New Approaches to Medical Computer Applications

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Edited by

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We would like to thank Rdissi Adel,
Teacher of English at the Faculty of Medicine of Monastir,
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Monastir. Tunisia

TABLE OF CONTENTS

INTRODUCTION

PROF. MOHAMED HÉDI BEDOUI

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UNIVERSITY OF MONASTIR, TUNISIA

Dear Colleagues,

It is thanks to you that we were able to hold this tenth edition of the AMINA2020 Workshop *New Approaches to Medical Computer Applications* despite the COVID-19 pandemic. In this context, you have been given the opportunity to participate at your convenience on-site or online. We would like to thank all those who contributed to the success of this tenth edition either by work, conferences, proofreading or by the animation and enrichment of the exchanges during this meeting.

Consistent with the traditions and specificities of this meeting, we targeted the consolidation of the scientific exchange and interaction between researchers in different fields. This was aimed at bringing together researchers from different research areas (IT, electronics, mechanics, mathematics, medicine, biology, etc.) to contribute to the implementation of multidisciplinary research for medical purposes.

The efforts made over the past few years by AMINA's national and international partners have helped achieve this objective, which is manifested by the setting up of session projects. In this year's meeting, we focused on four themes:

1. Neuro sciences: facets and achievements.
2. IoT in the medical field: prevention and improvement of quality of life.
3. Artificial intelligence and medical applications related to COVID-19.
4. Contribution of the biomechanics of movement in the characterization of pathologies.

These sessions brought together researchers from different laboratories and research units, and different hospital departments as well as socioeconomic partners. A synergy of promising cooperation was achieved and this has been manifested by projects and answers to calls for national and international tenders.

The other classic themes still contribute to the success of these scientific days and their outcomes maintain the vitality of our workshops.

We have chosen to end this meeting with a round table discussion entitled *Help in raising funds for young Technology and Health companies*. This was led by actors from the socioeconomic world and focused on four presentations:

1. An economic player's standpoint.
2. Donors and support programs
3. The quest for ideas
4. Project incubation.

We hope that the outputs of this round table session will open up new avenues to improve our research by promoting wealth creation through innovation, consolidating the socioeconomic impact of our projects and offering our young graduates some working opportunities through technology transfer.

You are kindly requested to reflect on the content and form of the next edition we are looking forward to organizing with you to give it more scope and to meet your expectations and your reputation.

Enjoy the congress
Prof. Mohamed Hédi BEDOUI

Neurosciences: facets and achievements.

Neurosciences are constantly evolving in different fields, namely the mathematical modelling of functioning, the prediction of behavioural evolution, and the development of nano-objects to explore (probe) and treat locally (pumps). They have also benefited from the contribution of artificial intelligence in analysing and decision-making.

This round table session is a special opportunity to bring together different specialists to present these various advances, discuss their contributions and identify the practical recommendations for integrating them into the clinical routine to improve patient care and quality of life.

IoT in the medical field: Prevention and improvement of the quality of life.

The significant technological development in the field of connected objects and embedded devices has brought about a great change in people's lifestyles and needs. The medical field has benefited from these connected objects. Telemedicine is becoming an increasingly essential tool for the delivery and provision of health care in all areas of medicine. The main interest is to make it easier for physicians in peripheral regions to access specialist advice to improve diagnosis and treatment. Lawmakers have also moved towards the establishment of a legislative framework pertaining to telehealth care. The current pandemic context further proves the need to set up Tunisian telemedicine solutions that are low cost, accessible to all and accepted by the various stakeholders. In such a situation, the challenge facing the health system is to be able to cope with the overload caused by the epidemic. This session is a new opportunity to share knowledge and learn about these approaches which have become an area of growth during the pandemic when access to hospitals has become relatively dangerous, especially for patients with chronic illnesses.

Artificial Intelligence and medical applications related to COVID-19.

The violent epidemiological shock related to the coronavirus has indiscriminately taken all countries by surprise. Different communities have reacted to curb this scourge. The research in signal, image and video processing, big data management and artificial intelligence has focused on this context to provide solutions and help fight the virus. This special session on the research in image and signal processing, Big Data and artificial intelligence dedicated to COVID-19 will be an opportunity to update and share knowledge and expertise in this field.

Contribution of the biomechanics of movement in the characterization of pathologies.

Human movement is achieved through a complex sensory-physical-chemical process allowing the movement, perception and control of body segments in time and space. As a result, movement is considered a biomarker of neuro-musculoskeletal performance. This round table session is aimed at providing an opportunity for exchange to discuss the challenges of the biomechanics of movement and the solutions to be recommended to prevent musculoskeletal disorders, improve physical performance and re-educate and rehabilitate patients. Particular attention will be dedicated to computer vision approaches in the characterization of movement for preventive, diagnostic and therapeutic purposes.

Combining BOLD fMRI Data and DTI Tractography for Studying the Human Brain Function

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Abstract. The neuroimaging field has newly become awash with multimodal neuroimaging findings to study brain connectivity through the combination of Diffusion Tensor Imaging (DTI) via tractography, and functional activation maps using a task related to functional Magnetic Resonance Imaging (fMRI).

However, in Tunisia, there is no protocol acquisition for this combination in the clinical routine.

In this paper, we propose a method to combine BOLD fMRI and DTI data to visualize nerve connections between the activated brain areas. Its validity was tested on two healthy subjects following a motor paradigm and a language paradigm. The obtained results showed that our proposed method offers the representation of the main nerve fibres connecting one or more active brain areas when performing a cognitive or experimental task.

Keywords: fMRI, BOLD, DTI, Tractography.

1 Introduction

The human brain can be explored by MRI to study its different components. Diffusion Imaging and the BOLD effect are a part of new medical imaging called functional imaging methods which have been developed in addition to morphological sequences because they provide information about the pathophysiology of encephalic infections which is not shown with conventional sequences. BOLD fMRI is a technique based on the measurement of neuronal activity when performing a cognitive or experimental task according to a well-defined experimental paradigm. It allows the localization of the functional regions for a surgical decision. Diffusion MRI offers the possibility to study the architecture of the White Matter (WM), arranged in bundles of nerve fibres. This technique is based on the physical notion of diffusion anisotropy to reconstruct the nerve fibres' path using the tensor model of diffusion. [1,2] The purpose of the present work is to combine the two medical imaging modalities to guide the generation of tractography that links the active brain areas extracted from the BOLD data. The combination of BOLD functional MRI and tractography allows us to explore and locate the fibres driving nerve information during a task-related fMRI. Also, it allows neurosurgeons to carry out a pre-surgical assessment to gain decision time and diagnostic accuracy. [3,4,5] Despite this significant interest, Tunisia does not have an acquisition protocol to combine these two functional imaging methods. Therefore, the present work is aimed at establishing a pipeline of preprocessing medical images, then extracting the active brain from the BOLD data, and finally combining them with DTI data to perform tractography.

2 Materials and Methods

2.1 The proposed Pipeline

Briefly, our pipeline is organized in such a way as to preprocess the data of the two acquisitions. Then, we analyze the preprocessed data and run the Independent Component Analysis (ICA) on the fMRI data which is used for cleaning purposes by identifying noise components and deleting them from the data. We extract the regions of interest from the activation count maps and thus, project the extracted ROIs into the native space of the DTI data, to finally combine them with DTI data to visualize the bundles of nerve fibres of the studied brain area (Fig. 1). To perform these functions, we used the accessible software tools: FSL, MATLAB and MRtrix3.

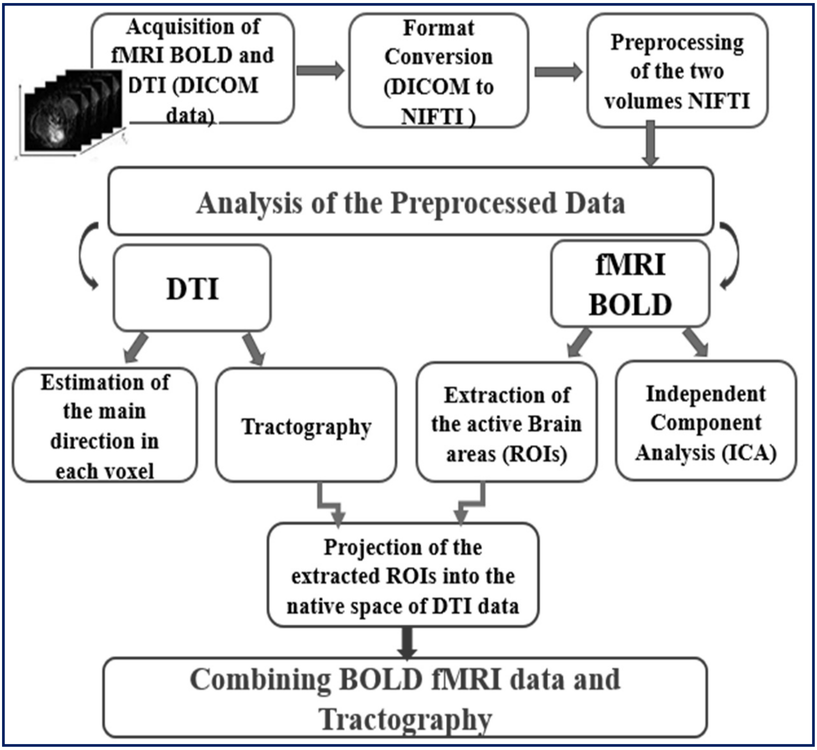

Fig. 1. Overview of the data processing pipeline

2.2 Participants

The study enrolled two healthy subjects (mean age=25 years). They were scanned on a clinical standard Siemens MagnetomVerio 3 Tesla at the Principal Military Hospital of Instruction of Tunis (HMPIT).

2.3 fMRI Paradigms

In this work, we created two experimental paradigms:

Language paradigm: The subject's task is to think of as many words as possible starting with the letter presented. Three different letters were presented during each word generation block. Each block was followed by a rest period.

Motor paradigm: The subject's task is to tap his fingers with his left hand for three blocks. Each block will be followed by a rest period.

3 Results and Discussion

After preprocessing the raw data, we estimated the diffusion tensor in each voxel, to generate the tractography of nerve fibres (Fig. 2). Then we extracted the active ROIs in the BOLD activation maps of the motor area and the language area. Next, we combined them with DTI data to generate the tractography to visualize the main fibres passing through these ROIs. (Fig. 3,4). In this study, we successfully applied a processing pipeline to functional MRI data. Then, we were able to extract one or more active brain areas from the BOLD activation maps. Finally, we combined the BOLD fMRI and tractography to visualize the nerve fibres between the active brain regions to understand the path of the nerve information.

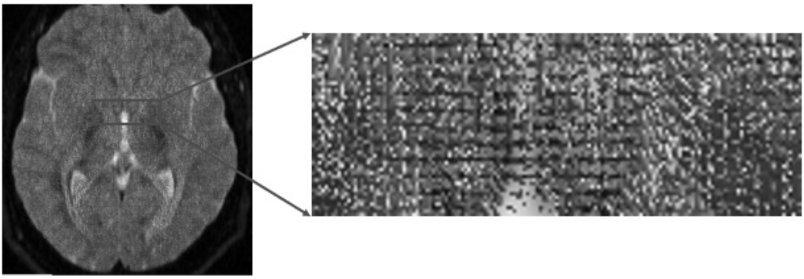

Fig. 2. Estimation of the main direction in each voxel (Red: left-right orientation, Blue: upper-lower direction, and Green: anteroposterior direction).

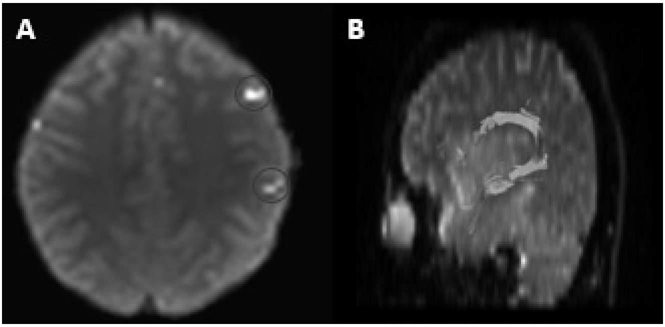

Fig. 3. A/ Axial slice of a BOLD activation map for language area.
B/ Sagittal slice of the combination performed for language area.

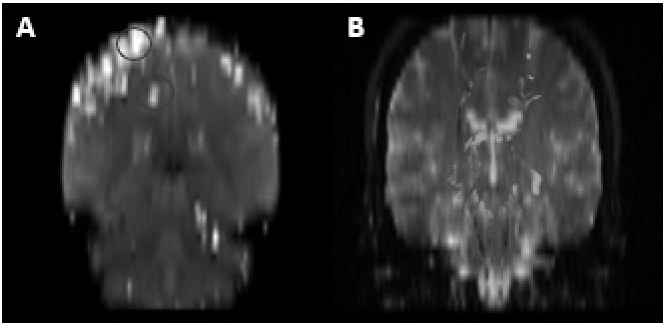

Fig. 4. A/ Sagittal slice of BOLD activation map for the motor area.
B/ Sagittal slice of the combination performed for the motor area.

Our results were very close to those of P. Marques et al. [1] who developed an automated data processing pipeline analysis tool for brain connectivity to combine the fMRI and DTI data. Also, F. Vassal et al [2] combined DTI and BOLD fMRI in healthy subjects, which allowed the monitoring of language fibres. They found consistent links between the fMRI activations and the White Matter fibre terminations. Also, J. J. Lemaire et al. [3] reported a new cortico-subcortical functional connectome of language circuitry in the human brain with the combination of fMRI and diffusion tensor imaging and they have explored the subject-specific structural and functional macroscopic connectivity. N. M. Hazzaa et al. [4] studied the somatotopic organization of the motor tracts in controls and tumour patients by combining fMRI with DTI.

The main goal of our work is to set up a directive allowing the tractography of the main bundles of linguistic and motor fibres. However, our study is limited to two healthy subjects, with a simple cognitive task and an experimental task. In addition, we extracted the active brain areas from the BOLD activation maps manually, which decreases the precision in the selection of ROIs. We also used the DTI model to generate the tractography which cannot estimate the crossing fibres. Thus, our future work will focus on increasing the number of healthy subjects for each paradigm applying it to affected patients with the application of the HARDI technique to visualize the cross fibres. Next, we will automate the method of extracting the active brain regions to optimize the acquisition protocol for the combination to avoid information loss, which carries the raw data.

4 Conclusion

In conclusion, we evaluated a combined approach using functional brain activation data to define several ROIs to follow the path of nerve fibres for the motor and language areas.

Our results suggest that the combination of BOLD fMRI and tractography could provide an accurate analysis of the White Matter fibres after a task-related fMRI that may possibly play a crucial role in preoperative planning, and therefore optimize the surgical treatment and improve the postoperative results.

5 Perspectives

As a perspective, we recommend increasing the number of healthy subjects and patients with brain tumours, as well as the execution of other paradigms and the application of the High Angular Resolution Diffusion Imaging (HARDI) model for the reconstruction and visualization of the nerve fibres which are crossed. [6]

We also recommend optimizing the protocol dedicated to the combination and applying it directly to pathological cases as a diagnostic aid.

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DROWSINESS DETECTION SYSTEM BASED ON EEG AND ECG SIGNALS

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Abstract. The decrease in alertness, the involuntary transition from wakefulness to sleep called hypo-vigilance, is responsible for a third of fatal accidents. In this study, we propose a system that can detect drowsiness in drivers with the use of features extracted from electroencephalography (EEG) and electrocardiography (ECG) measurements. The various time and frequency domain features were extracted from EEG and ECG signals including time domain and power spectral measures. Then the Support Vector Machine (SVM) was used to classify the alertness and drowsiness states. To verify the efficiency of our method, the proposed technique was tested using a database carried out at Sahloul-Sousse hospital, therefore, it can detect drowsiness better than similar published work, with an average accuracy of about 88%.

1 Introduction

Driving is a difficult task that needs mental and physical concentration and alertness to be performed effectively. Therefore, various sensor technologies have been used for monitoring drowsiness. In particular, the detection of the driver's bioelectric signal has been described as a promising approach because it relies on rapid internal changes directly associated with drowsiness. Electroencephalogram (EEG) and electrocardiography (ECG) are considered to be the most informative bioelectric signals and are commonly accepted as the reference method in sleep and drowsiness studies [1]. An EEG signal is commonly used to study brain activity related to drowsiness [2]. Numerous studies have proposed EEG-based methods to detect driver drowsiness [3]. Because of the easiness of measurement and the high correlation with the activity of the autonomic nervous system, ECG-based methods have also been proposed to detect driver drowsiness [4]. SVMs have been widely used to determine driver drowsiness levels based on these known indicators. SVMs are used to classify data in a variety of areas, particularly for the analysis of large datasets. Studies have evaluated the SVM for classifying driver drowsiness and alertness based on data sets including behavioural measures, physiological signals, and many other measures [5].

In this paper, we propose to apply an SVM for the identification of the drowsiness state of a driver using features extracted from the EEG and ECG signals.

2 Materials

The recordings used for the evaluation of our method come from tests carried out at Sahloul-Sousse hospital. The database is made up of 70 hours of data taken from eight subjects. Each recording includes one ECG channel and four EEG channels, two central zones (C3, C2) and two occipital zones (O1, O2); each physiological signal is acquired at 500 samples per second. The labelling of the different levels of hypo-vigilance is carried out manually by an expert doctor. The expert classifies these recordings in intervals of 10s. In total 5252 labelled alert datasets and 2970 labelled drowsy datasets were collected from eight subjects. The EEG signal was filtered using a second-order band-pass Butterworth filter between 0.5 and 50 Hz to remove low-frequency DC drifts and the power line noise at 60 Hz.

3 Methods

3.1 Proposed method

This study proposes a detection approach for driver drowsiness in a driving environment. Our system starts by extracting the descriptors from the EEG and ECG signals. Then we classify these descriptors using the SVM. As a result of the classification, we noticed that the EEG signals give better accuracy than the ECG signals, but on the other hand the ECG gives a better result in the classification of the drowsiness state. Therefore, we have created a special logic table for the combination of EEG and ECG signals, which increases the performance of our system.

3.2 Features extracted from EEG signal

The frequency range was divided into frequency bands: delta (<4 Hz), theta (4–8 Hz), alpha (8–12 Hz), beta (12–30 Hz) and gamma (1–40 Hz). Neuroscience studies show that the change in power during the transition from wakefulness to drowsiness is localized at specific bands that are the alpha and theta bands [6].

The relative power was computed for these two bands using the following equations:

$$P_{\theta-rel} = \frac{P_{\theta-abs}}{P_{Total}} \quad (1)$$

$$P_{\alpha-rel} = \frac{P_{\alpha-abs}}{P_{Total}} \quad (2)$$

$$P_{\alpha-\theta} = \frac{P_{\alpha-abs}}{P_{\theta-abs}} \quad (3)$$

Mean. The mean is the average of all the instances. The calculations of these parameters are represented in equations (4):

$$\text{Mean (X)} = \frac{\sum X(t)}{N} \quad (4)$$

Sample entropy (SampEn). SampEn offers an estimate of the complexity of time series by quantifying their self-similarity or regularity. For a random time series, similar vectors of observations are unlikely to be followed by additional similar observations, resulting in a higher SampEn. On the other hand, a periodic time series will have a relatively low

SampEn because it contains many repetitive patterns. The mathematical expressions to compute sample entropy are formulated in equation (5):

$$\text{SampEn (m,r)}= -\ln\frac{B^{m+1}(r)}{B^{m}(r)} \qquad (5)$$

Where BN(r) = 1∑N–N BN(r), BN(r) provides the probability of two sequences matching for m points N–Ni=1iand m + 1 provides the probability of matching for m+1 points, respectively, r=0.2*standard deviation, m=2 and N number of data points [7].

3.3 Features extracted from the ECG signal

The ECG signal, the heart rate (HR), could be calculated from the average of the intervals between two consecutive systolic peaks R.While there are two types of HR, linear and non-linear characteristics, this study uses the former, linear because the extraction of non-linear characteristics requires a long-term IRR measurement for a stable calculation [8], which is not appropriate for real-time applications such as the detection of drowsiness while driving. From the ECG signals we have extracted five features that are [9]:

- ✓ meanNN: Mean of RRI.
- ✓ SDNN: Standard deviation of RRI.
- ✓ RMSSD: Root means square of the difference of adjacent RRI.
- ✓ Total Power (TP): Variance of RRI.
- ✓ NN50: The number of pairs of adjacent RRI whose difference is more than 50 ms within a given length of measurement time.

3.4 Support Vector Machine (SVM)

The SVM classifier has been used in previous BCI applications for real-time EEG classifications [10]. The SVM is a machine learning technique that searches the hyperplane not only to obtain a better classification based on support vectors but also to maximize the geometric margin in the classification. This approach maximizes the margin, which is the closest distance between two corresponding samples in each separate class (the awake and the drowsy class). Using the kernel trick, the system can match the predictor data to the hyperplane using kernel functions [11]. In this study, an RBF SVM kernel was employed for the classification. The two parameters C and γ of the SVM were tested and optimized in the range [0.001, 10], and in the final algorithm, C was set to 1 and γ to 0.5.

4 Results and discussion

The objective of this research was to combine features extracted from various physiological signals to improve the performance of the driver drowsiness detection system. To this end, we first tested the performance of the EEG and ECG separately. Then, we combined the features using SVM to determine the effects of using both types of physiological signals on the performance of the sleepiness detection system. A confounding matrix and performance measures were obtained from the ECG and EEG separately and then combined (Table 1).

Table 1. Performance of system by combining physiological signals.

Signal	**Accuracy**	**False Positive**	**False-negative**
Only ECG	76%	1994	602
Only EEG	81%	412	1513
Combining EEG and ECG	85%	680	770

The performance measures presented in Table 1 show that the accuracy of the classification achieved by ECG features is 76%, the accuracy achieved by the EEG features is 81%, and the accuracy achieved by combining the EEG and ECG features is 85%.

Table 1 also shows that the ECG signals can detect the sleepiness stage better than the EEG signals. Therefore, a logical table has been made which shows the final state of the conductor according to the result of the EEG-SVM and ECG-SVM. This logical relationship between the results of the two physiological signals is detailed in Table 2.

Table 2. Logic table for the combination of the results of EEG and ECG signals.

Actualclass	**Predict class**		
	EEG-Result	**ECG-Result**	**Final Result**
1	1	1	1
1	1	0	X*
1	0	1	1
1	0	0	0
0	1	1	1
0	1	0	X*
0	0	1	1
0	0	0	0

X* is the result of a simple combination of different features extracted from the EEG and ECG signal.

From this table, the accuracy of our system is achieved at 88%. These results show that our proposed method of combining descriptors significantly improves the performance of our system.

5 Conclusion

The study presented in our paper focuses on the use of features extracted from the ECG and EEG signals for the detection of driver drowsiness. The experiment was performed with a database containing eight subjects. A series of EEG features were extracted, including statistical measures in the time domain and relative powers in the frequency domain. In addition, the HR features were extracted from ECG data during drowsy and alert states. All significant features obtained from the EEG and ECG analyses were applied to the SVM classifier to assess system performance.

The proposed combination of EEG and ECG features achieved a performance of 88%, highlighting the fact that the combination of physiological signals enhances system performance rather than using them alone.

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DETECTION DE LA BAISSE DE VIGILANCE CHEZ LE CONDUCTEUR AVEC UN NOMBRE LIMITE DE SIGNAUX PHYSIOLOGIQUES EEG

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Résumé. Diverses études ont déjà été effectuées pour essayer de discriminer les différents stades de vigilance d'un sujet humain. Le but de cet article est de proposer une méthode de détection de l'hypovigilance chez les conducteurs en adoptant une analyse en temps réel de l'activité EEG. Dans une première partie, nous présentons notre base de données collectée au sein de notre équipe à l'hôpital Sahloul de Sousse en Tunisie. Dans une deuxième partie, nous proposons un algorithme de détection de la baisse de vigilance en utilisant une seule électrode EEG. Cet algorithme, basé sur le classifieur SVM, a été testé sur la base de données et a donné des résultats allant jusqu'à 97,0476% en termes de précision pour la détection des états d'hypovigilance.

Mots clés: Hypovigilance, Electroencéphalogramme, Traitement des signaux, Classification, SVM.

1 Introduction

L'hypovigilance est la transition entre l'état d'éveil et l'état de sommeil durant laquelle l'organisme humain se trouve incapable de penser et analyser les tâches [1]. Cette réduction au niveau de la concentration est à l'origine de nombreux accidents de la route. Les recherches montrent que 25% à 30% des accidents de la route sont dus à l'hypovigilance [2]. Il