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Preventive detection of driver drowsiness from EEG signals using fuzzy expert systems

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Abstract. This document presents a drowsiness detection system based on electroencephalogram signals (EEG) using a pair of channels (Fp1 and Fp2), applied to drivers before they get into their vehicles. First, this model detects the relationship between the area under the curve (AUC) of alpha brain waves, this is mainstream parameter for detecting sleepiness. Afterwards, the extracted information is passed to a fuzzy expert system (FES) that classifies the subject's state as "alert" or "drowsy"; the criteria used was a threshold and training with subjective levels. The proposed system was compared with neural network models, such as support vector machine (SVM), K nearest neighbors (KNN) and random forest (RF). One hundred and twenty 1-minute measurements were performed on each of the 10 conductors over two days to test the system. The percentage of success obtained for the others learning methods were: SVM = 74%, KNN = 69% and RF = 68%. The classifier proposed obtained a percentage of 89.7%, exceeding the other classifiers.

Keywords: expert systems, sleepiness detection, electroencephalogram

1. Introduction

According to data provided by the World Health Organization (WHO) in the Report on the Global Situation of Road Safety 2015, the number of deaths due to traffic accidents amounted to 1.25 million in 2013, being the main cause of death people aged 15-29 years (more than 300,000 deaths) [1]. According to the World Report on the Prevention of Injuries Caused by Traffic of the Pan American Health Organization (PAHO) for the year 2020, if road safety actions are not taken, deaths caused by traffic will rise worldwide to 2.34 million, representing 3.4% of all deaths and road traffic injuries will rank sixth on the list of leading causes of death in the world and third on the list of causes of loss of physical abilities [2].

In Peru, the Instituto Nacional de Estadística e Informatica (INEI) registered 2,826 fatal victims of traffic accidents in 2017, with more than 2,487 homicide victims [3]. In addition, INEI recorded 174 fatal accidents in the department of Arequipa in the same year and 188 accidents in 2018 [3]. Recently, Dr. Helmer Huerta, a public health specialist, wrote that the statistics from the Ministry of Transport and Communications (MTC) of Peru revealed that, after a record of 3,531 deaths on the roads in 2011, 2,965 deaths have been registered in the 2015 and 3,245 deaths in 2018 [4]. That is, nine Peruvians die daily in a traffic accident, having one of the highest mortality rates from road accidents in the region, a rate of 10.1 out of every 100,000 inhabitants, exceeding the deaths due to citizen insecurity [5]. This information is supported by the latest calculation of death rates from traffic accidents in 180 countries, made by the WHO in 2018, the average death rate for developed countries is 9.3 deaths per year per 100 thousand inhabitants, while in middle-income countries the figure doubles, being 18.4 per 100 thousand inhabitants [5]. It is estimated that up to 30% of road accidents are caused by driver fatigue and drowsiness [6]. To avoid traffic accidents, the driver's state of drowsiness should be controlled before the accident occurs.

In the literature, the most used methods to detect drowsiness are: subjective measures, physiological measurements, Vehicle-based measurements and driver behavior measurements. the subjective measures monitor the subject's state of drowsiness through self-perception, they place scores according to a set range [7], the most widely used being the "Karolinska Sleepiness Scale" (KSS) [8, 9]. Physiological measurements are based on the use of signals, the most used are: Electrocardiogram (ECG), Electroencephalogram (EEG), Electrooculogram (EOG) and Electromyogram (EMG) [10, 11]. Vehicle-based measurements require constant monitoring, any variation could be a sign of drowsiness [12, 13], some examples are: steering wheel movement, difference in pedal pressure, deviation of the vehicle's position with respect to the road, etc. [14]. Driver behavior measurements use a camera to be detected, drowsiness is detected by blinking of the eyes, rolling of the head, yawning, etc. [15, 16].

In this document, we propose a novel drowsiness detection system for drivers based on fuzzy rules for the classification. A large part of previous work focuses on detecting the driver's yawns, prolonged closing of the eyes, the shape of the eyebrows and cameras that invade the privacy of the driver. Another group of jobs alert when the driver is already sleepy, giving very little time to respond to a possible accident. The proposed system focuses on transferring this detection of drowsiness to a moment before the start of driving; therefore, the algorithm is responsible for detecting patterns in the alpha waves of the EEG signal to determine if the driver is drowsy before starting the driving day as a preventive measure. In addition, the algorithm does not require an extensive database to train the system, this feature makes it a practical and easy to use system. For simplicity, the system classifies into two states: Not sleepy (alert) and sleepy.

2. Related work

There are several notable studies that focus on detecting the state of drowsiness in drivers. Some of these studies make use of artificial vision systems, which is a non-intrusive method, to detect patterns in drivers that show the presence of drowsiness; the most used patterns are: yawning, angle of inclination of the eyes, continuous blinking, nodding, drooping of the eyelids, etc.

Tayyaba Azima, Arfan Jaffar and Anwar M. Mirza [17] in their article describe a fatigue detection system based on video analysis of drivers. Their system uses two parameters to classify the state of drowsiness: Duration of ocular closure and yawning. In that system, the face is located using the Viola-Jones face detection method. Then, they extract a window from the mouth region, at the same time they also detect the pupils and their angle of inclination. Monitored information from the eyes and mouth is sent to a fuzzy expert system (FES) that classifies the driver's drowsy state. The system shows that it is good at detecting and classifying the level of fatigue. Furthermore, the fuzzy expert system proves to have good performance for a sleepiness classification system.

Vineetha Vijayan and Elizabeth Sherly [18] also propose an architecture based on the measurement of facial movements such as eye blinking, yawning and head rolling, through RGB video and deep neural networks. They successfully compare three neural models, ResNet50, VGG16 and InceptionV3, and a fused architecture of the three models (FFA).

Boon-Giin L., Boon-Leng L. and W. Chung [19] present a sleep detection system with mobile devices, using 8-channel EEG signal and driver's breath. First, they extract the EEG characteristics with the wave packet transform (WPT) method to separate the signals into four frequency bands: alpha, beta, theta, and delta. A mutual information (MI) technique selects the most descriptive characteristics to perform a classification with a support vector machine (SVM). The classification processing is carried out on a mobile device, verifying that this system requires very little computational cost, unlike other similar methods.

Yingying Jiaoa, Yini Denga, Yun Luoa and Bao-Liang Lu [20, 21] propose a model that detects driver drowsiness based on EEG and EOG signals. This model is capable of tracking the change in alpha waves and differentiating the two alpha-related phenomena: the alpha-blocking phenomenon and the fading-disappearing phenomenon. The LSTM (Long-Short Term Memory) network is used to manage the temporal information of the EEG and EOG signals. Additionally, the adversary generative network (GAN) is used in this paper to augment the training data set. The results show that their model has great precision when classifying the driver's condition. The same authors [22] also make another article in which they check the phenomena of alpha, they use the power spectrum density (PSD) of alpha to visually determine the phenomenon. Furthermore, it is observed that the attenuation-disappearance phenomenon does not take a long time to appear, around 10s.

Another author who does an article on alpha-related phenomena is Arcady Putilov. Putilov associates the phenomenon of alpha attenuation-disappearance with drowsiness, in addition, he indicates in his document that this phenomenon appears when the participant closes his eyes and keeps them closed [23].

3. Materials

3.1. Measuring devices

The tests were carried out on real vehicles, Figure 1 shows the instruments inside the vehicles of San Cristóbal del Sur company and Transportes Libertad company respectively.

a)

b)

Fig. 1. Measuring devices attached to vehicles. a) San Cristóbal del Sur company b) Transportes Libertad company.

EEG brain signals were recorded with the InteraXon Muse electroencephalogram. This device has four channels, uses Bluetooth to send data and has dry electrodes in order to be less invasive in data collection. According to the international convention for the placement of electrodes [24], the Muse electrodes are located at Fp1, Pp2, A1 and A2, with A2 being the reference electrode used, see Figure 2.

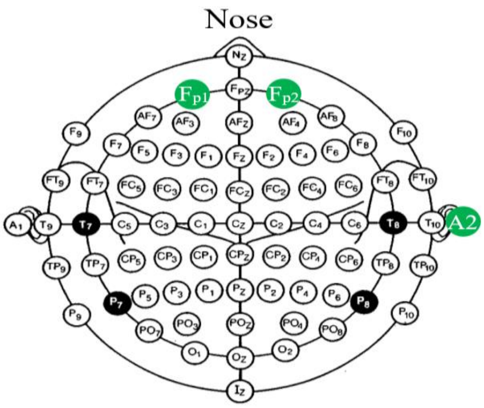

Fig. 2. Electrodes location.

3.2. *Data register*

The EEG signals recorded by the two selected channels, with a sampling frequency of 256 Hz, were subjected to low-pass and high-pass filters (0.5 and 40 Hz respectively), sampled and stored in *.csv* files. The raw signals are displayed in real time with a graphical Python interface, see Figure 3. All statistical analyzes and pre-processing of data were performed in Python with their respective scientific libraries.

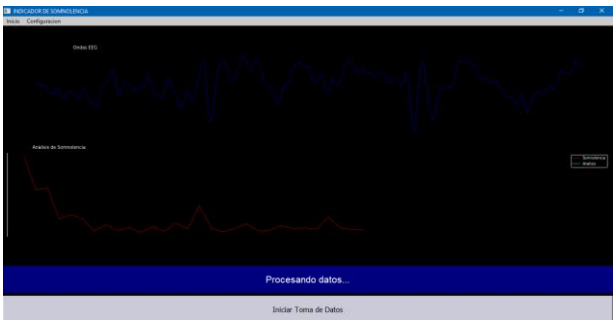

Fig. 3. Graphical interface of measurements.

3.3. *Alpha-related phenomena*

3.3.1. *Alpha wave*

Alpha waves originate in the occipital lobe and are seen in relaxed wakefulness during eye closure [25]. These waves correspond to the frequency range between 8 - 12 Hz [26]. In [27], it is mentioned that the range of the waves is generally between 0.5 and 100uV, in addition, in the literature it has been shown that there is an amplitude difference between the normal state and the drowsy state in alpha waves [28].

3.3.2. *Alpha blocking phenomenon*

Alpha waves appear when the eyes are closed under relaxed wakefulness and disappear rapidly when the eyes are reopened [20]. This phenomenon known as alpha blocking represents that the person does not have traces of drowsiness [21]; for this reason, it serves as an indicator that the person is alert.

3.3.3. *Phenomenon of attenuation-disappearance of alpha waves*

The attenuation of the alpha rhythm serves as a reliable EEG marker of sleep onset [20, 29], it is considered the most valuable marker of sleep onset during sleep [21]. Furthermore, objective assessment of sleepiness in permanently awake individuals could be facilitated by probing for alpha attenuation immediately after closing the eyes [30]. In this way, EEG tests can be performed in closed eyes for one minute.

3.4. *Experimental procedure*

A total of 10 volunteer subjects were evaluated. The age of the 7 men varied between 22 and 34 years (28 ± 6), and the age of the 3 women varied between 20 and 29 years (24.5 ± 4.5). The volunteers in the study did not report any mental or physical health problems and have no history of a history of psychiatric or sleep disorders. The experiment was carried out in accordance with the ethical standards established in the Declaration of Medical Examinations of Peru. The experimental protocol was approved by the Research Ethics Committee of the National Institute of Health of Peru. Written informed consent was obtained from each study participant.

3.4.1. *Pre-test preparation*

Before each EEG recording session, the participants were asked to use the modified Karolinska scale to indicate their level of alertness / sleepiness [7], this modification of the scale consisted of discarding the even levels, leaving the new scale as follows:

- *(1) Very Alert.*
- *(3) Alert*
- *(5) Neither Drowsy nor Alert*
- *(7) Sleepy, easy to stay awake*
- *(9) Sleepy, great difficulty staying awake*

After registering the data, it is recorded that there were no level 1 values, so this scale was discarded, leaving levels 3, 5, 7 and 9. The classification of two states is represented in Figure 4.

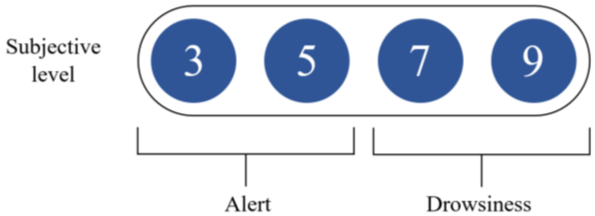

Fig. 4. Levels of Sleepiness status.

These subjective values were used as references of the real state of drowsiness of the participants, the precision values were obtained by comparing them with the value extracted from the system.

3.4.2. *Open-closed-open eyes experiment*

To visualize the phenomenon of alpha attenuation-disappearance, it was made a comparison between measurements of 15 seconds with eyes open (reference), 1 minute with eyes closed (detection test) and finally measurements for 15 seconds with eyes open (reference). see Figure 5.

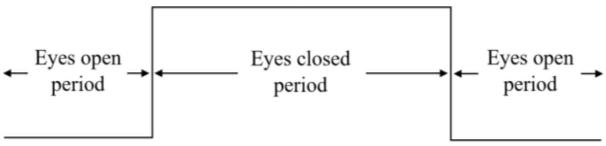

Fig. 5. Tests performed for 1 minute and a half.

For data collection, the participants were in a comfortable chair and a supervisor asked them to avoid any type of movement or distraction during the experiment. In addition, they were indicated to the participants the exact moments of when to close or open their eyes and not to blink during periods with eyes open. See Figure 6.

Fig. 6. Environment for driving tests.

3.4.3. *Test drive after analysis*

After conducting the evaluation, the drivers began their working day (accompanied by a co-pilot for greater safety). It was recorded whether or not the drivers showed drowsiness, for a later analysis of the success rate of the tests. This test demonstrates the success of prevention on the level of drowsiness.

4. Methods

When the two phenomena related to alpha waves are observed, two different patterns are distinguished, the key to detecting if the driver is in a state of acute drowsiness is to distinguish which of these two phenomena are most closely to the measurements. Therefore, the proposed model compares the alpha waves measured to the conductors with the waves that served as training for the model. The eye closure point (P1) is recognized as the point used to compare both samples. Figure 7 shows the flow diagram that the model follows in order to recognize an acute level of drowsiness (KSS = 9).

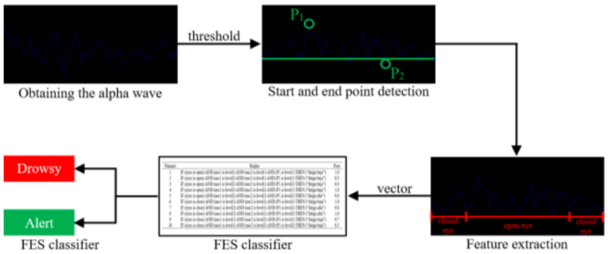

Fig. 7. System Flow diagram.

The following algorithms show the main step sequences used in the model. First, it is applied Welch's method to calculate the Alpha power spectrum (Algorithm 1) [31]. Then, it passes a filter to separate the wave by epoch, which improves the precision of the model. Then, the strategy to detect the beginning and end of the alpha wave when closing and opening the eyes, respectively, is presented. Finally, the fuzzy expert system (FES) used in this model is described.

4.1. *Alfa Obtaining the Alpha Wave Energy Threshold*

To calculate the absolute power in the alpha band, we will start by calculating an estimate of the power spectral density. The most widely used method to do this is the Welch periogram [32]. Welch's method makes it possible to drastically reduce the variations produced by the constant variation of the spectral content of EEG signals [33]. Frequency resolution is defined by:

$$F_{res} = \frac{F_s}{N} = \frac{F_s}{t.F_s} = \frac{1}{t} = \frac{1}{60}$$

Where:

- *F_s: is the signal sampling frequency.*
- *N: the total number of samples.*
- *t: the duration, in seconds.*

Algorithm 1 shows the procedure used to determine the alpha power using the "scipy" library.

Algorithm 1 Calculation of the potency of alpha

```
procedure POWER_ALFA(data, sf, window=None, relative=False)
    from scipy.signal import welch
    from scipy.integrate import simps
    import numpy as np
    low ← 8
    high ← 12
    if window == None then
        npersg ← window * sf
    else
        npersg ← (2 / low) * sf
    end if
    freqs, psd ← welch(data, sf, npersg=npersg)
    freq_res ← freqs[1] - freqs[0]
    idx_band ← np.logical_and(freqs >= low,
                              freqs <= high)
    bp ← simps(psd[idx_band], dx=freq_res)
    if relative then
        bp /← simps(psd, dx=freq_res)
    end if
    return bp
```

4.2. *Separation of energy in epochs*

By having a length of the data (1 minute = 60 seconds), the final frequency resolution would be: 1/60 = 0.0167 Hz, which is 60 frequency bits per Hertz. A window long enough is taken to span at least two full cycles of the lowest frequency of interest [34]. In this case, the lowest frequency of interest corresponding to the alpha band (8 Hz to 12 Hz) is 8 Hz, so it is chosen a window of 2/8 = 0.25 seconds, see the Algorithm 2.

Algorithm 2 Epoch separation

```
procedure EPOCHS(data, sf, sliding, seg)
    from scipy.signal import welch
    import numpy as np
    low ← 8
    high ← 12
    win ← sliding * sf
    alfa_abs ← np.array([])
    i ← 0
    j ← sf * seg
    for v = 0, 1, …, 60 do
        epoca ← data[i:j]
        b ← np.greater(epoca, 500)
        c ← np.less(epoca, -500)
        if b = True or c = True then
            freqs, psd ← welch(epoca, sf,
                               nperseg=win)
            idx_a ← np.logical_and(freqs >= low,
                                   freqs <= high)
            freq_res ← freqs[1] - freqs[0]
            alpha_power ← simps(psd[idx_a],
                                dx=freq_res)
            alfa_abs ← np.append(alfa_abs,
                                 [alpha_power])
        end if
    end for
    i ← i + sf * 2
    j ← j + sf * 2
    return alfa_abs
```

Before calculating the absolute alpha band power (average), it is needed to find the frequency intervals that intersect the Alpha range. For this purpose, it is defined the upper and lower frequency limits corresponding to this band (8 Hz to 12 Hz). Normalized measurements are used at all times in order to that any sample was outside the rang, the formula used is:

$$Alfa_{normalizado} = \frac{Alfa - Alfa_{min}}{Alfa_{max} - Alfa_{min}} \qquad (1)$$

These calculated alpha values will be used to obtain the ratio of the area under the curve (AUC), see Algorithm 3.

Algorithm 3 Calculation of AUC

```
procedure AUC_CALCULATION(alfa_abs)
    import numpy as np
    from scipy.integrate import simps
    media ← np.mean(alfa_abs)
    d_st ← np.std(alfa_abs)
    index ← np.array([])
    for k = len(alfa_abs) do
        z ← (alfa_abs[k] - media) / d_st
        index ← np.append(index, [z])
    end for
    ventana ← 3
    b ← np.ones(ventana) * (1 / ventana)
    normal ← []
    x ← np.arange(0, len(index))
    freqs, psd ← welch(data, sf, npersg=npersg)
    for i = len(index) do
        normal.append(index[i] - min(index)) /
                     (max(index) - min(index))
    end for
    area1 ← simps(normal[0:29], x[0:29])
    area2 ← simps(normal[30:59], x[30:59])
    return area1, area2
```

4.3. *Classification of levels using FES*

The purpose of this classifier is to determine the starting point of eye closure, the point that initiates the phenomenon of fading-disappearance of alpha waves. For this, the model must autonomously recognize when this phenomenon starts in the measurements made.

4.3.1. Feature extraction

Feature extraction algorithms are an important element in all machine learning models. The first step in developing this fatigue detection system is to determine the number of variables or characteristics involved, according to the criteria of the experts. The algorithm extracts the characteristics of the measurement during the test minute; the values of the measurements with the eyes open serve as a reference to have knowledge of the low alpha values of each individual. The characteristics chosen after conducting an adequate study of our system are: Initial point ratio (P1), End point ratio (P2), Eye condition, Area under curve 1 (AUC1), Area under curve 2 (AUC2) and fatigue level. Table 1 shows the characteristics and associated linguistic terms.

Table 1
Details of the input and output variables used by the expert system

Variable	Type	Range	Linguistic Terms
Ratio P1	Input	X	Level A1, level A2
Ratio P2	Input	X	Level A1, level A2
Eye condition	Output	[0 - 1]	Open, closed
AUC 1	Input	X	Level B1, level B2
AUC 2	Input	X	Level B1, level B2
Fatigue level	Output	[0 - 1]	Low, high

The area under curve 1 is taken from the first 30 seconds of the closed-eye tests, while AUC2 is taken from the remaining 30 seconds. Because the system is proposed as adaptive (to any gender, ethnicity, etc.), A1, A2, B1 and B2 levels of the input characteristics are determined according to the alpha values obtained during the first 15 seconds of the tests with Open eyes.

4.3.2. Detection of start and end points of alpha waves

As can be seen in Figure 8, to obtain the alpha energy value curve, it is applied the Welch periodogram, then a sharp change between two consecutive signals was detected. The largest in the entire measurement marks the point P1; then this information is passed to the trained model to make its classification.

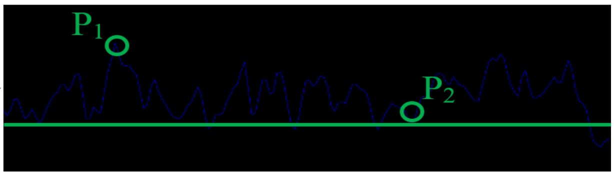

Fig. 8. Alpha Energy Graph.

4.3.3. FES classifier

FES use fuzzy logic through functions and rules instead of Boolean logic to reason about input data. These systems can be seen as an attempt to formalize two human capacities [17]. Fuzzy logic incorporates a comprehensive approach based on IF X AND Y THEN Z to solving a control problem rather than trying to model the system mathematically. The model is based empirically on the experience of the operator rather than his technical understanding of the system [35]. One of the greatest advantages that offer FES is that it generally does not require a large training set [17]. Due to the fact that there is not a large amount of data to train, this classifier was chosen.

In this step, it is determined whether the driver's state of drowsiness is acute. If the fatigue level value is higher than 0.55, the system informs with a message ("with drowsiness") that indicates the driver is not fit to drive. The system is able to detect drowsiness regardless of ethnicity, gender, etc. of the driver, so the system takes the first 15 seconds of measurement (during the eye-open portion of the test) to determine the range of the alpha level input. Based on the selected variables, rules have been declared to express the behavior of the system in a clear and understandable way. Different rules are enunciated to express the behavior that the system follows from the variables mentioned in section 4.3.1. We got a total of 18 understandable rules. According to these rules, the state of the eyes and the level of the characteristics play a major role in detecting the state of the driver. Of the set of rules, 10 are listed in Table 2 and the rest follow a similar pattern. In addition, the rules follow a hierarchy (added weight) according to their relevance when the system classifies.

Table 1
Rules for the expert system

Number	Rules	Weight
1	IF (eyes is open) AND (auc1 is level1) AND (auc2 is level1) AND (P1 is level1) THEN (“low fatigue”)	1.0
2	IF (eyes is open) AND (auc1 is level2) AND (auc2 is level1) AND (P1 is level1) THEN (“low fatigue”)	0.5
3	IF (eyes is open) AND (auc1 is level2) AND (auc2 is level1) AND (P1 is level2) THEN (“low fatigue”)	0.4
4	IF (eyes is open) AND (auc1 is level2) AND (auc2 is level2) AND (P1 is level1) THEN (“low fatigue”)	1.0
5	IF (eyes is open) AND (auc1 is level2) AND (auc2 is level2) AND (P1 is level2) THEN (“high fatigue”)	0.8
6	IF (eyes is close) AND (auc1 is level1) AND (auc2 is level1) AND (P1 is level1) THEN (“low fatigue”)	1.0
7	IF (eyes is close) AND (auc1 is level2) AND (auc2 is level1) AND (P1 is level1) THEN (“high fatigue”)	0.8
8	IF (eyes is close) AND (auc1 is level2) AND (auc2 is level1) AND (P1 is level2) THEN (“high fatigue”)	1.0
9	IF (eyes is close) AND (auc1 is level1) AND (auc2 is level2) AND (P1 is level1) THEN (“low fatigue”)	0.7

10	IF (eyes is close) AND (auc1 is level1) AND (auc2 is level2) AND (P1 is level2) THEN ("low fatigue")	0.5

The variables and rules were declared correctly, for this reason, now the fuzzy expert system process can follow the following steps [17]:

1. *Return sharp input values to fuzzy values.*
2. *Evaluation of all If-Then rules in parallel.*
3. *Adding of the consequents through the rules.*
4. *Converting the fuzzy response to a sharp value.*

5. Experimental Results and Discussion

To corroborate the performance of this model, a laptop was used, it was composed by Windows operative system, 6th Gen Intel (R) Core (TM) i5 processor, quad core, 8GB RAM, and an NVIDIA 840 with 2GB memory (GPU not accelerated). Each driver performed the open-closed-open eyes test once before getting into their vehicle, for a total of 20 sessions per driver.

The results are displayed in the graphical user interface. Then, different combinations were tried of window size and epoch length, to get the one that give the best results. Next, it is tested the eye opening and closing based on alpha measurements. For the FES system, it was tested its performance by comparing it with RNN, SVM and K-NN using training and testing each subject.

5.1. Result in the graphical interface

Figure 9 shows two levels of sleepiness found for the four most descriptive extracted features of the EEG signals. The upper part of the graph (blue signal) corresponds to the EEG signals without processing and in real time (a sampling frequency of 250 Hz), they were obtained from the derivative of Fp1 and Fp2. The middle part of the graph shows two signals, the first one in green corresponds to the entire signal captured during the test minute and the yellow signal corresponds to the signal after filtering. The lower part indicates the state of the driver, being "NOT Drowsy" or "Drowsy".

a)

b)

Fig. 9. Results in the graphical interface.

5.2. Different combinations of window size and epochs

It was compared the performance of the system for different combinations of window size and sliding step size on the Welch periodogram. For this purpose, it was used 120 samples of a single person with different configurations. Among the configurations that were tested, there was not overlap of sliding windows in the 0.25 s window size configuration with 0.25 s sliding step, while there was overlap in all other combinations.

Meanwhile, the total coverage of all windows over time was set to 2 s (epochs) for each configuration so that the amount of information contained in all configurations was the same. In Table 3, we can see that all windows with overlap outperformed the window without overlap.

Table 2
Comparison of epochs used

Subject	window = 0.25 sliding = 0.1	window = 0.4 sliding = 0.125	window = 0.5 sliding = 0.125	window = 0.5 sliding = 0.25
1	81.67	83.33	87.50	85.00
2	79.17	80.00	85.83	80.83
3	75.00	77.50	85.00	81.67
4	77.50	78.33	84.17	79.17
5	76.67	75.83	85.00	84.17
6	79.17	80.00	85.83	83.33
7	75.00	79.17	82.50	81.67
8	81.67	80.83	81.67	82.50
9	78.33	78.33	85.83	85.00
10	76.67	77.50	85.00	80.83
Prom	78.08	79.08	**84.83**	82.42

In Table 3, It can be seen that the 0.5 s window with 0.125 s sliding step size was the best. Therefore, this combination was chosen to be our window setup for extracting features from the EEG signal.

5.3. Alpha waves start and end point detection performance

As shown in Figure 8, the detection of start and end points rely only on Alpha waves, this generates a deviation at the exact moment. For this reason, the detection of these points was considered correct if they corresponded to the range of [I (s) ± 0.5s] and [F (s) ± 0.75s], a greater range was considered for the end point because in the attenuation-disappearance phenomenon, so it was more difficult to differentiate Alpha levels.

In Table 3, it is observed that the average of the percentages of successes of the start and end points is 90% for drivers in state of alert. For drowsy drivers the average was 87%. These values confirm that the system adequately detects the start and end points of the eyes closed event using only EEG measurement.

Table 3
Detection performance #A and #D

Subject	#A	Start (%)	End (%)	#D	Start (%)	End (%)
1	62	75.81	72.58	58	81.03	77.59
2	65	81.54	73.85	55	81.82	80.00
3	71	84.51	74.65	49	83.67	81.63
4	70	75.71	72.86	50	80.00	82.00
5	63	77.78	82.54	57	85.96	78.95
6	69	78.26	72.46	51	82.35	80.39
7	72	80.56	83.33	48	77.08	79.17
8	66	77.27	74.24	54	79.63	81.48
9	59	81.36	76.27	61	78.69	77.05
10	61	81.97	80.33	59	84.75	71.19
Prom ± SD		79.48 ± 2.78	76.31 ± 3.98		81.50 ± 2.63	78.94 ± 3.03

5.4. Classifier Comparison

To simplify the comparison of classifiers, only the samples that exceed the 25 detected values were taken, avoiding possible misrepresentations. We compared our FES classifier with k-NN, RNN, and SVM using an independent assessment of each subject. Table 4 shows that in each evaluation, the model obtains the best accuracy of hits, being the highest detected 81.01%. As indicated in Section 3.4.1, the KSS values of the subjects were used to determine if the person is in a state of alert or in a state of drowsiness, this determines the hit rate.

Table 4
Accuracy (%) of K-NN, RNN, SVM and FES to classify conductor states

Subject	K-NN (%)	RNN (%)	SVM (%)	FES (%)
1	79.17	83.33	78.33	87.50
2	83.33	80.83	80.00	85.83
3	77.50	80.83	80.83	85.00
4	76.67	84.17	75.83	84.17
5	75.00	85.00	75.83	85.00
6	75.83	85.83	76.67	85.83
7	74.17	81.67	79.17	82.50
8	73.33	80.83	79.17	81.67
9	76.67	82.50	80.83	85.83
10	75.83	83.33	78.33	85.00
Prom (%)	76.75	82.83	78.50	**84.83**
SD	2.70	1.72	1.78	**1.62**

5.5. Prevention hit rate

In Section 3.4.3 it was noted about the proof test that the system predicts the drowsy state of the driver. The tests consisted of determining if the driver during the journey showed signs of drowsiness (through the perception of the copilot and self-perception) and then comparing them with what the system had predicted. Table 5 shows the total hit rate of the prediction of drowsiness, due to there were 60 tests for each person.

Table 5
System prediction hit rate

Subject	Number of drowsiness	Accuracy (%)
1	2	80.00
2	1	83.33
3	2	91.67
4	0	88.33
5	3	86.67
6	1	83.33
7	1	81.67
8	3	86.67
9	1	85.00
10	0	86.67

6. Conclusions and future work

In this document was proposed a new system to detect driver drowsiness from EEG signals. This model aims to detect the change in alpha waves captured by the pair of electrodes located in the right frontal area (F2) and to detect the beginning and end of the samples during tests with eyes closed in order to detect the drowsy state of the driver before getting into the vehicle. The proposed model uses the Welch periodogram to extract the power of the alpha waves, a filter to improve the wave shape and FES to classify the states of the conductors. The results have shown that our model can detect the driver's condition with an average accuracy of 85%. These tests were compared with classifier models such as RNN, K-NN and SVM, being this model much superior to the others. Due to the fact that this model only places two electrodes on the subject, it is practical for routine use in real life scenarios.

Future work will focus on strengthening the weakest points when detecting drowsiness. The implemented system works as a good base, but it can be note that it has problems during the tests with the eyes open; future works will focus on filtering out the blinks that interfere with the alpha measurements. In addition, one more state will be added, in total there will be 3 states: alert, low drowsiness and acute drowsiness. In this document, the third state was discarded because it did not have sufficient precision for its validity.

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References

[1] World Health Organization. Report on the Global Situation of Road Safety 2015. In World Health Organization; Publishing House: Geneva, Switzerland, 2015; pp. 3–5.

[2] Pan American Health Organization. World Report on the Prevention of Road Traffic Injuries. In World Health Organization; Publishing House: Washington D.C., United States, 2015; pp. 6–9.

[3] Instituto Nacional de Estadística e Informática. Mortality Rate 2017. In Mortality Rate 2017; Publishing House: Lima, Peru, 2017.

[4] Ministerio de transportes y Comunicaciones. Muertos por Accidentes de Tránsito 2006 - 2017. December 2017.

[5] Elmer Huerta. La preocupante cifra de muertes por accidentes de tránsito en el Perú y sus principales causas. July 2019. ElComercio.

[6] Jorge Rey de Castro. Drowsy drivers on the roads of Peru: findings and proposals. Scielo 2011, vol. 4, pp. 155–156.

[7] Arcady A. Putilov, Olga G. Donskaya. Construction and validation of the EEG analogues of the Karolinska sleepiness scale based on the Karolinska drowsiness test. Clinical Neurophysiology, vol. 124, Issue 7, July 2013, Pages 1346-1352.

[8] V. Riethmeister, R.W. Matthews, D. Dawson, M.R. de Boer, S. Brouwer, U. Bültmann. Time-of-day and days-on-shift predict increased fatigue over two-week offshore day-shifts. Applied Ergonomics, vol. 78, 2019, pp. 157-163.

[9] A. Sahayadhas, K. Sundaraj, and M. Murugappan, "Detecting driver drowsiness based on sensors: a review," Sensors, vol. 12, no. 12, pp. 16 937–16 953, 2012.

[10] Varun Bajaj, Sachin Taran, Smith K. Khare, Abdulkadir Sengur. Feature extraction method for classification of alertness and drowsiness states EEG signals. Applied Acoustics, vol. 163, 2020.

[11] U. Budak, V. Bajaj, Y. Akbulut, O. Atila and A. Sengur, "An Effective Hybrid Model for EEG-Based Drowsiness Detection," in IEEE Sensors Journal, vol. 19, no. 17, pp. 7624-7631, 1 Sept.1, 2019.

[12] Margarida Fernandes. Driver Drowsiness Detection using Non-Intrusive Eletrocardiogram and Steering Wheel Angle Signals. Universidade do Porto.

[13] Sadegh Arefnezhad, Sajjad Samiee, Arno Eichberger, Ali Nahvi. Driver Drowsiness Detection Based on Steering Wheel Data Applying Adaptive Neuro-Fuzzy Feature Selection. Sensors 2019,19, 943.

[14] Meng Chai, shi-wu Li, wen-cai Sun, meng-zhu Guo, meng-yuan Huang. Drowsiness monitoring based on steering wheel status. Transportation Research Part D: Transport and Environment, vol. 66, 2019, pages 95-103.

[15] Carina Fors-VTI, Christer Ahlström-VTI, Per Sörner-Smart Eye, Jordanka Kovaceva-Volvo Cars, Emanuel Hasselberg-Smart Eye, Martin Krantz-Smart Eye, John-Fredrik Grönvall Volvo Cars, Katja Kircher-VTI, Anna Anund-VTI. Camera-Based Sleepiness Detection. Virtual Prototyping and Assessment by Simulation.VTI 2011.

[16] M. H. Baccour, F. Driewer, E. Kasneci and W. Rosenstiel, "Camera-Based Eye Blink Detection Algorithm for Assessing Driver Drowsiness," 2019 IEEE Intelligent Vehicles Symposium (IV), 2019, pp. 987-993, doi: 10.1109/IVS.2019.8813871.

[17] Tayyaba Azim, M. Arfan Jaffar, Anwar M. Mirza. Fully automated real time fatigue detection of drivers through Fuzzy Expert Systems. Applied Soft Computing, vol. 18, 2014, pp. 25-38.

[18] Vijayan, Vineetha and Sherly, Elizabeth. Real Time Detection System of Driver Drowsiness Based on Representation Learning Using Deep Neural Networks. 1 Jan. 2019: 1977 – 1985.

[19] Lee, B.-G.; Lee, B.-L.; Chung, W.-Y. Mobile Healthcare for Automatic Driving Sleep-Onset Detection Using Wavelet-Based EEG and Respiration Signals. Sensors 2014, 14, pp. 17915-17936.

[20] Yingying Jiao, Yini Deng, Yun Luo, Bao-Liang Lu. Driver sleepiness detection from EEG and EOG signals using GAN and LSTM networks. Neurocomputing, vol. 408, 2020, pp. 100-111.

[21] Y. Jiao and B. Lu. Detecting driver sleepiness from EEG alpha wave during daytime driving. 2017 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), 2017, pp. 728-731.

[22] Y. Jiao and B. Lu. An alpha wave pattern from attenuation to disappearance for predicting the entry into sleep during simulated driving. 2017 8th International IEEE/EMBS Conference on Neural Engineering (NER), 2017, pp. 21-24.

[23] Arcady A Putilov and Olga G Donskaya. Alpha attenuation soon after closing the eyes as an objective indicator of sleepiness. Clinical and Experimental Pharmacology and Physiology (2014) 41, 956–964.

[24] Ng S., Raveendran P. (2007) EEG Peak Alpha Frequency as an Indicator for Physical Fatigue. In: Jarm T., Kramar P., Zupanic A. (eds) 11th Mediterranean Conference on

Medical and Biomedical Engineering and Computing 2007. IFMBE Proceedings, vol 16. Springer, Berlin, Heidelberg.

[25] Simon Hanslmayr, Joachim Gross, Wolfgang Klimesch, Kimron L. Shapiro. The role of alpha oscillations in temporal attention. Brain Research Reviews, vol. 67, Issues 1–2, 2011, pp. 331-343.

[26] J. Katona, I. Farkas, T. Ujbanyi, P. Dukan and A. Kovari, "Evaluation of the NeuroSky MindFlex EEG headset brain waves data," 2014 IEEE 12th International Symposium on Applied Machine Intelligence and Informatics (SAMI), 2014, pp. 91-94.

[27] Malhar Pathak, A.K. Jayanthy. Designing of a Single Channel EEG Acquisition System for Detection of Drowsiness. 978-1-5090-4442-9/17/$31.00 c 2017 IEEE.

[28] Malhar Pathak, A. K. Jayanthy. Development of a Real-Time Single Channel Brain–Computer Interface System for Detection of Drowsiness. Biomedical Engineering: Applications, Basis and Communications, vol. 29, No. 3 2017.

[29] Schomer D.L. The Normal EEG in an Adult. In: Blum A.S., Rutkove S.B. (eds) The Clinical Neurophysiology Primer. Humana Press, 2007.

[30] Se-Hyeon Hwang, Myoungouk Park, Jonghwa Kim. Driver Drowsiness Detection Using EEG Features. Springer International Publishing AG, part of Springer Nature 2018.

[31] Dissanayaka, C., Ben-Simon, E., Gruberger, M. et al. Comparison between human awake, meditation and drowsiness EEG activities based on directed transfer function and MVDR coherence methods. Med Biol Eng Comput, vol. 53, 2015, pp. 599–607.

[32] Raphael Vallat, Mickael Eskinazi, Alain Nicolas, Perrine Ruby. Sleep and dream habits in a sample of French college students who report no sleep disorders. Journal of Sleep Research, vol. 27, Issue 5, 2018.

[33] Combrisson Etienne, Vallat Raphael, O'Reilly Christian, Jas Mainak, Pascarella Annalisa, Saive Anne-lise, Thiery Thomas, Meunier David, Altukhov Dmitrii, Lajnef Tarek, Ruby Perrine, Guillot Aymeric, Jerbi Karim. Visbrain: A Multi-Purpose GPU-Accelerated Open-Source Suite for Multimodal Brain Data Visualization. Frontiers in Neuroinformatics, vol. 13, 2019, pages 14.

[34] Paulo A.M. Kanda, Eliezyer F. Oliveira, Francisco J. Fraga. EEG epochs with less alpha rhythm improve discrimination of mild Alzheimer's. Computer Methods and Programs in Biomedicine, vol. 138, 2017, pp. 13-22.

[35] Jian-Da Wu, Tuo-Rung Chen. Development of a drowsiness warning system based on the fuzzy logic images analysis. Expert Systems with Applications, vol. 34, Issue 2, 2008, pp. 1556-1561.