Drowsiness Detection and Early Warning System

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***Abstract*—According to the National Highway Traffic Safety Administration, every year about 100 000 police-reported crashes involve drowsy driving, which has been raising an increased awareness towards the issue of drowsiness while driving. Therefore, the number of studies regarding this issue has been increasing, in an attempt to find methods to identify drowsiness in drivers, enabling the development of warning mechanisms and thus preventing vehicle crashes related to drowsy driving.**

Within the scope of the course Signal Processing in Bioengineering, we developed two different methods in order to address the issue of drowsy driving: firstly, a supervised learning classification algorithm that analyzes four different combinations of features of the EEG signal (derived from the spectral power density of the five frequency bands) of the subject and labels the subject's state (between, awake, drowsy and asleep); secondly, a probabilistic model that characterizes the features for drowsiness, based on the distribution of power spectral densities of the five frequency bands identifiable in EEG.

For the first method, the evaluation of performance of each feature set was done using K-Fold Cross Validation, obtaining a performance of 93.75%.

For the second method, we obtained five Normal distributions for each state (awake, drowsy and asleep), corresponding to the distributions of each of the frequency bands of EEG. The perfomance was lower.

***Index Terms*—EEG, drowsiness, classification, machine learning, probabilistic method, signal processing, matlab.**

I. Problem and Motivation

According to the National Highway Traffic Safety Administration, every year about 100 000 police-reported crashes involve drowsy driving [1].

Drowsiness is described by *Mosby's Medical Dictionary* [2] as "a decreased level of consciousness characterized by sleepiness and difficulty in remaining alert but easy arousal by stimuli. It may be caused by lack of sleep, medications, substance abuse, or a cerebral disorder".

Therefore, drowsy driving is characterized as driving in a state of drowsiness.

It is important to develop methods and algorithms of early drowsiness detection, since these could prevent the vehicle crashes related to it and the terrible consequences associated with it.

II. Background and Related Work

Within the scope of drowsy driving, several methods have been proposed to detect drowsiness, among which we can distinguish three major categories: drivers' driving pattern, eyelid and eye movement measurement and drowsiness detection using EEG. The first one is based on hand pressure and handle control pattern; the second one is an image processing technique that detects physical changes in the driver, such as "eyelid movement, average of eye-closure speed, percentage of eye-closure, and driver's head movements" [3]; the third one uses the analysis of EEG measurements.

III. Approach and Uniqueness

In this paper, for the first method, the detection of drowsiness is performed by a classification algorithm, through supervised learning, that analyzes certain features of the EEG signal of the subject and labels the subject's state. The algorithm manages to distinguish between three possible states: awake, drowsy and sleeping. Since previous studies relied on a wide range of features for classification, we decided to test some of them (although all obtained through the power spectrum of the signal), in order to determine which one had the best performance on detecting drowsiness.

For the second method, the classification of drowsiness is based on the probability of the segment being analyzed belonging to each of the distributions of the power spectral density of each of the EEG frequency bands. Conversely to many of the methods currently being developed, this one does not need the support of camera devices and eye movement analysis, since these methods can not accurately detect eye movement in the presence of sunglasses, for example.

One benefit common to both methods is that, if capable of correctly classifying drowsiness, they allow the use of only 2 electrodes opposed to the commonly used 21-electrode system, which proves impractical to apply while driving.

IV. Material

In order to train the classifier, the "Sleep-EDF Database Expanded" from *PyshioNet* was used [4], [5].

The sleep-edf database contains 197 whole-night PolySomnoGraphic sleep recordings, containing EEG, EOG, chin EMG, and event markers. Some records also contain respiration and body temperature. Corresponding hypnograms (sleep patterns) were manually scored by well-trained technicians according to the Rechtschaffen and Kales manual, and are also available. The data comes from two studies, briefly described below, and in detail in [6], [7].

For our study, only 153 files of the database were used and correspond to SC* files (SC = Sleep Cassette), which were obtained in a study of effects of age on sleep (1987-1991), in healthy Caucasians aged 25-101, without any sleep-related medication [7]. Two PSGs, of about 20 hours each, were recorded during two subsequent day-night periods at the subjects' homes.

The EOG and EEG signals were each sampled at 100 Hz. The EEG channels correspond to electrodes placed on Fpz-Cz and Pz-Oz (which is an alternative placement of electrodes to the usual C4-A1/C3-A2, widely used in 2-lead EEG analysis). The EOG electrodes were placed horizontally. Besides these three signals, the data contains also four more channels: "Resporonasal" , "EMGsubmental", "Temprectal" and “Eventmarker”. Only the first two channels, corresponding to EEG, were used in this work.

The **Hypnogram.edf* files contain annotations of the sleep patterns that correspond to the PSGs. These patterns (hypnograms) consist of sleep stages W, R, 1, 2, 3, 4, M (Movement time) and ? (not scored). All hypnograms were manually scored by well-trained technicians (identified by the eighth letter of the hypnogram filename) according to the 1968 Rechtschaffen and Kales manual [8], but based on Fpz-Cz/Pz-Oz EEGs instead of C4-A1/C3-A2 EEGs, as suggested by [9]).

The PSG files are formatted in EDF while the hypnograms are in EDF+. In order to read the annotations in the EDF+ files, the WFDB Software Package tools provided by PhysioNet [10] were used.

V. Methods

According to [11], the EEG power spectrum can be used to identify a transition from alert state to drowsy state. There is a more significant increase in alpha band and a decrease in theta band. The study also verified that the most significant channels are P3, P4, O1 and O2, while others do not showing notable changes. Therefore, the channels used are adequate.

For both methods, The power spectral density was computed using the Welch method (Matlab function *pwelch*), using the default definitions of Matlab. Power computation was performed for each EEG channel and was divided into frequency bands, namely:

Delta (δ): $f < 4\ Hz$
Theta (θ): $4 \leq f < 8\ Hz$
Alpha (α): $8 \leq f < 13\ Hz$
Beta (β): $13 \leq f < 31\ Hz$
Gamma (γ): $f \geq 31\ Hz$

A. Method 1 - KNN Learning Algorithm

Through the obtained annotations, a classification array of length N (number of points) can be generated. Each value of this array corresponds to a sample and can be classified as:

0 - awake
1 - drowsy
2 - sleeping

Since the drowsiness stage is not identified, we considered it safe to determine that the one minute preceding and one minute after the beginning of the annotated sleeping state corresponded to a drowsy state, in order to "teach" the algorithm.

Then, different features sets were tested in order to discover what is the most reliable feature combination in detecting drowsiness, namely: Relative power density, for the 2 channels in separate (RPD2); Relative power density, as the average of the 2 channels (RPDA); Quotient between frequency bands power density, for the 2 channels in separate (QPD2); and Quotient between frequency bands power density, as the average of the 2 channels (QPDA).

1) Relative power density - 2 channels (RPD2):

The relative power density of each band for each one of the 2 channels was calculated using the Equation 1, resulting in a $2 \times 5 \times L$ matrix, which corresponds to the 2 channels, 5 frequency bands and L number of time segments.

$$\mathrm{PD}_{\mathrm{relative}} = \frac{\mathrm{PD}_{\mathrm{band}}}{\sum_{\mathrm{bands}} \mathrm{PD}_{\mathrm{band}}} \quad (1)$$

The matrix was later reshaped to $10 \times L$ to be used in the KNN as L elements with 10 features.

2) Relative power density - Average channels (RPDA):

The relative power density of each band for the average of both the 2 channels was calculated using the Equation 1, resulting in a matrix $5 \times L$, which corresponds to the 5 frequency bands and L number of time segments.

3) Quotient between frequency bands power density - 2 channels (QPD2):

Using the calculated power density of each frequency band, the quotient between frequency bands was calculated for every possible pair combination for both channels, separately.

Therefore, for each channel, we obtained 10 features, corresponding to the following quotients of power density:

1) Delta/Theta
2) Delta/Alpha
3) Delta/Beta
4) Delta/Gamma
5) Theta/Alpha
6) Theta/Beta
7) Theta/Gamma
8) Alpha/Beta
9) Alpha/Gamma
10) Beta/Gamma

This resulted in a $2 \times 10 \times L$ matrix, which corresponds to the 2 channels, 10 quotients and L number of time segments.

The matrix was later reshaped to $20 \times L$ to be used in the KNN as L elements with 20 features.

4) Quotient between frequency bands power density - Average channels (QPDA):

We performed the same calculations as we did for the QPD2 features, but instead of calculating it for the two channels separately, the average of power density of both channels was calculated and then the quotients of the resulting channel were obtained, resulting in a $10 \times L$ matrix, which corresponds to the 10 quotients and L number of time segments.

5) K-Nearest Neighbors:

A first analysis using a K-Nearest Neighbours (KNN) algorithm was used. This algorithm allows to perform classification through supervised learning. It is a rather simplistic algorithm in which, at training time, the whole training set is stored (each example corresponds to its array of features and corresponding label) and, at test time, the test example ($\hat{x}$) is provided and it tries to find the K training examples (x_f) that minimize the distance d(x_f,$\hat{x}$), i.e. the ones most similar to $\hat{x}$ [12]. The

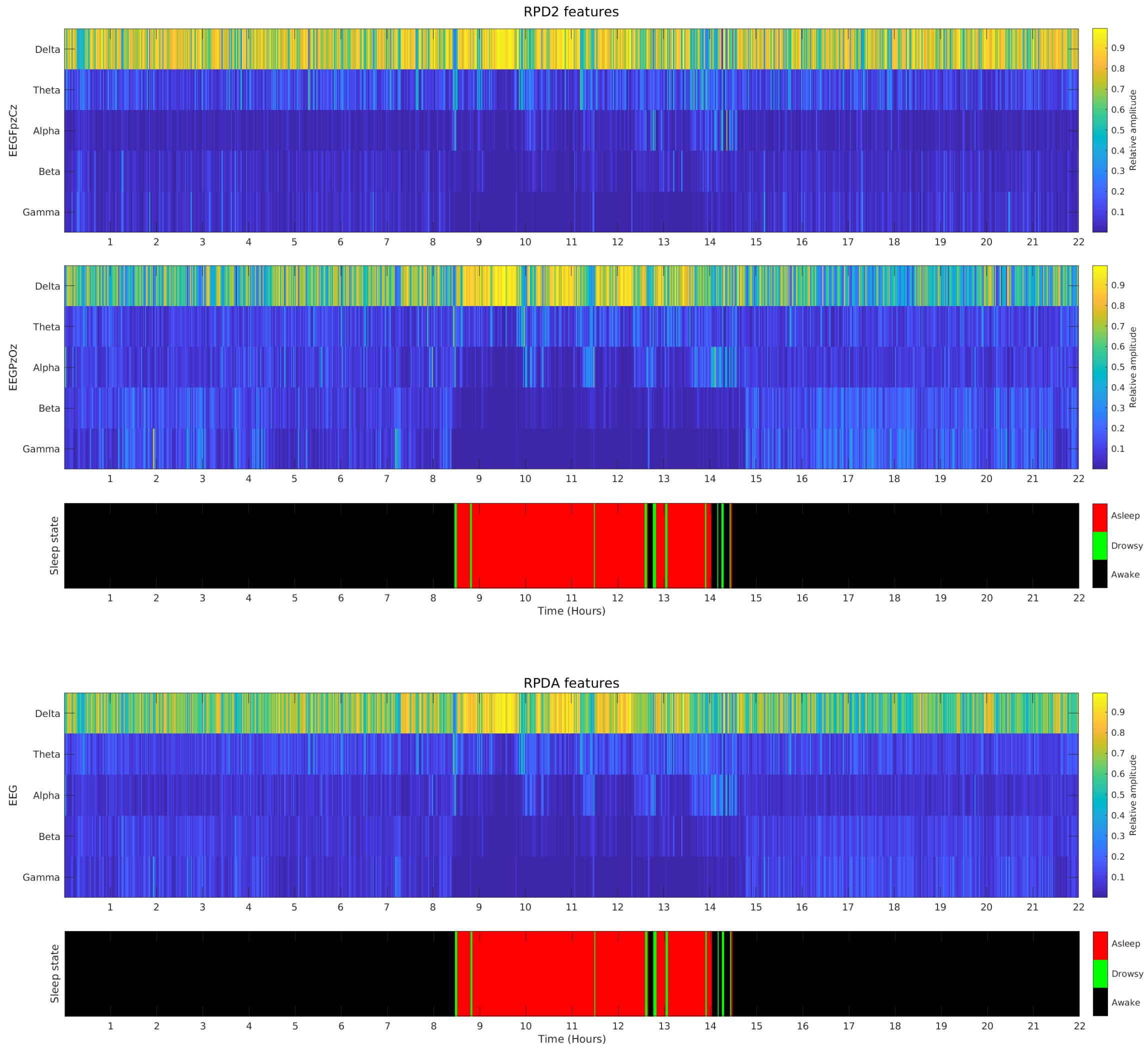

Figure 1. Relative power density of the brain waves frequency bands for subject *SC4001E*.

test example is labeled according to the mode label of the K-Nearest Neighbours.

In order to evaluate which set of features should be used in the proposed solution, we trained a KNN model with each set and then calculated the model error using K-Fold Cross Validation.

The parameters selected for the KNN models were:

- $K = 5$
- Standardized Euclidean distance
- Standardize data

Note that the Standardized Euclidean distance is given by:

$$d(a,b) = [\sum_{f=1}^{F}(a_f - b_f)^2]^{1/2}$$

where F is the number of features of each example.

For the K-Fold Cross Validation, the number of folds used were 5 and the same folds were used for testing all the KNN models.

The obtained results are in the Table I.

Table I
KNN MODEL ACCURACY CALCULATED USING K-FOLD CROSS VALIDATION FOR THE VARIOUS FEATURES SETS OF SUBJECT *SC4001E*. STATE 1* REPRESENTS THE ACCURACY FOR WHEN THE TRUE VALUE IS 1 AND THE MODEL PREDICTED 1 OR 2.

	Accuracy (%)				
Features Set	**State 0**	**State 1**	**State 1***	**State 2**	**Overall**
RPD2	97.83	6.09	56.27	94.38	95.40
RPD2-Fpz-Cz	97.40	6.09	59.86	92.73	94.70
RPD2-Pz-Oz	96.81	2.15	63.44	91.82	93.97
RPDA	97.39	3.23	54.84	92.27	94.53
QPD2	98.31	7.53	63.08	93.21	95.52
QPD2-Fpz-Cz	98.26	5.73	58.42	90.14	94.72
QPD2-Pz-Oz	97.40	2.51	65.23	92.06	94.47
QPDA	98.21	10.04	60.57	93.55	95.56
QPD2db	98.47	6.09	61.65	95.34	96.11
QPD2db-Fpz-Cz	98.17	9.32	59.86	91.77	95.10
QPD2db-Pz-Oz	97.59	4.30	64.16	92.81	94.82
QPDAdb	98.17	4.66	56.27	94.51	95.67

Analyzing the KNN model error for each feature set, the most accurate feature set seems to be the QPDA, which

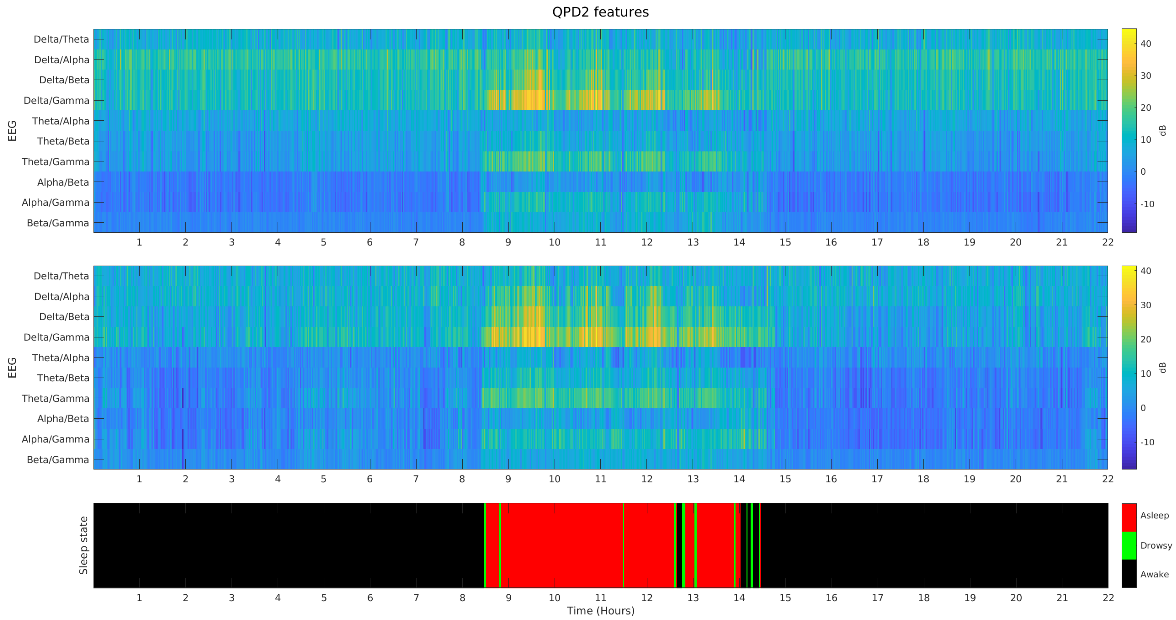

Figure 2. Quotients between the various power densities of the brain waves frequency bands for subject *SC4001E*.

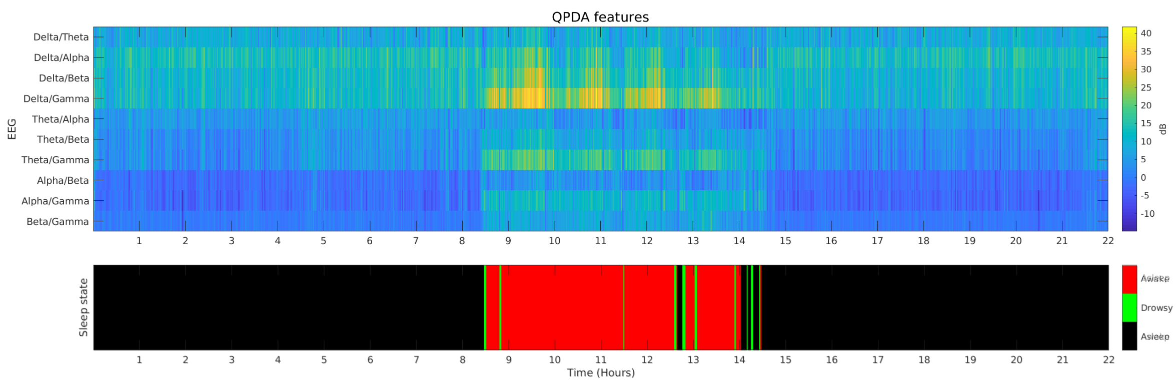

Figure 3.

corresponds to the quotient between frequency bands' power density for the average of the 2 EEG channels.

Using this set, we studied what k value resulted in a better accuracy. The results are in the Table II.

Table II
KNN MODEL ERROR CALCULATED USING K-FOLD CROSS VALIDATION FOR VARIOUS NUMBERS OF NEIGHBOURS.

KNN k value	**Model Error (%)**
1	6.00
3	4.92
5	4.76
10	4.53
15	4.41
20	4.45
50	4.55

Analyzing the obtained error values, we chose a k value of 15, since it presents the minimum prediction error.

6) Proposed Solution: In order to create a system to detect drowsiness and work as an early warning system, we proposed a system which uses EEG signals placed on Fpz-Cz and Pz-Oz, and, at every 5 seconds (due to the 50% overlap), a signal segment of 10 seconds is processed and fed to the classifier. The processing consists on calculating the power density for each brain wave frequency band, average the power densities obtained from the two EEG channels, and then calculate the ratios listed in section V-A3.

The obtained QPDA features are fed into the classifier which returns 3 possible classes: 0 (awake), 1 (drowsy), and 2 (asleep).

B. Method 2 - Probabilistic Modeling

In order to obtain a classification for drowsiness and to test its suitability for the purpose of the paper, the acquisition of the power spectral densities was performed for each subject

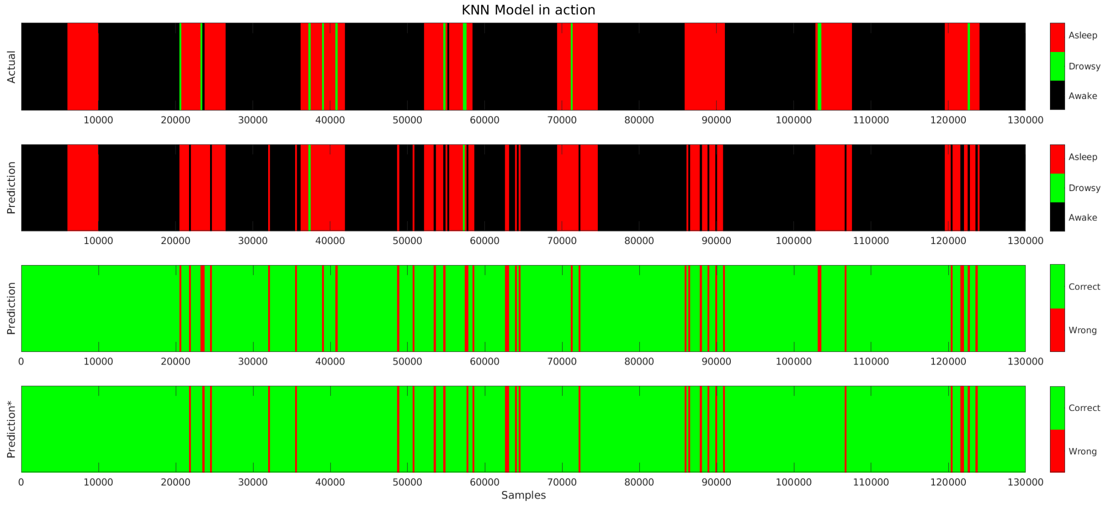

Figure 4. KNN model predictions for the K-Fold Cross Validation for the QPDA features set of 8 subjects. Prediction* corresponds to the case in which the detection of state 2 when the subject is in state 1 is considered correct.

and for both channels to specific segments of the EEG data, corresponding to awake, drowsy and sleeping periods.

To have a better probability that the data segments used correspond to the actual state they are meant to characterize, the following precautions were taken: the drowsy segments were defined as the 3 min preceding a transition between awake and sleeping (assuming that the subject is drowsy immediately before falling asleep); and both the awake and sleeping segments had a period of 10 min of *buffering*, before and after a transition between awake/sleeping state.

The distributions characterizing each of the three states were obtained by extracting the values of PSD of each frequency band for all of the segments but in periods of 10 seconds, which resulted in 107412 values for the awake state; 1440 values for the drowsy state; and 41610 values for the asleep state. These values were then used to obtain a Normal probability distribution, through the Matlab function *fitdist*, which returns the mean ( ) and standard deviation ( ) of the distribution.

1) Proposed Solution: The data acquisition for this method is the same as the one described in section V-A6.

Having a distribution that classifies each of the three states, we can use them as a system to detect periods of drowsiness: by obtaining the power spectral densities of the periods we are trying to classify, we can calculate the probability of that segment belonging to the three states and select the one with higher probability.

To obtain the probability of a certain set of features (power spectral densities of the frequency bands) belonging to each of the possible states, we obtain the cumulative distribution of each feature in the corresponding distribution (multiplied by 2, in order to have a maximum of 1, instead of 0.5) and multiply the five values, obtaining the final probabilities.

VI. Results and Contributions

A. Method 1 - KNN Learning Algorithm

A KNN classification model was trained using the QPDA features obtained from 8 different subjects: *SC4001E*, *SC4002E*, *SC4011E*, *SC4012E*, *SC4021E*, *SC4022E*, *SC4031E*, and *SC4032E*.

A total of 133 456 segments corresponding to the time intervals of 10 seconds with 50% overlap of the EEG signals of the different subjects was processed and the 10 quotient ratios were calculated from it.

The confusion matrix of the model obtained using a K-Fold Cross Validation is displayed in Table VI-A and it is useful to study how the model predictive results.

Table III
KNN model confusion matrix calculated using K-Fold Cross Validation for various numbers of neighbours.

		Predicted		
		Awake	Drowsy	Asleep
Actual	Awake	88292	78	2462
	Drowsy	807	88	1662
	Asleep	3245	91	36731

Table IV
KNN model accuracy calculated using K-Fold Cross Validation for the QPDA features set of 8 subjects. State 1* represents the accuracy for when the true value is 1 and the model predicted 1 or 2.

	Accuracy (%)				
Features Set	**State 0**	**State 1**	**State 1***	**State 2**	**Overall**
QPDA	97.20	3.44	68.44	91.67	93.75

Table V
MEAN AND STANDARD DEVIATIONS OF THE PROBABILISTIC DISTRIBUTIONS OBTAINED FOR THE THREE STATES: AWAKE (STATE 0), DROWSY (STATE 1) AND ASLEEP (STATE 2).

	State 0	**State 1**	**State 2**
Delta	$\mu = 0.6379$ | $\sigma = 0.2621$	$\mu = 0.6688$ | $\sigma = 0.2235$	$\mu = 0.7863$ | $\sigma = 0.1320$
Theta	$\mu = 0.0781$ | $\sigma = 0.0441$	$\mu = 0.0974$ | $\sigma = 0.0885$	$\mu = 0.1165$ | $\sigma = 0.0699$
Alpha	$\mu = 0.0545$ | $\sigma = 0.0539$	$\mu = 0.1330$ | $\sigma = 0.1500$	$\mu = 0.0416$ | $\sigma = 0.0480$
Beta	$\mu = 0.1080$ | $\sigma = 0.1006$	$\mu = 0.0602$ | $\sigma = 0.0517$	$\mu = 0.0398$ | $\sigma = 0.0421$
Gamma	$\mu = 0.1215$ | $\sigma = 0.1235$	$\mu = 0.0406$ | $\sigma = 0.0559$	$\mu = 0.0079$ | $\sigma = 0.0135$

B. Method 2 - Probabilistic Modeling

The probabilistic distributions obtained for the states awake, drowsy and asleep are shown in Figures 5, 6 and 7, respectively, and the corresponding mean and standard deviation values are present in Table V.

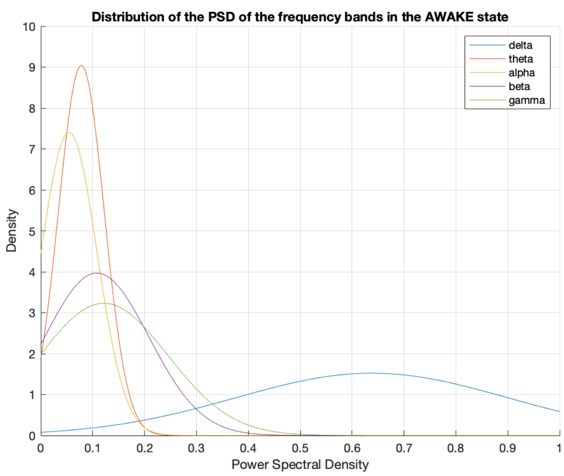

Figure 5. Probabilistic distribution for the state awake, obtained by the method described in section V-B.

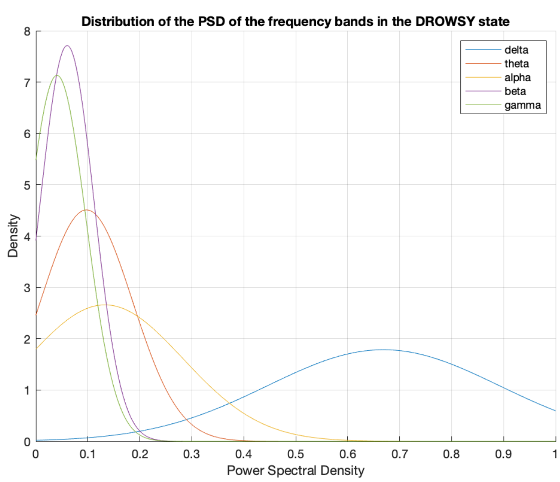

Figure 6. Probabilistic distribution for the state drowsy, obtained by the method described in section V-B.

Since, in this method, less assumptions were made regarding which segments were (or, more exactly, were not) considered

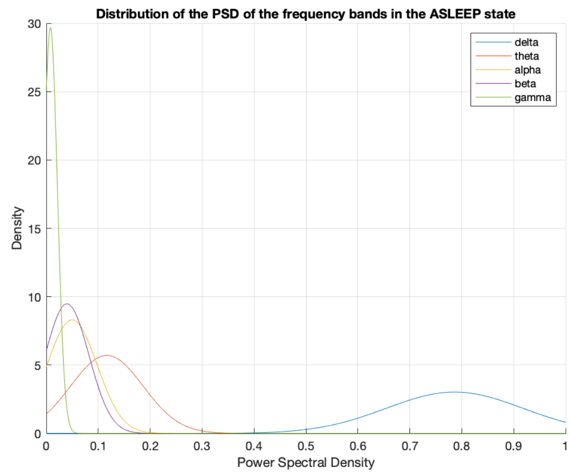

Figure 7. Probabilistic distribution for the state asleep, obtained by the method described in section V-B.

to be in state 1 (drowsy), instead of calculating the confusion matrices, a more qualitative performance analysis will be performed in the following section. In Figure 8, the predictions given by the algorithm (considering the probabilities of belonging to each of the three distributions) can be compared to the binary classification present in the annotations of the initial data.

VII. DISCUSSIONS AND CONCLUSIONS

As a group, we decided to use a different dataset from the one provided by the professor, since the dataset initially provided did not contain the classification of the different sleep stages, which implied that we had to do this ourselves, prior to the actual analysis. This is considerably out of our skill range, which is why we decided to obtain a different dataset that contained the time intervals corresponding to each sleep state.

Regarding the KNN results above and, especially, from the results in the Table I, the algorithm predicts accurately when a person is awake or when it is sleeping.

The accuracy for predicting the drowsiness state is very low. This low value is caused by multiple factors: the fact that the classification of this drowsiness states was done as an assumption that the 1 minute period before and after the moment in which the PSG annotations say the person fell asleep corresponds to the drowsiness state; the reduced number

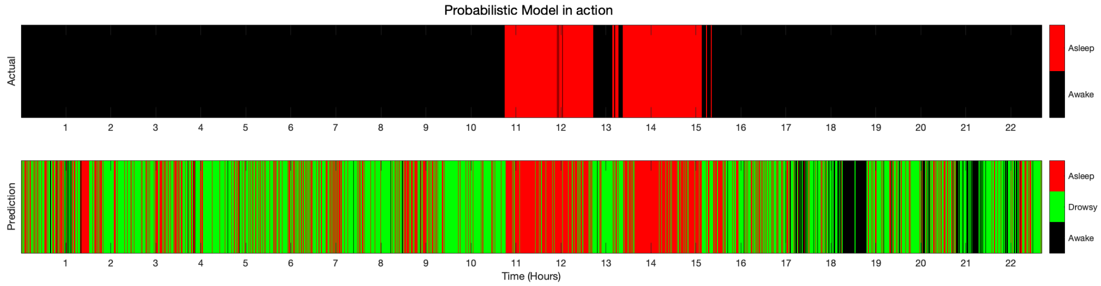

Figure 8. Predictions of the probabilistic model.

of data corresponding to this state, which will affect the accuracy of the classifier, especially, for this state.

When we scaled up the amount of data, the results (Tables VI-A and IV) got worse, having a noticeable decrease in accuracy for the state 1 detection.

However, it is important to notice that, in the Tables I and IV, despite the model having a hard time predicting the state 1, more than 50% the times the person was in a drowsy state, the algorithm classified it as being in that state or in the state 2, asleep, which would be good in a drowsiness detection since it would also trigger the drowsiness alarm. We can also verify this in the Figure 4, where we see a slight improvement in accuracy when we consider the detection of state 2 while in state 1 as correct as well.

The developed KNN classification model despite being able to identify accurately the awake and asleep states, struggles with the detection of the drowsy state, due to the facts mentioned above. Therefore, this system would not be adequate for an early warning system for drowsiness detection, since, for example, if it was used as a safety system for truck drivers, would not warn the driver before him falling asleep, however, it would, very likely, detect the sleep state and warn the driver.

Similarly, when using probabilistic modelling we struggle with the same problems. By analyzing Figure 8 we can see that it satisfactorily identifies sleeping periods but has an enormous difficulty distinguishing awake periods from drowsy ones.

This happens because of the same sets of reasons that justify the lack of ability of KNN to identify drowsy periods (as lower number of points for drowsy periods result in increased error in its PSD distributions' estimations) and also another problem arises, for which this last method is specially vulnerable.

This is the fact that no expert classification exists regarding drowsy periods. This means that we base our results solely on the hopeful correctness of initial assumptions, which, by their very time-dependent nature are probably incomplete, i.e. time-dependent drowsiness is defined as the period of time preceding sleep and that can have very variate duration, that are normalized in this work to two minutes around initial sleep annotation for KNN method and one minute before that same annotation for probabilistic modeling. Because of this longer periods of drowsiness are accounted as awake state and in shorter ones we interpret awake profiles as drowsy. On the other hand, drowsiness, as EEG can capture it, is a transient process where certain changes appear, but that normally is not determinately leading to sleep and are normally alternating with awake periods. This produces a mixture of Awake/Drowsy data in our probabilistic models that is responsible for the observed results. Again, this would be solved if expertise information exists prior to the models construction, allowing for much more precise predictions.

Finally, taking into account that, with the correct initial information, the predictive models is very stable but a rather heavy classification method, we propose a pipeline that uses this method to learn from a small set of PSG studies with high precision awake, drowsy and sleep annotations to amplify this type of data and then train a KNN model which, from having correct data and an enlarged population of drowsy points, a lighter and highly accurate model for drowsiness detection can be obtained.

Even though the results were not perfect, they are promising. We concluded that it is possible to identify awake and sleep states very accurately using only 1 or 2 EEG channels, which facilitates this implementation in real life systems (instead of the commonly used 21-electrode system). The next iteration of this work would pass by exploring in more depth Recurrent Neural Networks and how they could better deal with this issue. Also, it would be interesting to explore possible new features acquirable for each time segment.

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