Driver cognitive workload monitoring by IR imaging

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Traffic accidents, which are a leading cause of injury and death, are often induced by underestimation of driver' cognitive workload (CW) and fatigue (Kajiwara, 2014). Hence, predicting such states could be fundamental to prevent traffic accidents. Quantitative assessment of CW can be performed by means of neuroimaging and neurophysiological techniques and methods (Aghajani et al., 2017). However, their limitations in real life driving (contact probes, high sensitivity to driver's motion) prevent their large use in driver assistance systems (ADAS).

Infrared Thermography imaging (IRT) has been proposed as suitable alternative tool to infer CW in a contactless and ubiquitous manner. IRT is a non-invasive technology sensitive to the neurovegetative modulation of cutaneous temperature (Cardone and Merla, 2017). IRT capability to estimate CW has been investigated so far and compared with standard Electroencephalography (EEG) (Wang et al., 2019a), which is considered a gold standard technique for inferring brain activity. Particularly, the EEG β-band power increases when high CW occurs (Matthews et al., 2017).

In this work, a Support Vector Machine (SVM) regression was implemented to estimate the EEG β-band power from IRT features. Then, a Receiver Operating Curve (ROC) analysis was performed on the predicted CW to infer high or low CW, defined through a median split approach of the EEG β-band power. To the best of our knowledge, this study is the first attempt to evaluate CW through IRT as it is defined by the EEG β-band power in automotive.

The method was tested on 10 volunteers (6 males, age range 22–35 years, mean 28.4 years) performing cognitive tasks (i.e. Digit Span and Rey Auditory Verbal Learning test) while driving over an urban context on a static driving simulator. The administration of cognitive tasks allowed to manipulate the CW with respect to the baseline driving. The driving context was displayed on three 27-inches monitors with 1920 x 1080 pixels resolution. The distance between the driver and the monitors was set at 1.5 meters and the driver's horizontal view angle was 150 degrees. The software used for driving simulation was City Car Driving, Home Edition software (version 1.5) (Cardone et al., 2020a). The driving conditions were set a priori to ensure adverse driving condition and uniformity across the subjects (Cardone et al., 2020a). During the driving, the driver's facial temperature was acquired by using a FLIR Boson 320LW IR thermal camera optically co-registered with an Intel RealSense D415 camera. Both visible and IR videos were acquired at a sample frequency of 10 Hz. EEG was acquired through g.HIamp biosignal amplifier (g.tec medical engineering). The amplifier was able to acquire 19 channels at a sample frequency of 256 Hz.

Concerning IRT data analysis, visible videos were used to track facial landmarks (68 points) by means of OpenFace (Baltrušaitis et al., 2016), and, then, they were co-registered to the thermal videos by estimating the geometrical transformation between the visible and the IRT optics (Cardone et al., 2020b). Three Regions of interest (ROIs) were automatically determined on facial areas of physiological importance (i.e. nose tip and glabella) (Ioannou et al., 2014). For each ROI, the average value of the pixels was extracted over time and representative features (i.e. mean value, standard deviation, kurtosis, skewness, mean of the first 5 s – mean of the last 5 s, power content in the respiratory and myogenic band) were computed over consecutive temporal windows of 30 seconds (339 temporal windows were obtained among subjects). For the EEG data analysis, saturated or corrupted epochs were rejected by visual inspection. Moreover, an automatic procedure based on Independent Component Analysis was applied to remove physiological artifacts (Croce et al., 2018). Data were then band-pass filtered between 0.1 and 80 Hz with a 2nd order, zero-lag, Butterworth digital filter. Brain activity during the driving was estimated through the Power Spectral Densities (PSDs) evaluated through of Welch's method (2 s intervals, frequency resolution of 0.5 Hz) in the β-band power (15–25 Hz frequency ranges). An SVM with a linear kernel was employed to predict CW relying on normalized (z-score) features extracted from IRT signals. The generalization capabilities of the procedure were investigated employing a leave-one-subject-out cross-validation procedure. The performances of the classifier were tested on the out-of-training-sample prediction of CW by means of ROC analysis.

The SVM procedure delivered a regression with a correlation coefficient of 0.38 ($p<0.001$) and ROC analysis showed a good performance of the classifier with an average AUC of 0.67 (Figure 1). Notably, although the median split approach could provide information regarding the participants' CW, individual differences could occur. For this reason, in previous studies the classification of CW was conducted within each subject (Wang et al., 2019b). The findings of this study indeed deliver more generalizable results. Importantly, it should be highlighted that the CW evaluated in this study is mainly related to non-driving tasks rather than to a complex driving condition.

These findings might be related to modification of the facial superficial circulation associate to CW (Perpetuini et al., 2021). Moreover, the contribution of the feature related to the respiratory band in the CW estimation suggests a relation between the modulations of the breathing rate and the CW.

Although preliminary, these results demonstrate the feasibility to estimate the CW as evaluated by the EEG β-band power from thermal features. However, further studies with larger study samples are needed to corroborate these findings. In fact, a larger sample size would allow to employ non-linear and more complex machine learning approaches probably increasing the classification performance.

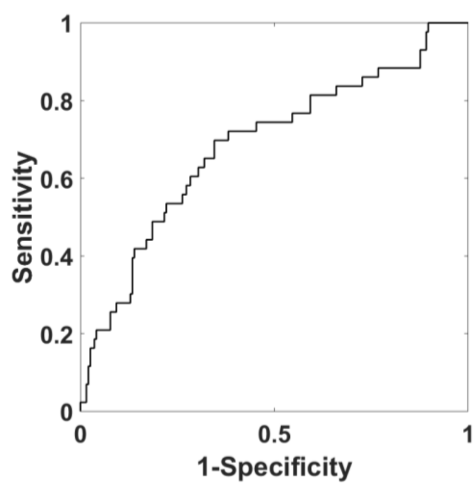

Figure 1. ROC curve delivered classifying low and high MW from the ML approach relying on the EEG β-band

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