THE RELIABILITY OF A SINGLE CHANNEL EEG FOR SLEEPY STATE DETECTION.

Computer science

Research question

To what extent detection of change in brain activity using a computer system allows reliable registration of a sleepy state?

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Introduction

The problem of falling asleep at the wheel

Traveling long distances by car is a tiring event that many professions are associated with. For example, truck drivers are often forced to drive for long hours or at night. Accumulated fatigue and lack of sleep can cause drivers to fall asleep at the wheel [1]. In this case, drivers risk loss of cargo, their own health and the health of those around them. Narcolepsy (sleep disorder that makes people very drowsy during the day) can also be a reason for falling asleep while driving [2]. Carriers of this disease may not even be aware of their disease. As a result, people get into fatal accidents. In a CDC (Centre for Disease Control and Prevention) 2014 survey [3], an estimated 1 in 25 adult drivers (aged 18 years or older) reported having fallen asleep while driving in the previous 30 days. Drowsy driving was involved in 91,000 crashes in 2017—resulting in 50,000 injuries and nearly 800 deaths [4]. In 2021, there were 684 deaths based on police reports [5]. However, these numbers are underestimated, and over 6,000 fatal crashes each year may involve a drowsy driver.

Various computer system, which prevent sleeping

Reducing accidents caused by drivers falling asleep at the wheel is a shared responsibility among drivers, traffic inspectors, police officers, and car manufacturers. Companies like Volvo, Toyota, and General Motors [6] have implemented driver monitoring systems in their vehicles. These systems use technical and computer-based approaches to monitor driver behavior and detect signs of drowsiness, such as changes in driving speed, blinking frequency, and body position. For example, Volvo has been using its Driver Alert System (DAS-W) since 2007, which monitors eye movements, adjusts cabin illumination, and recognizes the driver's identity to customize seat and steering wheel positions [7]. Similarly, Toyota monitors eye and eyelid movements through onboard computers and cameras to detect signs of driver drowsiness [8].

Alternative method

Some of the described methods determine driver fatigue through the analysis of external biological signs (for example, the blink rate described above). Drowsiness while driving varies from person to person, with some experiencing the inability to close their eyelids during sleep, making it difficult to detect if they are falling asleep. This poses a risk as systems may not be accurate in detecting drowsiness. Researching the accuracy of a sleep detection system based on brain activity is therefore crucial in addressing this issue. This study relates to topic 7.1 Computer Science “Control”, section Sensors, Higher Level, and it has sparked my interest, leading me to conduct further research in this area. And consequently, I defined the research question of my work: to what extent detection of change in brain activity using a computer system allows reliable registration of a sleepy state?

Proposed method

Brain rhythms

The method of analyzing brain activity was chosen to directly study the biological aspect of sleep. The human brain operates with electrical signals, generating brain rhythms that determine the general state of the brain. Changes in these biological processes during sleep are worth considering, as the brain is the center of the central nervous system. The border state between sleep and wakefulness is drowsiness, making it an important factor to analyze. The wakefulness is mostly supported with betta brain rhythm, which has frequency between 14 and 40 Hz *(figure 1)* [9].

Figure 1: Betta brain rhythm

Drowsiness is characterized by the alpha rhythm of the brain. Alpha rhythm has a frequency of 8 to 12 Hz (figure 2) [9].

Figure 2: Alpha brain rhythm

The transition from beta rhythm to alpha rhythm may indicate that the driver is falling asleep [10]. It is the registration of such frequency changes that underlies the proposed method. Thus, the system should recognize the change of betta rhythm to alpha rhythm of the driver's brain.

Use of electroencephalography

The rhythms of the brain are oscillations that are distinguished in the general frequency electrical activity of the brain. So, in order to study the electrical activity of the brain during sleep, the method of electroencephalography (EEG) can be used [11]. EEG is a non-invasive method for studying the functional state of the brain by recording its bioelectrical activity. It is a sensitive research method, it reflects the slightest changes in the function of the cerebral cortex (the outer layer of neural tissue of the cerebrum of the brain) and deep brain structures in the temporal dimension, providing millisecond temporal resolution.

Fourier Transform

In order to conduct an experiment, I defined the method for determining the change from betta rhythm to alpha rhythm by the program. Therefore, in order to determine the rhythm of the brain coming from the EEG signal, it is necessary to conduct the Fourier transform, using the algorithm. The Fourier Transform is a mathematical technique used to analyze signals in the frequency spectrum. It decomposes a function of time into its constituent frequencies (*figure 3*) [12].

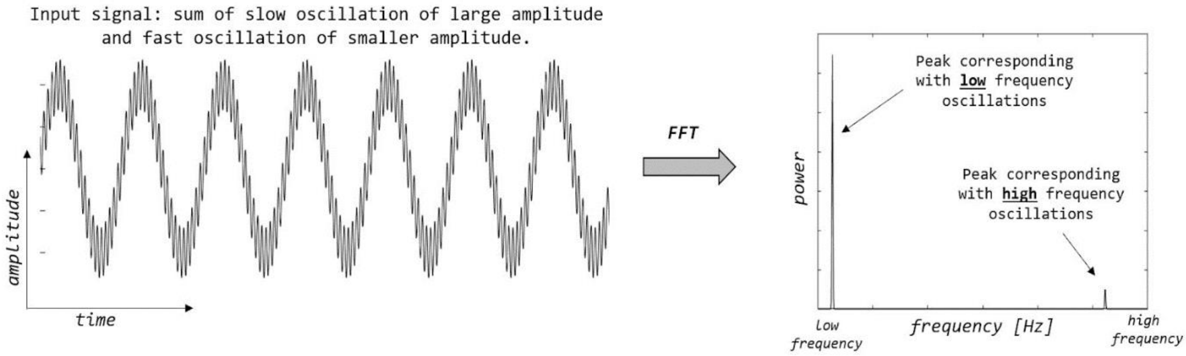

Figure 3: The picture represents the result of the Fourier transform

This process results in a complex spectrum, which represents the amplitude and phase of each component frequency. Therefore, using the Fourier transform, I can calculate the dominant frequency, and therefore determine the alpha rhythm when entering the non-REM state. Thus, I need to choose a device that will be able to process the signal in real time using the Fourier transform. The most suitable would be a control board with its own processor and memory. All these characteristics appear in microcontrollers [13].

A change in frequency from the beta rhythm range to the alpha rhythm range will indicate falling asleep. Consequently, over time, the dominant frequency range will change towards the alpha rhythm during falling asleep.

EEG apparatus

When falling asleep the brain enters the non-REM (not rapid eye movement) sleep state [10]. During this short period, heartbeat, breathing, and specifically eye movements slow. Brain waves begin to slow from daytime wakefulness patterns. That's why brain activity decreases in all brain lobes. However, as I am looking for a method that can be integrated into the vehicle, practical mobility is one of the key factors to create the sleep detection device. In this case, it is worth limiting the number of sensors in order to make the device most suitable for integration into a car. So, for my purposes I will use a single-channel EEG sensor, reading data only from one brain lobe (*Figure 4*).

Figure 4: Single EEG channel

It is worth noting that most often for sleep studies, a full EEG apparatus is used, consisting of sensors covering all lobes of the brain. A complete EEG can be used to determine which frontal lobe signal should be used to determine non-REM state

Product development

Hardware

For the device, I have chosen the Arduino Uno microcontroller [13]. The Arduino Uno controller has 14 digital I/Os and 6 analog inputs, making it suitable for connecting the EEG sensor. The Arduino software is based on C++, which is convenient for those with experience in the language, and there are many additional libraries available, including one for Fast Fourier Transformation [14].

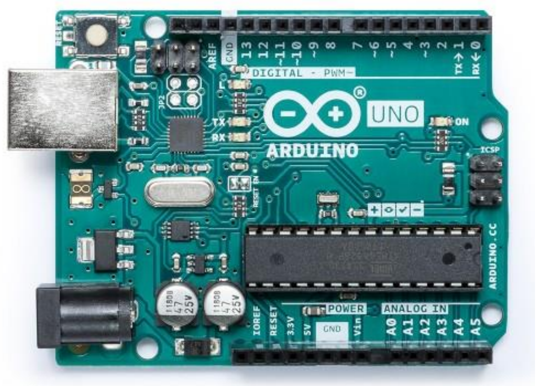

Figure 5: Arduino microcontroller

For the experiment I used sensors by the neurotechnological company Bitronics [15], an educational equipment developer, since they produce single-channel sensors for such studies *(figure 4)*. They also support the users with their seminars in which they talk about the correct use of their products in connection with the arduino microcontroller.

Data processing program

Also, for the experiment, I have developed the software, which responds to all conditions listed above. As a basis for creating my code, I used the Bitronics tutorials, which provide software for their devices [16].

The program digitizes the analog signal of the electroencephalogram from the A0 input of the Arduino board, and decomposes the signal into a spectrum (direct Fourier transform). When the alpha rhythm (corresponds to the frequency components of 8-12 Hz of the EEG signal) exceeds the threshold value, the LED lights up or the time of falling asleep is recorded. I this section I will discuss the pivotal code fragments, while the entire code is accessible in Appendix A.

The intance variables used in the code are: **num** (256-digitized EEG signal values for decomposition), **ERROR_LED_PIN** (Arduino pin for LED indicating high interference), **threshold** (transition threshold from alert to sleepy state), **im** and **data** (data arrays), **i** (counter), **val** (values from A0 port), **fail** (logical variable for high noise level), and spectrum variables (figure 6).

```
#define num 256

#define ERROR_LED_PIN 3
float threshold = 5.5;
int8_t im[num], data[num];
int  i = 0;
int val = 0;
bool fail = false;
float specter = 0;
float specter_old = 0;
```

Figure 6: Initial variables

In the main execution cycle (**void loop**), a variable **sum** is created to store the EEG signal sum. A loop fills the **data**[] array with digitized values **val** from pin A0 on the Arduino. Each value **val** is divided by 8 to match the array element size. Values below 2 or above 120 indicate high interference. If above threshold, fail is set to TRUE and the interference LED is activated. The im array is zeroed out, and the values in the **data**[] array are summed (figure 7).

```
void loop() {
  int8_t sum = 0;
  for (i = 0; i < 256; i++) {
    val = analogRead(A0);
    //Serial.print(val);
    data[i] = val/8;
    if (data[i] < 2 || data[i] > 120) {
      fail = true;
      digitalWrite(ERROR_LED_PIN, HIGH);
    }
    else {
      digitalWrite(ERROR_LED_PIN, LOW);
    }
    delay(2);
    im[i] = 0;
    sum = sum + data[i];
  }
```

Figure 7: Main loop

If the noise level is within limits, the LED is turned off to proceed with the Fourier expansion. The fft.h [14] library requires the removal of the constant component from the recorded signal values. The constant component in the Fourier transform corresponds to the average value of the original signal. This is achieved by subtracting this constant value from each signal value within a loop.

The fix_fft function decomposes the signal into a spectrum. The power of 2 specified (8 in this case) selects the number of spectral components for decomposition (256 components). With operation number 0, a direct Fourier transform is performed. The real and imaginary parts of the Fourier transform result are stored in arrays. The presence of imaginary numbers in the Fourier transform is due to its handling of complex numbers, enabling the decomposition of a function into sinusoidal components of varying frequencies [17].

```
if (!fail) {
  digitalWrite(ERROR_LED_PIN, LOW);

  for (i=0; i < num; i++) {
    data[i] = data[i] - sum/num;
  }
  fix_fft(data, im, 8, 0);

  bool flag = false;

  specter = 0;
  for (i = 8; i < 14; i++){
    specter +=  sqrt(data[i]*data[i] + im[i]*im[i]);
  }
  //Serial.println(specter);
  if(specter > threshold){
    digitalClockDisplay();
  }
```

Figure 8: Saving the transformed data

Using a loop, values from 8 to 14 hertz are searched in spectrum arrays. The spectral components are summed, which are calculated as the modulus of a complex number. If the value of the spectrum sum is greater than the set value, then a function is called in which the exact time is recorded (*figure 9*)

```
void digitalClockDisplay(){
  Serial.print(hour());
  printDigits(minute());
  printDigits(second());
}
void printDigits(int digits){
  Serial.print(":");
  if(digits < 10)
    Serial.print('0');
  Serial.print(digits);
}
```

Figure 9: Saving the sleeping time data

Planning the experiment

To identify the specific area of the brain experiencing the greatest changes during sleep, it is crucial to use a multichannel full EEG apparatus as a reference. This device allows for the recording of brain rhythm changes across various parts of the brain. By capturing EEG signals from all channels, it becomes possible to analyze and determine the region exhibiting the most significant activity alterations during the process of falling asleep [18].

I reached out to MIPT (Moscow Institute of Physics and Technology) [19], and they have agreed to provide me with their sophisticated EEG equipment for a two-week experiment. The equipment consists of 24 electrodes, which I will use along with the EEG hat. I plan to utilize the Neocortex software by Neurobiotics to record and analyze EEG data, allowing me to identify changes in brain rhythms and detect signs of drowsiness. Once I determine the appropriate placement on the frontal lobe for EEG readings, I will commence the sleep recording experiment.

To confirm the moment of falling asleep, I will utilize an Electrocardiogram (ECG) kit provided by MIPT. The Neocortex program accurately captures changes in heart muscle contraction frequency during drowsiness. An ECG measures heart electrical activity, enabling precise detection of falling asleep by analyzing heart rate and rhythm changes. The reason I use it is the need to record data from two devices in parallel and use them to determine the moment of falling asleep. Of course, the ECG will have a certain difference in definition due to biological aspects, but they can be ignored, since they are insignificant [20]. Comparatively, a single-channel EEG may not detect physiological changes as effectively as ECG.

I will compare the time of falling asleep recorded by my EEG device with that recorded by a medical ECG equipment [20]. By conducting multiple experiments over two weeks, I aim to determine the average deviation between the EEG and ECG recordings, assessing the EEG's accuracy in capturing the moment of falling asleep.

Method validation

First, I find out in which part of the brain the electrical signal experiences the greatest difference. For this I use the multi-channel EEG device described above. First I power the electrodes with the amplifier (figure 10), then I connect electrodes to the EEG hat (figure 11), finally I lubricate the electrodes with highly conductive electrode contact gel and put on the hat (figure 12).


Figure 10: amplifier; *Figure 11: EEG hat;* *Figure 12: Recording EEG*

After this, I started recording EEG using the Neocortex program. I started recording all connected channels, in addition to this I recorded a video showing how I gradually fall asleep (figure 13)

Figure 13: constantly falling asleep

After that, I compared the time stamps of the video of falling asleep with the EEG and determined the moment of transition of the brain state from the beta rhythm to the alpha rhythm (figure 14):

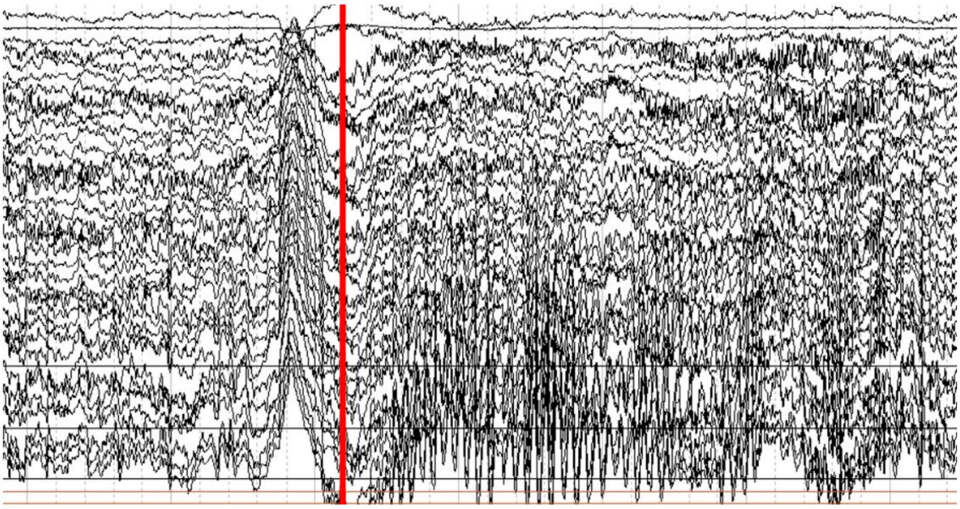

Figure 14: the moment of brain changing rhythm

The red line perpendicular to the oscillations corresponds to the transition of the brain state identified using video analysis. Before falling asleep, the program determined the dominant frequencies in the beta rhythm range, which corresponds to the awake state (figure 15). After falling asleep, the program determined the dominant frequencies in the alpha rhythm range, which corresponds to drowsiness state (figure 16).

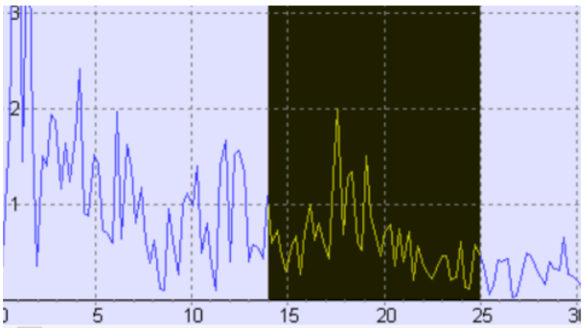

Figure 15: beta rhythm is dominant

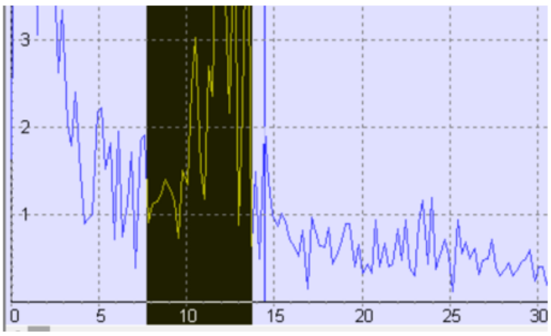

Figure 16: alpha rhythm is dominant

By superimposing several Fourier analyses on each other from the central canal CZ (blue), the occipital lobe OZ (yellow), the frontal lobe FZ (red) and the temporal lobes of each side F4 and F3 (green and purple), we can highlight what is most often the alpha rhythm was recorded in the occipital lobe of OZ (figure 17):

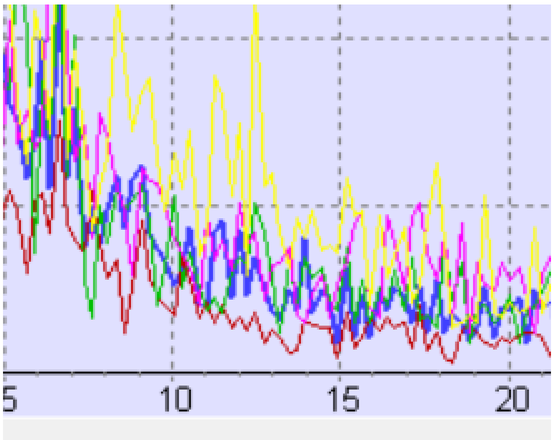

Figure 17: The OZ channel recorded the most noticeable frequencies of alpha rhythm

From this I can conclude that the change in brain rhythm is most pronounced in the occipital lobe. That is why I will attach a single-channel EEG electrode to the occipital lobe in order to get the most pronounced result.

Conducting the experiment

Now that I have determined which lobe of the brain to take the EEG from, we can begin to conduct an experiment to determine the time of falling asleep. To do this, you need to connect an ECG sensor and an EEG sensor at the same time.

I'll start by connecting the ECG sensor. To take an ECG, disposable electrodes will be used, including: electrodes for limbs, electrodes placed on the chest and highly conductive electrode conductive gel (figure 18).

Figure 18: ECG equipment

A complete ECG, which is used for heart disease research, has multiple connections to the chest and arms. Correct connection requires medical education and lengthy testing. For my purposes, it is enough to find out the number of heartbeats, so the number of connections will be reduced. According to "Two-Electrode ECG for Ambulatory Monitoring with Minimal Hardware Complexity" by Branko Babusiak, Stefan Borik and Maros Smondrk [21], two electrodes connected to the chest are enough to find out the most accurate number of heartbeats. To do this, it is necessary to connect the electrodes to contacts V1 and V2 on the chest (figure 19)

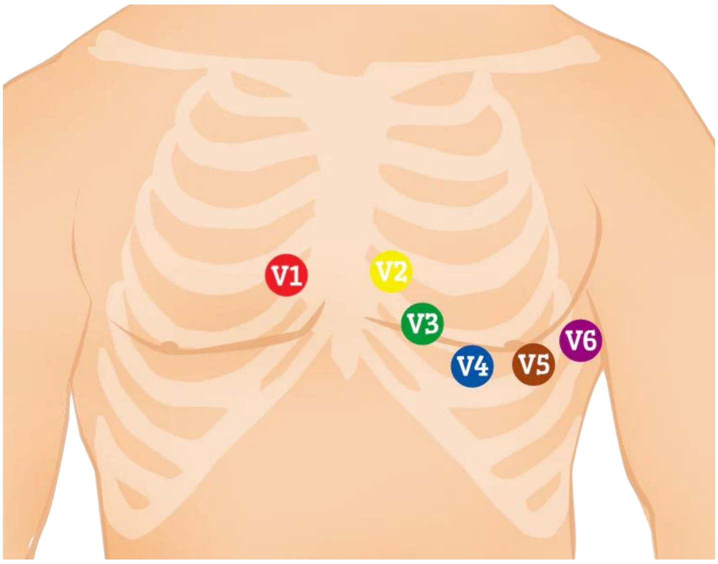

Figure 19: cardiogram sensor map

Next, the ECG is connected to the Neocortex program. The neocortex program can visualize the signal during the recording time (picture) and then subsequently analyze it.

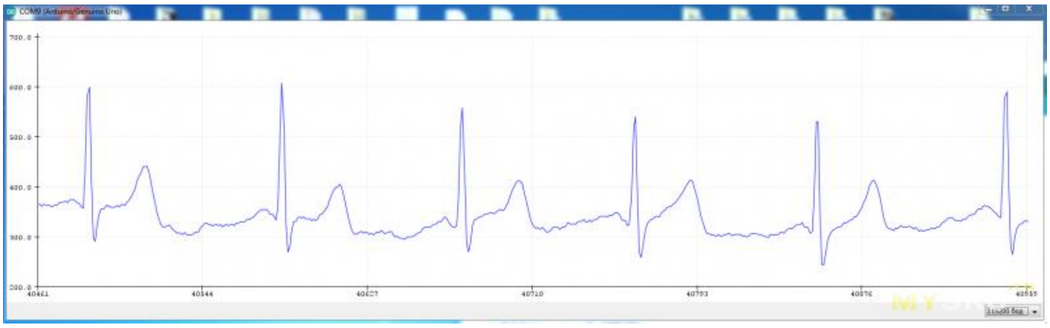

Figure 20: cardiogram

During every minute the program counts the number of heartbeats. In this way, it is possible to track the dynamics of the slowing heart rate and identify the transition from an alert state (60100 bpm) to a drowsy state (40-50 bpm) [22]. According to the Sleep foundation website [21], it takes a maximum of 20 minutes to go from an alert state to a drowsy state. That is why the experiment will be carried out for 20 minutes, tracking the dynamics of changes in heart rate.

At the same time, I assemble a single-channel EEG device with the software developed, which determines the time of falling asleep based on EEG readings from the visual cortex of the brain. For these reasons, I used a single EEG module of BiTronics, an Arduino board, an USB cable, a breadboard, a disposable electrode, jump plug-plug wires, a LED, a bezel with electrodes and cable to connect it to the EEG module. I connect the EEG module via a breadboard to the

Arduino, in parallel with this I connect an LED to the Arduino (it will be needed to indicate the noise level). Finally, I connected the bezel with electrodes to the EEG module.

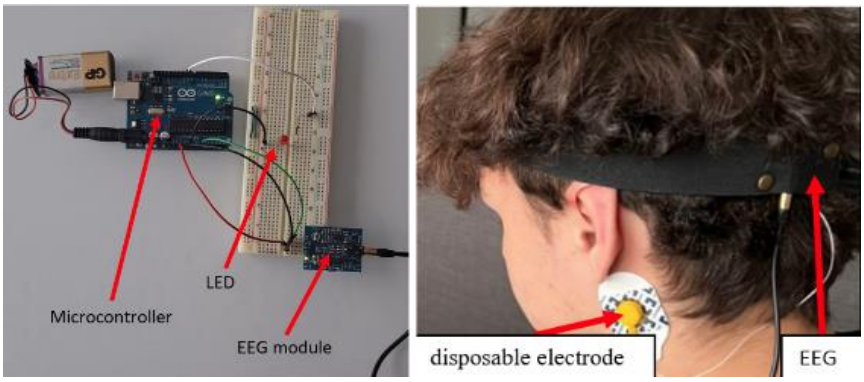

Figure 21: the experiment using single-channel EEG

All in all, I connected an ECG and an EEG and, using both devices, recorded the time I fell asleep for two weeks to average the results.

Results

The first preliminary experiment was carried out on 05.11.23 at 20:00. To begin with, I considered the results obtained using an ECG. Exporting data from Neocortex, I load it in tabular form into Excel in order to visualize it (figure 22).

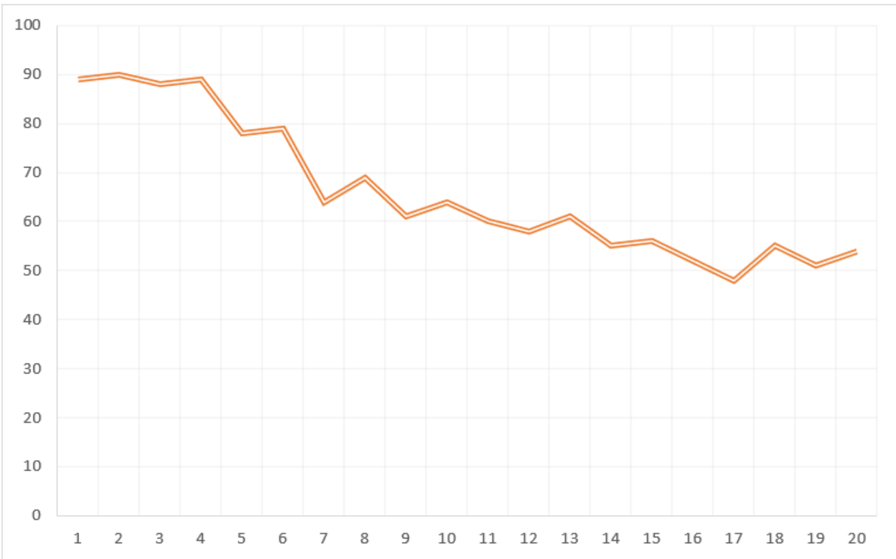

Figure 22: change of the pulse during 20 minutes

The data on the y-axis corresponds to the number of heartbeats, the x-axis indicates the number of minutes. The graph shows that the number of heart contractions decreases at 10 minutes. According to Neocortex data, the first time the heart rate decreases to a threshold level below 60 beats per minute is 10 minutes 21 seconds.

Then the time that my device recorded using a single-channel EEG was obtained. The exact transition time that was on the computer clock when the change in brain rhythms occurred at 20:09:32. Consequently, falling asleep occurred after 9 minutes 32 seconds. To determine more accurate readings, I used the Sample size increasing method [23]. Hence, I carried out the experiment over the next two weeks and got the corresponding results (figure 23)

Date of the experiment	Exact time of falling asleep according to EEG	Exact time of falling asleep according to ECG
06.11.23	9 minutes 32 seconds	10 minutes 21 seconds
07.11.23	12 minutes 24 seconds	13 minutes 32 seconds
08.11.23	10 minutes 48 seconds	11 minutes 27 seconds
09.11.23	15 minutes 01 seconds	15 minutes 58 seconds
10.11.23	12 minutes 55 seconds	13 minutes 34 seconds
11.11.23	8 minutes 22 seconds	9 minutes 01 seconds
12.11.23	19 minutes 05 seconds	20 minutes 38 seconds (over 20 minutes)
13.11.23	17 minutes 31 seconds	18 minutes 22 seconds
14.11.23	15 minutes 42 seconds	16 minutes 25 seconds
15.11.23	16 minutes 12 seconds	17 minutes 52 seconds
16.11.23	17 minutes 44 seconds	18 minutes 50 seconds
17.11.23	14 minutes 32 seconds	15 minutes 25 minutes
18.11.23	17 minutes 11 seconds	18 minutes 54 seconds

Figure 23: Results obtained using EEG and medical ECG

<u>Analysis</u>

To analyze the results, I used the discrepancy method. The discrepancy method is based on searching the error between two results and expressing it as a percentage of the result obtained. In the preliminary experiment the falling asleep time recorded by EEG appeared at 9 minutes 32 seconds after the start of the experiment. Medical ECG, being more accurate device showed 10 minutes 21 seconds. So, the absolute difference between EEG and medical ECG is 49 seconds. This indicates a time discrepancy of 49 seconds between the two devices, which accounts for 8% of the result obtained using EEG. It shows that in this experiment the EEG had the error in 8% of the received result (9 minutes 32 seconds or 572 seconds). Next, I will calculate the percentage discrepancy for each experiment, determining an approximate margin of error (the mean number of percentage discrepancy over the sample) (figure 24).

Date of the experiment	**Exact time of falling asleep according to EEG**	**Exact time of falling asleep according to ECG**	**Error of the the device**
06.11.23	9 minutes 32 seconds	10 minutes 21 seconds	8.5%
07.11.23	12 minutes 24 seconds	13 minutes 32 seconds	9.1%
08.11.23	10 minutes 48 seconds	11 minutes 27 seconds	6.0%
09.11.23	15 minutes 01 seconds	15 minutes 58 seconds	6.3%
10.11.23	12 minutes 55 seconds	13 minutes 34 seconds	5.0%
11.11.23	8 minutes 22 seconds	9 minutes 01 seconds	7.7%
12.11.23	19 minutes 05 seconds	20 minutes 38 seconds (over 20 minutes)	8.1%
13.11.23	17 minutes 31 seconds	18 minutes 22 seconds	4.8%
14.11.23	15 minutes 42 seconds	16 minutes 25 seconds	4.5%
15.11.23	16 minutes 12 seconds	17 minutes 52 seconds	10.2%
16.11.23	17 minutes 44 seconds	18 minutes 50 seconds	6.2%
17.11.23	14 minutes 32 seconds	15 minutes 25 minutes	6.1%
18.11.23	17 minutes 11 seconds	18 minutes 54 seconds	9,90%

Figure 24: Error discrepancy

The margin of error of a single-channel EEG relative to the accurate medical ECG using the Neocortex medical software is 7.2%. Therefore, the accuracy of the device regarding ECG is 92.8%. However, this is not absolute accuracy, because it is relative to the accuracy of the ECG device and the fineness of data recognition using the Neocortex program.

Interview with the expert

In order to evaluate how the results obtained are close to absolute accuracy, I decided to interview an employee of the Bitronics company. Doctor Alexey Slonov is a master's student at MIPT in Applied Mathematics and Physics. At Bitronics he holds the position of methodologist for the use of neurotechnologies for educational needs. Here I will discuss the pivotal interview fragments, while the entire interview is accessible in my Appendix B to the Essay.

Commenting the obtained results, Dr. Slonov suggested that using lower frequencies like theta rhythm can help detect changes in brain activity earlier, potentially indicating drowsiness before the driver is aware of it. However, he pointed out limitations in using ECG data to assess sleep detection accuracy compared to EEG. Changes in brain rhythms may precede changes in heart rate, making ECG less precise for determining the moment of falling asleep. Instead, he 16 suggested exploring alternative methods such as video analysis or more comprehensive ECG studies with respiratory sensors for improved accuracy

I can partially agree with Dr. Slonov's opinion. Indeed, Theta waves may be more relevant for studying the moment of falling asleep, however, unlike other rhythms, they are more pronounced not in the cerebral cortex, but in the hippocampus, which will be very difficult to obtain [24]. Regarding the comment about using an ECG as a comparison device, I can agree. As an improvement, a full ECG study using the respiration sensor can be performed several times to determine the approximate threshold value

Limitations and improvements

Due to limited time and resources, my research also has a certain amount of inaccuracy. In my research, I used empirically established data, and due to time constraints, I had to act as a test subject in the experiments. I had to take into account my own anatomical characteristics, and not rely on generalized data. For example, I determined the threshold value for changing the rhythm in the program for determining falling asleep on Arduino empirically. I also used generalized data for heart rate when falling asleep, but these did not guarantee complete achievement of sleep.

A similar study "EEG-Based Detection of Braking Intention Under Different Car Driving Conditions" conducted in 2018 at the Technical University of Cartagena [25] also encountered this problem. To solve this problem, they developed a neural network that classified data based on previous sequential training. Moreover, this study included several experimental subjects, on the basis of which the neural network also learned itself, increasing accuracy. In the same way, my research could be improved by using self-learning neural networks and increasing the number of experimental subjects

Moreover, the University of Cartagena used driving simulators in the study. Thus, this increased the applicability of the data obtained as a result of the study, since the data is closer to reality. In my case, I conducted the experiment in conditions that were more conducive to sleep. Consequently, the time to fall asleep will increase under plausible conditions, and the boundary between sleep and wakefulness will be less noticeable.

It's important to consider the issue of artifacts [26] in EEG recordings, as they can distort the brain activity signal and complicate analysis and interpretation. Artifacts can be caused by various factors, such as eye movement, muscle activity, electrical noise, and interference. Biological artifacts such as blinking and body movement affected the accuracy of sleep determination in my study, despite the presence of an LED indicator for interference. A study from the University of Cartagena also found artifacts caused by movement when driving a vehicle. This suggests that using my device in a car may also result in high levels of interference. A potential solution could be implementing a neural network to eliminate artifacts from the signal, although this may impact sleep detection accuracy.

Conclusion

The study proposed an alternative method for detecting falling asleep while driving. This method used the EEG signal and its spectral analysis. When testing this method in relation to the determination of falling asleep using an ECG, sufficient accuracy was identified for using the method of determining sleep using an EEG in laboratory conditions, taking into account factors regarding a particular person. However, the creation of a final device for detecting sleep while moving will require a wider range of test subjects to create a general pattern of changes in brain rhythms. Also, more experiments will be required to test the device in real conditions.

Now, it is possible to answer the research question: to what extent does the computer system allow reliable registration of a sleepy state by a single EEG sensor? Compared to ECG in laboratory conditions, the single-channel EEG method determines the time of falling asleep with an accuracy of 92.7%. That is why this method of falling asleep deserves attention and further development.

Links

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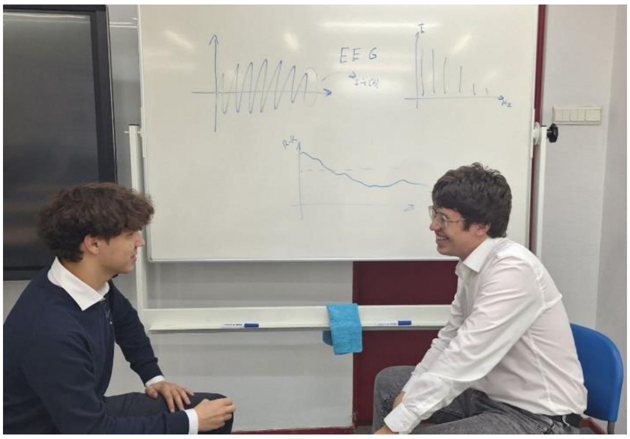
Appendix A

```
#include <fft.h>

#include <DateTime.h>

#define num 256

FAN_PIN 7

#define ERROR_LED_PIN 3

float threshold = 11;

int8_t im[num], data[num];

int  i = 0;

int val = 0;

bool fail = false;

float specter = 0;

float specter_old = 0;

void setup() {

  Serial.begin(115200);

  pinMode(FAN_PIN, OUTPUT);

  pinMode(ERROR_LED_PIN, OUTPUT);

}

void digitalClockDisplay(){

  // digital clock display of current time

Serial.print(DateTime.Hour,DEC);

  printDigits(DateTime.Minute);

  printDigits(DateTime.Second);

  Serial.println();
```

```
}

void printDigits(byte digits){

Serial.print(":");

  if(digits < 10)

    Serial.print('0');

  Serial.print(digits,DEC);

  }

void loop() {

  int8_t sum = 0;

  for (i = 0; i < num; i++) {

  val = analogRead(A0);



  data[i] = val/8;

  Serial.write("A0");



Serial.write(map(val, 0, 1023, 0, 255));

    if (data[i] < 2 || data[i] > 120) {

            fail = true;

    }

    delay(2);

    im[i] = 0;

    sum = sum + data[i];

  }
```

```
 if (!fail) {

   digitalWrite(ERROR_LED_PIN, LOW);

   for (i=0; i < num; i++) {

     data[i] = data[i] - sum/num;

       }

   fix_fft(data, im, 8, 0);

    bool flag = false;

    specter_old = specter;

    specter = 0;

   for (i = 8; i < 14; i++){

     specter +=  sqrt(data[i]*data[i] + im[i]*im[i]);

     }

   specter = 0.3 * specter + 0.7 * specter_old;

          if(specter > threshold)

{

             digitalClockDisplay();

}

      }

}
```

Appendix B



Me: Good afternoon, Dr. Slonov. I appreciate you taking the time to discuss my research on the reliability of a single-channel EEG for detecting sleeping states. In my study, I aimed to explore to what extent changes in brain activity, detected using a computer system, can reliably register a sleepy state.

Dr. Slonov: Hello, it's my pleasure to discuss your research. Could you explain the method you employed to determine falling asleep for a better understanding of the results?

Me: Certainly. I utilized Fourier decomposition as a spectral analysis of the EEG signal to pinpoint the moment of falling asleep. It seems that this method, particularly when focusing on the occipital lobe, yielded accurate results in determining sleep onset.

Dr. Slonov: Fourier decomposition is a robust technique for analyzing brain activity, and focusing on the occipital lobe can indeed provide valuable insights into sleep onset. It's interesting how changes in brain rhythm may precede other physiological processes, potentially allowing for early detection of falling asleep.

Me: Yes, precisely. I also compared the EEG data with ECG data to assess the accuracy of sleep detection. However, it seems that the ECG approach may have introduced some inaccuracies in the results.

Dr. Slonov: That's a significant observation. Changes in brain rhythm might occur before changes in heart rate, making reliance on ECG alone for sleep detection less precise. The correlation between heart rate and falling asleep might not be as straightforward as assumed.

Me: I also mentioned in my findings that achieving a specific heart rate range, like 40-50 beats per minute, did not consistently align with the moment of falling asleep. Would you suggest exploring alternative methods, such as combining video analysis or integrating ECG with other techniques, to improve sleep detection accuracy?

Dr. Slonov: Integrating video analysis or utilizing a combination of methods, including ECG and EEG, could indeed enhance the accuracy of sleep detection. While ECG can provide valuable information, its ability to determine sleep onset in isolation may be limited. The timing of brain activity changes compared to heart rate fluctuations is crucial to consider for a more comprehensive understanding of falling asleep.

Me: I think that's all, thank you so much for your help

Dr. Slonov: Thank you for sharing your research outcomes with me.