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Quantitative Evaluation for the Wakefulness State Using Complexity-Based Decision Threshold Value in EEG Signals

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Abstract— **Fully awake state of the subjects tends to be an early drowsy state as a result from the prolonged time of electroencephalography (EEG) measurements. Such situations can complicate the interpretation of EEG signals and hence, the wakefulness of the subject should be considered in the inspection. Thus, in the present study, a new index for quantitative evaluation of the wakefulness (whether either early drowsy or fully awake) state of subjects by using a complexity-based decision threshold value was developed. The proposed index was based on approximate entropy (ApEn) to quantify the complexity metric, but with new parameter values by using a new systematic approach. This index was evaluated using occipital-alpha rhythm during eye closure for 45 healthy adult subjects for each one of two groups: fully awake and drowsy groups. Our index could show more superiority than other conventional spectral-based indices used for evaluating the wakefulness state of subjects including relative delta sub band power (*$R.\delta$*), relative theta sub band power (*$R.\theta$*), power ratio between theta and alpha (* $P_{\theta/\alpha}$*), and between theta and beta (* $P_{\theta/\beta}$*) over occipital lobe. Our index is superior than *$R.\delta$*, *$R.\theta$*, * $P_{\theta/\alpha}$* and * $P_{\theta/\beta}$* with 10%, 5.5%, 8.9% and 24.4% respectively.**

I. Introduction

The transition to an early state of drowsiness (i.e., light drowsy or sleep stage 1) is a hardly detectable state as it represents a phase of a mixture of alertness and sleep. Recently, numerous reports have used complexity metrics to distinguish fully awake state from early state of drowsiness [1]. Traditionally, quantitative electroencephalography (EEG) studies of wakefulness state have focused on continuous eye closure. Considerably, less effort has been devoted to the study of the early drowsy state during repetitive eye closure and eye opening tests in routine examination. Usually, complexity measures are nonlinear measures and used to capture the macroscopic spatial temporal dynamics of the electrical activities of the brain. In this respect, the complexity in EEG signals is often quantified by computing approximate entropy (ApEn). However, calculation of ApEn requires a priori determination of three user-defined parameters and the recommended values for those parameters had been suggested by Pincus [2] who first introduced ApEn measure. Although the values of ApEn parameters play a critical role in determining the outcomes of ApEn, no guidelines exist for optimizing their values. The recommended values for the parameters of ApEn are applicable to relatively slow dynamics signals (i.e., slow fluctuation within a narrow range) such as heart rate [3], and respiratory signals [4]. Alternatively, Lu et al. [5] found that the recommended range of ApEn parameters values may not always be appropriate to assess the complexity of neural signals. However, in the present study, we propose a new index to evaluate quantitatively the wakefulness state of the subjects by determining a quantitative border in complexity term by using best decision threshold value that satisfies minimum misdiscrimination rate between the two given groups. This evaluation was performed by using systematic approach to determine ApEn parameter values by using occipital-alpha rhythm (8-13Hz) during eye closure.

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II. Materials and Methods

A. EEG acquisition

EEG signals of healthy adults subjects were acquired from two groups: fully awake and light drowsy groups, where each one of those groups has 45 subjects. All signals from occipital lobe only, corresponding to O1 and O2 were analyzed and those signals were digitized at a sampling frequency of 200Hz with a cut off frequency of 60Hz. We used data from an eyes opening and closure test during a routine EEG examination. Each EEG recording period lasted for 70 seconds, beginning with the eyes-closed state for 10 seconds, followed by a period with eyes open for 10 seconds, as shown in Figure 1. Further details on the used EEG signals can be found in [6].

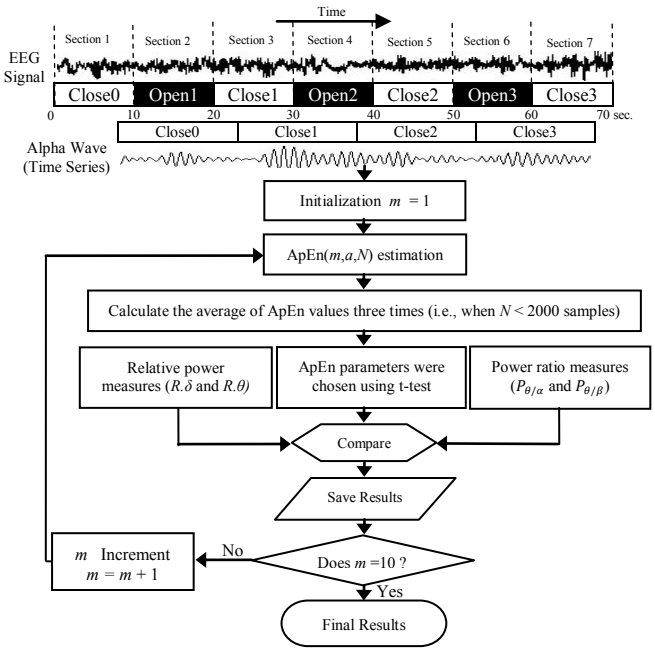

Figure1. Flowchart for the proposed method

B. Approximate entropy (ApEn)

ApEn is a measure of complexity (i.e., irregularity) of a time series. This measure is calculated by segmenting the given signal into a series of amplitude-based vectors (i.e., each vector has a prescribed length of EEG-discrete time series), where each of which, in turn, is used as a template vector for comparison with all other vectors in the signal toward the determination of the regularity metric of a given signal. ApEn aggregates the probability that associates with each vector into an ensemble measure of regularity. Thus, repeated patterns in the data give rise to lower ApEn value, because two vectors similar at length m will also be similar at length m+1 due to the repeating patterns. Usually, ApEn is calculated by using a priori determination of three user-defined parameters m (length of the vectors), r (tolerance for accepting similar patterns between two vectors), and N (length of the time series of the signal). ApEn is computed using widely established parameters values as suggested by Pincus [2], where m = 1 or 2 and r which is defined by the multiplication of a coefficient a value, where $0.1 \leq a \leq 0.25$, and the standard deviation (*STD*) of the original data sequence whose length is N.

However, in the present study, all the parameters of ApEn over a range wider than the previous studies typically recommended was examined in EEG signals. The mathematical perspective of ApEn algorithm has been described in details elsewhere [2, 4]. In the present study, ApEn was applied to alpha waves extracted by fast Fourier transform. Usually, when small m value (i.e., short templates) and large r value (i.e., wide tolerance) are used to compute ApEn, the number of similar vectors as a result from the aforementioned comparison process will increase and vice versa. To specify a proper m, r, and N values that are consisted with the degree of the irregularity which typically embedded in EEG signals as a result from the wakefulness state of the subject, one must choose an adequate value for those parameters. For instance, when small N values are used to compute ApEn, the estimates may be inaccurate as they show large variance. On the contrary, large N value may contain abrupt changes in amplitude that could result inaccurate estimates. Similarly, the value of r parameter depends on a value because ($r = a \times STD(N)$). To determine the optimal values of N and a, ApEn was computed with different N and a values for eyes-closed periods. The most adequate selection of m, a and N parameter values were chosen, after a careful investigation for ApEn values by using a range of values for ApEn parameters wider than previous studies typically recommended. More specifically, different values of m which ranged from 1 to 10 were used. Similarly, the selected values for N parameter were chosen to be multiple integer of 2000 samples (i.e., 50, 80, 100, 125, 200, 400, 500, 1000, 2000), while the various values of a ranged from 0.05 to 1 with a step of 0.05. Conveniently, a matrix of 20×10 elements was used to express the values of ApEn, where each of which was estimated by different combinations of a multiplied by *STD* of the analyzed section whose length is N. This matrix was calculated using different values of m lengths, where $1 \leq m \leq 10$. In this matrix, all the ApEn values that correspond to sub-sections whose lengths were less than 2000 samples; the average of ApEn values was calculated three times in sequence. To clarify further, first average (AVG1) was calculated for the ApEn values across the sub-sections whose lengths are less than 2000 samples. Second average (AVG2) was calculated for the ApEn values across two channel signals (i.e., O1 and O2) for each subject in both groups. Third average (AVG3) was calculated for the AVG2 values across eyes-closed periods for each subject within the two groups. Correspondingly, the remaining sections which each of which, has length 2000 samples, AVG2 and AVG3 were calculated in sequence as we described earlier.

To determine the best values of ApEn parameters that could classify the two groups with the maximum distance between their population means, two-sample Student t-test was performed using AVG3 values that corresponded to the two groups. Since the estimation of ApEn values were expressed by using matrix of 20×10 elements for each subject within the two groups, the best parameter values that correspond to the smallest p-value ($p < 0.01$) for all the different combinations of ApEn parameter values was expressed by a matrix of 20×10 elements as well, as shown in Figure2.

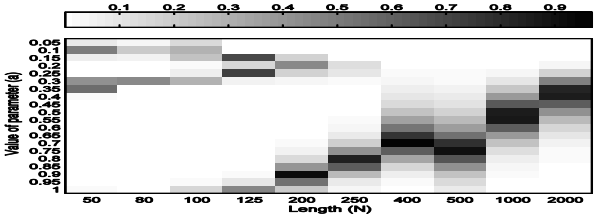

Figure 2. Example of gray scale grid of 20×10 matrix, where each element shows the p-value by using two-samples Student t-test for 45 subjects per group

C. Conventional spectral analysis-based indices

Spectral analysis-based measures are widely used as quantitative indices for the wakefulness state of the subjects. All of those indices were evaluated and previously reported as best indices for distinguishing the early state of drowsiness from the fully awake state over occipital lobe during eye closure in healthy subjects [7]. Those indices are divided into two types: relative spectral power-based indices and power ratio-based indices. All power spectra were calculated using Welch averaged modified periodgram method for 2000 samples corresponded to eyes-closed periods without overlapping. Similar to ApEn calculation, AVG2 and AVG3 were calculated for the sections whose lengths were 2000 samples. The details of those indices were listed with their frequency bands, as shown in Table I.

TABLE I. SPECTRAL ANALYSIS-BASED INDICIES

Spectral analysis-based indices	Frequency band (Hz)
Relative delta (sub band) power (R.δ)	2 – 4
Relative theta (sub band) power (R.θ)	4 – 6
Power ratio between theta and alpha($P_{\theta/\alpha}$)	θ: 4 – 8 α: 8 – 13
Power ratio between theta and beta($P_{\theta/\beta}$)	θ: 4 – 8 β: 16 – 30

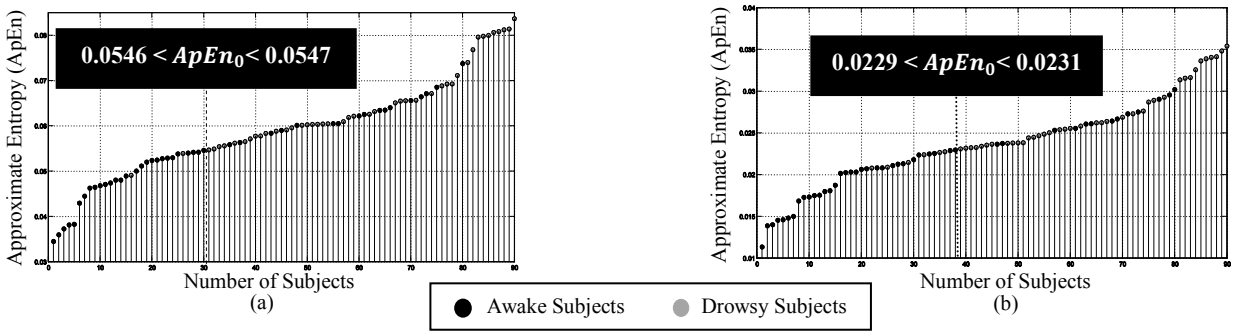

Figure 3. Best results that related to the estimation of the wakefulness using complexity-based threshold value, where the dashed line denotes the complexity-based descion threshold value ($ApEn_0$) (a) The complexity of the subjects in the two groups was estimated using ApEn (m = 8, a = 0.5, N = 100). (b) The complexity of the subjects in the two groups was estimated using ApEn (m = 9, a = 0.95, N = 50).

D. Biological justification for using alpha rhythm and eyes-closed periods

Generally, alpha rhythm (8-13Hz) is prominent over occipital lobe during relaxed state with closed eyes in healthy adult subjects [8]. By contrast, alpha rhythm is dramatically suppressed in drowsy subjects over occipital lobe. Correspondingly, alpha rhythm is suppressed by eyes-opening in the both groups. Thus, eyes-closed periods can be considered more efficient than eye opening for evaluating the wakefulness state of the subjects due to alpha prominence and suppression during eye closure in awake and drowsy groups respectively.

III. RESULTS

Complexity-based decision threshold value ($ApEn_0$) was used to evaluate the wakefulness state of the subjects. This threshold was derived from satisfying the condition of the minimum misdiscrimination rate between the two groups. Stated differently, once the optimal combination of N and a parameters were obtained for a particular value of m, all the corresponding ApEn values for awake and drowsy groups were sorted in ascending order. Next, all the possible locations of the decision threshold values were examined, where each of which could divide the ranks of ApEn values into two groups. The best $ApEn_0$ value was obtained when the left side of $ApEn_0$ was considered the region of the correct discrimination of awake subjects while the right side was considered as the region of correct discrimination of drowsy subjects, as shown in Figure 3. Misdiscrimination rate of awake and drowsy subjects can be expressed by $ApEn_A$ and $ApEn_D$ respectively, and can be calculated by:

$$ApEn_A = \frac{The\ number\ of\ misdiscriminatedSubjects}{Number\ of\ Awake\ Subjects} \times 100\% \quad (1)$$

$$ApEn_D = \frac{The\ number\ of\ misdiscriminatedSubjects}{Number\ of\ Drowsy\ Subjects} \times 100\% \quad (2)$$

$$Total\ Misdiscrimination_{ApEn} = \frac{Total\ Number\ of\ misdiscriminatedSubjects}{Total\ Number\ of\ Subjects} \times 100\% \quad (3)$$

Similarly, the misdiscrimination rates of the conventional spectral analysis-based indices were calculated by using the aforementioned equations. All results are shown in Table II.

TABLE II. MISDISCRIMINATION RATES FOR ALL THE MEASURES

	ApEn m = 8 (%)	**ApEn m = 9 (%)**	**R.δ (%)**	**R.θ (%)**	**$P_{\theta/\alpha}$ (%)**	**$P_{\theta/\beta}$ (%)**
Awake Group	37.7	28.8	37.7	28.8	13.3	28.8
Drowsy Group	4.4	13.3	24.4	24.4	46.6	62.2
Total Misdiscrimation	21.1	21.1	31.1	26.6	30	45.5

Total misdiscrimination rates for all the values of m parameter were calculated, and the minimum misdiscrimination rate was obtained using ApEn (m = 8, a = 0.5, N = 100) and ApEn (m = 9, a = 0.95, N = 50), as shown in Figure 4.

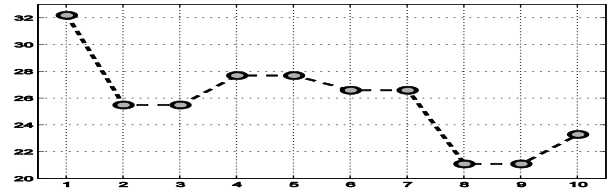

Figure 4. Total misdiscrimination rates for the ApEn where the values of parameter m were ranging from 1 to 10

IV. DISCUSSION

Although, eyes-opening periods were not used in our proposed method, but eyes opening and closing tests can be considered more appropriate than continuous eye closure test in evaluating early drowsy state, because early drowsy state is typically contains frequent transitions from eyes closing to eyes opening. However, such transitions may affect on the complexity of alpha wave during early state of drowsiness and make it to be close to that in the wakefulness state [6]. As a consequence, any quantitative evaluation for the wakefulness state during repetitive eyes opening and closing using complexity term will be more difficult than continuous eyes closure. As a result, complexity-based decision threshold value was determined to be used as quantitative-distinct border in EEG signals, where the effects of ApEn parameters were jointly studied. Several studies were

developed to characterize the performance of parameter *a* only and (*a* and *N*) of ApEn parameters in EEG signals [5, 9], but a survey on all optimal parameter values of ApEn in EEG signals during repetitive eyes opening and closing was not previously done. In this respect, our results demonstrate that when inadequate values of ApEn parameters are chosen, the complexity metric of EEG signals that is used to discriminate fully awake from light drowsy group will not be optimally apparent. In the present study, the two groups were discriminated after performing two subsequent steps. First step, optimal values of *a* and *N* parameters of ApEn were determined by using the statistic of maximum distance between the two population means of the two groups for the corresponding *m* value. Second step, iterate the previous step by increasing *m* value by 1 until 10, to determine the best values of *m* that could minimize the misdiscrimination rate between the two groups. As reported in a previous study [5], the widely established parameter values of ApEn may not appropriate to assess the complexity of neural signals and our findings agree with this result. Our results indicate that the range of ApEn parameter values typically recommended and used in literature may not include optimal values for discriminating fully awake from light drowsy groups in an adequate form. Thus, a systematic approach to determine the best values of ApEn parameter was used. To evaluate the effectiveness of the ApEn estimation using the proposed approach quantitatively, we compared our proposed index with conventional spectral analysis-based indices which were evaluated as best indices in distinguishing fully awake state from early state of drowsiness (stage I) over occipital lobe (i.e., O1 and O2) in healthy subjects [7]. This comparison was performed using the decision threshold value which satisfies the minimum misdiscrimination rate between the two groups. Thus, other measures reported in [7] as best measures in either O1 or O2 were not evaluated in the current study. Although, the missdiscrimination rates of ApEn, when $m = 8$ and $m = 9$, were higher than other conventional spectral analysis-based indices and $P_{\theta/\alpha}$ respectively in evaluating the fully awake state, but the total misdiscrimination rates of conventional spectral analysis-based indices were still higher than ApEn (when $m = 8$ and $m = 9$), as shown in Table II. It is worthy mentioned that when the minimum misdiscrimination rate condition is satisfied, the ApEn values of awake group exhibited relatively small values when compared with ApEn values of drowsy group for all values of *m* parameter. This observation indicates that alpha prominent is associated with low complexity while alpha suppression is associated with high complexity.

In the present study, the maximum value of *m* parameter was 10 for two reasons. First, when $m > 10$, the ApEn values become too small as the chance of finding similar vectors is too small and hence, any determination task of the best threshold value will become too difficult accordingly. Second, higher *m* values lead to higher computational cost.

In the present study, all the aforementioned results of ApEn as shown in Table II were associated with sub-sections whose lengths were less than 2000 samples. Thus, three kinds of averages: AVG1, AVG2 and AVG3 were calculated, as we described earlier. Such calculations of averages three times lead to more reliable results than other results where the average values were not used as reported by [1,7].

In the present study, alpha rhythm was considered (8-13Hz), as reported by wide range of literature [8,9] while alpha band was considered as (8-12Hz) in [7]. Nevertheless, this difference in the frequency band of alpha rhythm would not significantly affect on the reported results. In the present study, we did not apply any feature extraction or automated classifier technique to improve the results. Thus, the reported results may be further improved by applying such techniques.

V. Conclusion

Selection of ApEn parameters values plays a critical role in determining the outcomes of ApEn and we view this as a severe shortcoming in ApEn algorithm. As a consequence, a systematic approach was used to produce ApEn values that consistent with degree of the irregularity typically embedded in EEG signals by examining wide range of ApEn parameter values. The reported results indicate that the range of ApEn parameter values that widely used in literature may not include optimal values for distinguishing the two groups in an adequate form. ApEn index using the proposed approach was superior to other spectral analysis-based indices for evaluating the wakefulness state. Further studies are required to minimize the computational time cost and this issue was addressed as a future work.

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