Electroencephalography signal processing based on textural features for monitoring the driver’s state by a Brain-Computer Interface

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Abstract

In this study we investigate a textural processing method of electroencephalography (EEG) signal as a indicator to estimate the driver’s vigilance in a hypothetical Brain-Computer Interface (BCI) system. The novelty of the solution proposed relies on employing the one-dimensional Local Binary Pattern (1D-LBP) algorithm for feature extraction from pre-processed EEG data. From the resulting feature vector, the classification is done according to three vigilance classes: awake, tired and drowsy. The claim is that the class transitions can be detected by describing the variations of the micro-patterns’ occurrences along the EEG signal. The 1D-LBP is able to describe them by detecting mutual variations of the signal temporarily ”close” as a short bit-code. Our analysis allows to conclude that the 1D-LBP adoption led to significant performance improvement and capturing theclass transitions from the EEG signal is effective, although the overall performance is not yet good enough to develop a BCI for assessing the driver’s vigilance in real environments.

A system for drowsiness detection

Starting from Ref. [1], which developed a multimodal approach for vigilance estimation regarding temporal dependency and combining EEG and forehead EOG in a simulated driving environment, we wanted to exploit the temporal evolution of the mental state during the transition from an awake to a drowsy state, to detect the event and alert the driver.

We hypothesize that these transitions can be represented by a sequence of a set of bit-codes computed by the one dimensional version of the Local Binary Pattern operator (1D-LBP) [2]. The analysis is done over a given time window, named epoch.

The goal is to identify the epochs where the subject is getting tired or falling asleep and send a signal (e.g. an audio alarm) to wake the driver up. The second point is to investigate if this representation can generalize the drowsiness detection to any user or requires user-specific settings.

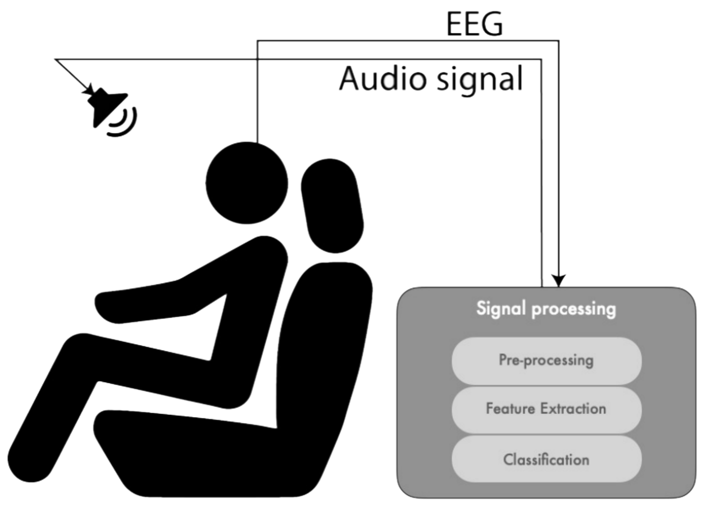
Experimental Protocol

- SEED-VIG dataset [1]: 23 subjects that were asked to drive for approximately two hours in a simulated scenario and abstain from assuming caffeine, tobacco, and alcohol before the experiment.
- 1D-LPB method and DE method [1] were applied for the feature extraction.
- Three vigilance classes, based on the PERCLOS index, were defined:
  - *Awake* class: PERCLOS < 0.35;
  - *Tired* class: 0.35 ≤ PERCLOS < 0.7
  - *Drowsy* class: PERCLOS ≥ 0.7
- Two classification models: the linear Support Vector Machine (SVM) and the SVM with a Gaussian kernel (RBF).

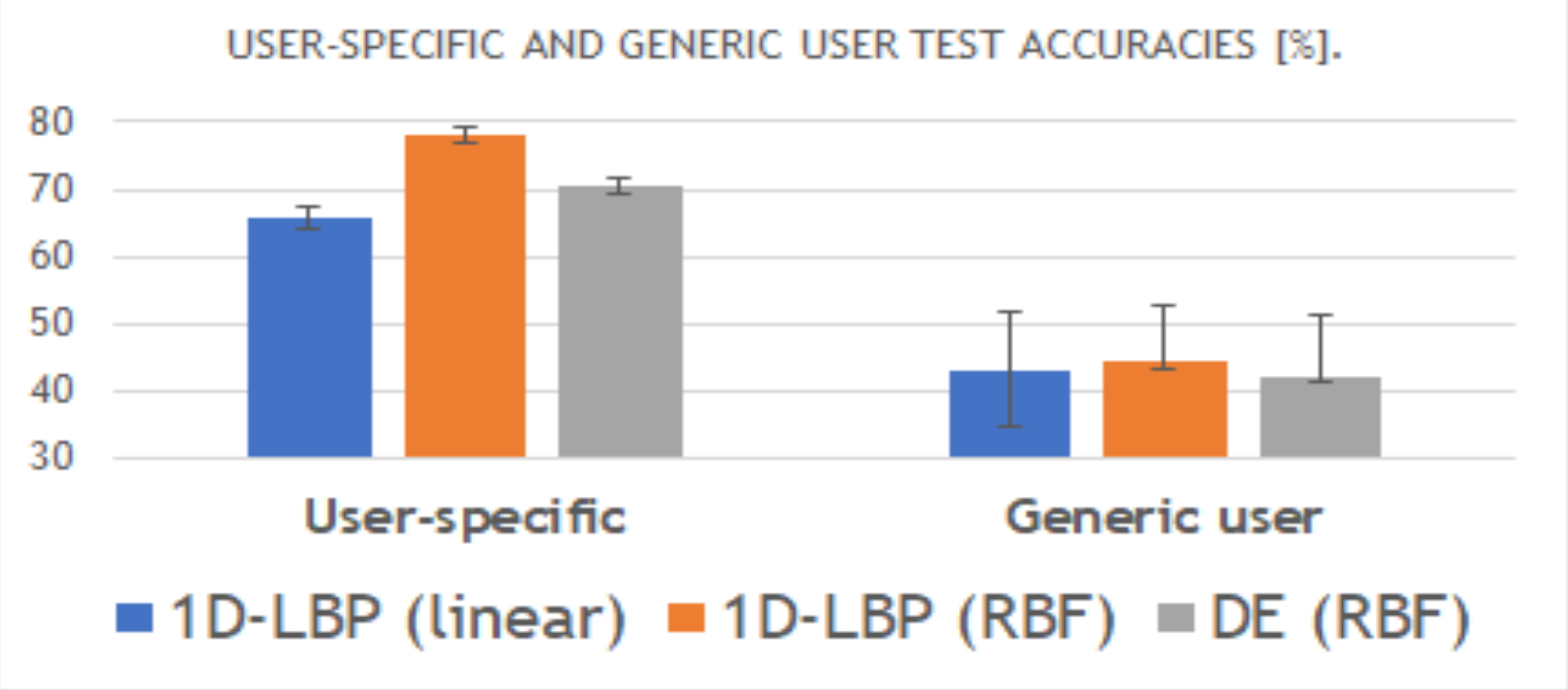
To evaluate the classifier’s temporal response, we defined new metrics to determine the system’s performance in awake to tired (AT) and tired to drowsy (TD) transitions:

- $Hit\ rate\ (HR) = \frac{H_{AT}}{n_{AT}} + \frac{H_{TD}}{n_{TD}}$ — Ratio of successfully recognized class transitions (hits) to the total count of state changes.
- $0\text{ - }delay\ hit\ rate\ (ZDHR)$ — Percentage of hits that happen on the first sample of the state change.
- $Mean\ hit\ delay\ (MHD) = \frac{\sum_{i=0}^{n_{AT}} \Delta_i^{AT} + \sum_{i=0}^{n_{TD}} \Delta_i^{TD}}{n_{AT} + n_{TD}}$ — Mean of seconds of delay with which the response of the classifier correctly identifies a state change. $\Delta^{xy} = t(hit)_{xy} - t(change)_{xy}$
- $False\ hit\ rate = \frac{FN_{(awake)}}{FN_{(awake)} + TP_{(awake)}}$ — Rate of misclassified “awake” samples.

To test the BCI performance, we carried out two types of tests:
- **User-specific**: we train and test the system on the same group of users, a common approach when designing BCI interfaces.
- **Generic user**: we train the system on a user population that is totally different from that involved for the final use.



Results



1D-LBP is compared to DE in terms of accuracy in classification. Results for generic user tests show how a generic user system could have very low performance.

Awake to tired transition			
Metric	1D-LBP (linear)	1D-LBP (RBF)	DE (RBF)
HR [%]	96,2 ± 6,3	**98,1 ± 2,7**	92,4 ± 8,7
ZDHR [%]	72,8 ± 15,1	**73,4 ± 13,2**	70,7 ± 16,8
MHD [s]	16,55 ± 19,97	**6,52 ± 5,66**	10,35 ± 8,72

The detection of this transition is very accurate, especially for the 1D-LBP method. The content of each cell is written as: "mean ± standard deviation".

Tired to drowsy transition			
Metric	1D-LBP (linear)	1D-LBP (RBF)	DE (RBF)
HR [%]	**86,8 ± 13,4**	80,1 ± 18,8	48,8 ± 24,9
ZDHR [%]	**31,1 ± 17,6**	20 ± 14,1	13,8 ± 10,08
MHD [s]	70,96 ± 58,65	**66,4 ± 43,47**	118,64 ± 98,21

The comparison with the previous table shows how this status change is detected less than the awake to tired transition. However the use of the 1D-LBP features with respect to the state of the art considerably increases the detection of this transition.

False hit rates [%]			
Awake misclassified as	1D-LBP (linear)	1D-LBP (RBF)	DE (RBF)
Tired	**52,25 ± 15,66**	56,21 ± 14,1	74,12 ± 15,96
Drowsy	**6,52 ± 10,59**	8,79 ± 11,55	5,45 ± 7,03
Tired or drowsy	**58,77 ± 15,76**	65 ± 15,63	79,57 ± 17,14

The awake class is more confused with the tired class. The low confusion between awake and drowsy classes is a positive result for the BCI operation.

Conclusions

- 1D-LBP first application to driver’s state monitoring.
- Introduction of novel performance parameters for the transition's detection and the related time delay.
- Strong effectiveness of the proposed method in detecting the awake-to-tired transitions (only 6 s of delay and the best hit rate).
- Overall performance is not yet good enough to develop a BCI for assessing the driver’s vigilance in real environments.

References

[1] W.-L. Zheng and B.-L. Lu, “A multimodal approach to estimating vigilance using eeg and forehead eog,” Journal of neural engineering, vol.14, no. 2, p. 026017, 2017
[2] N. Chatlani and J. J. Soraghan, “Local binary patterns for 1-d signal processing,” in Signal Processing Conference, 2010 18th European.