mollazadeh Azari, Yashar Sarbaz, Behrooz Koohestani, and Ali Farzamnia

Abstract Keeping track of time is regarded as an essential human behavior. The question of how the brain deals with temporal information remains a subject of scholarly debate. The current investigation aims to explore the mechanism underlying time perception by extracting fractal dimension from an electroencephalogram (EEG) signal and its frequency bands. To accomplish this, Higuchi's fractal dimension was calculated for 42 healthy subjects' electroencephalogram (EEG) signal and its sub-bands during the time perception task. The EEG signal was recorded from 19 channels. Subsequently, a statistical analysis was conducted to compare participants who underestimated versus those who overestimated the elapsed time and significantly different channels were presented. The findings suggest an elevated level of fractal dimensionality in persons who displayed a tendency to overestimate time. The EEG signal and Gamma rhythm emerged as the most distinguishing signals between the two cohorts. The contrast in fractal dimension between the two groups was predominantly apparent in the parietal and central channels. To summarize, an increased level of complexity is discernible in the EEG signal and high-frequency rhythms when there is an overestimation of temporal duration. It can be asserted that the employment of FD yields presents an exceptional approach to comprehending cerebral functionalities, notably temporal perception.

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Keywords Complexity · Electroencephalography · Fractal dimension · Time perception

1 Introduction

Time perception has a crucial role in our daily life. Several cognitive and motor functions, including temporal planning, circadian rhythm, and the execution of various activities, are intricately linked to the perception of time. Despite scientists' efforts to understand the neural mechanism used to measure time, the neuroanatomical basis of temporal information remains indecipherable.

The temporal processing mechanism has been studied from different viewpoints, including, perceptual models, functional magnetic resonance imaging (fMRI), and electroencephalography (EEG) analyses.

Gibbon introduced the Internal Clock Model in 1984. Their model comprises several components: accumulator, pulse maker, memory, and comparator [1]. An extension to their model was presented in 1998 by Lejeune et al. emphasizing attention's role in the temporal mechanism. The present model has been designated as the Attentional Gate Model (AGM) [2]. Besides attention, divergent emotional states [3, 4] and levels of arousal may exert an impact on temporal perception [5].

In contrast to other senses, time perception is not assigned to a specific sensory cortex area [6]. To date, it is not clear exactly which brain regions are involved in time perception. However, a sundry collection of neuroimaging research has attempted to elucidate and characterize the mechanisms underlying time perception using different tasks. Considering that fMRI studies could investigate the function of cortical and subcortical brain regions in different tasks, diverse cortical areas such as the dorsolateral prefrontal cortex (DLFC) [7, 8], supplementary motor area (SMA) [9], [10, 11], insula [12], posterior cingulate cortex (PCC), and anterior cingulate cortex were presented as the most influential cortical areas in time perception [12]. On the other hand, subcortical areas such as various nuclei of the basal ganglia namely, putamen [13] and Caudate nucleus [7], cerebellum [14], thalamus [15], and precuneus [16] were presented as the main nuclei of temporal processing.

EEG is a potent tool to probe and explore the brain's functioning. Despite its limitation to recording cortical area activation, given that cortical regions are influenced by the function of subcortical regions, it could be one of the best tools for studying brain function during temporal judgments. Several event-related potentials (ERPs), specifically the Contingent Negative Variation (CNV) [17], P300 [18], and Late Appearing Positive Component (LPC) [19], have been linked to the domain of time perception. A recent study conducted in 2020 posited that during time perception tasks, the alpha and beta power of participants exhibited a reduction, thereby leading to imprecise temporal judgments [20]. A supplemental examination revealed a significant variation in beta rhythm energy while comparing EEG signals of overestimating and underestimating time [21].

Biomedical signals, notably the electroencephalogram (EEG), serve as valuable indicators of the functioning of the brain, which is a highly complex and dynamic system. Effective processing techniques for EEG signals offer supplementary information that can aid in the diagnostic interpretation of neurological disorders. Numerous nonlinear characteristics have been postulated and employed in diverse investigations about pathological conditions.

Brain signals are inherently complex, and the fractal dimension (FD) has emerged as a useful feature for calculating that complexity [22]. In 2020, it has been asserted that since the brain is a complex dynamic system, global characteristics could be utilized to describe its function, particularly how it perceives time [23]. The objective of this manuscript is to create a structure to examine the validity of this hypothesis through the study of FD in the overestimation and underestimation of time.

2 Material and Method

The present study used electroencephalogram (EEG) recordings from a group of healthy participants with either an underestimation or overestimation of elapsed time. Following the preprocessing, fractal dimension feature was extracted from the EEG signal and its rhythms. Subsequently, the statistical test was used to evaluate the significance of the difference in two groups of FD in EEG channels. The process is depicted as a flowchart in Fig. 1.

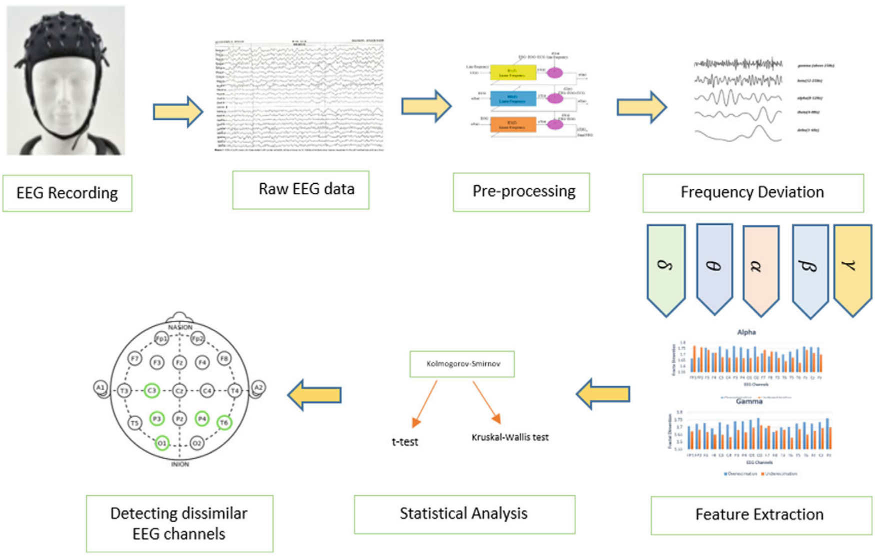


Fig. 1 Flowchart of EEG actuation and data analysis

2.1 Clinical Data Collection

In 2018, EEG signals were recorded from 42 healthy subjects with normal hearing and vision and no history of psychiatric or neurological disorders. Seventeen women and 25 men aged 18 to 35 were participated in the test, and EEG signals were recorded on 19 channels for 15 min. The EEG signal was recorded using twenty-one Brain-master amplifiers in a Faraday room with Ag/AgCl electrodes [21].

2.2 Preprocessing

EEG signals were filtered by a notch filter and then a low-pass filter to eliminate the signal frequency upper than 60 Hz. Wavelet transforms with db6 mother wavelet were used to divide the EEG signals into five known EEG sub-bands.

2.3 Feature Extraction

Considering that EEG signals have been demonstrated to possess a nonlinear character [24], we aim to prove the hypothesis that FD could show misjudgment of time [23]. Since the variety of algorithms available for FD calculation such as Higuchi FD, Katz FD, and Petrosian FD [25], and recognizing the significant usage of Higuchi FD, particularly in the context of biological signals [26], we have opted to utilize this method for FD calculation.

Higuchi FD

This method for calculating fractal dimension has been proposed by Higuchi in 1988 [27]. From the original time series $X(1)$, $X(2)$,… $X(N)$, time series X_m^k is defined as Eq. (1):

$$X_m^k = X(m) \cdot X(m+k) \cdot X(m+2k). \tag{1}$$

Here, m and k are the initial time and the interval time, respectively. The length of the curve is denoted as $L_m(k)$.

$$L_m(k) = \frac{N-1}{\left[\frac{N-m}{k}\right]k^2} \sum_{i=1}^{\left[\frac{N-m}{k}\right]} |N_m(m+ik) - N_m(m+(i-1)k)|, \tag{2}$$

$$L(k) = \frac{1}{k} \sum_{m=1}^{k} L_m(k), \tag{3}$$

$$HFD = \frac{\ln L(k)}{\ln L(1/k)}. \tag{4}$$

Here, $L(k)$ is the average of $L_m(k)$ as Eqs. (2) and (3). FD would be calculated as the slope of least square linear best fit of the plot $(L(k))$ versus in $(L(1/k))$ as Eq. (4) [28].

2.4 *Statistical Analysis*

After extracting FD values, statistical tests are used to determine the significant difference between two groups, usually through two types of tests. The Kolmogorov–Smirnov test determined the distribution type, while the t-test and Kruskal–Wallis for getting the *P*-value in normal and non-normal distribution, respectively [29].

3 Results

Participants who had overestimated and underestimated elapsed time were subjected to EEG signal recording. Figure 2a shows the EEG signal of participants with an underestimation of time, while Fig. 2b shows participants' EEG who overestimated time. The EEG signal of the two groups does not significantly differ in the time domain of the signal.

Table 1 displays the outcomes of statistical analysis performed on the data utilizing the Kolmogorov–Smirnov test, documenting the *P*-values of both the t-test and

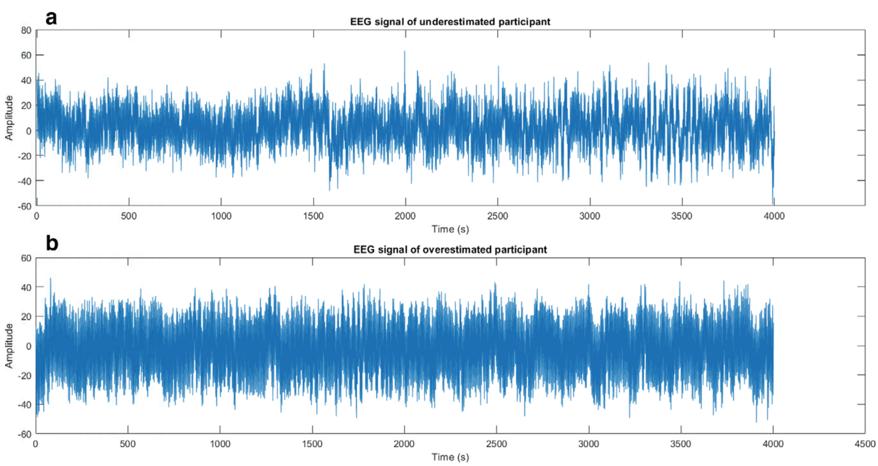


Fig. 2 EEG signal of overestimated and underestimated participants

Kruskal-Wallis test, carried out for evaluating the normal and non-normal distribution of the data. The significance of the observed difference between the two groups was established by *P*-values that were deemed to be statistically significant at a threshold of 0.05.

Subsequently, Fig. 3 compares the fractal dimension of the EEG signal and its sub-bands across each channel. The results of this analysis are summarized in the following section.

Delta: The findings illustrated that in Fig. 3a, a significant disparity was observed in the fractal dimension of the delta rhythm between participants who overestimated and underestimated elapsed time. As is discernible, the fractal dimension of the majority of channels, except for the FP1, FP2, F4, F7, and F8, is comparatively greater. Referring to Table 1, Fig. 3b reveals that FP1, C3, P3, P4, and O1 were the channels with the highest degree of significance when distinguishing between the two groups.

Theta: The result of the analysis of the fractal dimensions of the theta rhythm can be observed in Figs. 3c and d. A considerable number of EEG channels exhibit

Table 1 *P*-values of the statistical tests showed a significant difference between underestimation and overestimation in the fractal dimension

Signals channels	Delta	Theta	Alpha	Beta	Gamma	EEG signal
FP1	0.008151	0.028366	0.028366	0.150927	0.226476	0.675078
FP2	0.112411	0.082099	0.13057	0.13057	0.150927	0.675078
F3	0.364346	0.54535	0.00650	0.069642	0.198765	0.974789
F4	0.939743	0.939743	0.87602	0.04125	0.289919	0.006899
C3	0.04125	0.226476	0.006502	0.004072	0.015564	0.031047
C4	0.096304	0.405679	0.049366	0.058782	0.028366	0.006899
P3	0.012611	0.049366	0.008151	0.034294	0.028366	0.031283
P4	0.01911	0.023342	0.003197	0.034294	0.034294	0.006899
O1	0.034294	0.049366	0.023342	0.023342	0.049366	0.312853
O2	0.058782	0.028366	0.028366	0.325751	0.13057	0.031047
F7	0.325751	0.325751	0.596701	0.939743	0.596701	0.11084
F8	0.198765	0.069642	0.256839	0.650147	0.820596	0.11084
T3	0.069642	0.198765	0.150927	0.256839	0.762369	0.312853
T6	0.364346	0.150927	0.198765	0.112411	0.112411	0.006899
T5	0.112411	0.198765	0.289919	0.289919	0.364346	0.312853
T6	0.082099	0.015564	0.003197	0.256839	0.01911	0.031047
Fz	0.325751	0.762369	0.705457	0.082099	0.173617	0.006899
Cz	0.173617	0.256839	0.150927	0.405679	0.325751	0.312853
Pz	0.082099	0.058782	0.13057	0.028366	0.058782	0.11084

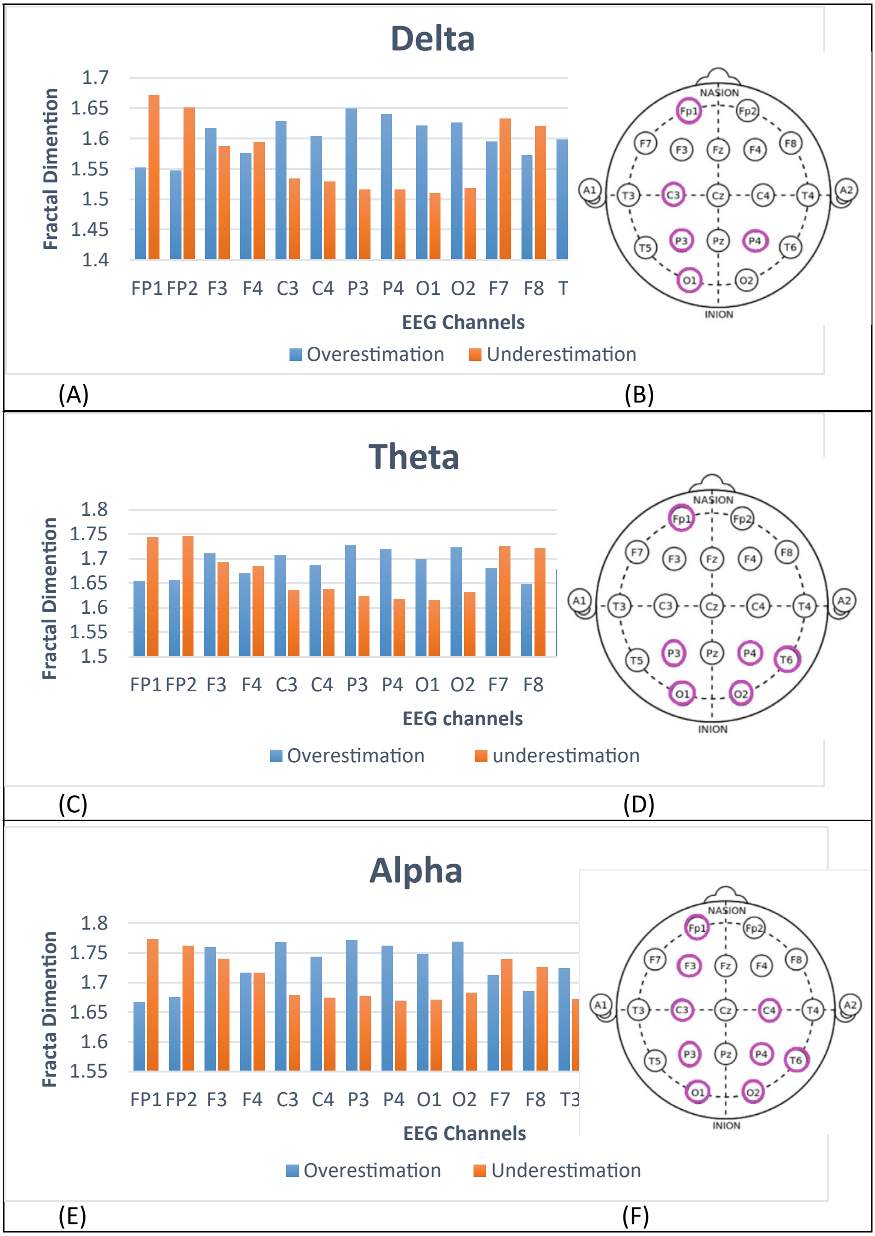


Fig. 3 Left, fractal dimension of EEG and its sub-bands in each channel. Right, significantly different channels. **a** Delta FD. **b** Channels with a significant difference in FD of delta rhythm. **c** Theta FD. **d** Channels with significant differences in FD of theta rhythm. **e** Alpha FD. **f** Channels with significant differences in FD of delta rhythm. **g** Beta FD. **h** Channels with a significant difference in FD of beta rhythm. **i** Gamma FD. **j** Channels with a significant difference in FD of gamma rhythm. **k** EEG signal FD. **l** Channels with a significant difference in FD of EEG signal

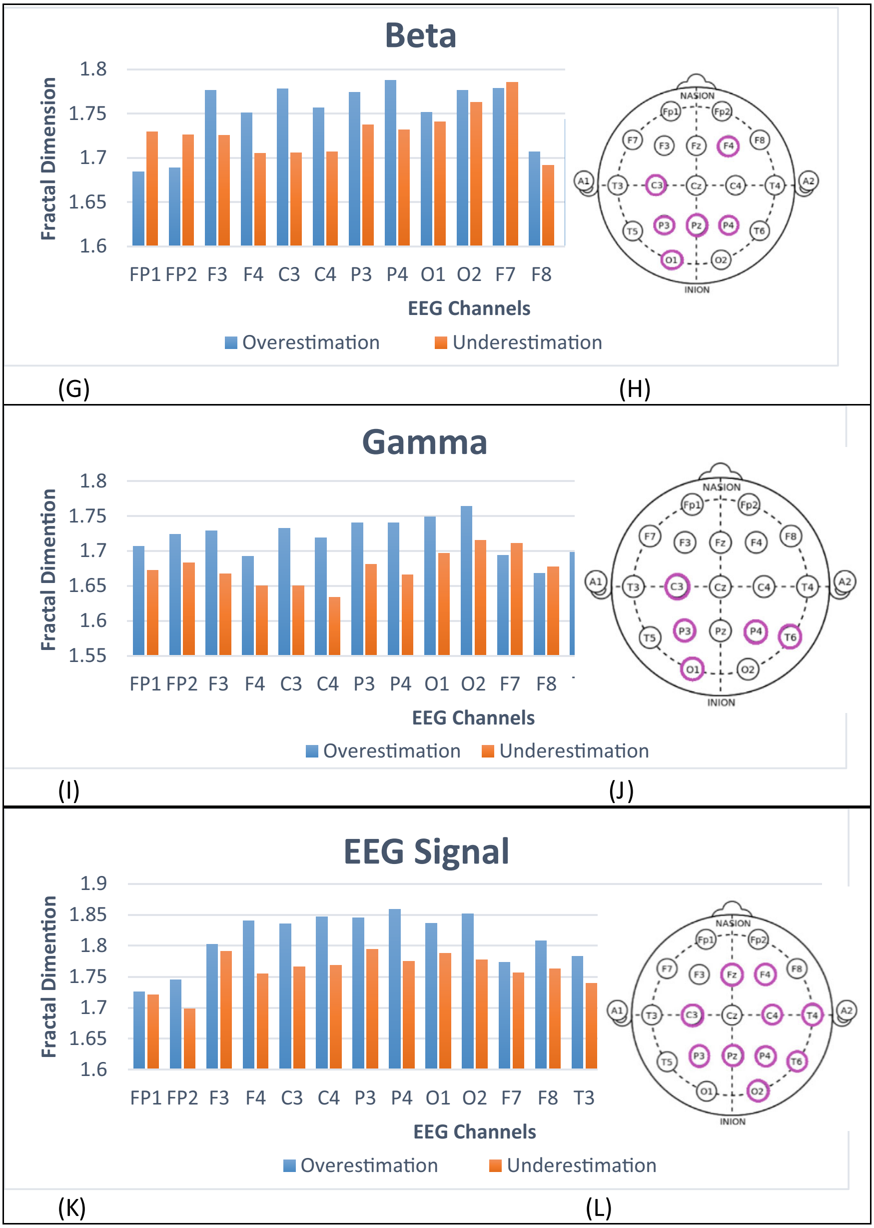


Fig. 3 (continued)

elevated fractal dimensions during the condition of overestimation. Figure 3d demonstrates that the O1, O2, P3, P4, T6, and FP1 channels exhibit the most significant differentiation between the two analyzed groups.

Alpha: Figure 3e exhibits the fractal dimension of the alpha rhythm in participants who were overestimated and underestimated, respectively. Based on the findings illustrated in Table 1, it can be inferred that the substantial disparity in fractal dimension values between the two groups was discernible in the absorptive patterns of the brain's lateral regions, encompassing both the right and left hemispheres. Notably, this divergence was particularly prominent in numerous electrode channels, including FP1, F3, C3, C4, P3, P4, O1, O2, and T6.

Beta: Figure 3g demonstrates that a considerable increase in FD occurred in more than 85% of the channels among the overestimated participants. Based on the data presented in Table 1, it is observed that the recorded *P*-values for the F4, C3, P3, P4, Pz, and O1 channels were all found to be below the predetermined significance level of 0.05 (P-value > 0.05). As shown in Fig. 3h, parietal channels differed most in FD of beta rhythm.

Gamma: Figure 3i displays the FD of the gamma rhythm. The FD of the overestimated participants was more outstanding in nearly all channels, except for F7 and F8 where the FD of both groups was almost the same. The gamma rhythm exhibited the greatest discrepancies in the FD within channels C3, P3, P4, T8, and O1, as evidenced in Table 1.

EEG Signal: Figure 3k compares the extracted FD of EEG signals in participants who overestimated and underestimated elapsed time. It is noticeable that participants who were overestimated had a greater value of FD in all channels. Figure 3l reveals that there was a notable divergence between the two groups in many of the central, parietal, and right temporal channels.

This section's brief analysis reveals that the overestimation of time is closely associated with a greater degree of fractal dimension. In the comprehensive examination, participants who demonstrated overestimation of time exhibited greater FD in the EEG signal and its correlated rhythms. Figure 3 shows that the most significant channels between the two groups are P3, P4, C3, T6, and O1.

4 Discussion

Behaviors rely heavily on the proper processing of time-related information [30]. The significance of time is equivalent to comprehending the environment as well as executing actions. Thus, it can be posited that a precise representation of the passage of time is essential for both fundamental activities like motor movements and more complex cognitive functions such as the discernment of causality [31].

Considering time perception's importance, however, its physiological and psychological bases and underlying mechanisms are still poorly understood. A review of

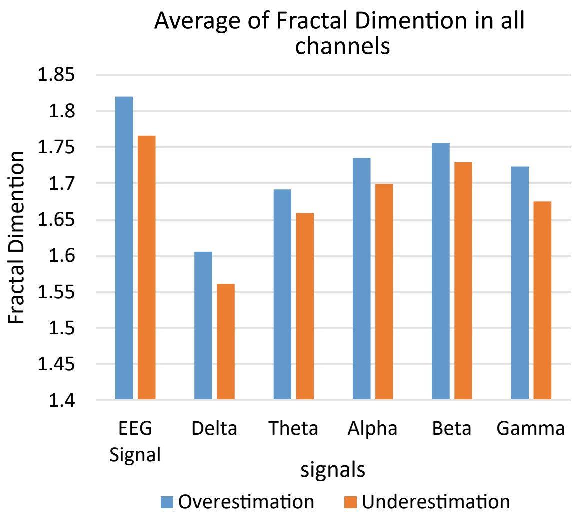
FMRI studies recommends that networks of cortical and subcortical brain regions are involved in various tasks related to time perception. Apart from FMRI research, EEG studies revealed the potential of ERPs and frequency bands to indicate the temporal perception mechanism in the brain.

Brain signals exhibit a high degree of complexity, and the global features, such as FD, facilitate the examination of their intricate nature. In this investigation, the feasibility of detecting disparities in time estimation through the utilization of FD was scrutinized and validated. Considering the intricate and ever-changing nature of cognitive processes, such as the processing of temporal information, the exploration of EEG signals and their sub-bands through the utilization of global features such as FD could potentially serve as a significant milestone in comprehending the mechanisms underlying brain function, particularly in relation to temporal processing.

The results of this study showed that FD differed between the two groups with different judgments about elapsed time. Figure 4 shows that overestimating time leads to a higher mean of FD for the EEG signal and all rhythms. Figure 5 compares the difference in underestimated and overestimated participants' fractal dimensions for each signal. The results showed that EEG signals and rhythms could perfectly demonstrate the two groups' differences. In rhythm, Gamma, better than any other rhythm, could indicate the difference between the two groups.

The FD serves as a metric for quantifying the intricacy of a time series, particularly in the context of one-dimensional time-series observation data, such as EEG. Our finding demonstrated a lowering of the FD in participants with underestimation of time in the resting state, eyes opened condition, which showed reduced resting state EEG complexity in underestimation of time. The regional increase of FD is evident in the parietal and occipital channels of overestimated participants. Thus, our results

Fig. 4 Each signal's average FD across all channels



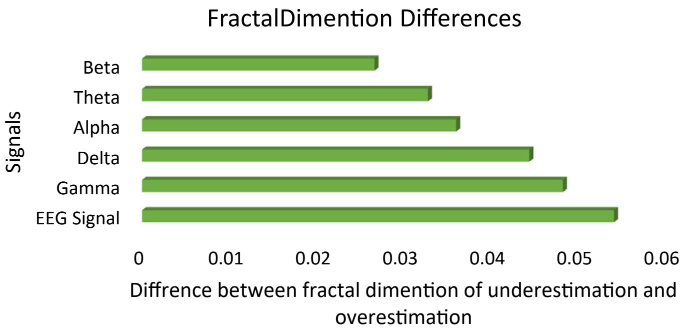


Fig. 5 Difference between FD of underestimation and overestimation in each signal

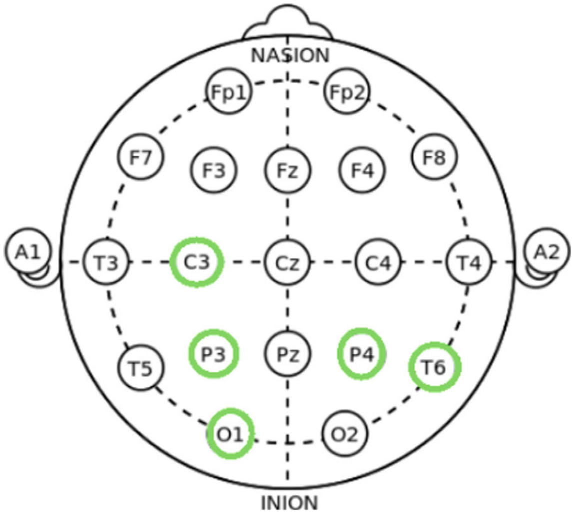
support the previous hypothesis that measuring complexities could show a time perception mechanism.

The investigation unveiled a noteworthy dissimilarity in the fractal dimension of every sub-band of the signal, notwithstanding a substantial dissimilarity in the feature measurement and its average value between the two cohorts. The performance of feature extraction was evaluated through the application of statistical analysis.

Subsequently, a total of 19 channels were subjected to analysis, with the outcome portrayed in Fig. 6. According to the findings presented in Fig. 6, C3, P3, P4, O1, and T6 channels were identified as the channels displaying the most notable distinctions between the two groups examined. So, analyzing healthy human EEG signals shows that FD can reveal participants' judgment about elapsed time. FD has greater value in participants with overestimation of time, and this is most evident in parietal and central channels. Other studies examining EEG signals have employed the energy and power of those signals to analyze temporal judgment. The findings display significant differences in alpha [32] and beta rhythms [33]. Therefore, when analyzing EEG signals for temporal processing, it may be useful to consider utilizing various features.

Despite the small sample size, the FD has uncovered noteworthy variances in neural structure associated with the misinterpretation of time. Moreover, the inclusion of a variety of features in forthcoming investigations may enhance our comprehension of temporal mechanisms. Consequently, this will facilitate a more profound understanding of the phenomenon being studied and augment the precision of the findings.

Fig. 6 Most significant channels between two groups



5 Conclusion

This study attempts to bring light to the time perception mechanism by applying FD on the EEG signal of healthy people with overestimation and underestimation of time. Using this approach, we found an incensement of complexity in the parietal and central regions of the brain in the overestimation of time. These findings could provide further insights into the altered brain dynamic in time perception.

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3D Modeling for Indoor Structure Using Omniverse Create

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Abstract Following the increasing demand for 3D reconstruction of indoor structures, this study focuses on the current state of 3D mapping and modeling software available. However, reconstructing 3D models of indoor environments is more challenging due to spatial constraints and the complexity of objects within them. By using an application known as Polycam, a 3D map of an indoor building is generated. Polycam has a feature called the Photo Mode that enables the user to capture multiple sets of images of an object or surrounding to create a 3D model from the data acquired. It will automatically stitch the image together to create a single 3D model of the object. By utilizing this feature, several images of a room are captured for data acquisition. Additionally, NVIDIA Instant-NGP is also utilized for data acquisition which uses the NeRF technology and COLMAP to extract a video input into several frames or images which can then be trained to obtain the 3D data as a whole. The data acquired are then exported to a format that is supported by Omniverse Create to complete the 3D reconstruction. Omniverse Create is 3D modeling software that can be said which is relatively new to the 3D modeling scene and it is able to simulate real-time lighting situation. Nevertheless, the outcomes of the 3D mapping process failed to align with the initial anticipations as a result of various constraints and limitations.

Keywords 3D modeling · NeRF · Instant-NGP · Omniverse Create · Polycam · Indoor structure

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