NEURAL DYNAMICS IN EPILEPSY: A PARADIGM SHIFT

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Abstract The human brain and the human mind are two separate entities that have baffled and mystified mankind since time immemorial. The human brain is the morphological or structural precept of the central nervous system, and the human mind represents the working vignette of the structural moiety in real–time mental phase space characterised by a specific stochastic trajectory sub-serving a precept specific to a mental function. The dictum of designing and developing of automated algorithms for EEG-based seizure detection and epilepsy diagnosis based on the quantitative parametric representation of the qualitative or visual aspect of the markers still needs to evolve to enhance its specificity and sensitivity. The exploration of nonlinear dynamics has led to the development of methods that can measure and understand the complex behaviours associated with epileptic seizures. These approaches are valuable because they can uncover information that traditional linear and spectral signal analysis methods cannot, thereby enhancing the potential for identifying the pre-seizure state. This capability could enable the use of devices designed to intervene before a seizure occurs, employing physiological or pharmacological means to prevent it. The field of seizure prediction and prevention is rapidly evolving, with a focus on how chaotic neural dynamics within nonlinear systems can offer new insights into managing epilepsy. This research area seeks to delve deeper into the transition from non-seizure to seizure states (interictal to ictal transitions) to improve our comprehension of how seizures develop, potentially leading to more effective treatments for epilepsy.

Keywords: Chaos, Dynamical EEG Process, EEG and Chaos, Epilepsy, Non-Linear Analysis

Introduction The *Human Brain* and the *Human Mind* are two intertwined and interlinked entities that have bemused and bewildered mankind since times immemorial. The Human Brain is the morphological or structural precept of the Central Nervous System and the Human Mind represents the working vignette of the structural moiety in real–time mental phase space characterised by a specific stochastic trajectory sub-serving a precept specific to a mental function. The Human Mind represents the neuropsychophysiological precepts of *memory, higher mentation, and abstruse thinking* that are instrumental in shaping an individual’s persona and psyche. Skarda and Freeman's [1] research on odour recognition revealed groundbreaking insights into how the brain processes sensory and motor information. They observed that EEG activity across different regions of the cerebral cortex follows patterns of nonlinear chaos, rather than being steady or randomly disordered. This chaotic activity is foundational to all neural processing, serving as a regulated mechanism for generating orderly yet random neural activity. This mechanism is crucial for both recalling learned sensory patterns and acquiring new ones. It highlights chaos as an essential element in the brain's ability to handle and interpret sensory information dynamically. The key to understanding the “*Functional Brain: The Human Mind”* as an interactive switching device in real-time lies in the appreciation of *dynamical nonlinearity* that profiles the behaviour of neurones in an interactive pool mass. The interacting and functional neurones in their dedicated neuronal pool observe and adhere to the *tenets of chaos*. Birbaumer et al [2] worked on the ambit and depth of the human brain and documented that nonlinear correlates of *electroencephalograph (EEG)* increase in dimensions and evolve with higher neural information processing. The *neural dynamics* during the complex associative thinking process etch a more evolved esplanade as compared to that observed during simple neuropsychophysiological processes that do not mandate complex association. Likewise, Pijin et al (1991) [3] worked on the electrical complexity of EEG signals within select brain areas and further documented that EEG signals are a manifestation of random neuronal processing, generated as a consequence of the *non-linear dynamic system*. Chatrian et al [4] and Elbert et al [5] further documented the fact EEG lead-pairs overlying the frontal lobe generate EEG signals with more evolved nonlinear chaotic neural dynamics during the process of imagination of objects as compared to that observed during the actual perception of the object. However, in *path-neuropsychophysiological* states of *schizophrenia* and *epilepsy*, reduced chaos, and less variable and more rigid neural dynamics can be observed. The spatiotemporal patterns of neocortical oscillations have documented that behavioural information exists in spatial quantal patterns of activity in the somatosensory and visual cortices [6]. The EEG, or electroencephalogram, captures the fluctuating electrical activity of the brain as a time series of voltage measurements. Traditional time series analysis techniques, such as power analysis, linear orthogonal transforms, and parametric linear modelling, often struggle to identify the essential characteristics of EEG data. These methods may mistakenly interpret the complexity of EEG signals, which arise from a self-driven (autonomous) nonlinear system, as mere random noise [7]. Research into the EEG's statistical nature has shown that it is influenced by both temporal and spatial factors [8]. The EEG exhibits features typical of nonlinear dynamics, including limit cycles (observed in alpha wave activity), bursting patterns during light sleep, jump phenomena (sudden changes in signal behaviour), amplitude-dependent frequency changes (where smaller amplitudes are associated with higher frequencies), and frequency harmonics, especially under conditions like photic driving [9]. Numerous studies have confirmed that the EEG signal is inherently nonlinear, displaying both deterministic and chaotic attributes, which underscores the complexity and richness of brain activity as captured through EEG [10], [11], [12], [1]. Iasemidis [13] introduced a method for mapping the dynamic behaviour of complex, multidimensional systems through the creation of phase space portraits. In this approach, every time-dependent variable of the system is considered a vector in the phase space, with each vector representing the system's instantaneous state. These vectors are plotted over time within the phase space to illustrate the system's evolution. This visualisation technique results in a graphic representation where the system's trajectory is confined to specific areas within the phase space, known as “*attractors*”. The shape and properties of these attractors offer insights into the overall state and behaviour of the system, providing a powerful tool for understanding its dynamics. Iasemidis and Sackellars [14] noted that the geometric characteristics of a system's phase portrait can be quantitatively described by metrics that encapsulate the system's dynamics. Specifically, the complexity of an attractor within the phase space is quantified by its dimension. An attractor with a larger dimension signifies greater complexity, presenting a more intricate pattern within the phase space. This distinction emphasises the difference between the embedding dimension, which represents the overall phase space, and the dimension of an attractor, which highlights the complexity of the system's behaviour captured within that space. Holden [15] described chaotic attractor as the rapid divergence of trajectories that start from points close to each other in ictal conditions, where the divergence occurs exponentially, indicating a brief period of closeness before expanding. This expansion gives rise to a complex, layered structure within the attractor. To quantify the level of chaos within an attractor, two key measures are used: the Kolmogorov entropy and the Lyapunov exponents. An attractor is considered chaotic if it has a positive Kolmogorov entropy or if at least one of its Lyapunov exponents is positive. The Kolmogorov entropy, also known as Sinai or metric entropy, quantifies the uncertainty or unpredictability about the system's future state based on its past states within the phase space. On the other hand, the Lyapunov exponents measure the rate at which trajectories either converge or diverge in the phase space, reflecting the dynamics of expansion and folding in different local directions within the attractor. [16], [17], [18] Bullock and Horridge [19] worked on models that process information using digital computers and have conceptualised neurones as binary decision elements, arranging them into networks to perform straightforward Boolean operations. This approach underscores the presence of sensory and motor-specific information within the spatial aspects of EEG activity in the central nervous system, laying the foundational theory for *Brain-Computer Interface (BCI) technology*. BCIs leverage the "*coded*" pathways of peripheral sensory systems, known as "labelled lines," to interpret brain signals. Such models have successfully demonstrated their utility in understanding the operations of peripheral motor systems and certain areas of the central nervous system. Through this framework, researchers have been able to identify specific neurones that act as "*feature detectors*" and "*command units*", further validating the model's effectiveness in mapping and interpreting neural activity.

Chaos "*Chaos is aperiodic long-term behaviour in a deterministic system that exhibits sensitive dependence on initial conditions*". *Chaos* is defined as "*Stochastic behaviour in a deterministic system*". Chaos is a seeming lawless random behaviour ruled by a deterministic system. Skarda and Freeman [1] further defined chaos as "*Pseudorandom Noise*". It should be noted that chaotic behaviour excludes fixed points as well as periodic behaviour. A dynamic system is considered stable when it can return to its original state following a disturbance. If the system's base state is constant and does not oscillate, it is described as being in equilibrium. Plotting the system's amplitude or energy levels against each other on a graph yields a curve or trajectory that concludes at a singular point as the system reaches equilibrium. This particular point can be arrived at from various initial conditions after experiencing perturbations, indicating its role as an "attractor." The range of initial conditions that lead to this attractor forms what is known as the attractor's 'basin'. When the input of the system is manipulated to fall within the basin of an attractor, the system's dynamics are effectively dictated by that attractor [30]. The model to understand central associative functions postulates the following [30]:

• There exists for some time during the interval between the onsets of the stimulus and response, some stimulus–specific information in the respective cortex to serve as the basis for the correct response.

• This information is then encoded in the form of a space-time pattern of neural activity, exemplifying the spatial–temporal phase space of receptors and synaptic mechanisms, for each stimulus.

• These patterns are then manifested, however indirectly, in the electroencephalographic (EEG) potentials recorded from the scalp. Some postulated patterns have been identified [30]. The formation of new, unlearned percepts and sensory–motor patterns can be conceptualised and simulated neurophysiologically after profiling and patterning of *ongoing chaotic neural electrical processes*. The *chaotic activity* essentially needs to be a deterministic system that can generate new sensory–motor patterns which control the environment in an ever–changing dynamic way contingent upon slightly differing initial conditions and consequences. The chaotic systems exhibit strong dependence on initial conditions and the ability to show *self–organisation* and *self-iteration*, i.e., to evolve towards ordered temporal and spatial patterns [20]. Lorenz [21] discovered that such a simple-looking deterministic system has extremely erratic dynamics; over a wide range of parameters, the solutions oscillate irregularly never exactly repeating but always remaining in a bounded region of phase space. When trajectories are plotted in three dimensions, they settle onto a complicated set, known as *strange attraction*. Unlike stable fixed points and limit cycles, the strange attraction is not a point or a curve or even a surface; it's a fractal, with fractional dimensions between 2 and 3. The motion of the attraction exhibits sensitive dependence on initial conditions exemplifying the fact that two trajectories starting very close together will rapidly diverge from each other, and therefore have different futures. Lorenz [21] explains how a *random, non-linear dynamical system with an implicate structured premise* operates behind a complex phenomenon that is perceived by the human mind.

The main features of Lorenz's proponent are as [22], [23]:

1. *Nonlinearity*: Chaotic systems are essentially nonlinear dynamic systems, but all nonlinear dynamical systems are not chaotic.
2. *Sensitivity to initial conditions*: All *chaotic systems* are sensitive to initial conditions with a small perturbation in the system that may result in catastrophic drastic change subsequently, more popularly known as the *butterfly effect*.
3. *Strange attractor*: This is an important predictable factor that influences the operation of a *chaotic system*, with one or more hidden rules or principles dominating the evolution of the system in select specific tasks.
4. *Non–periodic time path*: The *nonlinear qualia of chaos* predates and defines the essence of the flow of time and space, with the system evolving accordingly. There is a regular cycle sequence that occurs in a nonlinear system at a time when two same states are present in a system and such cyclic variability can never be prognosticated. Some researchers have proposed that there are *three essential ingredients of a chaotic system* namely, *determinism*, *aperiodicity*, and *sensitive dependence on initial conditions* [24]. Skarda and Freeman [1] found that chaos allows the neural cells to return to old already formed neural cell assemblies or neural pools leading to *exhausting repetition of self-iteration*. With increasing competition between neural cell assemblies, the phase space, in which a corresponding EEG activity varies, becomes multi–dimensional and the available measure of the chaotic complexity of the time-series events of human EEG is known as its *fractal dimension* [2].

Fractals The word *fractal (irregular, fragmented)* is about an object in the space or temporal fluctuations that possess a *self–iterative* form that cannot be described in a single absolute scale. Self–similarity and fractal dimension are the most important features of fractals. Self–similarity has recursive qualia resembling the shape of the whole, even if cut off from any part of the shape through constant repetition. Fractal dimension value is usually a non-integer fractional number; hence this dimension is referred to as fractals helping in the process of pattern – recognition [25]. Barabási [26] studied the *dynamic phenomena of fractal theory* in the human body and nature and observed that *fractal dictum* allows a representative approximation of the complexities in processes that are nonlinear and lack linearity. It is interesting to note that *fractal structural behaviour* seems to be a primal physiological and structural feature of the human body that can be appreciated across all organ systems physiology like the *bronchial ramifications*, *vascular system architecture*, and *neuronal system connectomes*. The *fractal organisational ramifications* allow organ system physiology optimisation accommodating an increased surface area in a minimal viable space framework.

Dynamical Systems Creating a phase space portrait is a recognised method for analysing the dynamic behaviour of complex, multidimensional systems. In this approach, every time-dependent variable of the system is considered a vector component within the phase space, with each vector capturing a snapshot of the system's state at a particular moment [13]. By plotting these vectors in sequence within the phase space, one can visualise the progression of the system's state over time. Often, this visualisation reveals that the system's dynamics are confined to specific areas within the phase space, known as "*attractors*". These attractors' geometric characteristics offer valuable insights into the overall behaviour and state of the system, allowing for a deeper understanding of its dynamics. The theory of dynamical systems is concerned with the behaviour of the system including *classifying the types of trajectories that can occur*, *determining their behaviour on charging initial conditions*, *chaos*, and *effects of charge of parameters on trajectories (bifurcations)*. The basic theory classifying the trajectories into *discrete structures*, includes *fixed points*, l*imit cycles*, and *the transient basis of attraction stability complexity*.

Analysis of Dynamical Systems The salience of topological features of a dynamical system can be reconstructed from a time series measurement of a single variable, known as *state space reconstruction on the embedding of the time series and the two available approaches for reconstruction of state space* include *time delay embedding* (usually used in EEG analysis) and *spatial embedding*. The complexity of a dynamical system is measured and quantified through the *correlation dimension* that is related to the *topological dimension of attraction* and assays the *fractal dimension of the attraction*. The strength of chaos and its degree of unpredictability is measured by *Lyapunov exponents*, wherein the motion of two attraction exhibits sensitive dependence on the initial condition, with the two trajectories starting very close together diverge subsequently from each other as described by Strogatz [28].

Wavelet Analysis Electroencephalographic wave-frequency bands of *delta*, *theta*, *alpha*, *beta* and *gamma waveforms* can further be processed and digitally evaluated through *wavelet methodology of chaos* for the detection of seizures and epilepsy focus (or foci). The complex nature of EEG waveforms, characterised by their non-linear dynamics, can be quantified using specific measures such as the Correlation Dimension (CD) and the Largest Lyapunov Exponent (LLE). The CD is a metric that reflects the system's complexity, while the LLE indicates the degree of chaotic behaviour within the system. Employing a wavelet-based approach allows for the isolation of variations in the Correlation Dimension and Largest Lyapunov Exponent within distinct sub-bands of EEG signals [31]. It is observed that while there may not be significant differences in the values of the parameters obtained from the original EEG, differences may be identified when the parameters are employed in conjunction with specific EEG sub–bands. Moreover, it has been observed that *the CD wavelet variable* has a high index of sensitivity and specificity for seizure detection in the high-frequency waveform sub-bands of *beta* and *gamma* and the *LLE wavelet variable* categorises *epileptic (neuronal avalanche cascade)* focus (or foci) in the lower frequency waveform sub-bands of *alpha* [31].

EEG and Chaos The EEG, *time-series*, has been conceptualised as a *series of numerical values (voltages) recorded across time*. Traditional time series analysis techniques, such as power analysis, linear orthogonal transforms, and parametric linear modelling, often fall short of accurately identifying the nuances of time series data produced by autonomous nonlinear systems, which operate without external inputs. These conventional methods may inaccurately characterise the majority of the data as random and insignificant noise [7]. However, in recent years, advanced methods designed for the dynamic analysis of complex time series have been increasingly applied to study signals from biological systems, including the electroencephalogram (EEG). These newer approaches are better equipped to uncover the intricate patterns and meaningful information hidden within the seemingly chaotic data of biological signals. The statistical properties of the *EEG, nonlinear signals,* spread across the coordinates of both *time* and *space* [8] and are nonlinear, deterministic and chaotic [1 and 12]. The *qualia of the EEG*, namely the *existence of limit cycles (α activity)*, *instances of bursting behaviour (during light sleep)*, *jump phenomena (hysteresis)*, *amplitude-dependent frequencies (the smaller the amplitude, the higher the EEG frequency)*, and *frequency harmonics (e.g., under photic driving conditions)*, are among the long catalogue of characteristic designate essence of nonlinear systems [9]. The characteristic dynamical features of *EEG time series* corresponding to specific states, such as mental tasks, sleep, dementia, and coma have also been profiled by respective studies [5].

Epilepsy *Epilepsy* is a chronic disorder of the brain that affects 2% of people worldwide which is characterised by a *burst of neuronal avalanche cascade* that is recurrent. The seizures may be brief episodes of involuntary movements of hands and feet that may involve a select area of the brain (known as *partial seizures*) or the entire cerebral hemisphere (known as *generalised seizures*) and are sometimes accompanied by loss of consciousness [32]. Epilepsy was redefined conceptually in 2005, as a disorder of the brain system characterised by an enduring predisposition to generate an incessant burst of neural activity termed the *neuronal avalanche* or *seizures* [33]. The International League Against Epilepsy [34] accepted the practical definition for special circumstances that do not meet the two unprovoked seizure criteria in the *task force*. "*The task force proposed that epilepsy be considered to be a disease of the brain* defined by any of the following conditions: (1) At least two unprovoked (or reflex) seizures occurring >24 h apart; (2) one unprovoked (or reflex) seizure and a probability of further seizures similar to the general recurrence risk (at least 60%) after two unprovoked seizures, occurring over the next 10 years; (3) diagnosis of an epilepsy syndrome".

Epilepsy and Chaos Dynamical analysis of EEG recordings from patients with epilepsy has provided novel perspectives regarding epileptogenesis, documenting the fact that epileptic seizure activity can be patterned and profiled with a high degree of sensitivity and specificity making use of *nonlinear chaotic dynamical systems*. Babloyanz and Destexhe [35], perhaps for the first time, could categorise and assign the EEG signals specific to epilepsy with a high degree of sensitivity making use of the principles of *nonlinear chaotic dynamics*. Research into partial seizures, particularly those originating in the temporal lobe, has revealed the existence of limit cycles—a feature typical of nonlinear systems— within the seizure discharges captured by subdural electrodes placed over the epileptogenic focus. These findings underscore the presence of chaotic attractors in seizure activity, which are often characterised by a fractal dimension and the presence of at least one positive Lyapunov exponent, indicating a system's sensitivity to initial conditions and chaotic behaviour. Further evidence supporting the nonlinear chaotic dynamics in EEG signals comes from studies, including work by Frank et al. [37], which observed such dynamics in patients with mixed generalised seizures. Collectively, these studies support the conclusion that epileptic seizures arise from deterministic nonlinear chaotic systems. This suggests that the manifestation of epileptic seizures could be viewed as intermittent phase transitions, a hallmark of the behaviour of such complex systems [9]. Iasemidis and Sackellers [14] observed that the *chaoticity of the signal* is highest during the postictal state, lowest in seizure discharge and intermediate in the pre-ictal state. The onset of a seizure represents the spatiotemporal transition from a complex to a less complex state. Birbaumer et al 1995[2] concluded that the feedback of cortical negativity and positivity during seizure trained to develop higher variability of brain processes and learned to become flexible modification of that situation before the patient reaches any dangerous rigidity. Iasemidis et al [13], [38], [39], [40] stated that dynamical changes in EEG preceded the seizure activity several minutes before seizure onset in which large areas of the cortex are dynamically entrained. During the pre-ictal phase, the dynamical characteristics of EEG signals from the epileptogenic hippocampus show notable differences compared to those from the contralateral (opposite side) hippocampus, which behaves more typically. Specifically, the epileptogenic hippocampus [40] displays patterns of behaviour that are more ordered and exhibit less complexity both inter-ictally (between seizures) and pre-ictally (before seizures) than its contralateral counterpart. This observation was further supported by Iasemidis and Sackellares [14], who identified that, in the period leading up to a seizure, the dynamical state of the epileptogenic hippocampus is significantly distinct from the state of the contralateral hippocampus, which does not exhibit epileptogenic activity. This distinction underscores the unique dynamical properties of the epileptogenic regions in the brain, offering potential avenues for targeted intervention and monitoring in epilepsy management. Iasemidis and Sackellares [14] described that "*epileptic brains repeatedly make abrupt transitions into and out of the ictal state as the epileptogenic focus drives them into self–organising phase transitions from chaos to order as evinced by the observations of 1) positive Lyapunov exponent in EEG signal (2) nonlinearities in interictal EEG generated by the epileptogenic focus, (3) existence of a spatiotemporal transition in EEG dynamics (from chaos to order, drop in Lmax values at electrode sites) preceding seizures by minutes to hours to days and (4) resetting of spatiotemporal dynamics by the seizure (from order to chaos), leading to the more favourable interictal condition*". Consequently, *scalp EEG* is being extensively used in many fields of neuroscience including *neurology*, *pathology*, *sleep medicine* and *neuroscience research* and has been proven to be an important diagnostic tool observed by Schroder [41].

Conclusion The advancement in understanding the dynamics of epileptic seizures has been significantly propelled by the development of complex nonlinear dynamics and quantitative measures. These methods are particularly advantageous as they do not rely on predefined models of brain function, either normal or epileptic. They are capable of uncovering information that traditional linear and spectral signal analysis methods cannot access. Recent applications of these sophisticated mathematical techniques have consistently supported the notion that the EEG is produced through mechanisms that adhere to nonlinear deterministic principles, with compelling evidence pointing towards chaotic processes. Delving deeper into these nonlinear dynamical processes is crucial for the eventual creation of realistic mathematical models of epileptogenic brain function. Such models could provide insights into the episodic nature of epileptic seizures. The ability to distinguish between the signal dynamics of epileptogenic and non-epileptogenic regions, especially during the interictal (between seizures) phase, presents a significant opportunity for improving the localisation of seizure origins. Traditionally, clinicians depend on recordings during seizures (ictal recordings) for diagnostic evaluations and to precisely determine the seizure onset zone before surgery. This often requires extended recording periods to capture enough seizure events. However, identifying the unique interictal dynamical properties of the seizure focus through EEG could dramatically shorten the time needed for diagnostic and pre-surgical evaluations, leading to more accurate localisation of the epileptogenic focus. The observation that the evolution of a seizure encompasses not merely the binary states of interictal (between seizures) and ictal (during a seizure) phases but includes a distinct pre-ictal phase, which dynamically diverges from the other two, presents significant insights for both research and clinical practice. This nuanced understanding underscores the complexity of seizure dynamics and opens up new avenues for exploring the underlying mechanisms that trigger seizures at specific times and locations. The potential to identify the pre-ictal state through advanced monitoring could revolutionise epilepsy management, enabling preemptive actions to avert seizures before they fully manifest. The prospect of utilising implanted devices for the real-time detection of the pre-ictal state introduces a promising strategy for seizure intervention. Such devices, equipped to deliver timely physiological or pharmacological interventions, could significantly mitigate the impact of epilepsy on individuals' lives by preventing seizures from occurring. This approach exemplifies the concept of controlling chaos, a burgeoning area of research that seeks to apply principles of chaos theory for practical interventions in complex systems. The ability to control or influence chaotic systems, such as the neurological dynamics leading to seizures, holds great promise for improving patient outcomes and enhancing our understanding of brain functions [42]. Schiff et al [43] have shown through their research on hippocampal slices that it's possible to manage epileptic seizures by influencing the chaotic dynamics characteristic of these conditions. Their experiments reveal that applying electrical stimuli at specific intervals can significantly alter the course of these dynamics, offering a promising method for seizure control. This work highlights the effectiveness of targeted, low-voltage electrical interventions in modulating the complex behaviour of epileptic seizures, illustrating a novel approach to managing these episodes. The foundational assumptions underpinning this research include the premise that the electrical activity originating from the epileptogenic hippocampus exhibits unique dynamical properties compared to those from analogous, non-affected areas (such as the contralateral hippocampus). Furthermore, it is hypothesised that these variations hold predictive markers for forthcoming epileptic episodes and that through the application of nonlinear dynamics methodologies, these signal attributes can be effectively measured and analysed. A reasonable model, based on studies to date, is that: 1. The epileptogenic hippocampus, due to alterations in its neuronal composition and disruptions in neural connectivity, becomes prone to spontaneous shifts towards more structured states. These transitions are indicative of the brain's predisposition to epilepsy, and 2. The involvement of the epileptogenic hippocampus in initiating or contributing to seizure activity is contingent upon the long-term (spanning several minutes) spatiotemporal synchronisation of a critical volume and/or the wave dynamics involving interconnected areas of the temporal and frontal lobes. The above is an attempt to appreciate the working of the *Functional Human Brain/Human Mind* in the disease process of epilepsy wherein it has been proposed on documentary evidence that the *Human Mind idles in a state of Chaos through a phase – space of stochastic trajectory vide varied dedicated neuronal pools and sub serves and responds to space–time–locked stimulus across the framework and mould so evolved with the neurophysiological phenomenon of memory.* However, the disease process of epilepsy tends to dampen the non–linear chaotic oscillations essential for the working of the *Human Mind!*

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