EVALUATING ELECTROENCEPHALOGRAM CHANNELS USING MACHINE LEARNING MODELS FOR DROWSINESS DETECTION

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ABSTRACT

Catastrophic accidents in the oil and gas (O&G) industry have been registered over the years, in which human factors represent one of the main causes of their occurrence, either directly or indirectly. Human reliability remains to play an important role in safety-critical tasks, especially when considering complex and often routine operations that induce fatigue and consequently drowsiness, influencing the performance of operators. In this context, it would be beneficial to monitor the operator's drowsiness level through biological information, for example, electroencephalogram (EEG) signals. In this study, an ensemble model based on the Bagging Model is proposed. Multilayer Perceptron (MLP), a well-known Machine Learning (ML) classification technique, is used to detect the drowsiness of several subjects from three EEG channels (C3, C4, and Pz). Here, the data is processed based on different representation of the signals in the time domain. The tested models are evaluated considering a real and public database for human drowsiness. Despite the analysis of three well-known features for EEG in the time domain (Higuchi's Fractal Dimension, and Hjorth's mobility and complexity parameters), the results indicate a better performance for the raw data, achieving a higher balanced precision than 90% for the ensemble model. Therefore, our results indicate a strong correlation of the estimated drowsiness with the central and posterior areas of the EEG channels, which agrees with previous studies.

1. INTRODUCTION

Throughout its history, the oil and gas (O&G) industry has experienced some devastating accidents. The Piper Alpha disaster of 1988 is one of the best known, with hundreds of lives lost on offshore oil platforms [1]. In Brazil, the P-36 platform in the Campos Basin after two explosions, resulted in more than ten deaths and the platform was totally submerged in the sea in 2001 [2]. In both accidents mentioned, the conclusion indicated that one of the main cause was attributed to human factors. Other accidents in the O&G industry in which human error in emergency response was a relevant factor were mentioned by [3].

Human reliability plays an important role in safety-critical tasks, despite the use of modern equipment and interventions to increase process safety. It is discussed in the literature that human factors (e.g., poor rest habits and nutritional imbalances) as well as task-related factors (e.g., night shift, stress and monotony) are associated with fatigue, reducing overall employee performance in work environments and leading to drowsiness [4], [5]. In fact, drowsiness is linked to several types of accidents with drivers, but it is also investigated for organizations that present complex systems as is the context of the O&G industry [6], [7].

Biological information (e.g., electroencephalogram - EEG) can be one of the possibilities to access the drowsiness level [8]. The patterns found in the EEG signals provide a detailed characterization that can be associated with the subject's level of drowsiness [9]. Typically, studies use different EEG channels, as well as different feature extraction procedures to identify states of alertness and drowsiness. However, in practice, the use of multiple electrodes to collect numerous EEG signals can become quite invasive in work environments, in addition to increasing the computational cost to process the data. This led authors to search for reduce the number of EEG channels [9], [10].

Based on the aforementioned investigations, there is no strict consensus on which EEG channels are more appropriate to differentiate alertness and drowsiness, although there seems to be a high correlation in the detection of drowsiness in the central (C) and posterior (P) regions of the brain area [11], [12]. In this study, we analyze the performance of an ensemble model to create an automatic drowsiness detection based on EEG signals. There are several ML techniques useful for classifying the state of drowsiness, however, ensemble models considering EEG signals for this purpose are rare.

2. DESCRIPTION

Our model was based on the Bagging Model, or Bootstrap Aggregating, originally proposed by Breiman [13], wherein, by using the training dataset, this technique generates bootstrap samples in which some of the samples are replicated and some of them are omitted. Thus, these bootstrap samples are used to construct based classifiers using the same classification algorithm and, based on that, these based classifiers are then combined using some strategy, e.g. the majority voting [14].

Here, in our proposed model, we recognize another advantage. It is possible to obtain different subsamples synchronously from the same subject with different EEG channels. Thus, it is possible to create the new hybrid model, coupling a single classifier with different sub-samples (EEG channels) to detect drowsiness. Our model considers three EEG channels (C3, C4 and Pz) available in the database called DROZY [15].

The “ULg multimodality sleepiness database”, also called DROZY, is a database that contains various types of data related to sleepiness (including EEG). The system recorded the EEG channels sampled at 512 Hz, considering fourteen subjects/participants. The experimental protocol required subjects to complete a Karolinska Sleepiness Scale (KSS) form on each of the three psychomotor vigilance tests (PVT) for two consecutive days under conditions of increased induced and prolonged sleep deprivation. After subjects performed the first PVT, they could not sleep until the third PVT, resulting in total sleep deprivation of 28 to 30 hours. Here, for the binary classification, we consider two possible categorizations, previously used in the literature and also suitable for EEG: alert (KSS $\leq$ 3) and sleepy (KSS $\geq$ 7) [16].

The signals from each channel are separated into training and testing sets for the five subjects (1, 5, 6, 8 and 10) that have the first and third PVTs available. The signal segments were tested from raw data as well as three well-known time-domain features for EEG (i.e., Higuchi Fractal Dimension [17], and the Hjorth parameters mobility and complexity [18]). As the ensemble model requires different sub-samples, but only a single classifier, through numerous tests, the Multilayer Perceptron (MLP) technique showed the best overall accuracy. MLP is one of the most popular networks with the ability to solve non-linear problems and high efficiency calculations [19].

To consider real-time drowsiness detection, the segments of each EEG channel are divided containing 100 points, which at a sampling frequency of 512 Hz represents <0.2 s. All the experiments were run on a PC running Python Version 3.7 with a 2.3GHz Intel CORE i3 processor (7th generation), 4GB of RAM, and Microsoft Windows 10 operating system. The Python computer language was used together with the *sklearn* package [20] for the MLP classification technique considering the default parameters. For each time series analyzed, we divided the dataset into 80% for training and 20% for testing, considering that a dedicated model for each subject is created.

3. DISCUSSION

For the Bagging-based model with raw data, in Fig. **1**, it is possible to observe that the predictions of almost all ensemble models presented balanced accuracy above 90%. Therefore, a better performance of the ensemble model was obtained when compared to the predictions of the individual channels in almost all subjects, except for subject 5, which obtained slightly lower accuracy compared to channel C4, and subject 8, which had the accuracy of the model for the Pz channel superior to the bagging-based model. The low precision for subject 5 can be explained by the poor performance in some classifiers, which brings some noise to the subjects' final prediction. In addition, it is possible to note that for a better detection of drowsiness, in addition to depending on the selected EEG channels, it is also affected by interpersonal variability.

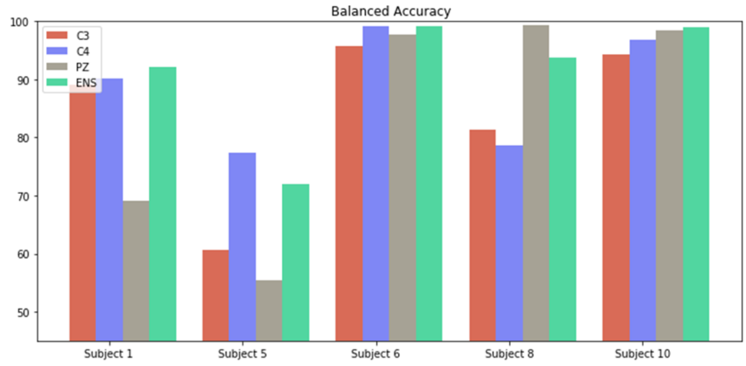

Fig. 1 - Results for five specifics subjects from the MLP technique with raw data

Then, the same steps were applied for the three features (Higuchi Fractal Dimension and the Hjorth parameters mobility and complexity). In Fig. **2**, subjects 1 and 5 present the worst results among all subjects, while subject 8 presented balanced accuracy above 98%. This demonstrates once again the interpersonal variability, which even when considering features adequate to deal with EEG, it is not always possible to classify with good accuracy between awake and sleepy for all subjects.

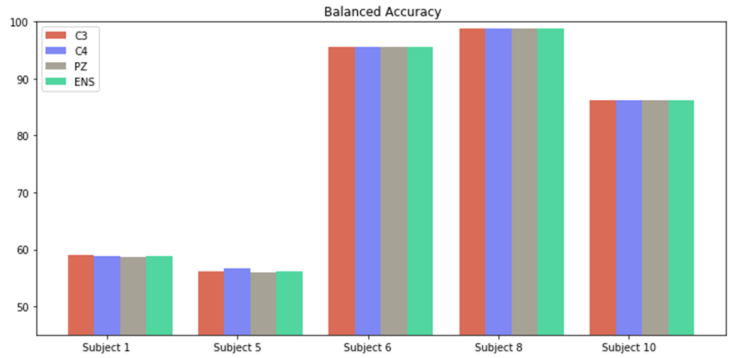

Fig. 2 - Results for five specifics subjects from the MLP technique with features extraction

Furthermore, it is possible to notice that the performances of the MLP technique for the selected EEG channels are analogous, making the prediction of the proposed model bring an equally similar result. Thus, the application of the bagging-based model is not remarkable when considering the three features, as it would increase the operational cost and would not bring any significant improvement in the result when compared to the performance of the same features in individual EEG channels (i.e., C3, C4 or Pz).

4. CONCLUSION

The results indicate that the use of three channels for the elaboration of the ensemble model was adequate and presented an accuracy above 90% for most subjects considering raw data, in addition to being superior to most classifiers alone. For the set of three features, the performance of the proposed model presents similar results when compared with the results of the classifiers that compose the ensemble model. However, the results presented suggest that it is possible to extract significant information even with a quick period (~0.2 s).

Furthermore, the result corroborates the studies that mention the strong correlation of the drowsiness estimate with the EEG channels of the central and posterior areas. However, not only is the consideration of specific channels essential, but it is equally important to realize the influence of interpersonal variability. As future work, we intend to consider models based on deep learning to be used as classifiers, as well as considering other biological signals, and incorporate other model performance measures.

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