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DEVELOPMENT OF A SYSTEM OF DETECTION AND PREDICTION OF SOMNOLENCE THROUGH ELECTROENCEPHALOGRAPHIC SIGNAL PROCESSING

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ABSTRACT

This paper presents an algorithm for the processing of EEG electroencephalographic signals with the objective of detecting drowsiness and wakefulness stages, mainly directed at individuals prone to cause accidents due to fatigue and/or numbness. The device selected for the acquisition of EEG records used during the development of this project is EPOC +, designed and manufactured by Emotiv Systems. Electroencephalographic samples, regularly contaminated by artifacts, must be subjected to a pre-processing step before proceeding with the logical steps in the characterization process. The artifact attenuation process was performed using the Wavelet discrete transform along with the soft threshold method, to then reconstruct the signal with its inverse transform. By means of the power spectral density function, we proceed to determine the stages of wakefulness and drowsiness. From this process, it was possible to extract six characteristics per channel, to construct a final vector of 84 characteristics, which represent a window of time of four seconds of duration. The Gaussian kernel support vector machine algorithm was the finally chosen supervised learning technique, which was responsible for the procedures for classifying and recognizing patterns that would establish the state of the person and with which it was reached 92% of accuracy.

Keywords: EEG, EPOC+, artifact, PSD, wavelet transform, thresholding, SVM.

INTRODUCTION

Drowsiness is the state in which a person tends to sleep during the day, usually at different times to regular sleeping, its main cause lies in poor sleep habits and becomes a problem when it leadsto the subject to fall asleep in inappropriate situations. (Pérez, 2016)

Drowsiness can be classified in two according to its origin, physiological drowsiness, related to age or with specific situations, such as Premenstrual Syndrome PMS, pregnancy, intense physical exercise, among others; and pathological somnolence, which manifests itself when there is a disease that originates it. (Health, 2016)

The current rhythm of life has tried and achieved that the process of sleep becomes altered by factors such as stress, depression and work addiction, producing bad habits of rest, which lead to intensify the ailments that already each human has.In addition, creates new ones such as neurodegenerative conditions, gastrointestinal disorders, increased appetite and obesity, directly affecting the quality of life of individuals, affecting their work performance, personal relationships and increasing the risk of accidents.

According to the epidemiological bulletin issued in December 2007 by the National Institute of Forensic Medicine and Forensic Sciences of Colombia, there are studies in different countries that have documented that traffic accidents tend to be more frequent between midnight, dawn and late in the afternoon, coinciding curiously with the peaks tending to normal sleep in the general population. (Forensic Services Expert Reference Division, 2007).

A permanent vigil for more than 17 hours is sometimes similar to having consumed an amount of alcohol similar to the maximum limit allowed to drive. Hence, hypersomnia decreases labor productivity and social functioning in affected people. In Colombia, the effects of hypersomnia on the health of workers are unknown, with shift workers being more vulnerable, such as health workers, night watchmen, pilots, military personnel, drivers, among others. (Espectador, 2009)

ELECTROENCEPHALOGRAPHY AND SOMNOLENCE

Brain electrical activity

The brain is composed of two kinds of cells: neurons and glial cells, the latter being greater in quantity by a factor of ten compared to neurons; (Kandel, Schwartz, & Jessell, 2000). In addition, the different classes have structural support, metabolic and development modulation functions.

Neurons are the functional units of the nervous system; they play the role of fundamental, structural and functional units of the brain. It is estimated that within the cerebral cortex there are between 15,000 and 30,000 million neurons and each of them is interconnected with up to 10,000 synaptic connections, having as a specialty the communication between cells through the generation, transmission and reception of signals (Portellano, 2005)

The transmission of information and sensations within the brain is produced by the activity of substances capable of causing the transmission of nerve impulses, these are called neurotransmitters. These, in turn, are received in dendrites and are emitted in axons, where the former are ramifications that connect with other cells and the latter, a long extension of the body of the cell ending in branches through of which the neuron can communicate

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through electrical signals with other cells (Portellano, 2005).

Electroencephalogram

Electroencephalography is the collection and evaluation of brain bioelectrical activity originated by brain neurons in basal conditions of rest, in wakefulness or sleep, and during various activations. This can be performed in isolation or associated with simultaneous and synchronized videographic recording of the patient. (Diaz, 2012)

The frequencies of these waves move between 0.5 and 100 Hz and depend greatly on the degree of activity of the cerebral cortex. In turn, this large range of frequencies is divided into 5 bands called "cerebral rhythms", which is given more detail later. The amplitude of the registers may vary depending on the location of the electrodes, if they are located on the surface (scalp) this can be 100 μV and if it is in the cerebral cortex, it can reach 10 mV.

Any unwanted interference that may affect the biological signal studied is considered an artifact and these can be classified according to the source that generates them in physiological and external. The former have as main source the body of the subjects themselves, while the latter come from outside the body, such as the environment or other measuring instruments, for example. (Tandle & Jog, 2015)

Emotiv EPOC+

EPOC + is the second version of the popular EPOC designed and distributed by Emotiv Systems. It is a device that allows BCI and is used in different applications in this area. It is not considered a medical device, but it allows the EEG capture. As can be seen in Table 1, it has a significant number of channels.

Table-1. Characteristics of Emotiv EPOC+.

Characteristic	Description
Number of channels	14 (plus CMS/DRL references, P3/P4 locations)
Channel names	AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4
Sampling method	Sequential sampling. Single ADC
Sampling rate	128 SPS (2048 Hz internal)
Resolution	14 bits 1 LSB = 0.51μV (16-bit ADC, 2 bits instrumental noise floor discarded)
Bandwidth	0.2 – 45 Hz, digital notch filters at 50 Hz and 60 Hz
Filtering	Built in digital 5th order Sinc filter
Connectivity	Proprietary Wireless, 2.4GHz band

Brain rhythms

The brain rhythms allude to the electrical activity produced by the brain, which is subdivided into Delta "δ" (from 0.5 Hz to 4 Hz), Theta "θ" (from 4 Hz to 8 Hz), Alpha "α"(from 8 Hz to 14 Hz), Beta"β"(from 14 to 30 Hz) and Gamma"γ"(frequencies above 30 Hz).

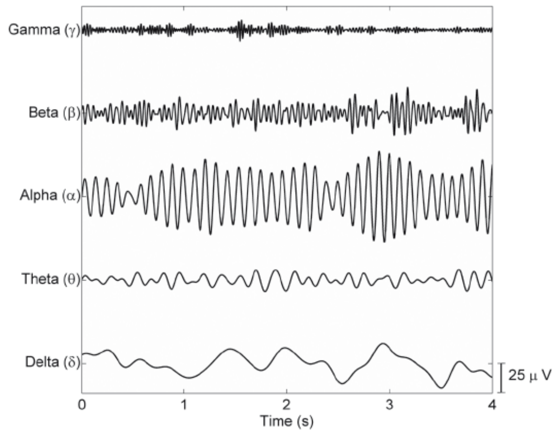

Figure-1. EEG waveforms. https://www.computer.org/csdl/mags/co/2012/07/mco2012070087-abs.html

In the following table, is shown the most relevant characteristics of each cerebral rhythm, necessary to carry out the analysis of the EEG signal for the detection of the state of drowsiness

Table-2. EEG Rhythms.

Rhythm	Frequency range	Location	Charasteristic
Delta	0.5 – 4 Hz	Frontal lobe	Deep sleep
Theta	4 – 8 Hz	Temporal and parietal lobe	Drowsiness and meditation
Alpha	8 – 14 Hz	Frontal and occipital lobe	Relaxation and vigil with eyes closed
Beta	14 – 30 Hz	Frontal lobe and central area	Action, work and concentration
Gamma	> 30 Hz	---	Anxiety and panic. Cognitive functions

It can be stated from Table-2, that Theta and Alpha activities are necessary for the identification of drowsiness and / or states of relaxation (Dkhil, Neji, Wali, & Alimi, 2015).Thus, the transition between wakefulness and sleep is produced by the decrease in Alpha power and the increase in Theta frequency.

Sleep phases

There are two stages in the sleep period, called the slow sleep phase or the non-REM sleep phase, and the REM sleep phase (Rapid Eye Movement). The REM sleep is divided, in turn, into four phases with different characteristics.

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In Figure-2, the distribution of the five phases is shown alternating cyclically while the person remains asleep (every 90/100 minutes approximately, a new sleep cycle begins in which the last 20 or 30 minutes correspond to the REM phase)

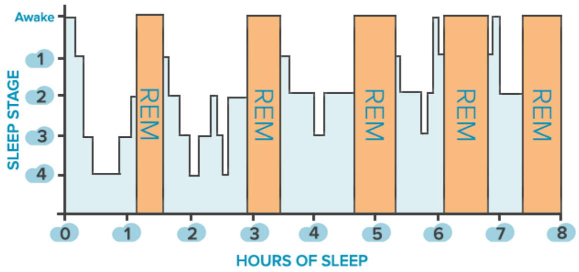

Figure-2. Sleep phases. http://www.centerforsoundsleep.com/sleep-disorders/stages-of-sleep.

In Table-3, it is described the behavior of the organism as it enters each stage of sleep, which do not necessarily occur sequentially as shown in the graph above.

Table-3. Sleep phases description.

Phase	Description
I	Light sleep. Drowsiness. The person is still able to perceive most of the stimuli. Sleep is little or nothing at all.
II	Decrease muscle tone, blocking sensory information, facilitating sleep.
III	Decreases blood pressure and breathing rate. Sensory block intensifies.
IV	Greater depth of sleep. Muscle tone too low. Deficits of this phase cause daytime drowsiness.
REM	It activates the central nervous system. Presence of dreams. Paralysis prevents the person from materializing what he dreams.

EEG SIGNAL PREPROCESSING

It starts with the acquisition of the signal from a SDK with GNU license that allows to capture data from the Emotiv EPOC +. Samples were taken within a set period of 300 seconds (5 minutes) at a sample rate of 128 SPS (Samples per Second) and in each session it was possible to capture between 12 and 18 samples.

Figure-3 shows the signals acquired through channel F3, in drowsiness and wakefulness states.

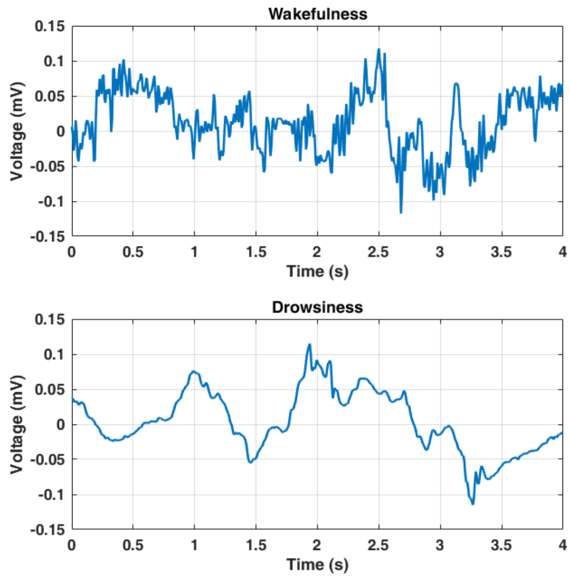

Figure-3. Raw EEG signals fromF3.

All the dimensions of the signal must be on the same scale, since it is easier to make decisions when classifying EEG signals (Russell, Norvig, Canny, Malik, & Edwards, 2003). A simple approximation is to compute the mean and standard deviation of the values in each dimension, and normalize them according to their values.

Windowing

In the bibliography consulted (Russell, Norvig, Canny, Malik, & Edwards, 2003), sampling windows of 1 or 2 seconds were established in order to analyze the EEG signal as stationary in small moments. However, considering that most of these investigations were performed with EEG equipment of high resolution and high sampling frequency, it was decided to experiment with different window times, to finally choose 4 seconds as minimum window duration.

In addition, an overlap of 50% is applied to the window to ensure that no signal information is lost, allowing the distinction to be made between one state and another.

IIR Butterworth filtering

Infinite Impulse Response (IIR) filters are types of digital filters, which, as their acronym indicates, if their input is a pulse signal, the output will have an infinite number of nonzero terms. Which means that it never returns to rest (Martínez, Gómez, Serrano, Vila, & d 'Enginyeria Department d'Enginyeria Electrònica, 2009). This type of filters have poles and zeros that determine the stability and causality of the system.

The properties of these filters are very similar to those of the FIR (Finite Impulse Response) filters, but they have a great advantage over these, and they can meet the same requirements, with a lower filter order, leading to a smaller computational expense.

Butterworth filters are among the basic filters. These are obtained by imposing that the response in

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magnitude of the filter is as flat as possible (with minimum ripple) in the pass band up to the cut-off frequency and makes its approximation through the criterion of maximum uniformity in the pass band (Oppenheim, Willsky, & Nawab, 1983).

Knowing the characteristics of the filters suitable for the present case, and bearing in mind that the quality of the measured EEG signal is usually evaluated by how high its Signal Noise Ratio (SNR) is,the objective is to maximize the amplitude of the signal while minimizing the noise, choosing to apply a 5th order Butterworth IIR band pass filter between 0.2 Hz and 35 Hz.

The filter order was chosen by means of empirical tests on a bank of 30 samples made to a single subject only by varying this parameter in the range of 1 to 10, with 5 being the value that offered the best response (Figure-4).

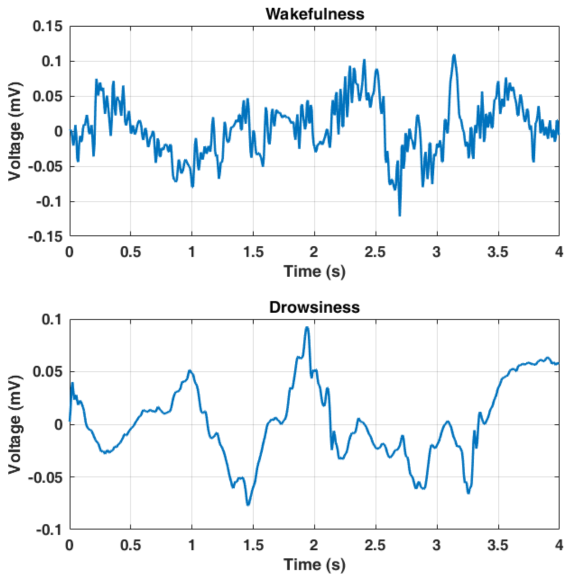

Figure-4. EEG signals from F3 after the Butterworth IIR filter was applied.

Discrete Wavelet TRANSFORM (DWT)

The Wavelet Transform has recently become very popular when it comes to analysis, de-noising and compression of signals and images; this is a mathematical function that allows data to be obtained from a signal by dividing them into smaller frequency-time components, facilitating their analysis separately (Cano, Salcedo, & Soto, 2010)

Compared with the Fourier transform, the Wavelet Transform allows working on non-stationary waves with discontinuities or peaks and is distinguished by its multiresolution capability (Samir Kouro & Rodrigo Musalem, 2002).

The DWT Wavelet Discrete Transformation allows a multilevel analysis through different frequency windows, by means of which the threshold level (in this case soft threshold) can be found that will be applied to the signals to attenuate the impurities and obtain EEG content (www.pybytes.com, Discrete Wavelet Transform (DWT), 2012).

With the decomposition at different frequency levels, it continues applying soft thresholding, this to finish attenuating parasitic frequency values that may affect the EEG signal in some way (Rodríguez & Bueno, 2010).

In order to apply the DWT, the parameters chosen were Wavelet Mother Symlet type, 4thorder, with a window of 512 samples, duration of 4 seconds and sampling period of 128 Hz. With these parameters, it was obtained Table-4 containing the approximation coefficients and Table-5 containing the coefficient of detail.

Table-4. Approximation coefficients.

D1	**64 – 32 Hz**
D2	32 – 16 Hz
D3	16 – 8 Hz
D4	8 – 4 Hz
D5	4 – 2 Hz
D6	2 – 1 Hz

Table-5. Coefficient of detail.

A7	**1 – 0 Hz**

Figure-5 shows the graphs obtained when applying the DWT together with the soft-threshold technique.

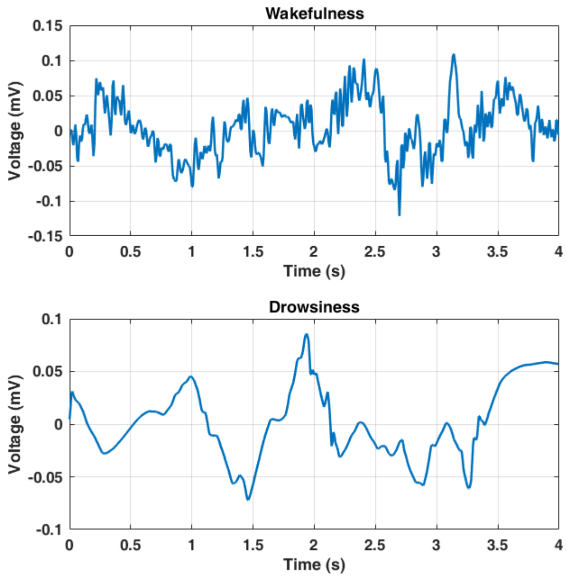

Figure-5. EEG signal from F3 after the DWT application.

After the soft thresholding processes are applied to the detail and approximation coefficients, the signal is reconstructed for further processing, by means of the

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Inverse Discrete Wavelet Transform (Inverse Discrete Wavelet Transform) & De Castro Fernandez, 2002).

The signal that is decomposed in different windows must be reconstructed from a reverse filter bank that was used for its decomposition in multilevel, which is why it is vitally important that the mother wave of decomposition and reconstruction be the same, in this case Symlet 4.

PROCESSING AND CHARACTERIZATION OF THE EEG SIGNAL

After the process of pre-processing of the signal where the artifacts that distorted the EEG were attenuated, the EEG was processed in order to take on characteristics of the sleep or vigil states. For this reason it is used the analysis of the signal by the Power Spectral Density PSD (Power Spectral Density), which is in a plane of frequency vs power where each frequency value is assigned a Power value that results from the calculation of Fast Fourier Transform FFT (Fast Fourier Transform) (Proakis & Manolakis, 2007) (Garces, Orosco, & Laciar, 2014).

As explained in the previous section, the EEG signal is analyzed as a stationary wave in windows of 4 seconds duration at 128 SPS, resulting in 512 samples. When applying FFT in order to obtain a PSD for the window, the first 256 values offer frequency information between 0 Hz and 64 Hz, which obeys the Nyquist criterion (Figure-6).

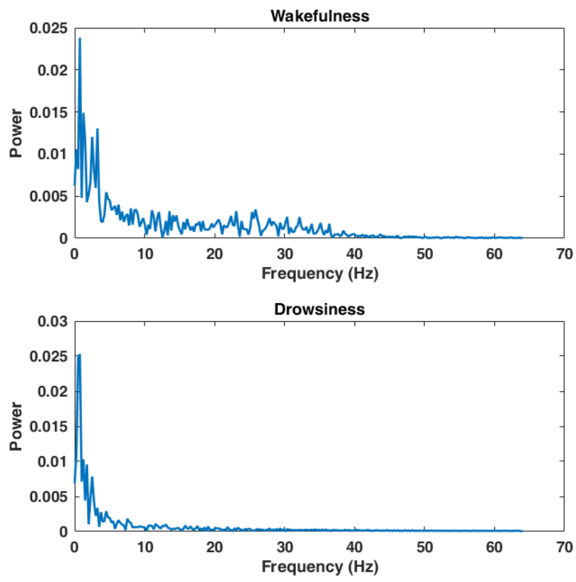

Figure-6. PSD of EEG signals after preprocessing stage.

Characteristics extraction

Based on the doctoral thesis of Agustina Garcés, who takes 6 characteristics of the signal to determine states of drowsiness using a classifier based on neural networks with an average accuracy percentage of 84% (Garcés, Orosco, & Laciar, 2014), and also complemented by the work proposed by Anindya Bijoy Das and Mohammed Imamul Hassan Bhuiyan (Das & Bhuiyan, 2016), where the entropy processes of the PSD are present, the following method of characterization of the signal is proposed, considering the parameters that are exposed later.

The energy band between 4 Hz and 8 Hz is of vital importance in detecting early drowsiness; therefore, its calculation from the PSD in this frequency band can be taken as a key feature to differentiate between both states (Garcés Correa, Brain Signal Processing for Drivers Drowsiness., 2011). Theta is the EEG rhythm present in this band, and as it is know its characteristics, the greater presence of this rhythm, the more evident the appearance of drowsiness in a person; (Bermudez, Laencina, González, & Dorda, 2012). In this study, it was found that the number of people with a high level of sleep deprivation was higher than in the previous years.

The energy band between 8 Hz and 12 Hz provides equally important characteristics in the early detection of drowsiness (Garcés Correa, Brain Signal Processing for Conductor Drowsiness Detection, 2011). Alpha is the EEG rhythm present in this band, and as its characteristics are known, the greater presence of this rhythm more evident will be the appearance of somnolence in a person, also its energetic concentration becomes greater in the early stages of sleep and when the patient's eyes are closed (Bermudez, Laencina, González, González, & Dorda, 2012).

The maximum power usually concentrates in low frequencies, emphasizing that it is located between 5Hz and 7Hz for a state of wakefulness; And below 1Hz for drowsiness. The frequency that contains the maximum power is considered a differential characteristic between wakefulness and drowsiness (Garcés Correa, Brain Signal Processing for the Dysnolence Detection in Conductors, 2011).

As shown in previous work, taking the entropy to characterize the EEG signal in the window of short duration, proves to be a very efficient method to distinguish between the dominance of an electroencephalographic rhythm and another (Chai, et al., 2016) (Das & Bhuiyan, 2016). Shannon's entropy measures the uncertainty of the signal and was introduced mainly as part of information theory (Proakis & Manolakis, 2007) (Das & Bhuiyan, 2016). Its mathematical concept measures the probability of the logarithm of probability with which a data can be repeated in a given signal.

$$H_{shannon} = \sum_{i=1}^{N} p_i^2 * \log_2(p_i^2)$$

The entropy of the energy logarithm measures the irregularity of the spectrum of the signal produced by its PSD. A high number of this entropy indicates that the signal is highly regular (Das & Bhuiyan, 2016), being thus determined that in sleep states the energy concentration is grouped in low frequencies; Therefore, its value is lower in comparison to the entropy of the vigil state, where the signal energy is mostly distributed up to a frequency of 30Hz. This entropy is calculated from:

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$$H_{\log_{Energy}} = \sum_{i=1}^{N} \log_2(p_i^2)$$

Renyi's entropy measures how random the data that makes up the PSD of the signal to be analyzed are, a high number in this entropy means a highly random signal (Das & Bhuiyan, 2016), typical PSD trait for a sample in vigil state,because in drowsiness the signal is more concentrated in a band and the rest of its energy distribution is very symmetrical with each other.

$$H_{Renyi} = -\log \sum_{i=1}^{N} p_i^2$$

Up to this point,six defined characteristics have been obtained for each four-second EEG window. The information is taken from the 14 channels available on the Emotiv EPOC +, obtaining 84 features per window.

Principal Component Analysis (PCA)

The Principal Component Analysis (PCA) is a statistical technique that evaluates a list of parameters and chooses only those that are orthogonal to each other. This is done with the objective of reducing the number of parameters to be analyzed and leaving only those that are highly separable, providing relevant information for the classifier (Bishop, 2007) (Proakis & Manolakis, 2007).

This method allows obtaining a set of characteristics that are not correlated with each other, which efficiently increases the classification and allows to make even more differentiable one state of the other (Pajares & de la Cruz Garcia, 2011).

By means of different experiments and observing the incidence of decreased characteristics obtained, it is observed that the number of PCA's that needs a classifier to discern between a state of wakefulness and one of drowsiness, is intrinsically linked to the type of classifier used. Which means that the number of major signal components expected to be obtained should be analyzed in conjunction with the classifier design.

ALGORITHM OF RECOGNITION AND CLASSIFICATION OF PATTERNS

Support Vector Machines (SVM)

A classifier is a computational algorithm that, through supervised learning, is able to model or learn a series of data in order to be able to discern between two or more types of data. The classification labels for the characteristics vector obtained are "Awake" for the vigil state and "Asleep" for the state of drowsiness. The classifier algorithm used is the Support Vector Machine (SVM) with a radial base Gaussian Kernel.

SVM is a supervised and parametric algorithm, very popular in the field of classification and recognition of parameters in the digital processing of biomedical signals (Bishop, 2007) (Bengio, Courville, & Vincent, 2013) (Bermúdez, Laencina, González, González, & Dorda, 2012). It was developed by Vladimir Vapnik and his team at AT&T Laboratories (Pedregosa, *et al*., 2011). This algorithm takes the different training vectors and begins to raise them to a hyperplane whose dimension is much larger than the original, so that one can be reached, where a border can be drawn between vectors from one state to another, in order to provide a prediction for future unknown vectors.Among its main advantages is that SVM uses a convex classification process (Pedregosa, et al., 2011), that is, that its training will always give the same result for the same group of parameters and hyper-parameters, offering an advantage over other methods such as neural networks whose function is not convex.

Classifier hyperparameters

Kernel: sets the way in which the vectors or characteristics will be divided into a hyperplane of order much higher than the original of the vectors to be classified (Bishop, 2007). There are different types of kernel, in this case a Gaussian kernel of radial basis was used, that traces a Gaussian border between the data, with the objective of separating them and making them differentiable with each other.

C: It is a penalty parameter that tells the SVM how tight the kernel adjustment method will be (Bishop, 2007). If itis had a very low C, the training will be very permissive and the kernel will not be adjusted efficiently, giving space to a sub-training (Pedregosa, *et al*., 2011). In the opposite case, with a large C, a kernel function is obtained that is highly adjusted to the training data, which leads to the system being unable to predict data that does not approach the value of the support vectors.

In Figure-7 it can be seen how the hyperparameter C varies in different levels in the correct detection, being the one of the left overtraining, the one of the center the correct training and the one of the right the subtraining.

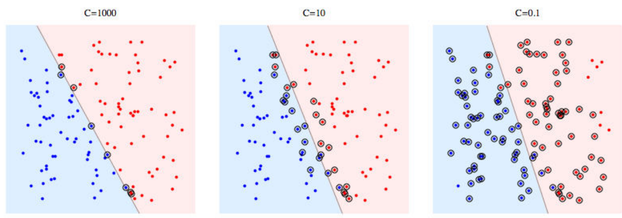

Figure-7. Graphical representations of the variation of the hyperparameter C (Pedregosa *et al,* 2011).

Gamma: It is the hyperparameter of Gaussian variance (Bishop, 2007). A small Gamma indicates that the kernel function will have high variance and little polarization, which determines the influence that some vectors will have on the classification to be considered support vectors, which means that if Gamma is not chosen correctly, it could cause the Vectors to be predicted are incorrectly classified by not estimating very well the variance of their gaussianity (Pedregosa *et al*., 2011)

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Classifier design

Once the parameter matrix, the characteristic vector, and the hyperparameters to be tuned are established, it is necessary to set the percentage of the data that will be used for the training and the validation, and which will be used for the classifier test. Classically, 80% of the data are taken for training and validation, and finally the remaining 20% for testing (Pedregosa *et al*., 2011).

From the above, a training pipeline is proposed to combine parameters and hyperparameters in different ways, in order to obtain the best possible intrapersonal classifier. The pipeline is carried out using the Python Scikit-Learn library, in which the following hyperparameters were set:

Table-6. Hyperparameters for the pipeline.

Hyperparameter	Value
Number of PC	linspace (35,75,2)
C	logspace (10^-1, 10^5, 20)
Gamma	logspace (10^-7, 10^0, 20)
Cross validation	5
Resultant Pipeline Sets	38400

RESULTS AND DISCUSSIONS

The proposed methodology makes a correct detection between records of sleep and wake states at the intrapersonal level. The system proposed in this document meets high standards in the detection of drowsiness, even though it is compared with the results obtained with high-end medical equipment

The Emotiv EPOC + was sufficient to obtain the signals that could be processed and classified. They serve as a basis for applications for the detection of drowsiness in drivers, operators and other people who require permanent monitoring in their work, without the risk of falling into a state of numbness. This state is sometimes visually imperceptible, but easily perceived by the potential changes in the frequency bands that make up the EEG.

This work proposes the implementation of a training system and a pattern recognition system, which have the same blocks for acquisition, pre-processing and signal processing. In the training system, one-time tasks are performed (parallel tasks are shown in Figure-8), while the pattern recognition and classification system is cyclical and is executed whenever it attempts to recognize patterns ofdrowsiness or wakefulness through a previous history of EEG obtained from the Emotiv EPOC +.

The division of this process into two systems may facilitate the integration of the same into different computers, taking into account that the training process generates a higher computational cost than the process of classification and recognition of EEG patterns.

The system has a high accuracy in the process of detection of early drowsiness intrapersonal level, so it will be necessary to train it for each individual who intends to use it.

The test results of the radial Kernel SVM designed and tuned for classification between states of sleepiness and wakefulness are shown below.

Table-7. Training indicators for radial SVM testing.

Label	Precision	Sensitivity	F-score	Vectors
Asleep	98 %	88 %	93 %	146
Awake	87 %	98 %	92 %	111

From the above it can be can see that the algorithm is more accurate than sensible in drowsiness, being completely inverse in wakefulness, due to this the accuracy of the algorithm is almost the same for any of the two states; This is because the records used for training were more for drowsiness than for wakefulness, producing such effects.

The results also show how a Gaussian kernel SVM can make a highly efficient separation between two frequency-differentiable states, opening a window to the automation of drowsiness detection for supervised tasks.

EEG is the most reliable way to obtain physiological information related to sleepiness and wakefulness; a very important contribution is made to process this signal with different types of applications such as supervision of drivers and operators who perform repetitive tasks requiring a high state of attention.

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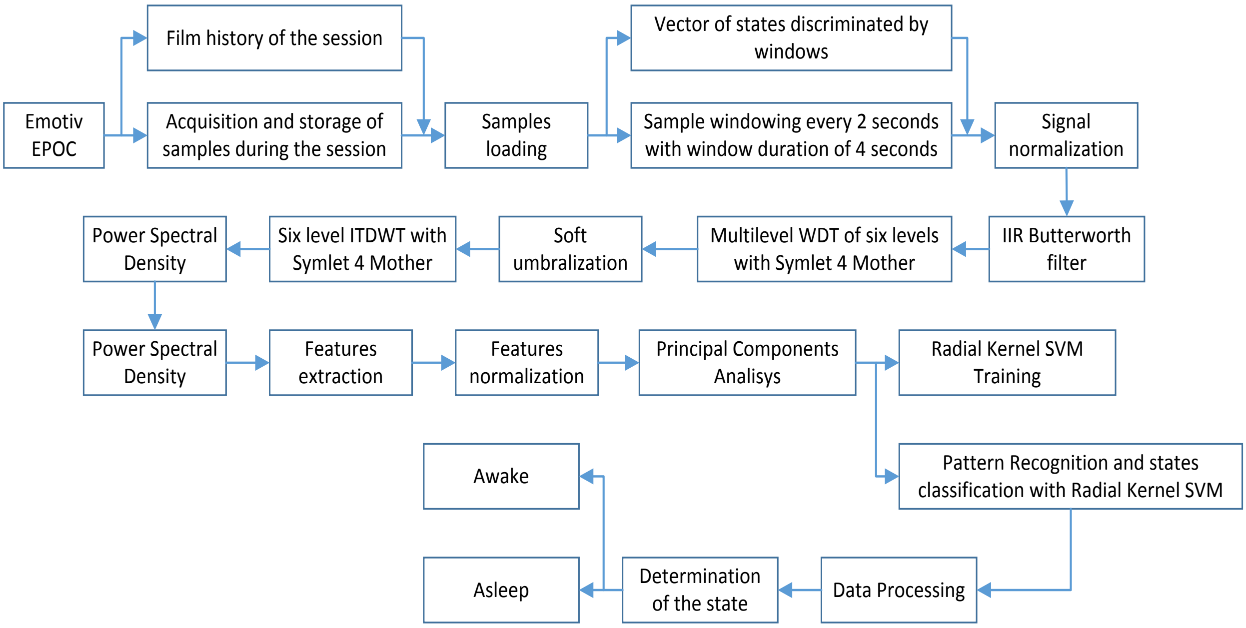

Figure-8. General block diagram of the proposed system.

CONCLUSIONS

BCI systems are the future for assistance and monitoring of people's activities in order to avoid accidents. The proposed methodology allows the design of a signal processing system at the digital level, which is able to characterize and recognize patterns of brain signals characteristic of wakefulness and drowsiness.

The combination of classical preprocessing methods such as LTI filters and contemporaries such as DWT allow attenuating the artifacts enough to be able to characterize the EEG signal at a frequency level through a PSD, and later by PCA find the most relevant characteristics of each state. Finally, vigilance or drowsiness patterns are recognized through a radial kernel SVM with an accuracy of 92%.

The proposed system for classification and pattern recognition proves to be highly functional intrapersonally without the need for expensive EEG equipment. The opportunities that are opened with this methodology are especially numerous taking into account that it is a scalable system to embedded and portable equipment.

The heart of the project is in the radial kernel SVM classifier, which proved to be a robust algorithm for classification because of its convex error function, which always guarantees proper training if the hyper parameters, signal parameters and classifier are the same.

This kind of kernel was necessary because the data obtained physiologically are not as separable from each other, or at least in a linear fashion. A Gaussian kernel offers the possibility of a nonlinear separation with a significantly lower training cost than if one were working with a polynomial kernel.

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