Real Time Sleep Onset Detection from Single Channel EEG Signal Using Block Sample Entropy

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Abstract

In recent years, driver’s temporary state has been one in each of the foremost causes of road accidents and would possibly lead to severe physical damage, mortality and necessary and noticeable economic losses. Maximum road accidents possible to avoid if possible, if properly monitored driver’s drowsiness and a system are given warnings. In this work, a simple and inexpensive method has been offered to detect driver’s drowsiness or sleep onset detection with single channel EEG signal analysis. The key novelty of this work is to identify the sleep onset detection from a publicly available graph signal dataset by exploitation only one feature, simply implementable filter in any microcontroller device or smartphone and a threshold based mostly classification. Since, threshold-based classification techniques don’t need to train the classifier, hence, new subject adaptation is comparatively easier and real time implementation is more feasible. This novel approach can be easily implemented in smartphone to design and expand a drowsiness detection and alarming system for vehicle’s driver. On a variety of subjects, the experimental results show 95.68% accuracy.

Keywords: drowsiness; sleep onset; electroencephalography; block sample entropy

1. Introduction

The primary a locality of the brain is sleep and its plays a necessary role in a very personal performance, physical movement and wit. Sleep is a lively and controlled method with a necessary restorative operate for physical and psychological state, an amount of consolidation of memory and brain recovery.

In mortals, sleep may be a universal revenant impulsive and physiological activity that influences our daily lives in various ways in which. Performance at work, morale, mood and relationships with alternative people square measure however many of them. Scientists have indicated that sleep covers concerning one third of an individual’s being’s life [1]. The biological rationalization of this could like remains unknown. Sleep is vital for the brain to remain healthy. it has been distinguished in several studies that sleep is crucial for energy preservation, for the restoration of biogenesis (a simple structure regenerate to a fancy structure in living organisms), facilitating learning and memory. once a personal is sleeping, the mind is strengthened, and motor functioning and performance area unit improved [2, 3]. it has been counseled that sleep is coupled to metabolic operate and blubber [4].

Sleep can impact negatively on aspects of data, like alert attention, and another individual’s health. Sleep deprivation makes an individual drowsy and unable to concentrate. The term “drowsy” is similar with sleepy headed, that merely means that an inclination to doze off. Drowsiness, conjointly mentioned as somnolence, will be outlined as “the have to be compelled to fall asleep”. so, as to research driver sleepiness, researchers have largely studied Stage I, that is that the sleepiness part. Sleep restriction or disorders will lead with somnolence and should end in the involuntary onset of sleep, (falling asleep) inflicting car/truck accidents [5, 6, 7].
In recent years, driver sleepiness has been one in all the foremost causes of worldwide death in traffic accidents and might result in severe physical injuries, mortality and vital and noticeable economic losses.

Based on police information’s, the U.S. National route Traffic Safety Administration (NHTSA) cautiously survey that total of 1 hundred,000 vehicle crashes annually unit the direct results of driver temporary state, additionally, many various accident reports named “Drift-Out-Of-Lane” crashes, that can be related to temporary state aspects still. These crashes resulted in around one,550 deaths, 71,500 wound and $12.5 billion in monetary losses [8, 9]. Also, per reports of Korean expressway Cooperation is that, 1223 people died from 2010 to 2013, in Korean street traffic accidents, thirty initial of that place up characteristics to driver temporary state [10, 11].

According to World Health Organization (WHO) statistics in Associate in Nursing passing 2009 report [12] showed that human die over one.2 million on roads around the world annually. Moreover, an additional twenty to fifty million individuals suffer non-fatal wounded. according to the survey of World Health Organization, road traffic injuries caused Associate in Nursing determinable one.25 million deaths worldwide in 2010. Where, one person is killed per twenty-five seconds. A follow-up report discovered in 2013 by the World Health Organization [13] showed that albeit some progress has been created, the shocking figure of one.24 million deaths caused by road accidents annually remains primarily a similar. Over a 3rd of road traffic deaths in low- and middle-income countries unit among walker and cyclists. the standard proportion was seventeen.4 each 100,000 people. Low-income countries presently have the simplest annual road traffic fatality rates, at 24.1 per 100,000, whereas the speed in high-income countries is lowest, at 9.2 per 100,000 [14]. In Bangla Desh, annual road traffic death rate is thirteen.6 per 100,000 inhabitants [15]. according to out their maths info, over 1.3 million persons die once a year on the road and twenty to fifty million people suffer non-fatal injuries because of road accidents [16].

A report by Bangladesh Road Transport Authority (BRTA) shows that, 1422 folks were killed and 1289 lacerate in route road accidents in January, 2016 to July 2016 and 2376 folks were killed and 1958 lacerate in route road accidents in 2015 in Bangladesh [17]. At least 2,297 folks were killed and 5,480 lacerate in road accidents in January, 2017 to June 2017, a pointy rise within the toll compared to constant amount last year, National Committee to safeguard Shipping, Roads and Railways (NCPSRR), academic degree organisation effort for safety at intervals the transport sector, said throughout a report. National Committee to safeguard Shipping, Roads and Railways (NCPSRR) throughout a report aforementioned casualty in road mishaps has increased by 18.35 gift and also the total variety of road accidents increased by 8.6 percent. The report was ready on the idea of reports in 22 domestic and ten regional dailies and eight online news portals and news agencies [18]. per this report, the 2,297 victims, as well as 315 kids and 292 ladies, were killed in 1,983 accidents between January and Gregorian calendar month this year. Last year, a complete of 1,941 people, as well as 261 kids and 262 ladies, were killed and 4,794 wounded within the first six months. withal, several run-off-roadway crashes those don't seem to be reported or cannot be verified by police, suggesting that the foremost vital downside is way larger than antecedent denumerable. state is one among the foremost vital causes of road accidents that is advocate by vital sort of report, studies and survey.

In the year 2009, the use of America National Sleep Foundation (NSF) rumoured that fifty four of adult drivers have driven a vehicle whereas feeling drowsy and twenty eighth of them really fell asleep [19]. The German Road Safety Council (DVR) claims that one in four road traffic fatalities unit of measurement a results of short driver somnolence [20]. These statistics advocate that driver somnolence is one in all the foremost causes of high approach accidents. Powell et al. [21] over that somnolence can impair driving performance the most quantity or quite alcohol. An additional fashionable report [22] from the yankee Automobile Association (AAA) estimates that one out of every six (16.5%) deadly traffic hazards, and one out of eight (12.5%) crashes requiring hospitalization of automotive drivers or passengers is attributable to drowsy driving. In summary, there is a goodish amount of proof that means that somnolence is one in all the large factors in road accidents.

If it doable to properly monitored driver temporary state and given early warning then most of those high manner accidents and wound will evitable. Once country extended periods driving with monotonous state of affairs on road that point driver temporary state occurred, which is, excessive drowsiness. To live drowsiness there have customary take a look at clinical trials that area unit Multiple Sleep Latency check (MSLT) and even have a customary clinical test to live weakness the upkeep of Wakefulness check (MWT), used to produce dataset of Polysomnograph. most cases terribly overpriced of those styles of measurements and to perform cumbersome of a minimum of eight channels area unit uses: one EMG, two Electrooculogram (EOG), three ECG (ECG) and four EEG; detection driver temporary state these formula isn’t doable to implement much in time of associate degree actual driving state of affairs. Most cases driver feels uncomfortable thanks to multiple detector and even his/her movement. thus, easy-to-use driver temporary state detection (DDD) machine is high demand.

There many formula have been employed, including physiological-signal-based formula (those ways in which supported the variability of the centre rate and EEG (brain waves)) percentage of high frequency to low frequency. video-based methods
(detect rate of eyelid closure pupils by time) and vehicle-based methods (such as steering wheel movement system and lane departure warning system).

From these ways that, physiological-signal-based formula square measure examine to be the foremost reliable suggests that of detection as these signals prepare mark of being internal state to the driver [23]; and assimilate with various physiological signals, the non-invasive encephalogram physiological show live brain activity, is take into consideration the nearest link with drowsiness [24,25,26,27].

In this paper, a less complicated and a completely unique algorithmic rule to notice driver’s somnolence or sleep onset victimization single channel graphical record signal analysis is introduced. Threshold primarily based classifier is employed that don’t want any coaching and may be used for online sleep onset detection.

2. Methodology and Procedure

2.1 Proposed Method

The key innovation of this work is to propose academic degree economical classification technique that might merely be implemented in golem mobile to differentiate between wakefulness and stage one in all sleep. this could modification physicians moreover as sleep specialists to identify certain patterns like police investigation fatigue, drowsiness and/or varied upsets like primary sleep disorder, psychosis, apnea etc. The technique derived throughout this work are usually used in vogue and development of golem Smartphone primarily based Automatic drowsiness Detection and frightening System (ADDAS). The flow chart of the methodology is shown in figure one. First, the input encephalogram signal is acquired from Physio Net Sleep-EDF [Expanded] dataset. The encephalogram signal then band-pass filtered of vary zero.5 to 47.5 Hz. Infinite Impulse Response (IIR) Butterworth band-pass filter is supposed to filter the input encephalogram signal. in addition, discriminating feature, block sample entropy is computed and extracted from the Pz-Oz channel encephalogram signal. Finally, a thresholding primarily based classification technique is used to envision this feature to be ready to acknowledge the awake and sleep stage one.

![Classification of EEG sleep stages](image)

2.2 Data Description

The dataset employed in this work is publically on the market from the Sleep-EDF [Expanded] info. this is often freely on the market through Physionet web site and has been wide employed in the literature.

This information could be an assortment of 61 PSGs with attending hypnograms (expert annotations of sleep stages) obtained from 1987–2002 together with the older Sleep EDF info recordings before 1991. The Sleep container (SC) information were collected between 1987-1991 age effects with sleep study in seventy-nine healthy individuals aged 25-101, while not impact of sleep-related medication.

Two PSGs with lengths of roughly recorded throughout two consecutive day to night-time period twenty hours every were collected at the placement subjects’ homes. File SC4ssnE0-PSG.edf contains the PSG of subject ss (00 ≤ ss ≤ 82) for night n (1 or 2). The primary nights recorded variety of subjects thirty-six and fifty-two, and therefore the second night recorded variety of subject thirteen, were lost thanks to a failure within the recording container. This recordings embody information from twenty healthy subjects numbered 00 through nineteen, including ten male and ten feminine participants between the ages of 25 and 34 years recent throughout the instant of recordings. Subjects wore a bespoke Walkman-like cassette-tape recorder however maintain their traditional daily activities.
The Sleep mensuration (ST) information were collected in an exceedingly 1994 by learning of Restoril effects over sleep in twenty-two Caucasian males and females while not different quite medication. Their placebo nights area unit offered here. File ST7ssn0-PSG.edf contains the PSG of subject ss (01 ≤ ss ≤ 24; subjects 03 and twenty-three born out of the study) and night n (1 or 2). Subjects bear a little mensuration theme with higher signal quality. The PSG recordings (*PSG.edf files) square measure full-night polysomnographic sleep recordings that contain EEG (from Pz-Oz and Fpz-Cz conductor position) EOG (horizontal), submental chin myogram and an event marker signals. Most files (SC*PSG.edf files) conjointly contain oro-nasal respiration and body part blood heat.

The encephalogram signals were sampled at 100 Hz; solely the encephalogram Pz-Oz signal was utilized in this planned study because the mono encephalogram. The associated hypnogram files (*Hypnogram.edf files) enclose sleep patterns recorded from every subject. These patterns consist with sleep stages one, 2, 3, 4,W, REM, M (Movement time) and ? (question mark symbol) as a sign that it’s not been recorded. All hypnograms were manually scored by well trained advisor according with 1968 Rechtschaffen and Kales manual however supported Fpz-Cz/Pz-Oz EEGs rather than C4-A1/C3-A2 EEGs. The hypnograms are in EDF+ whereas the PSG files are formatted in EDF. Every EDF and EDF+ recorded file encompasses a header deciding the patient (in files anonymized to solely gender and age), recording details (recorded specifically time period), and signals together with their amplitude activity as a Characteristics.

The EEG Pz-Oz channel of 10 subjects’ signals were utilized in this work. Stage labels were provided beside the info by Physionet, exploitation to boot recorded signals, and consistent with customary rating rules. Epochs marked as Stage two, Stage 3, Stage 4, REM, Movement and Unscored were rejected for additional analysis. Every signal is processed in thirty s time-frames in our planned work. For the aim of illustration, Figure two and Figure three show samples of Wake and Stage one Sleep EEG signals, that were used as inputs to the designed filters. Table 1 shows the quantity of thirty s epochs of Wake and Stage one for every subject utilized in this work.

| Subjects     | No. of Wake Epochs | No. of Stage 1 Sleep Epochs | Total No. of Epochs |
|--------------|--------------------|-----------------------------|---------------------|
| SC4001E0     | 1987               | 58                          | 2045                |
| SC4002E0     | 1875               | 59                          | 1934                |
| SC4042E0     | 1763               | 137                         | 1900                |
| SC4081E0     | 1975               | 68                          | 2043                |
| SC4112E0     | 2094               | 18                          | 2112                |
| SC4121E0     | 1799               | 48                          | 1847                |
| SC4141E0     | 1929               | 27                          | 1958                |
| SC4142E0     | 1993               | 41                          | 2034                |
| SC4151E0     | 1826               | 31                          | 1857                |
| SC4182E0     | 2039               | 131                         | 2210                |
| **Total**    | **19300**          | **636**                     | **19936**           |

**Table 1. Subjects Information**

![Fig. 2. Awake EEG Signal](image)

![Fig. 3. Stage 1 Sleep EEG Signal](image)
3. Feature Extraction

Only one feature is taken into account because the discriminating feature during this work, extracted from electroencephalogram signal for the classification method

3.1 Block Sample Entropy

Entropy may be a conception handling foregone conclusion and randomness, with higher values of entropy continuously associated with less system order and bigger randomness [50]. In recent years, researchers projected numerous estimators to quantify the entropy of your time series. These estimators will be roughly divided into embedding entropy and spectral entropy [51]. Embedding entropy assess however electroencephalogram statistic signals modification with time by examination on every occasion series signal with a lagged kind of itself [52].

In this work, embedding entropy-based quality parameter, sample entropy is employed to quantify the quality of graph beneath 2 states: awake and drowsy (sleep stage 1) but on short time interval. We have made 1 s block and calculated Sample Entropy for each block (BlockSample Entropy) to quantify the complexity of the 1 s block time series data. Based on the complexity value, a threshold value has been determined to distinguish between awake and sleep stage 1.

By the above feature extraction, 19300 awake state and 636 drowsy (stage 1 sleep) epochs were fed into the threshold based classifier for testing. First 5 minutes EEG data (i.e. 10 epochs of 30 s duration) from Pz-Oz channel for each subject has been used to determine threshold for that subject and subsequent recording has been tested for determining whether the subject is in awake state or in drowsy state. Different block sizes for calculating Block Sample Entropy has been experimented for the classification and we get best accuracy using 1 s block size. Two parameters m and r are fixed before calculation. The embedding dimension = 2 and therefore the vector comparison threshold, r = 0.2 x Standard Deviation are utilized in this work whereas conniving Block Sample Entropy.

Compare with alternative non-linear dynamic parameters, SE is a smaller amount sensitive to noise and may be applied for short-length statistic knowledge. For conniving the SE, the embedding dimension (m) and vector comparison threshold (r) should be such.

The sample entropy of the signal is outlined because the negative Napierian logarithm of the chance that 2 sequences similar for m purposes stay similar at succeeding point, wherever self-matches don’t seem to be enclosed in conniving the chance. SE is that the negative log of the chance that 2 sequences similar kind purposes stay similar at succeeding point, wherever self-matches don’t seem to be enclosed in conniving the chance. Thus, a lower worth of SE additionally indicates a lot of self-similarity within the statistic [52].

The value of SE is calculated in the following steps:

Given a time series \(\{x(n)\} = x(1), x(2), \ldots, x(N)\) with \(N\) data points, take \(m\) vectors \(X_m(1) \ldots X_m(N - m + 1)\) defined as \(X_m(i)[x(i), x(i+1), \ldots x(i+m-1)]\) for \(1 \leq i \leq N - m + 1\).

Two parameters \(m\) and \(r\) area unit mounted before calculation, during which \(r\) denote the noise filter level and is outlined as:

\[ r = g \times SD_{asg} = 0.1, 0.2, \ldots, 0.9 \]  

(6)

Subsequently, define the distance between \(X(i)\) and \(X(j)\), \(d(X(i), X(j))\) as follows:

\[ d(X(i), X(j)) = \max_{k=0, \ldots, m-1} |x(i+k) - x(j+k)| \]  

(7)

For a given \(X_m(i)\), count the number of \(j(1 < j < N - m, j \neq i)\), so \(d(X(i), X(j)) < r\), denoted as \(B_i\).

Then, calculate:

\[ B_m^r(r) = \frac{1}{N-m+1} B_i \]  

(8)

Define \(B_m(r)\) as:

\[ B_m(r) = \frac{1}{N-m} \sum_{i=1}^{N-m} B_i^r(r) \]  

(9)

Increment the dimension to \(m = m + 1\) and compute \(B_{m+1}(r)\), finally, calculate SE as,

\[ SE(m, r) = \ln \frac{B_{m+1}(r)}{B_m(r)} \]  

(10)

4. Threshold Based Classifier

To differentiate between the stage of wakefulness and stage one of sleep during this study, threshold for a selected subject has been determined from initial 5 minutes electroencephalogram knowledge of that subject. When crucial threshold worth for a subject matter, later recording has been classified as awake or stage one sleep counting on the magnitude of the extracted options of the following epochs. If the magnitude of the feature is larger than the brink worth, then classifies it as
awake, else stage one sleep. In this work, first 5 minutes EEG data from Pz-Oz channel has taken as baseline data and this recording is segmented into 30 s epochs. Block sample entropy has been calculated for each 1 s block and median of these block sample entropy is also calculated. The median is that the price separating the upper half the quality measures of EEG statistic information from the lower 0.5, the fundamental advantage of the median describing the quality information compared to the mean (often merely delineated because the “average”) is that it's not inclined such a lot by extraordinarily giant or little prices so it's going to provides a higher plan of a “typical” value. owing to this, the median is of central importance in strong statistics, because it is that the most resistant datum, having a breakdown purpose of 50%; goodbye as no quite 0.5 the info is contaminated, the median won't offer Associate in Nursing haphazardly giant or little result. For these reasons, we have calculated the median value of the Block Sample Entropy of 1 s blocks as a representative of the complexity measures of an epoch. In this way, we have also calculated the median value of the Block Sample Entropy for rest 9 epochs. Next, the minimum values, mean and standard deviation of these 10 median values has been calculated to determine the threshold with which the real time data will be compared. Finally, threshold has been calculated using the following formula:

$$Th = \frac{(Min + Mean)}{2} - SD$$

5. Results and Discussion

In order to differentiate between the stage of wakefulness and stage one amongst sleep throughout this study, total 9,968 minutes encephalogram recording from Pz-Oz channel of 10 subjects has been used. 19,936 epochs were used for testing where, each epoch are of 30 seconds duration. By using IIR Butterworth band-pass filter, EEG signal from Pz-Oz channel is band-passed from 0.5 Hz to 47.5 Hz. Figure 3 and Figure 4 show the input of awake and stage one graph signals severally. This study was performed in MATLAB R2011a.

![Fig. 4. Median BSE Value of 50 Epochs of Wake and Stage 1 Sleep Signal of SC4001E0](image)

![Fig. 5. Median BSE Value of 59 Epochs of Wake and Stage 1 Sleep Signal of SC4002E0](image)

Table 2 illustrates the range of median of block sample entropy. From the ends up in Table 2, the median of block sample entropy of awake signals isa lot oflarger than the median of block sample entropy of stage one sleep signals.

During this work, the feature was extracted from the graph Pz-Oz channel. Initial five minutes knowledge of a topic was wont to calculate threshold worth for that subject. Remainder of the awake epochs and stage one sleep epochs were used for testing. The performance of the string primarily based classifier square measure usually determined by the computation of

$$\text{Accuracy} = \frac{(TP+TN)}{(TP+FP+TN+FN)}$$

where TP is true positives, TN is true negatives, FP is faux positives, and FN is faux negatives. the performance of our work is everywhere in table 2.

| Subjects      | Total No. of Epochs | Correctly Classified Epochs | Incorrectly Classified Epochs | Overall Accuracy (%) |
|--------------|---------------------|-----------------------------|-----------------------------|----------------------|
| SC4001E0     | 2045                | 1957                        | 88                          | 95.70                |
5. Conclusions

A novel approach which may be merely enforced in embedded hardware or smartphone to differentiate wakefulness from stage one amongst sleep from single channel EEG signal is introduced throughout this paper. The filtering methodology of EEG signal employs digital choices that have an easy to use transfer operate once used on digital signal processors or embedded systems or smartphones. The feature that was chosen throughout this study: median of block sample entropy may be apart of the foremost effective and useful ways in which to research the EEG signal capability in designation of brain activity states. Threshold value has been determined from the first 5 minutes Pz-Oz channel EEG recording of the subject and this threshold values utilized for future unknown info classification. Testing has been performed on 166 hours and eight minutes EEG recording of 10 subjects from Pz-Oz channel. The experimental results indicate that the projected methodology achieves the standard classification accuracy of ninety 5.68%. Therefore, our easier, quicker, non-training-based classification, makes our work engaging for easy implementation in smartphone or any embedded microcontroller device for distinctive drowsiness. Our projected methodology can work effectively in real time.

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