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A Review on the Phenomenon of Synchronization in EEG Signals of Humans and its Application in Detection of Neurological Disorders

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Numerous physical and biological systems demonstrate synchronization phenomena. Early investigations focused on the synchronization of dual pendulum tickers connected by a common shaft (it was within this system that Huygens discovered synchronization), the synchronized flashing of fireflies, or the interactions of adjacent channels capable of effectively annihilating one another. The exploration of chaotic synchronization did not gain significant attraction until the 1980s. The synchronization pattern was observed in the biological signals and it was observed through studies that these patterns show changes with respect to change in the body activities. So further studies were being conducted to refine and record these signals and convert them inti human readable form. Later on, these synchronization patterns in the recorded bio signals like EEG (Electroencephalogram), ECG (Electrocardiogram) etc. were used for detection of neurological disorders. This study discusses about the works related to the detection of neurological disorders with the help of synchronization in the EEG signals that are recorded from brain and gives a clear view how EEG signals and their synchronization has been used time and again for studying and diagnosing disorders like epilepsy, bruxism etc.

Keywords: EEG Signals; Epilepsy; Order Patterns; Recurrence; Synchronization.

The exploration of coupled systems began in the seventeenth century, initially focusing on the investigation of synchronization in nonlinear periodic systems. Subsequent studies on synchronization yielded various discoveries with crucial implications for the design of secure communication devices. The synchronized chaotic trajectories can be employed to encrypt messages and protect them from being deciphered. The notion of complete synchronization of chaotic systems was later generalized, allowing for non-identity among the coupled systems.

In a later development, Rosenblum[4] examined a form of synchronization between chaotic oscillators where the associated phases become locked or synchronized while the amplitudes remain uncorrelated. They termed this type of synchronization as “synchronization of phase.” Research has not only demonstrated synchronization among chaotic oscillators such as electronic circuits, lasers, and electrochemical oscillators but also observed synchronization phenomena in biological systems.

Examples encompass elements within the cardiorespiratory system, expansive biological networks, and the electroencephalographic patterns of individuals with Parkinson's disease, all displaying synchronization characteristics. Figure 1 elucidates the categorization of neurological disorders that are generally considered by different researchers in their works. Understanding the circumstances in which the coupling of chaotic systems occurs is crucial, as is identifying the moments of coupling. Numerous studies are dedicated to investigating instances of phase synchronization (PS) and generalized synchronization (GS). Several methodologies have been devised to date for the identification of phase synchronization (PS) and generalized synchronization (GS). However, challenges arise when pinpointing the instances of coupling in systems, primarily due to the extremely small-time intervals during which coupling takes place or the specific signal values at which synchronization occurs.

The initial concrete endeavour in this field began with the concept put forth by Andreas Groth[1] in his paper titled "Visualization of coupling in time series by recurrence plots." Before this work, in the exploration of coupled systems, several non-graphical strategies had been developed to identify instances of cooperation in time series[2,3,4].

The methods and techniques proposed in the aforementioned papers address a variety of needs. While direct methods based on correlations are inadequate for managing nonlinear conditions, many nonlinear methods require significantly long, stationary time series. In situations where stationarity is maintained only for brief periods, cross recurrence plots (CRPs) have been introduced[6,7].

The CRP strategy relies on calculating distances of trajectories, which can be particularly challenging in real-time systems. An overarching challenge in analyzing multivariate data from real-time systems such as electroencephalograms (EEG) is that measurement conditions fluctuate over time. Among other factors, offsets and amplitude ranges can vary differently across channels [20,21]. To tackle these challenges, we turn to an innovative method that encodes the entire time series into an array of zeros and ones. This approach helps mitigate the impact of varying values in the time series due to diverse external factors, as it discretizes the entire series into a pattern of zeros and ones.

This concept of order patterns was introduced by Bandt and Pompe[8], who proposed a straightforward model that quantifies time series values by comparing them with neighbouring values. Subsequently, this method was utilized to detect epileptic seizures in patients. Building upon the notion of cross recurrence plots (CRPs), a visualization tool was developed.

The concept of recurrence has been employed to detect relationships between interacting systems, leading to the introduction of synchronization probability. This approach incorporates a multivariate analysis of aggregated synchronization. Furthermore, recurrence has been used to quantify a weaker form of synchronization known as phase synchronization. In this context, we expand these measures to identify the direction of coupling. The proposed method is relatively straightforward to calculate compared to more complex information-theoretic methods. Additionally, it is applicable to both weak and strong directional coupling, as well as to nonlinear systems.

For assessing the direction of coupling, the methods utilized are entirely based on the mean conditional probability of recurrence or directionality, which is computed and based on shared information [24,25].

In this study, several methods have been compared from various works that estimate the direction of the coupling. Most of these methods can be categorized into the following three groups: **(I)** Methods Based on a Functional Relationship between the Stages, **(ii)** State-Space Based Methods and **(iii)** Data Theory Based Methods.

Synchronization Behaviour in EEG Signals

Synchronization in electroencephalographic (EEG) signals is crucial for interpreting data recorded from the human brain. The brain governs all activities of the body, and since each activity in the body is synchronized with others, this synchronization can be monitored by analyzing signals recorded from the brain. EEG

(Electroencephalography) is highly effective for detecting neurological disorders due to several factors:

Real-time Brain Activity Monitoring

EEG measures the brain's electrical signals produced by neuronal activity, allowing clinicians to observe brain function in real time. This capability is crucial for detecting abnormal patterns associated with conditions like epilepsy, seizures, and sleep disorders.

Non-invasive Technique

As a non-invasive method, EEG doesn't require surgical intervention or penetration into the body, making it safe for repeated use and less risky for patients.

High Temporal Resolution

EEG excels in capturing rapid changes in brain activity due to its high temporal resolution. This ability to track short-lived electrical fluctuations is key for identifying transient events, such as epileptic discharges or specific sleep stages.

Detection of Specific Abnormal Patterns

Various neurological conditions exhibit distinct EEG signatures. For example, epilepsy is often associated with characteristic abnormal discharges, while disorders like encephalopathy, sleep disorders, or brain trauma also show unique EEG patterns.

Portable and Cost-efficient

Compared to other neuroimaging techniques like fMRI or PET scans, EEG is more affordable and portable, making it accessible for use in diverse clinical settings, including smaller hospitals or outpatient facilities.

Assessment of Consciousness States

EEG is particularly valuable in evaluating brain activity in unconscious or comatose patients, aiding in the diagnosis of brain function levels in conditions like coma, vegetative states, or brain death.

Broad Clinical Application

EEG is versatile, used in diagnosing a wide range of neurological conditions beyond epilepsy, including brain tumors, strokes, infections, and neurodegenerative diseases such as Alzheimer's disease.

These features make EEG an indispensable tool for diagnosing and understanding various neurological disorders, thanks to its real-time monitoring, accessibility, and ability to detect specific brain activity abnormalities.

The techniques utilized for brain mapping are contingent upon either bivariate measures (BM), which entail averaging across pairwise values, or on multivariate measures (MM), which directly assign a singular value to the synchronization within a group.

To contrast Multivariate Measures (MM) with Bivariate Measures (BM), nine distinct estimators were utilized on simulated multivariate time series with known parameters and on actual EEG recordings. The investigation unveiled noteworthy correlations between BM and MM [34,35].

Examining the performance of synchronization measures in simulated scenarios featuring diverse coupling strengths, association probabilities, and parameter discrepancies, it was observed that certain measures, such as the S-estimator, S-Renyi, omega, and coherence, exhibit higher sensitivity to direct dependencies. On the contrary, additional measures such as mutual information and phase locking parameters demonstrate reduced sensitivity to nonlinear effects.

These attributes should be taken into account alongside the fact that Multivariate Measures (MM) are computationally less demanding and, consequently, more effective for large-scale time series analysis compared to Bivariate Measures (BM) in evaluating synchronization within EEG signals [43]

Dynamic behaviors and specific spatiotemporal patterns are observed in oscillatory patterns within the alpha and beta bands (<35 Hz) during a range of cognitive, sensory, and motor tasks, as depicted in the work of Neuper and Pfurtscheller[11]. The event-related desynchronization (ERD) seen in the alpha band and beta rhythms can be explained as a link between an activated cortical region and heightened excitability of neurons [12,13].

Additionally, the act of opening one's eyes usually results in the suppression of alpha waves, whereas alpha power tends to elevate during closed-eye states [50]. This latter phenomenon is often associated with a decrease in the dynamic processing of data, caused by interruptions in the flow of data from the visual system. The initial discoveries of occipital and frontal alpha synchronization have proposed that sudden surges in alpha activity might signify a state of “hypofrontality,” where cognitive abilities linked to methodical reasoning and critical thinking could be temporarily impaired.

Fink[27] conducted an additional investigation to ascertain whether alpha synchronization during innovative ideation signifies elevated or deteriorated activity of EEG. This was done by employing frontal magnetic resonance imaging method.

For example, Jensen [19] discovered that synchronization in the alpha band (9-12 Hz) increases when individuals are required to retain information for brief durations. This heightened synchronization in the alpha band can be studied to gain insights into memory-related disorders such as dementia, where patients face challenges in memory retention.

Similarly, Klimesch[12] suggested that alpha band desynchronization occurs when individuals engage in mentally demanding tasks.

Furthermore, Sauseng[21] observed synchronized alpha band frequencies in EEG signals recorded from frontal areas of brain when it is involved in any memory retention based task.

Cooper[18] examined the activity in the alpha band of EEG signals, particularly in tasks involving sensory processing of visual, auditory, and tactile stimuli, as well as tasks requiring mental visualization of these stimuli.

Additionally, internally directed mental imagery tasks result in stronger alpha power compared to externally directed tasks. Moreover, alpha power increases with greater task demands and complexity.

Moreover, frontal alpha synchronization is noted during tasks requiring high levels of internal processing in the brain, but not during tasks with low internal processing demands[28].

Benedek[22] investigated synchronized alpha band frequencies in EEG signals when brain is involved in any creative task. They concluded that there is high degree of synchronization in alpha band signals when brain is involved in different creative tasks. This view was supported by Von Stein and Sarnthein [24].

Drawing from the aforementioned studies, numerous researchers in the field suggest that neurological disorders can be explored and potentially diagnosed by analyzing the synchronization patterns in brain signals across various frequency bands. Some of these works are summarized in Table 1.

EEG Alpha Synchronization

Activity variations of various EEG bands have been observed to detect and study cognitive activity and its various aspects. During periods of rest, the alpha band frequencies (8–12 Hz) become the predominant spectrum of EEG, marked by synchronized signals recorded from the brain, where as substantial deterioration in intensity and synchronism is observed when brain is involved with some task i.e. when it is not idle[25].

ERD Based Synchronization

Investigations utilizing ERD/ERS reveal a diverse pattern of alpha resynchronization observed across the broad alpha frequency band.

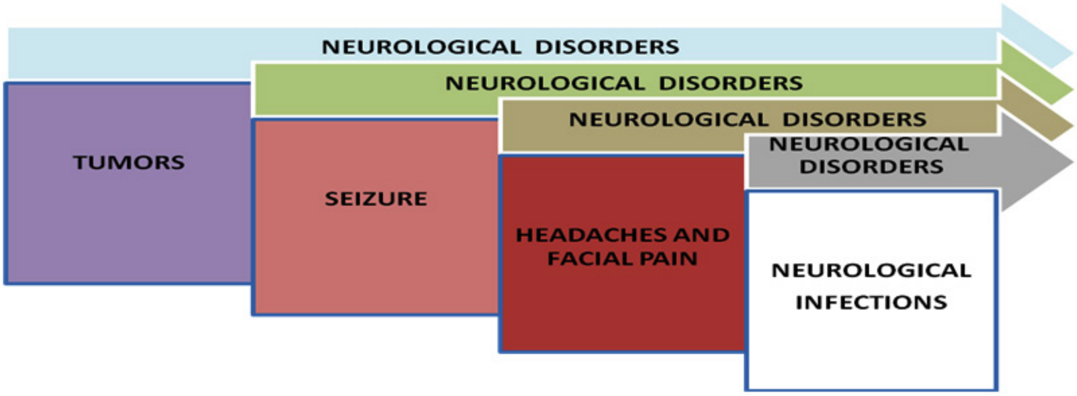

Fig. 1. A Systematic Level Of Neurological Disorders

Table 1. A systematic contribution chart of experts

S. No.	Experts	Year	Contributions
1.	Mitchell D. Woodbright [33]	2024	They proposed a feature extraction method from the EEG signals to predict neurological disorders. Deep learning concepts have been utilized to acquire visualizations of the predictions.
2.	Goel, S[34]	2024	Transformation of recorded EEG signals into recurrence graphs has been the main the main focus here. The features have been extracted from the recurrence graphs for detection of disorders. Principal Component Analysis has been used for extracting the features, which has resulted in reduction of computational steps.
3.	Ali, L. [35]	2023	This paper has proposed a new and efficient feature extraction method with the help of deep neural network and has also compared its performance with the contemporary works.
4.	Singh, A. K [36]	2023	This works has facilitated the pipeline design for the analysis of signals recorded from brain. For this purpose, extensive use of artificial intelligence and machine learning has been advocated.
5.	Kidwai M.S[37]	2022	Proposed an algorithm that is based on Order Recurrence Plots (ORPs) and Machine Learning, for the detection of neurological disorders. Has also compared the performance of the proposed algorithm with the contemporary works and the performance of the proposed algorithm has been much better in terms of specifity, precision and other parameters.
6.	Lima [38]	2022	This study is focussed on reviewing various Machine Learning based signal conditioning techniques for acquired EEG signals and has compared and analyzed their performances.
7.	Xie, Q [39]	2021	They had utilized dynamic functional connectivity network for feature extraction from EEG signals for the efficient diagnosis of neurological disorders.
8.	Vandana, J.[40]	2021	Provided an up-to-date comprehensive overview of the research focused on utilizing machine learning techniques to diagnose bruxism,epilepsy and dementia.
9.	Raghavendra, U [41]	2020	Offered a contemporary survey of research spanning the previous two decades on the automated detection of epilepsy and Bruxism by emphasizing on analysis of physiological signals and images.
10.	Wanzeng Kong [42]	2019	Employed synchronization in the phase of recorded EEG data for the analysis of signals and for finding the reason of epileptic seizures in patients.
11.	Miaolin Fan [43].	2019	Investigated the spatial-temporal synchronization patterns within the brains of epileptic individuals by utilizing spectral graph theoretic features extracted from scalp EEG data.
12.	Anwesha Sengupta[44]	2018	Has discussed a specific method to acquire data from EEG machine so that it can be analyzed effectively for detection of neurological disorders.
13.	L. Moumdjian [45]	2018	Observed what effect does the auditory stimulus has on the EEG signals that are already synchronized in the patients of neurological disorders.
14.	Marila Rezende Azevedo[46]	2018	Employed the neuronal groups for analyzing the changes in EEG signals of a patient having sleep bruxism.
15.	Alotaiby[47]	2018	Outlined the signaling pathways associated with neurological disorders.
16.	Li S. [49]	2018	Introduced the concept of network synchronization with periodic coupling

17.	Notbohm [50]	2016	Studied the effect of light as a stimulus on the EEG signals.
18.	Oleksandr Popovych[51]	2014	Explored methods to counteract abnormal neuronal synchronization through invasive and non-invasive brain stimulation techniques.
19.	Lialiana [52]	2013	Designed a brain-computer interface that depends on the elevated correlation levels among EEG signals.
20.	Milan Brázdil [53]	2013	Employed synchronization patterns to investigate cortical activity in response to stimuli.
21.	Lai Y M[54]	2013	Outlined the distinctions between clustering, de-synchronization, and synchronization in EEG signal states.
22.	Akam [55]	2012	Described a method to study EEG signal states through the oscillatory dynamic techniques.
23.	Lehnertz[56]	2011	Provided fundamental terminology regarding neurophysiological signals.
24.	Katharine Brigham[57]	2010	Utilized synchronization in EEG signals to decode an individual's thoughts.
25.	Ermentrout [58]	2010	Has discussed about the Neuroscience empirically.
26.	Schroeder[59]	2009	Discussed how neuronal oscillations can be instrumental in detecting various disorders in humans.
27.	Velazquez [60]	2007	Focused on activity in EEG signal states during epileptic seizure in patients.

This approach has been recognized through the substantial body of work conducted by Klimesch[12]. Their research revealed that lower alpha ERD is linked to general task demands such as attention processes (basic alertness, attentiveness, or arousal), while ERD in the upper range of the alpha band can indicate specific task requirements. Similarly, the upper alpha frequency band has been identified as particularly responsive to demands associated with insight. As outlined in Neuper and Pfurtscheller[11], the Event-Related Desynchronization (ERD) of EEG activity in the alpha band likely reflects increased excitability and firing of neurons in the underlying cortical areas, which can be associated with an enhanced transfer of information in thalamo-cortical circuits[11].

On the other hand, Event-Related Synchronization (ERS) of alpha activity is believed to signify a reduced level of dynamic information processing in the underlying neuronal networks, often referred to as 'cortical idling' [13].

Nonetheless, recent developments in this field of study also propose that the synchronization phenomenon observed in alpha-based activity is connected to the dynamic execution of cognitive tasks, potentially involving processes of cognitive control[28].

Data Acquisition of Synchronization Concepts

For the investigation of cortical activity, EEG signals are acquired using an EEG amplifier at a sampling rate of 500 Hz. Gold electrodes (9.1 mm of diameter) are placed on an electrode cap following the standard 10-20 system with spaced positions. A single electrode is positioned on the forehead (Fpz), and an orientation electrode is located on the nose.

The EEG signal is adjusted for ocular artifacts using an automated regression-based method, supplemented by visual inspection to identify any remaining artifacts stemming from eye movements and muscle tension. Typically, the calculation of power in various bands of the EEG signal employs a standard Fast Fourier Transform (FFT) applied to time windows lasting 1000 ms with 900 ms overlap. This process enables the extraction of features within the upper alpha frequency band (10.5–12.5 Hz). Additionally, for complementary analysis, power computation in the lower alpha band (8.5–10.5 Hz) is carried out.

Based on the EEG outcomes and the task-related synchronization of frontal alpha activity, a substantial level of synchronization is observed during top-down processing. Conversely, tasks involving bottom-up processing demonstrate marked desynchronization [24,28,30].

Detection of neurological disorders on the basis of oscillations

Several investigations suggest that the

Table 2. List of few main neurological disorders that have been studied along with the researchers' names

No.	Researchers	Year	Parkinson disease	Epilepsy	Bruxism	Hearing Loss	Schizophrenia	Stroke
1.	Woodbright, M. D [33]	2024	√	√	√	√	√	√
2.	Goel, S.[34]	2024		√				
3.	Gulay[61]	2023	√					
4.	Tawhid[62]	2023		√	√		√	√
5.	Alalayah, K. M. [63]	2023	√					
6.	Mary, G. [64]	2022	√	√				
7.	Lima, A. A.[65]	2022	√	√				
8.	Saravanan, N. P.[66]	2021		√				
9.	Boonyakitanont, P. [67].	2020		√				
10.	Raghavendra, U.[41]	2020	√		√			
11.	Logroscino [68]	2019		√	√	√	√	√
12.	Yannick [69]	2019	√	√	√	√	√	√
13.	Kidwai [70]	2019	√	√				√
14.	Acharya [71]	2018	√	√	√	√		
15.	Kidwai [72]	2017	√	√	√			
16.	Uva[73]	2015	√	√	√	√		
17.	Kumar, Y [74]	2014		√				√
18.	Jiruska, P [75]	2013	√	√		√	√	√
19.	Kumar, S. P[76]	2010		√				√
20.	Wirrell E [77]	2008	√	√				
21.	Loddenkemper T [78]	2007	√	√				
22.	Wirrell E [79]	2006		√	√			

rise in bilateral frontal alpha activity observed during a standardized test for divergent thinking is connected with enhanced creativity. This discovery presents the primary direct evidence for the functional significance of alpha oscillations in creative ideation.

A notable consequence of oscillations in the alpha band of EEG signals during imaginative thinking is cortical idling. Previous research has indicated that alpha band oscillations may indicate reduced mental activity, as a decline in alpha power is commonly observed during brain activations in tasks. Therefore, the increase in alpha power in the frontal cortex is suggested to represent a hypoactive state of this brain region, termed "hypofrontality," which in turn may lead to enhanced creativity.

However, current research suggests that creativity is an active cognitive process rather than an outcome of decreased activity in the frontal cortex. Several studies have shown a decrease in alpha power during various other demanding cognitive tasks[16].

More specifically, creative ideation involves internal thought processes combined with an inhibitory cognitive control mechanism [79,80]. This mechanism acts to shield the internal process from potential disruption caused by incoming, attention-grabbing, but ultimately irrelevant stimuli [31,32].

Hence, the amplified alpha activity triggered by frontal 10Hz- transcranial alternating current stimulation (tACS) could boost the top-down management of internal processes, thereby aiding in improved creative ideation [81].

A consolidated chart summarizing the significant recent works by various experts is presented in Table 1.

The current state-of-the-art techniques for acquiring EEG signals and using them to detect neurological disorders involve significant advancements in both hardware and software, including improvements in signal acquisition, processing, machine learning, and brain-computer interfaces (BCIs). These developments have enhanced the precision, usability, and clinical effectiveness of EEG in diagnosing neurological conditions. The current state-of-the-art techniques for EEG signal acquisition and analysis have been significantly advanced through high-density EEG, portable systems, sophisticated signal processing, and the application of AI and machine learning. These innovations have greatly enhanced the accuracy, accessibility, and real-time capabilities of EEG in detecting and diagnosing neurological disorders, ranging from epilepsy and Parkinson's disease to Alzheimer's and autism spectrum disorders.

CONCLUSION

This paper has discussed the presence of synchronization among bio-signals generated in the brain, and has highlighted its significance in the study and analysis of the brain through relevant and recent research findings. It is evident from the relevant literature that several authors have discovered that various brain activities can be examined by observing the synchronization patterns in EEG signals, with changes in these patterns observed when the brain responds to specific stimuli. Furthermore, existing research by scientists and doctors suggests that the correlation between neuronal groups can also serve as a means to detect various neurological disorders in humans. The desynchronization patterns of EEG signals can also be utilized to investigate cortical activity[82,83]. From the existing literature, it is also apparent that there are numerous techniques available for detecting various neurological disorders. However, there is a research gap in the development of a versatile and simple technique that can detect seizure-based neurological disorders with minimal or no alteration to its approach[84,85].

The synchronization phenomenon in EEG signals has been widely employed in the study of brain activities and for the detection of neurological disorders. However, different parameters and approaches are utilized for detecting various neurological disorders. Additionally, experts have proposed various theories to observe changes in EEG signal synchronization using graphical methods. Yet, there has been limited work in developing a method that quantifies synchronization to facilitate brain study. Therefore, there is potential for developing a single-feature-based technique that can specifically detect seizure-based neurological disorders.

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Ethics Statement

This research did not involve human participants, animal subjects, or any material that requires ethical approval.

Informed Consent Statement

This study did not involve human participants, and therefore, informed consent was not required.

Clinical Trial Registration

This research does not involve any clinical trials

Author contributions

Mohd. Suhaib Kidwai: Conceptualization and writing the original draft; Mohd. Maroof Siddiqui: Arranging the literature review of the related works in chronological and tabular form, editing and proofreading.

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