IIETA International Information and Engineering Technology Association
Advancing the World of Information and Engineering

Traitement du Signal
Vol. 40, No. 4, August, 2023, pp. 1673-1679
Journal homepage: http://iieta.org/journals/ts

Entropy and Fractal Analysis of EEG Signals for Early Detection of Alzheimer's Dementia

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https://doi.org/10.18280/ts.400435

Received: 3 March 2022
Revised: 20 June 2023
Accepted: 20 July 2023
Available online: 31 August 2023

Keywords:
Alzheimer, early detection, complexity, SpecEn, fractal

ABSTRACT

The rapid progression of diseases in the elderly, such as Alzheimer's Dementia (AD), necessitates effective early detection mechanisms to ensure appropriate healthcare provision. Given the consistently increasing prevalence of AD, the potential for emerging socio-economic challenges is significant. This underlines the importance of developing early detection strategies to mitigate the progression of this disease. Electroencephalograms (EEG) present a promising avenue for the early diagnosis of AD. EEG signals harbor crucial information pertaining to neuronal death triggered by amyloid plaque accumulation, a characteristic feature of AD. Spectral analysis reveals a deceleration in signal activity in AD patients when compared to healthy elderly individuals. However, this method is frequently compromised by low-frequency noise, necessitating the exploration of alternative approaches for analyzing EEG signal features for early AD detection. Considering the complex nature of EEG signals, it is hypothesized that pathological conditions, such as AD, may induce alterations in signal complexity. In this study, an early detection model for AD was simulated utilizing an approach that focused on EEG signal complexity. Complexity analysis, incorporating Spectral Entropy (SpecEn) and fractal dimensions, was calculated across 19 EEG channels from a total of 34 subjects (16 normal and 18 with Mild Cognitive Impairment (MCI)). Performance validation of the proposed method was achieved through Linear Discriminant Analysis (LDA), yielding an accuracy of 82.4%, specificity of 77.8%, and sensitivity of 87.5%. The findings from this study suggest that EEG analysis can serve as a reliable tool for the early detection of AD.

1. INTRODUCTION

Alzheimer's Dementia (AD), the most prevalent form of dementia globally, continues to experience a rise in its incidence [1]. This chronic, neurodegenerative condition, predominantly afflicting the elderly population, is marked by cognitive impairment and memory loss [2, 3]. Despite not being directly lethal, AD's rapid progression significantly diminishes quality of life. The disease often induces considerable dependence on others, impacting social life and imposing substantial costs [4].

As of present, no definitive treatment protocols for AD exist [5]. Delayed intervention can precipitate swift deterioration, underscoring the importance of early detection and subsequent treatment in curbing this potentially aggressive degenerative process [6]. The primary pathogenesis of AD is believed to be attributable to extensive neuronal death and neurotransmitter damage. The accumulation of beta-amyloid plaques is strongly implicated in the disruption of inter-neuronal information transmission [7].

Biochemical modalities and medical imaging serve as standard biomarkers in AD diagnosis [3]. Biochemical modalities such as cerebrospinal fluid (CSF) are sensitive to pathological changes due to AD [8, 9]. However, these medical modalities necessitate invasive procedures and find limited use in clinical practice. Medical imaging techniques, including MRI, CT-Scan, and FDG-PET [10, 11], whilst sensitive to AD, are costly and typically available only in central hospitals [3].

In light of neuronal degradation and brain electrical activity, electroencephalogram (EEG) offers an alternative in AD analysis, encompassing early detection and severity assessment [12]. EEG's advantages of being low-cost, non-invasive, easily installed, and readily available in public health centers render it a preferred choice. EEG has long been relied upon as a primary biomarker or auxiliary tool in AD studies. Early detection of AD can occur well before the onset of pre-clinical symptoms or at the stage of mild cognitive impairment (MCI). The neuronal damage or death pivotal to AD induces changes in EEG signal characteristics. Power spectral analysis of EEG reveals a slowdown of waves [13, 14], indicative of reduced alpha wave activity [15, 16]. Furthermore, coherence and synchronization analyses exhibit a decrease in AD compared to normal aging [17, 18].

While EEG spectral analysis has been employed to characterize AD and assess its severity, it is notably sensitive to noise, a common issue in EEG signal. Therefore, a supplementary method is required to bolster spectral-based analysis. Given that the EEG signal is a cumulative result of complex, dynamic processes by neuron cells, a signal complexity-based analysis is considered proficient in characterizing EEG. Consequently, this study proposes an early detection methodology for AD based on EEG signals utilizing a signal complexity approach. The study analyzed recorded EEG signals from normal elderly individuals and those with MCI. A complexity approach integrating Spectral

Entropy (SpecEn) and fractal dimension was deployed for EEG characterization. Linear discriminant analysis (LDA) was employed for evaluating the proposed method. This study aims to serve as a supportive and complementary method for AD early detection, supplementing spectral-based characterization.

The ensuing sections of the paper are organized as follows: Section 2 outlines the EEG dataset and the methods employed in this study. Section 3 presents the study findings and subsequent discussions. Section 4 concludes the paper, delineating the implications of the study, its conclusions, and prospects for future work.

2. MATERIAL AND RESEARCH METHODS

2.1 System design

Figure 1 shows our proposed system. First, EEG signals entered the pre-processing stage that included Independent Component Analysis (ICA) denoising and Band Pass Filter (BPF) from 1-30 Hz. ICA denoising was applied because it is superior in separating noise from signal in the raw dataset. Not only that, but ICA also improve the data quality [19]. Pre-processing stage resulted filtered signals. Then, four different calculations were performed to extract the features, i.e., SpecEn, Katz, Higuchi, and Sevcik fractal dimension. In the final stage, the features were classified using LDA classifier. Each stage of the proposed system is briefly explained in the following subsections.

2.2 Normal dan MCI EEG dataset

This study used the scalp EEG dataset containing two conditions, namely normal and Mild Cognitive Impairment (MCI). There are 34 selected subjects (16 normal and 18 MCI) who were hospitalized in the units of cardiac catherization of Sina and Nour Hospitals located in Isfahan, Iran. In the current dataset, there are more EEG recordings than the previous release where there are 27 EEG recordings (16 normal and 11 MCI). Patients' age range is 60-77 with coronary angiography history in recent year. Patients with a track record of major psychiatric disorders, dementia, head trauma, substance misuse, and other serious medical disease were not included. However, all subjects had to complete the neuropsychiatric interview considering Peterson's criteria for MCI. An assessment tool, neuropsychiatry unit cognitive (NUCOG), has been used in confirming the diagnosis of MCI [20].

The recording session for all EEG signals were done in the mornings while subjects were comfortably rested with closed eyes in a quiet room and using the same EEG amplification system. There are 19 channels (Fp1, Fp2, F7, F3, Fz, F4, F8, T3, C3, Cz, C4, T4, T5, P3, Pz, P4, T6, O1, and O2) which represent 19 electrodes positioned corresponding to the 10-20 international system. The sampling frequency is 256Hz when recording the EEG signal continuously. During the recording process, patients were being checked out repeatedly to keep them aware and awake [20]. The length of the recording was about 30 minutes. In this dataset, EEG signals are stored in the European Data Format (*.edf) as a standard for exchange and storage.

2.3 Spectral entropy

Generally, entropy is a measurement of signal complexity. As the complexity increases, the resulted entropy value is higher. There are various entropy calculations that have been used in lots of EEG signals complexity measurement [21-24]. In this study, we estimate the signal regularity using spectral entropy (SpecEn). SpecEn calculates the power spectral distribution of the Fourier transform using Shannon entropy. SpecEn estimates signal dynamics in the frequency domain. Meanwhile, entropy is a measure of the uncertainty of a data series. So that, high spectral entropy represents the high dynamics of the power spectral at a certain frequency range. While low SpecEn represents spectral power with low dynamics or condensed into a single frequency [24].

SpecEn represents the probabilities of power spectral densities using Shannon's entropy equation. The spectral entropy is normalized according to the range of frequency $[f1, f2]$ with Eq. (1) below.

$$Spectral\ entropy\ [f1, f2] = -\frac{1}{log[N[f1,f2]]}\sum_{fi=f1}^{f2} P_n(f_i)\ log\big(P_n(f_i)\big) \quad (1)$$

where, $[N[f1, f2]]$ is the total components of frequency in range $[f1, f2]$ and $P_n(f_i)$ is the probabilities of the total components of frequency [25, 26].

2.4 Fractal Dimension

One of the EEG characteristics is high complexity with self-similar patterns. Fractal Dimension (FD) is a useful technique to handle the self-similar pattern complexity. Generally, FD measures the waveform complexity in time series analysis [27]. A few methods of FD have been developed to support the EEG signals classification [28-30]. This study proposes an AD early detection method utilizing Higuchi, Katz, and Sevcik FD to estimate the EEG waveform complexity

2.4.1 Higuchi Fractal Dimension

Higuchi Fractal Dimension (HFD) occurs in a time-series $A(t)$ to calculate the value of FD that represents the complexity of EEG waveform. A new time-series $A(t)_k^m$ and the length of the series are defined in Eqs. (2)-(3) [31].

$$A(t)_k^m = a_m, a_{m+k}, a_{m+2k}, ..., a_{m+\left[\frac{N-m}{k}\right]k} \quad (2)$$

$$L_m(k) = \frac{\left(\sum_{i=1}^{\left[\frac{N-m}{k}\right]} | a_{im+k} - a_{(i-1)k} |\right)\frac{N-1}{\left[\frac{N-m}{k}\right]k}}{k} \quad (3)$$

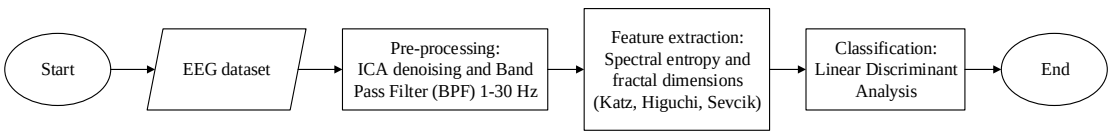

Figure 1. The proposed system

where, $m = 1, 2, \ldots, k$ is integer which state the time delay with the maximum interval time is k_{max}, symbol of $[\ldots]$ is the Gauss notation, and the term of (4) [32], specifies the factor of normalization at the length of FD. Then, the average length of the series is obtained using Eq. (5) below.

$$\frac{N-1}{\left[\frac{N-m}{k}\right]k} \tag{4}$$

$$\langle L(k)\rangle = \sum_{m=1}^{k} \frac{L_i(k)}{k} \tag{5}$$

Then, if the results are plotted on a log-log graph, the HFD can be obtained from a slope of the linear regression plot between $ln(L(k))$ to $ln(1/k)$. The obtained curve defines the HFD with D dimension after the value $L(k)\alpha k^{-D}$ is complied.

2.4.2 Katz Fractal Dimension

Katz Fractal Dimension (KFD) is a direct calculation from the time-series $A(t)$ that starts with its transpose array [33, 34]. When N is length of the curve, the measurement of KFD is written as Eq. (6) [35].

$$D = \frac{\log(n)}{\log(n) + \log\left(\frac{d}{L}\right)} = \frac{\log\left(\frac{L}{a}\right)}{\log\left(\frac{d}{a}\right)} \tag{6}$$

where, L represents the signal length, a defines average distance between the successive points, and n is the total of steps presented in the graphic of curve [32].

2.4.3 Sevcik Fractal Dimension

A newer method to calculate the FD of a waveform in a quicker way is Sevcik Fractal Dimension (SFD) [36]. The waveform dimension, complexity, and randomness can be quickly estimated and measured since the calculation characteristics are simple and fast [37]. SFD approximates the FD D from the sampled time series of N dimension. Based on [36], the estimation of D is obtained from the Hausdorff Dimension D_h of a waveform by plotting the N points of curve L to cells of a unit square $N \times N$ in a metric space that has been normalized, through transformation of double linear. Eq. (7) defines the SFD calculation [35].

$$D_h = 1 + \frac{\ln(L)}{\ln[2.(N-1)]} \tag{7}$$

where, L is the length of a curve.

2.5 Linear Discriminant Analysis

Linear Discriminant Analysis (LDA) is a supervised classifier that creates a combination of the original predictors as its new variable [38, 39]. The target of LDA is to achieve a predictor value from the new variable which combines the actual class and the actual predictors [40]. LDA does the grouping process of the objects into groups which are mutually discriminative. If there are two classes in the EEG dataset, the used discriminant function will be one. The required training samples are fewer, yet the results are as good as the other classifiers [41]. The discriminant function can be written mathematically in Eq. (8) [38].

$$D = \sum_{j=1}^{p} w_j Z_j \tag{8}$$

where, w is the weight factor.

3. EXPERIMENTAL SETUP

Essential features are calculated using SpecEn, HFD, KFD, and SFD for each EEG channel. So that each channel will produce four features. These features then become predictors in the classification stage. The proposed method was validated using LDA. Seeing that the number of datasets is relatively small, the distribution of training and test data uses the cross validation (CV) method where 5-CV is used in this study. Several scenarios were simulated to observe which method generated the highest accuracy. The scenario includes grouping features by area, combining the resulting feature vectors from all feature extraction methods, and observing accuracy when applying one feature extraction method. The average of features calculated in each area includes frontal (Fp1, Fp2, F3, F4), right temporal (F8, T4, T4), left temporal (F7, T3, T5), central (C3, C4, Fz, Cz, Pz), and occipital (P3, P4, O1, O2) [20]. Table 1 shows the details of each scenario.

Table 1. Scenarios used in simulation

Scenario	Classification Feature
A	Average area (SpecEn, HFD, KFD, SFD)
B	All channels (SpecEn, HFD, KFD, SFD)
C	SpecEn (Average area)
D	HFD (Average area)
E	KFD (Average area)
F	SFD (Average area)

This study implements the measurement accuracy, specificity and sensitivity to validate the performance of the system which defined in Eqs. (9) (10) and (11), respectively.

$$Acc = \frac{TP + TN}{TN + FP + TP + FN} \times 100 \tag{9}$$

$$Spec = \frac{TN}{TN + FP} \times 100 \tag{10}$$

$$Sen = \frac{TP}{TP + FN} \times 100 \tag{11}$$

where, Acc is accuracy, $Spec$ is specificity, Sen is sensitivity, TP is true positive, TN is true negative, FP is false positive, and FN is false negative.

4. RESULTS AND DISCUSSION

In this study, the duration of the EEG signal processed was five minutes, which was taken from the beginning of the

recording. This is indeed an assumption, to avoid EEG signals containing drowsiness as a consequence of a long recording. The EEG signal resulting from noise rejection by ICA and BPF is then calculated for its spectral entropy and fractal. Figure 2 and Figure 3 show the estimated signal complexity calculated using spectral entropy and fractal dimension.

Figure 2 shows that the SpecEn value of the MCI group is lower than that of the normal group. With the T-Test (confidence level = 95%), significant differences were found at the electrodes Fp1, Fp2, T6 and O1. These results indicate that there is a decrease in the complexity of the EEG signal in MCI patients, particularly in the frontal and occipital areas. The same trend is also shown in Fig. 3 where the signal complexity of the MCI group is lower than the normal group. These characteristics will then be used for MCI and normal discrimination in the next stage. The results of the performance validation using LDA and 5-CV for each scenario are shown in Table 1.

Table 2 shows that the highest accuracy is 82.4% with specificity and sensitivity 77.78% and 87.5%, respectively. The confusion matrix is presented in Table 3. The highest accuracy was obtained in scenario B, where all features from SpecEn and FDs are used. Meanwhile, if only one feature extraction method was applied (scenario C-F), the highest accuracy was achieved by the scenario F with an accuracy of 76.5%. In scenario C, SpecEn generated the lowest accuracy among the other methods. This occurred because the SpecEn is very distorted to the natural noise of the EEG so that it delivered greater bias between normal and MCI than the fractal method. Additionally, SpecEn estimates the complexity of the signal based on spectral analysis, which is very vulnerable to the influence of noise. Scenario A was done by grouping of features based on brain area and the accuracy was 70.6% which indicates lower than when all features were used as predictors, as in scenario B.

The brain represents a complex process of resultant large amounts of neuronal activity. Pathological changes due to a disease can affect the electrical activity of neurons including changes in the degree of signal complexity. The decline in complex biological mechanisms can be an indicator of decreased ability to respond to stimuli. Decreased cognitive function in the elderly with AD occurs due to damage to neurons or neurotransmitters in the brain, causing disruption of communication between cells. This affects changes in the EEG signal and thus may underlie the early detection of AD proposed in this study.

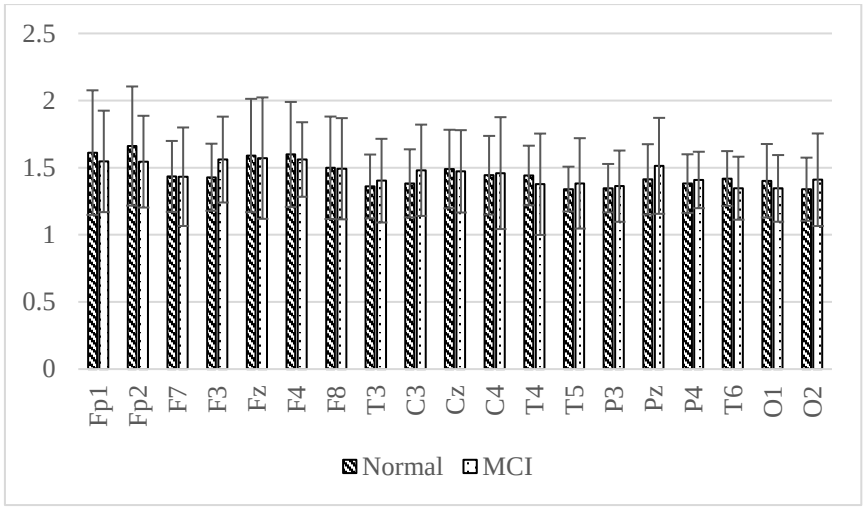

Figure 2. Mean of the SpecEn values of each electrode in the normal and MCI groups

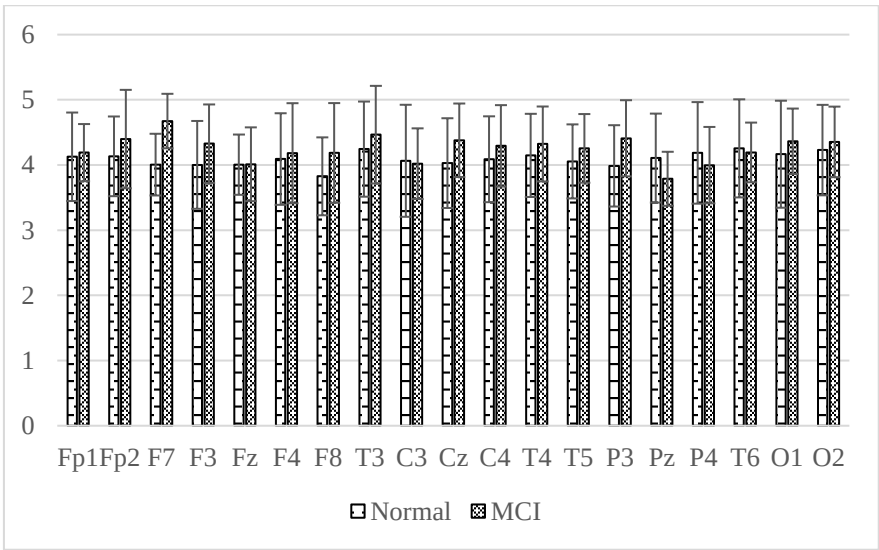

Figure 3. Mean of the KFD values of each electrode in the normal and MCI groups

Table 2. Accuracy, specificity, and sensitivity of each scenario

Scenario	Linear Discriminant		
	Acc (%)	Spec (%)	Sen (%)
A	70.6	68.75	72.22
B	**82.4**	**77.78**	**87.5**
C	55.9	53.33	57.89
D	73.5	76.92	71.43
E	70.6	71.43	70
F	76.5	72.22	81.25

Table 3. The confusion matrix of the highest accuracy

	MCI	Normal
MCI	14	4
Normal	2	14

From all the simulated test scenarios, it is known that the highest accuracy was achieved by scenario B, which was the combination of all feature extraction methods. This study is superior to previous studies because in this study uses a larger amount of data. The proposed method in this study yielded a classification accuracy of > 80% and can be considered for early detection of AD in this case as a supplementary diagnostic criterion besides memory testing. From the low specificity values, it could be seen that it was very challenging to detect AD in the early stages since EEG MCI has similar characteristics to normal EEG signals. This happened because in the early stages of AD, neuronal damage only occurs in a partially human brain. But, an EEG analysis for early detection of AD can be considered a tool with several advantages that it is low-cost, non-invasive, and can be used continuously compared to medical imaging techniques.

5. CONCLUSION

People with AD tend to have particular changes of the brain waves that can be examined through EEG signals. To decide the most suitable treatment, the examination needs to be as accurate as possible. Meanwhile, the transformation from normal elderly to AD, and vice versa, is slightly different, so an automated diagnosis is indispensable. One of the characteristics of EEG signals is complex and dynamic. Therefore, this study proposed an early detection of AD based on EEG signals focusing on the signal complexity to distinguish the conditions defined in the EEG dataset used which are normal and MCI. SpecEn and FD were used as the methods for signal complexity-based approach. All features were classified using LDA to classify the normal and MCI conditions using six scenarios. The highest accuracy was performed by scenario B that employed features from all feature extraction methods in all areas. Obtaining accuracy more than 82.4% verifies that EEG is suitable for further analysis of AD detection. Furthermore, the specificity and sensitivity reached 77.8% and 87.5%, respectively, show that the proposed method is ready to support the early detection of AD in large population. However, detecting AD still faces many challenges seeing that only partial locations of brain that are affected by neuronal damage.

ACKNOWLEDGMENT

All authors would like to thank Telkom University for funding this research. The authors are also grateful to the Laboratory of School of Applied Science and School of Electrical Engineering for providing research facilities.

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