

Research Article

EYE: A New Method for Detection of Electrode Disconnection in Sleep Signals

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Abstract

Biological signals that occur during sleep are recorded and classified by specialists. This process is called sleep staging. However, this is a very long and laborious process. Therefore, automatic sleep staging systems are needed. Nevertheless, automatic sleep staging studies to date have not provided satisfactory performance. The main reasons for this are inter-channel interference, electrode disconnection, and noise. In this paper, a new method (eye method) based on the Euclidean distance measurement method has been developed to solve the electrode disconnection or non-contact problem. This method was applied to three different datasets and detected all electrode disconnections with 100% accuracy. Thanks to this advanced method are aimed to increase the success of automatic sleep staging systems to be designed in the future.

Keywords: EEG, electrode disconnection, sleep staging, euclidean distance, eye method.

1. Introduction

About one-third of human life is spent in sleep. For this reason, in any sleep disorder that may occur in people, as a result of not reaching sufficient sleep time, the body cannot rest enough, and many related problems may arise. Considering the research on this issue, it has been observed that more than one psychological and physiological problem may occur in individuals depending on these problems [1]. For this reason, sleep staging is done by experts, these problems are determined, and necessary precautions are taken.

In the sleep staging process, signals such as electroencephalogram (EEG), electrooculogram (EOG), and electromyogram (EMG) are first recorded with devices called polysomnography (PSG). These signals are then divided into segments called 30-second epochs [2]. Each epoch is called a sleep stage. However, this process is time-consuming, and the accuracy rate may vary depending on the knowledge and experience of the experts. For such reasons, automatic sleep staging systems are needed, and many articles are published every year. However, when the studies in the literature are examined, it is seen that acceptable performance is still not achieved [3]. Among the biggest reasons for this are problems such as inter-channel interference, electrode disconnection or non-contact, and noise.

In particular, EEG signals usually oscillate at amplitude levels of $\pm 500\mu\text{V}$ and in the frequency range of 0-100 Hz or 0-128 Hz [4]. For this reason, it is of great importance to eliminate components that will adversely affect this process since it is challenging to measure and record accurately [5]. For this reason, conductive gels are generally used when recording these signals, thereby increasing the conductivity at the contact point [6]. Electrode disconnection or non-contact may occur due to gel quality, electrode failure, or environmental factors. In this article, a new method called the eye method based on the Euclidean distance measurement method has been developed to solve the problem of electrode disconnection or non-contact in sleep signals. As far as we know, when a literature review is made on this subject, it is seen that an algorithm developed by Yücelbaş et al. is the first and only study [7]. However, the main problem of this algorithm is that the threshold level coefficient changes for each data set, and it is complicated to determine the optimum value of this coefficient. In addition, the method has been tried on different data sets, and it has been observed that there are severe performance losses.

The eye method developed to solve all these problems has been tested on three data sets: SleepEdf-20, SleepEdf-78, and Necmettin Erbakan University hospital's Sleep Laboratory (NESL). In addition, when we look at the literature, it is seen that EEG signals are used more in sleep staging (because they are not deterministic and do not have particular formations like electrocardiogram (ECG) signals [8]). Therefore, EEG signals were used in this study as well. In addition, the obtained results were evaluated with sensitivity and specificity measurements.

The main contributions of this study are:

- Electrode disconnections and non-contacts can be easily detected within seconds.

- The proposed method can be easily applied to any dataset as it is effortless to implement. So it can be generalized.
- Electrode disconnections and non-contacts are detected in recorded sleep signals, so these data can be extracted before the training phase, improving the classification performance of automatic sleep staging systems.

The remainder of the article consists of the following sections: The datasets, eye method, and analysis methods used in the experiment are described in Section 2, and performance and comparisons are discussed and evaluated in Sections 3-4.

2. Materials and Methods

2.1. Dataset and data preparation

A total of 3 different data sets, SleepEdf-20, SleepEdf-78, and NESL, were used in the study.

Necmettin Erbakan University hospital's Sleep Laboratory (NESL): This data set was obtained from the sleep laboratory of Necmettin Erbakan University Hospital in Konya. The records in this data set belong to 5 people with Obstructive Sleep Apnea Syndrome (OSAS). The signals were sampled at a sampling frequency of 128 Hz. In addition, sleep experts performed manual scoring according to the American Academy of Sleep Medicine (AASM) guidelines [9]. This data set consists of 4400 epochs, each 30 seconds long; each epoch consists of 3840 data. In addition, all EEG signals were obtained from channel C4A1, as seen in Figure 1.

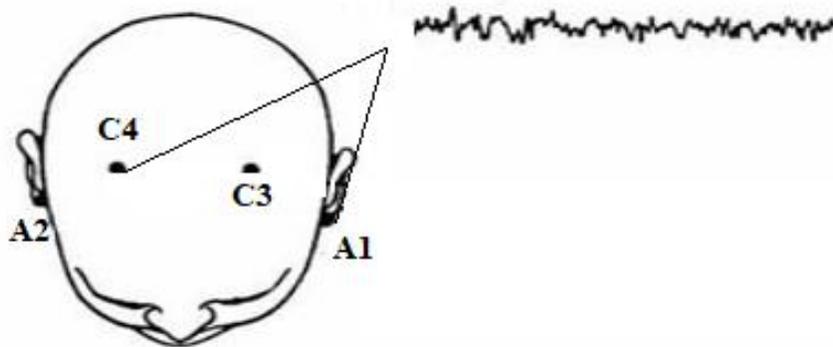


Figure-1 EEG-C4A1 channel connection

SleepEdf-20 and SleepEdf-78: This data set consists of 20 people, ten men and ten women. These persons are between 25 and 34, and each has 2-night recordings (except subject 13). Each of these records is 30 seconds long and has 43141 epochs. In addition, each recording was sampled with a sampling frequency of 100 Hz. These records have eight different labels: W, N1, N2, N3, N4, REM, MOVE, UNKNOWN. For this reason, the Movement and UNKNOWN categories have been removed, similar to the studies in the literature. Stages N3 and N4 were considered N3, and all data were categorized according to the AASM standard with five labels.

The SleepEdf-78 dataset is an extended version of the SleepEdf-20 dataset. Similarly, this data set was also sampled with a sampling frequency of 100 Hz and consisted of 78 healthy individuals. The age range of people varies between 25 and 101. The same procedures were performed on the SleepEdf-78 dataset, and the total number of labels was reduced to 5. In addition, experiments were performed using only Fpz-Cz EEG channels from both datasets. The epochs' numbers of all data sets used in this study are shown in Table 1.

Table 1. Number of Epochs

Dataset	W	N1	N2	N3	REM	Total
SleepEDF-20	9118	2804	17799	5703	7717	43141
SleepEDF-78	66822	21522	69132	13039	25835	196350
NESL	674	235	2952	505	34	4400

2.2. Euclidean distance

The Euclidean distance method takes its power from the Pythagorean theorem. It is used when finding the distance between two points and is a widely preferred distance measurement method, especially in artificial intelligence applications [10].

$$D(x, y) = \sqrt{\sum_{i=1}^n (x_i - y_i)^2} \quad (1)$$

The x and y used here are the Cartesian coordinates of each point and are shown in Figure 2.

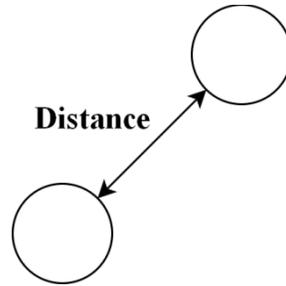


Figure-2 Euclidean distance between two points

2.3.Eye Method

Firstly, as seen in Figure 3, the signal was divided into epochs with a length of 30 seconds, and after normalization, the signal was divided into 60 sub-particles consisting of 64 samples, each 0,5 seconds long. This way aims to detect electrode disconnections or non-contacts that occur for at least 0,5 seconds or longer.

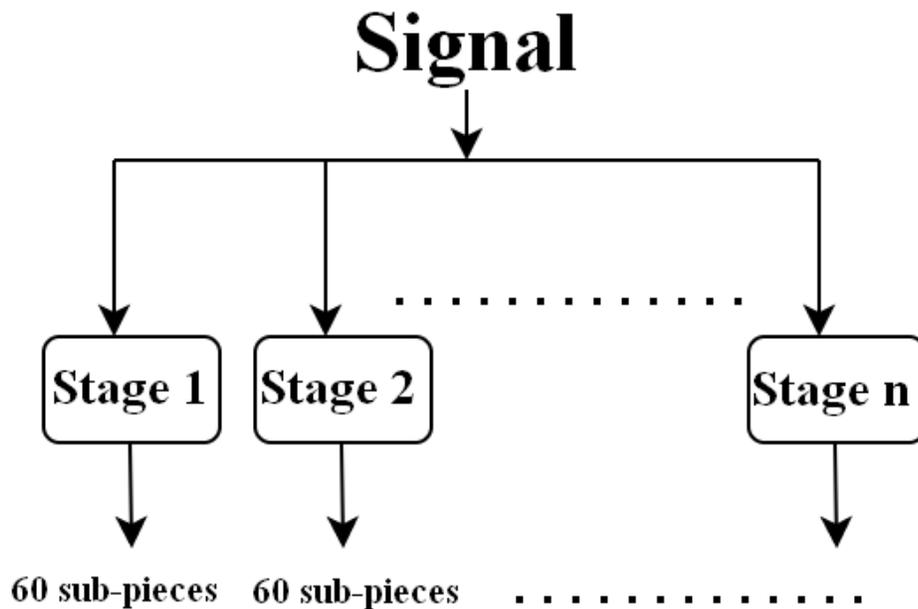


Figure-3 Data processing stages

As a first step, the maximum point of each sub-piece was found, as shown in figure 4. Then, in step 2, the maximum point is converted to a vector array of the same length as the subpart. This part is positioned so that it is at the maximum point of the signal, as shown in step 3.

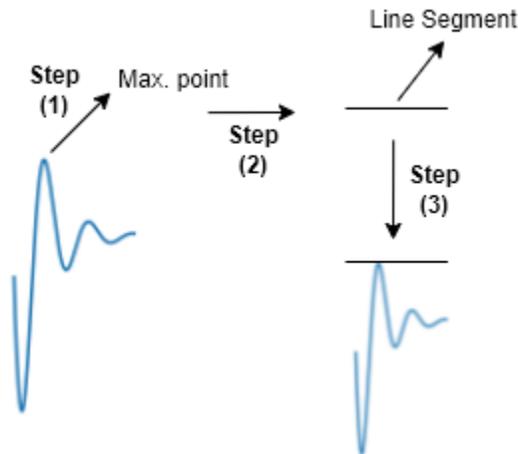


Figure-4 Steps

As seen in Figure 5, firstly, the distance between the line segment $v(t)$ signal and the subpart $x(t)$ signal was calculated using the Euclidean distance measurement method. Secondly, one eye is assumed to be looking at this distance. Finally, if the eye cannot distinguish $v(t)$ and $x(t)$ signals, it can be said that there is an electrode disconnection or non-contact at this stage. So distance (d) is 0 or very close to 0.

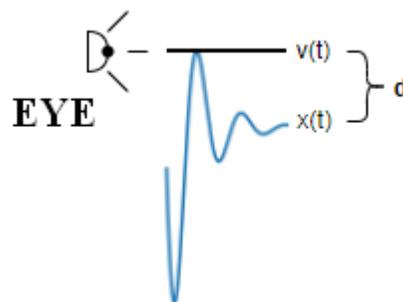


Figure-5 The eye method used in the study

After many rigorous trials, 0.001 was chosen as the distance threshold. In other words, if d is higher than 0.001, there is no mention of the electrode being disconnected or non-contact.

To better understand the process, the structure of Siamese Neural Networks can be studied [3]. A siamese neural network consists of two identical parallel neural networks. These networks are used for feature extraction, and the extracted features are vectorized, and the distance between them is found. Classification is made according to this distance.

However, no neural network is used in the eye method. Also, there is no need to separate the data as any test and training data. Thanks to a simple algorithm created, it can practically be applied to all signals.

2.4.Evaluation

Sensitivity and specificity performance evaluation criteria were used to evaluate system outputs. Sensitivity methods were used to find the detection rate of the part with electrode disconnection or non-contact, and specificity methods were used to find the detection rate of the part without electrode disconnection or non-contact. The mean sensitivity and specificity determined the mean recognition rate (auto).

$$\text{Specificity} = \frac{DN}{DN + YP} \times 100 \quad (2)$$

$$\text{Sensitivity} = \frac{DP}{DP + YN} \times 100 \quad (3)$$

$$\text{Auto} = \frac{\text{Specificity} + \text{Sensitivity}}{2} \quad (4)$$

Here, true positive (DP), true negative (DN), false positive (YP), and false negative (YN) are data on how many parts with and without electrode disconnection or non-contact were detected correctly or incorrectly.

3. Results and Discussion

As seen in Figure 6, a new method, called eye, has been developed to detect the stages with the electrode disconnection or non-contact in sleep signals. This method has been tested on three data sets, SleepEdf-20, SleepEdf-78, and NESL.

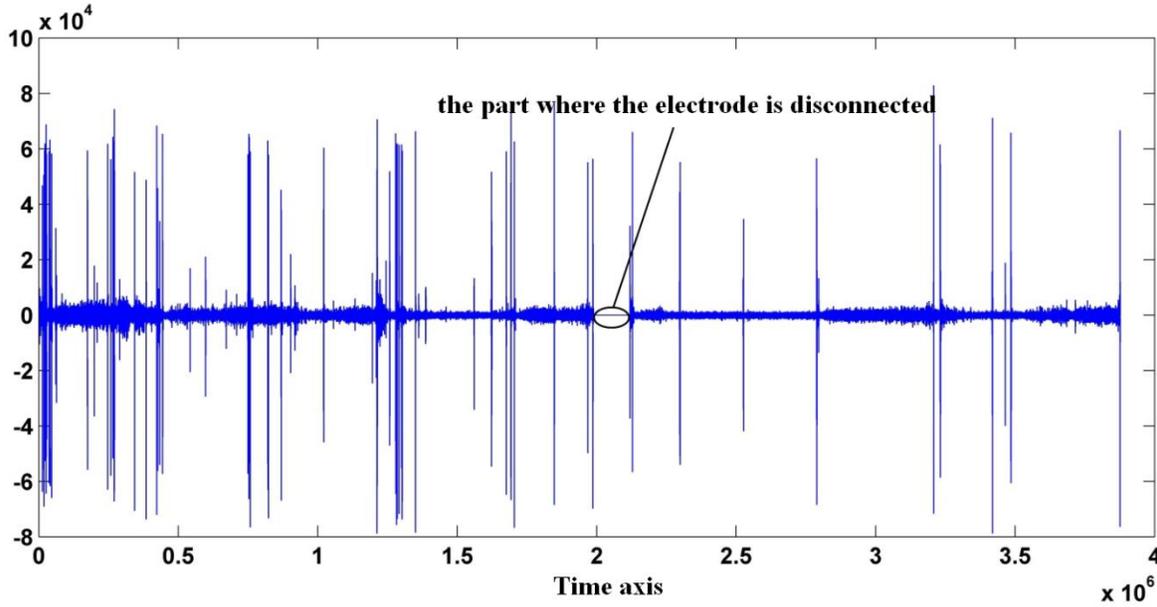


Figure-6 The stage with an example electrode disconnected [7].

The epochs in each data set were divided into 60 parts, and the eye method was applied to each part one by one. This way, electrode disconnections or non-contacts of 0.5 seconds or longer can be detected. The results are shown in Table 2.

Table 2. Experimental results

Method	Dataset	Sensitivity %	Specificity %	Auto %	Support
[7]	NESL	82.97	100	91.48	1010
EYE	NESL	100	100	100	4400
EYE	SleepEdf-20	100	100	100	43141
EYE	SleepEdf-78	100	100	100	196350

When the results are examined, it is seen that the new method developed can successfully detect all disconnections without making any mistakes.

Sleep disorders can be detected thanks to automatic sleep staging. However, negative factors such as noise, inter-channel interference, electrode disconnection, or non-contact may occur during sleep signal recording. Such factors cause system performance to be adversely affected. Minimizing these factors improves sleep staging classification performance. Thus, sleep experts aim to increase the person's quality of life by performing the necessary treatments.

Only one study has been conducted on electrode disconnection or non-contact in sleep signals to improve the performance of automatic sleep staging systems. As seen in Table 2, this study achieved a sensitivity of 82.97% and an average recognition rate of 91.48% in our dataset. On the other hand, the proposed eye method has succeeded in all data sets. In addition, with this method, electrode disconnections or non-contacts can be detected concisely, such as an average of 2,97 seconds. As far as we know, there is no study similar to the proposed method in the literature. For this reason, we think that the obtained results are pretty remarkable in terms of being used in automatic sleep staging systems to be designed in the future.

4. Acknowledge

The codes of the method proposed in this study can be found at the following address:
<https://github.com/efeenes/disconnection>

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