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Research Report

COMPLEXITY QUANTIFICATION OF DENSE ARRAY EEG USING SAMPLE ENTROPY ANALYSIS

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In this paper, a time series complexity analysis of dense array electroencephalogram signals is carried out using the recently introduced Sample Entropy (SampEn) measure. This statistic quantifies the regularity in signals recorded from systems that can vary from the purely deterministic to purely stochastic realm. The present analysis is conducted with an objective of gaining insight into complexity variations related to changing brain dynamics for EEG recorded from the three cases of passive,eyes closed condition, a mental arithmetic task and the same mental task carried out after a physical exertion task. It is observed that the statistic is a robust quantifier of complexity suited for short physiological signals such as the EEG and it points to the specific brain regions that exhibit lowered complexity during the mental task state as compared to a passive, relaxed state. In the case of mental tasks carried out before and after the performance of a physical exercise, the statistic can detect the variations brought in by the intermediate fatigue inducing exercise period. This enhances its utility in detecting subtle changes in the brain state that can find wider scope for applications in EEG based brain studies.

Keywords: Dense array EEG; brain dynamics; complexity analysis; surrogate data; sample entropy.

1. Introduction

In recent times, the application of nonlinear methods to the analysis of data obtained as output from complex systems in nature has been of interest to the scientific world. In cases where the governing equations of motion or even the number of dynamical variables involved are unknown, the nonlinear time series analysis tools have gained greater importance. The Electroencephalogram (EEG) signal generated within the human brain is one of the complex signals, which is being strongly pursued with the techniques based on nonlinear dynamics and deterministic chaos [3]. This line of approach involves the computation of invariant parameters such as generalized dimensions, entropies, Lyapunov exponents etc. from the EEG signal considered as a time series to characterize the dynamics of particular brain states [15, 20].

The studies based on the above mentioned characterizing parameters have been applied in many cases to distinguish normal subjects from those suffering from pathological conditions such as epilepsy [13]. Among the generalized dimensions, the correlation dimension that estimates the active degrees of freedom and among entropies, the Kolmogorov-Sinai (K-S) entropy that gives information regarding the dynamics have been the subjects of much research [15]. However the computation of these based on the Grassberger-Procassia algorithm [4] and its variants make the assumption of infinite length, stationary and noise-free data. These stringent conditions are rarely met in the context of biological or physiological data such as the EEG. Many authors have proved the nonstationary aspect of EEG signals arising probably from the presence of a number of time scales in the underlying dynamics [8]. A direct consequence of such nonstationarity is the slow variation of the computed 'invariants' with time [9,19]. The computation of another important parameter, Lyapunov exponent, which estimates the long-term average rate of exponential growth of small perturbations to initial conditions, is very sensitive to noise besides being tedious and cumbersome [10, 28].

Nevertheless, the computational studies are useful in distinguishing between various functional as well as pathological brain states and have even been found to be suitable functional markers with intra-individual stability [24]. The application of these methods in the prediction of the onset of epileptic seizures [12] and in delving into the co-ordination of cortical regions under different conditions cannot be undermined [26]. Hence, while the utmost care is to be exercised in accepting the quantitative results of the time series analysis of the EEG signal; the validity of such parameters with statistical significance as comparative measures across varying mental states has been more or less widely established.

Complexity measures are another class of statistics characterizing a time series that have arrived recently on the scene. Measures characterizing the relative 'randomness' in data sets have been thought of as useful markers discriminating between the conditions generating them in each case. Although other measures of complexity are also prevalent [27], entropy measures that quantify the rate of information generation in the system have been observed to be more widely useful in practical applications. The much used K-S entropy, which is usually used to quantify time series 'randomness', however suffers from the drawback of being affected by the presence of low magnitude noise in the data. Hence, to ensure convergence of this measure, very long data sets that tend to make the computation tedious and time consuming are required. The need is thus for a statistic that remains robust against noise; yet gives a meaningful measure of the regularity embedded in the time sequence of a limited length of elements. The Approximate Entropy (ApEn) introduced by Pincus [17] is one such measure that explores the time ordering of data points in a finite set by measuring the logarithmic likelihood that runs of patterns that are close remain close on next incremental comparisons. This statistic can compute a complexity measure for systems ranging from the purely deterministic to totally random realms and was applied to many clinically relevant studies in biological systems. Lately, Moorman and Richman [21] devised the Sample Entropy (SampEn) as a new and related measure that rectifies some of the in-built drawbacks of ApEn such as bias and inconsistency in results. This novel measure has been demonstrated to be useful in the discriminatory study of cardio-vascular data [21], which is typical of short, noisy data occurring in biological systems. As mentioned above, the discrimination between various mental states using invariants characterizing the EEG signal is now largely accepted. The computation of measures such as SampEn scores above the more popular complexity quantifiers such as the correlation dimension due to the fact that these are algorithmically simpler to implement and hence easier to compute. Also the effect of nonstationarity of the time series, as in the EEG, is also dealt with effectively since these complexity measures are designed to suit short data segments. Such and other attractive features have made these measures popular in physiological data analysis.

In this study we investigate the efficacy of the sample entropy statistic in differentiating the complexity nature of human EEG pertaining to three different states (a) passive, eyes closed state (E.C.), (b) a mental task state (M.T.) and (c) the same mental task state following a fatigue inducing physical exertion task (M.T.F.). In particular, states (b) and (c) which are identical tasks are of interest since a complexity variation detected by the statistic between these states may be directly linked to the fatigue in the system. The fatigue is induced by a physical exertion task that the subjects undergo after the completion of mental task (b) and just before commencement of task (c). A recent study reports the use of ApEn statistic in distinguishing between different levels of human consciousness ranging from the relaxed eyes closed to the deep sleep stage [5]. We go a step further in attempting to detect complexity changes in similar looking EEG records pertaining to relaxed, eyes closed state and a task state of mental arithmetic and finally the same mental task state performed after onset of fatigue induced by a physical exercise. In order to distinguish between brain functioning during task performance in a relaxed state and after the onset of physical fatigue, a mental numerical calculation task is chosen since it has been suggested as a complex task integrating multiple processes sub served by a large network of widely separated and interconnected local networks [14]. The details of the EEG recording are included in section 2.1. The motivation in undertaking this complexity study lies in assessing the variations in complexity exhibited by the scalp-recorded EEG due to the underlying neuronal dynamics in these distinct conditions of no-task and a mental task performed under the absence and otherwise of physical fatigue using the sample entropy statistic.

2. Methods

2.1. *Data acquisition and classification*

In recent times, the limited spatial resolution of the conventional EEG technology has been tackled by introducing high resolution EEG (HR- EEG) [2]. To adequately cover the surface of the scalp with electrodes, EEG equipment supporting up to 256 channels has been designed. In this study, we resort to the use of data recorded using a 128-channel Electrical Geodesic^{TM} system, with a sampling frequency of 200Hz referenced to a vertex electrode. The electrode configuration of the recording system is shown in Fig. (1). An online band pass filter from 0.1 to 70 Hz was used and impedances were kept below 25kΩ . Vertical and horizontal eye movements were monitored with a subset of 128 electrodes.

The experiment was conducted with the approval of concerned authorities and informed consent was obtained from each subject. EEG's were recorded from 12 normal subjects with mean age 29 under these conditions (a) Passive relaxed eyes closed (E.C.) (b) mental arithmetic with eyes closed (M.T.), where subjects were instructed to serially subtract 7's from 1000 silently for 2 minutes. In order to study the effect that fatigue from physical exertion may have on the mental task performance, subsequent to condition (b) each subject underwent a fatigue test. This test required the subject to perform an isometric leg extension at 20 % of his maximum voluntary contraction (MVC) until the subject became fatigued and

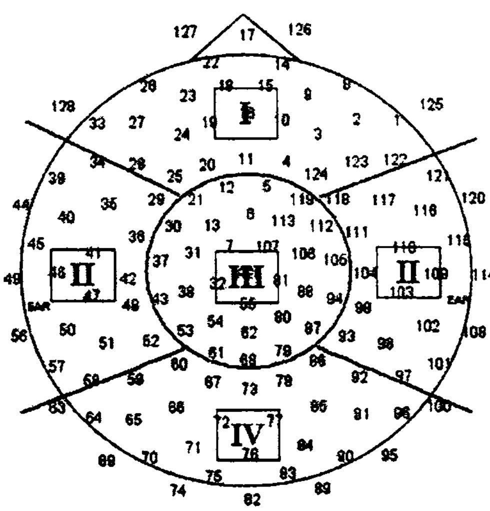

Fig. 1. An illustration of the 128-electrode configuration of the dense electrode array and the classification of the channels into 4 groups numbered from I to IV representative of the major cortical regions of the brain.

could no longer achieve the desired level of power output. At the end of this, subjects repeated the mental arithmetic task in (b) during which EEG was again recorded. The resultant EEG records were transferred from the Net Station acquisition system for further off-line analysis on a personal computer.

2.2. *Sample entropy: Quantification of regularity of experimental data*

A measure of the regularity of a time series will be informative about the underlying complexities in the processes giving rise to it. However, the problem encountered in developing such a meaningful quantity in experimental situations is the short and noisy data generated in complex systems especially in biology. Pincus [17] developed a regularity measure related to the Kolmogorov entropy known as the Approximate Entropy (ApEn), which was found to be effective in the classification of complex systems from the deterministic chaotic to the stochastic realms. The measure found widespread application in model systems as well as actual data from experimental situations especially from biology [16, 23]. This entropy measure assigns a nonnegative number to a time series with larger values corresponding to greater apparent randomness of the process underlying the data while smaller values point to regular features in the data. Despite the many features that make it a popular complexity measure, the ApEn suffers from the drawback of being a biased statistic. This leads to the measure being heavily dependent on the length of the data set under consideration as well as failing to produce consistent results [21]. This and other discrepancies are rectified in the newly developed Sample Entropy algorithm, which is related to the ApEn measure. A detailed description of the drawbacks in the ApEn algorithm and the better results accorded by the sample entropy statistic in the case of model as well as clinical data is available in Richman and Moorman [21].

In order to evaluate the SampEn statistic for a given time series of N points, the following method is adopted [21]. Suppose the time series is represented by $x(i)$ where i = 1,2,... ,N; then for a fixed window length m, vector sequences of the form

$$\bar{y}_m(i) = [x(i), x(i+1), ..., x(i+(m-1))] \tag{2.1}$$

where k = 1,2,.. ,m and for each i, $1 \leq i \leq N-m+1$.

Let $B_i^m(r)$ be $(N-m-1)^{-1}$ times the number of vectors $\bar{y}_m(i)$ within r of $\bar{y}_m(j)$ with j ranging from 1 to $N-m$ and $i \neq j$. The latter condition is in keeping with the idea of eliminating self-matches between templates $\bar{y}_m(i)$ and $\bar{y}_m(j)$ whenever $i = j$ which were the main sources of bias in the ApEn statistic.

Define the function,

$$B^m(r) = \frac{\sum_{i=1}^{N-m} B_i^m(r)}{N-m} \tag{2.2}$$

In a like manner,$A_i^m(r)$ is defined as $(N-m-1)^{-1}$ times the number of vectors $\bar{y}_{m+1}(i)$ within r of $\bar{y}_{m+1}(j)$ with j ranging from 1 to $N-m$ and $i \neq j$ and the funtion $A^m(r)$ as,

$$A^m(r) = \frac{\sum_{i=1}^{N-m} A_i^m(r)}{N-m} \tag{2.3}$$

Hence while $B^m(r)$gives the probability that the two sequences match for m points; $A^m(r)$ is the probability that the match is for m+1 points. The sample entropy is defined as,

$$SampEn(m,r) = lim_{N \to \infty}[-ln\frac{A^m}{B^m}] \tag{2.4}$$

which is estimated by the statistic $SampEn(m,r,N)$ defined as

$$SampEn(m,r) = [-ln\frac{A^m}{B^m}] \tag{2.5}$$

The $SampEn(m,r,N)$ is a 'family' of statistics in the sense that for a given application, comparison of the measure between different systems holds only for fixed values of m and r. Since SampEn varies in direct correlation with changing background noise characteristics, it is suited for comparison of data sets from a common experimental protocol. This makes it a useful tool in the analysis of multichannel EEG recordings pertaining to different mental states. The choice of N, m and r usually depends on the specific application of the measure just as in the ApEn case. As a comparison of the complexity values computed by the two related algorithms, we have plotted the same in Fig. (2) for a normalized set of random numbers. It can be observed that at higher values of r and also at high N, the measures agree.But at lower values of the parameters, the self-biasing nature of ApEn leads to lower estimates of complexity. It has been reported that for numerous applications for $m = 1$ and $m = 2$ with N varying from 50 to 5000 points, values of r between 10%

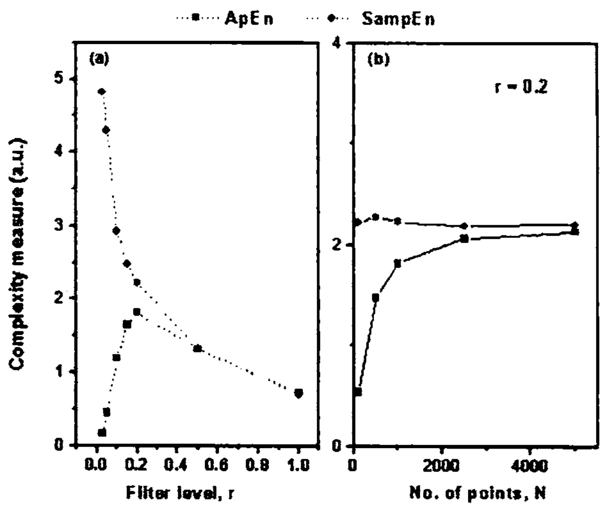

Fig. 2. The comparison between the ApEn and SampEn measures for a random data set at varying parameter values (a) filter level (r) at fixed number of data points, $N = 1000$ and (b) N at fixed value of $r = 0.2$.

to 25% of the standard deviation (S.D) of the data $x(i)$ are seen to produce good statistical validity of ApEn [17 and references therein]. All these conditions appear to hold good for SampEn as well, which is a measure related to ApEn.

3. Results

The study is undertaken with the objective of looking at the complexity variations exhibited by a global EEG recording as a result of the varying dynamics of the system with the change in brain state. Complexity studies so far have been on a limited number of electrodes placed strategically on the main locations of the scalp surface [1]. The advantage of the dense array recording configuration made use of in this work, over the conventional International 10-20 electrode placement system is that it provides a much better spatial resolution to reveal characteristics that had remained unseen due to the limited number of recording channels. The complexity of the EEG time trace emerging from each of the recording channels is quantified by the statistic of Sample Entropy (SampEn). EEG signals have been revealed to be nonstationary in nature leading to a drift of the system invariants with time. A prescription to handle such data is the division of time series into short time windows [18] and in keeping with this principle; the data is divided into non-overlapping windows of 400 data points and the SampEn measure evaluated for each of these. Prior to the complexity analysis, surrogate data testing is carried out to check the validity of application of nonlinear measures to the recorded EEG data. Thirty-nine surrogate data sets were generated by the Fourier shuffling method and SampEn statistic evaluated for each of these in the three cases of E.C., M.T. and M.T.F. The computed statistics in each of the original and surrogate sets were compared by applying the Mann-Whitney U test following Theiler et. al. [25]. Significant difference of $P < 0.005$ in all the three cases gave reasonable ground for assuming the presence of nonlinearity in the data and this is also obvious in the plots in Fig.(3) that present the variation of SampEn for the surrogate data sets along with the original EEG data. The surrogate sets lead to complexity values that form a cluster and as expected, the stronger randomness inherent in these data is reflected in the higher values of sample entropy in comparison with that for the EEG data.

The SampEn measure evaluated for the passive state of eyes closed condition when compared with mental arithmetic shows that the complexity was lowered in the mental task state. Fig.(4) shows the plot for the evaluated complexity measure for the two conditions for the 128 channel data. Since on visual inspection most of the channels exhibit almost similar complexity values, the channels are grouped into 4 major regions, named I - IV covering the channels pertaining to the prefrontal, frontal-temporal, central-parietal and occipital regions and these are more closely examined. The classification of the dense array electrodes into these four groups is depicted in Fig.(1).

After confirming the validity of equal variances for the test populations, two-way repeated measures analysis of variance (ANOVA) is carried out for examining the

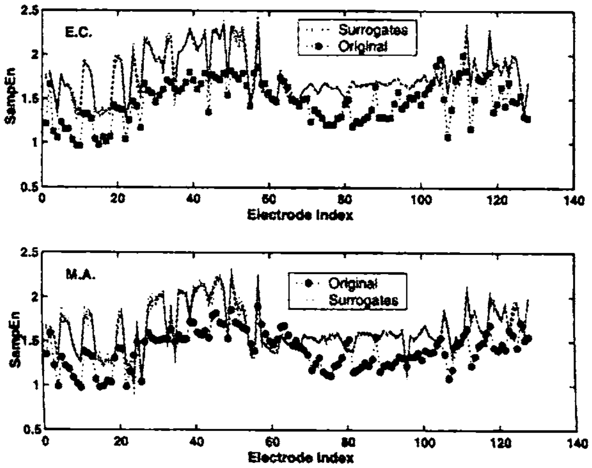

Fig. 3. The plots for the SampEn statistic in the case of the E.C. and M.T. conditions along with those for the surrogate data sets generated in each case. Identical results exhibiting a significant difference were obtained in the case of M.T.F. condition as well.

effect of mental arithmetic on the mental state as characterized by the complexity statistic. Two-within subject factors were used: state (2 levels- eyes closed and mental arithmetic state) and electrode (n levels). The analysis was carried out individually over the set of electrodes based on the classification mentioned earlier. In each of these groups i.e. regions I to IV as in Fig.(1), there are about 30 electrodes and the number of electrodes in each of the regions is the number of levels (n) in the electrode factor specified in the repeated measures analysis. It was observed that the main effects due to state (all four regions) and electrode (in regions I, II

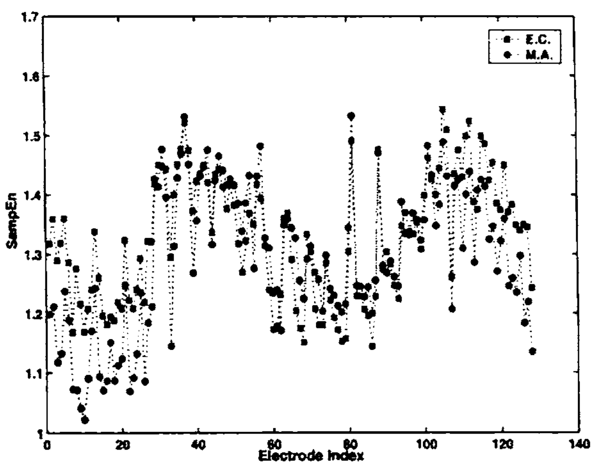

Fig. 4. Variation in the Sample Entropy (SampEn) for the normal eyes closed state (E.C.) and during a mental calculation (M.T.) task for the 128 channel data set.

and III) were significant for the sample entropy (SampEn) measure. The electrode effect is non-significant in the region IV comprising most of the channels over the occipito-parietal region. The variation in SampEn with state at the electrodes is characterized by the (state*electrode interaction) which is found to be insignificant in region III. However regions I, II and IV show a significant interaction between the state and electrodes. Hence we may infer that apart from the electrodes in the prefrontal and the occipito-parietal regions the effect on SampEn statistic due to mental arithmetic is almost the same at the other sites. A brief description of the statistical analysis is as depicted in Table 1. The dense array set up is obviously advantageous in it that it allows for more detailed analysis of the major cortical regions as compared to the conventional EEG recording methods using a limited number of electrodes to cover the scalp surface.

Table 1. A brief description of the two- way repeated analysis ANOVA used for the statistical analysis of the complexity variation as the mental state changes from a passive state (E.C.) to a mental task state (M.T.)

	Region I		Region II		Region III		Region IV	
Effect	F value	P value	F value	P value	F value	P value	F value	P value
State	6.186	<0.05	6.245	<0.05	6.581	<0.05	6.723	<0.05
Electrode	3.698	<0.001	2.744	<0.001	3.860	<0.001	0.659	0.908
State * Electrode interaction	1.476	<0.001	1.457	<0.05	1.296	0.149	1.746	<0.05

Fig. (5) plots the SampEn measures over these four major brain regions where the complexity variation during mental arithmetic as compared to the eyes closed state is seen in regions I and IV. Over the rest of the brain, there is not much complexity difference in the two states. The reduction in SampEn for the prefrontal region may be looked upon as the reduced neuronal complexity of this region during mental arithmetic as compared with the others. While small yet statistically insignificant rise in Kolmogorov entropy, K2 during arithmetic task over rest state has been reported [14], SampEn clearly illustrates the decrease in complexity for the frontal regions. Moreover the change in complexity in the parieto-occipital regions points to the involvement of this region in the subtraction task. Mental arithmetic is a complex task that requires integration of multiple processes carried out by a large-scale network of distributed yet interconnected local networks [14]. The complexity analysis supports this idea and is also in accordance with imaging evidence that suggests the participation of parietal areas in addition to the prefrontal areas in mental calculation [11]. The complexity variation in the occipito-parietal channels suggests the activation of visuo-verbal regions while the frontal activation has been always been linked with working memory and attention [7]. The task here being serial subtraction, the processes can be comprehended as the sequential procedure of

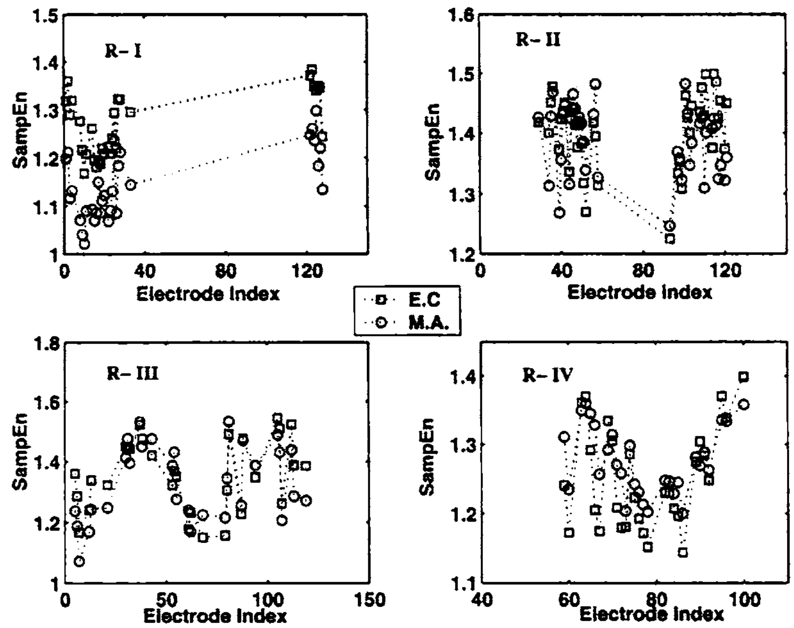

Fig. 5. A detailed comparison of SampEn measure for the mental arithmetic state with that of eyes closed case for each of the four groups numbered I to IV.

recognizing the numerals, forming a mental picture of the mental operations before the actual processing, storage of the current data in the working memory before going on to the next subtraction. The ease with which the areas participating in the task can be identified is a point in favour of the use of this complexity measure as a marker of activity of brain regions under specific conditions.

The temporal variation in complexity of some channels belonging to the right and left hemispheres is shown in Fig. (6). It is indicative of stronger sequential regularity in the EEG signal from the prefrontal regions during eyes closed than during mental arithmetic task. No significant inter-lobe complexity differences are discernible between symmetrically placed electrodes indicating homogeneity in the system complexity over the scalp. The bilateral activation suggested in the fMRI study of mental arithmetic [22] also supports such a finding.

The pilot study on the effect that fatigue may have on EEG complexity during a mental task performance also reveals interesting features. The primary discernible fact appears to be a lowered complexity in the mental state followed by onset of fatigue (M.T.F) as compared to the task performance before the physical exertion (M.T.). Fig. (7) plots the complexity variations during M.T. and M.T.F. across the four cortical regions. It is evident that the lowered complexity of the M.T.F. state is predominant in the electrodes in regions II, III and IV while over the prefrontal channels the two states M.T. and M.T.F have almost same sample entropy values. This again is a pointer to the involvement of the frontal region in mental arithmetic task performance while the electrodes overlying the central, temporal and parietal

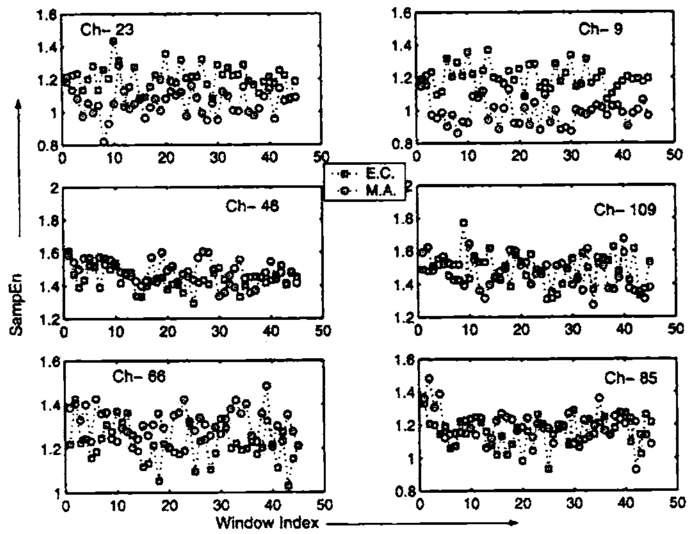

Fig. 6. The plots comparing the temporal evolution of sample entropy (SampEn)in the case of symmetrical channels in each brain lobe. The channels are chosen at random to be representative of a particular region.

regions associated with the motor cortex exhibit distinctive changes. The lowered complexity over the rest of the brain other than the prefrontal-frontal cortex may be directly attributed to the difference in mental dynamics caused by the presence of physical fatigue in the system. Fatigue that results from the physical exertion task appears to persist in the system and makes its presence known subtly through a complexiy variation when identical tasks are carried out before and after its onset.

A statistical analysis using repeated measures as performed in the former case is carried out to gauge the complexity variations in these self-similar states of mental arithmetic task is summarized in table 2. Here again it is observed that the main effect of state is not significant in the region I comprising mainly of the prefrontal-frontal electrodes while the state is clearly distinguished in the other three regions. Similarly the electrode effect is significant only in regions I, II and III while the interaction effect is non-significant in all four regions. Hence the electrode effect does not depend on the change of state to produce the observed SampEn changes in these two conditions, which are distinct only by the presence of the fatigue during the performance of the latter task. The SampEn analysis thus appears to be successful in bringing out features of brain dynamics in the presence of intangible effects such as fatigue which have not been fully investigated so far. The advantage of non-invasive techniques like the EEG, in comparison with relatively expensive imaging methods as the first tool in studying the human brain under myriad conditions is brought to the fore by such studies. A more thorough discussion on the effect of fatigue of mental task performance will be discussed elsewhere.

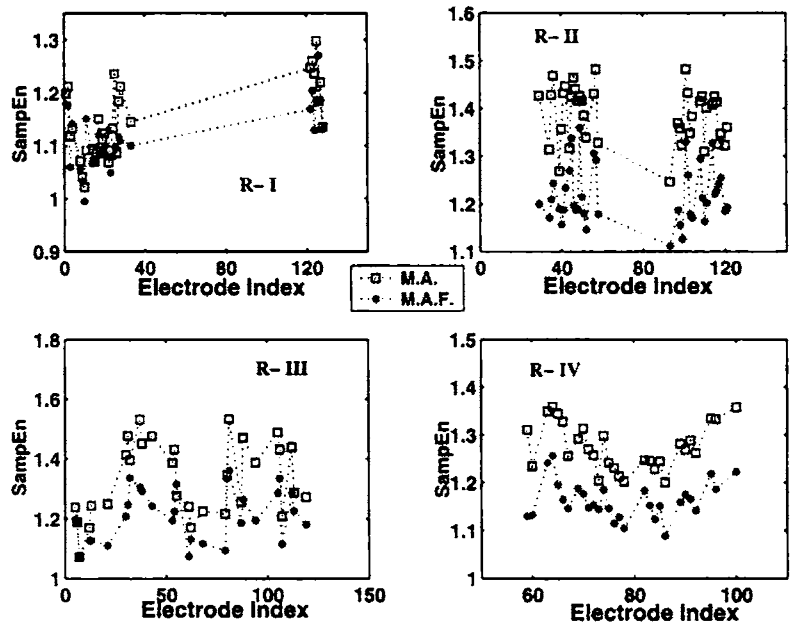

Fig. 7. The complexity analysis for mental arithmetic performed before (M.T.) and after (M.T.F.) onset of fatigue pertaining to the four representative cortical regions is presented.

Table 2. The results of the repeated measures ANOVA carried out to study the complexity variations contained in the SampEn statistic between the mental arithmetic task carried out before (M.T.) and after (M.T.F.) the onset of fatigue

	Region I		Region II		Region III		Region IV	
Effect	F value	P value	F value	P value	F value	P value	F value	P value
State	0.005	0.947	7.105	<0.001	7.356	<0.001	7.055	<0.001
Electrode	1.717	<0.05	1.920	<0.001	2.115	<0.001	1.095	0.345
State * Electrode interaction	1.083	0.360	1.219	0.185	1.494	0.056	0.794	0.762

4. Discussion and Conclusion

It is being widely acknowledged that the understanding of the human brain rests on an integration of various methodologies and techniques that are currently employed. These may be broadly organized into conceptualization, experimentation, theoretical formulation and modeling. In order to comprehend the complexity exhibited by the brain at functional as well as structural levels, a binding between these varying methodologies seems imperative. This would lead to a better understanding of how from the initial point of the behaviour of individual neurons, networks that carry out specific functions come to be assimilated and how finally these are organized into performing complex functions such as perception, memory, emotion, intelligence and other diverse patterns of human behaviour. Yet another motivation l ies in obtaining greater understanding of pathological conditions of the brain such as epilepsy and Alzheimer's disease that may lead to more effective methods of treatment or even prevention of these and other mental disorders. An important role in this integrative approach is played by numerical or computational methods that validate many of the conceptual as well as theoretical and modeling studies conducted at various levels of brain organization. One of the computational techniques involves analysis of the electric signal generated within the brain by applying various signal processing techniques extending from the linear to nonlinear and stochastic realms. Our study is in the genre of such computational studies that aims at understanding the dynamical nature of the brain pertaining to varying mental states by analyzing the nonlinear EEG signal. While being computationally less tedious, it further has the advantage of being non-invasive as well as inexpensive in the actual procurement of the signal. Our findings in this study point to the potential use of nonlinear measures such as the sample entropy in the quantification of signals under various cognitive as well as pathological conditions which may lead to clinical as well as diagnostic uses. A combination of these methods with the recent advancements in imaging technology can be a very useful tool in quickening the pace of a comprehensive understanding of the human brain functioning.

In this article, we have looked at the Sample entropy as a quantifier for complexity of EEG data recorded during the three conditions of (a) normal eyes closed, (b) mental arithmetic and (c) mental arithmetic performed after onset of fatigue. The dense array configuration provides simultaneous records of the EEG signal from a large number of channels that is useful to gain a more complete picture of the activity distributed over the cortex. The analysis of states (b) and (c) is carried out with the motive of testing whether the complexity statistic can be used as a quantifier to discern differences if any, in apparently similar yet subtly different mental states. In this case, the test states (b) and (c) pertain to an identical mental arithmetic task performed before and after a fatigue inducing physical exertion task. In the initial part of this work, the mental task state M.T. is compared with the baseline state of relaxed eyes closed condition, E.C. It is found that even during a cognitive task such as mental arithmetic that consists of a series of processes such as perception of information, processing of arithmetical signs, retrieval and memorization mechanisms; the complexity in most of the brain regions remains the same as that during the relaxed, passive state. The prefrontal region and some parts of the occipito-parietal region exhibit lowered complexity during serial subtraction task in comparison with the corresponding regions during the passive eyes closed condition. Moreover the dynamical complexity pattern of symmetrical regions over time also remains largely identical indicating both the brain lobes exhibit synchronous behaviour in complexity variations.

The sharp reduction in the SampEn measure is observed in the mental task state performed under the presence of fatigue (M.T.F) as compared to that in the absence of fatigue (M.T.). This effect is particularly localized in the regions of the motor cortex and the motor association cortex that point to the possibility of the effect of physical exertion persisting in the system for sometime and affecting the dynamics during the performance of other mental tasks. The complexity analysis thus proves to be a useful tool in understanding the effects of so far less understood phenomena such as fatigue. Perception of exertion during exercise is a topic of great interest to sport physicians and sportsmen worldwide. The idea of effort during exercise and its relationship to fatigue is still not well understood [6]. Moreover, the effect of fatigue on the brain state during performance of mental tasks is yet to be addressed. Once the relationship among fatigue, intensity of effort and pacing strategies during exercise get established; this knowledge will benefit groups engaged in activities requiring exertion in daily life such as sprinters, athletes, weightlifters and so on. This report finds that the sample entropy statistic can efficiently detect complexity variations in apparently similar task states differing only in the presence or otherwise of fatigue. It thus supports the fatigue models that point to the presence of brain activity in the perception and regulation of fatigue consequent to physical exercise[6].

In this paper, we have discussed the sample entropy measure as a complexity statistic that can effectively deduce changes in the underlying brain state from the EEG time trace during a given condition. Moreover it can also detect changes in complexity patterns during identical task states performed under altered brain conditions such as fatigue. The complexity analysis can thus be considered as a first tool for classifying mental processes. This may be useful in gaining a deeper insight into various cognitive and task conditions as also for understanding abnormal conditions such as schizophrenia, mental depression and so on. A comprehensive application of the statistic to various brain states including pathological conditions such as epilepsy is being undertaken by this group and will be reported elsewhere.

Acknowledgments

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