Cognitive Workload Assessment via Eye Gaze and EEG in an Interactive Multi-Modal Driving Task

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The Big Question

How to assess human cognitive workload for the robust development of autonomous multi-modal interactive systems?

Introduction

- To develop autonomous multimodal interactive systems, we need:
  - To improve mixed-initiative team performance.
  - To determine human cognitive demands.
  - To support human needs.
- To predict human cognitive workload, we use different physiological signal types such as:
  - Pupillometry
  - Electroencephalography (EEG)

Experimental Design

- **Primary Task:** 20 minute 52.4 km driving simulation.
- **Secondary Tasks:**
  1. **DRT:** Tactile stimulation every 6-10 seconds.
  2. **Braking:** 10 braking events per session.
  3. **Dialogue:** 20 questions per session such as:
     - "What is your favorite color?"
     - "What pets do you have?"
     - "What type of movies do you like?"
- Two driving scenarios: DRT and non-DRT.
- Two sessions per participant.

Workload Evaluation

- Generation of different workload levels with the combination of tasks (Figure 1):
  1. **Level 0:** Only the simulated driving.
  2. **Level 1:** Dialogue events added to the driving task.
  3. **Level 2:** Dialogue and braking events along with driving.
  4. **Level 3:** All secondary events added to the driving task.
- **Balanced Dataset:** 77 samples collected from 47 subjects for each level.

Machine Learning Methods

Two Distinct Settings:

1. **Single-modality:** Single physiological signal as an input to the learning modality.
2. **Multiple-modality:** Combination of different physiological signal types as an input to the learning modality.

Learning Models:

1. K-Nearest Neighbor
2. Naive Bayes
3. Random Forest
4. Support Vector Machine
5. Neural Network-Based Models (NNM):
   - Multi Layer Perceptron
   - EEGNet

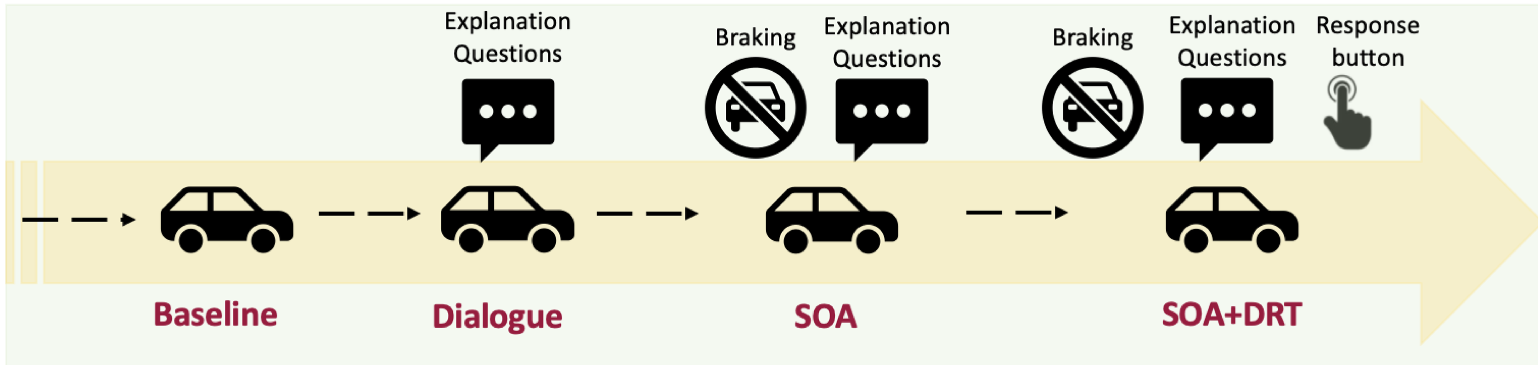


Figure 1: Workload evaluation.

Data Acquisition

PUPILLOMETRY

- Pre-processing with amplitude thresholding (0.8 mm-10 mm), linear interpolation, and low-pass filtering with 10 Hz cutoff frequency.
- Percentage change in pupil size (PCPS) and average PCPS (APCPS) from pupillometry:

$$PCPS = \frac{\text{CVPD-BVPD}}{\text{BVPD}} \times 100\% \quad (1)$$

$$\text{APCPS} = \frac{1}{M} \sum_{i=1}^{M} \text{PCPS}_i \quad (2)$$

CVPD: The current value of pupil diameter.
BVPD: The baseline value of pupil diameter.
M: The number of samples in time domain.

EEG

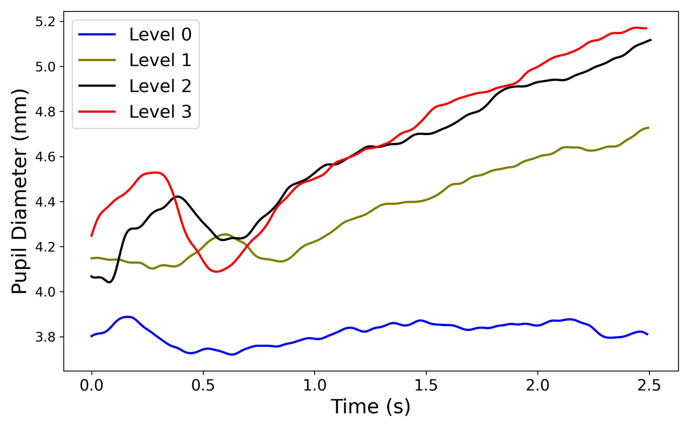
- Eight EEG channels: FC1, FC2, FC5, FC6, CP1, CP2, CP5, and CP6.
- Three-step pre-processing:
  1. 6^{th}-order Butterworth band-pass filter (0.1 Hz – 32 Hz).
  2. Independent component analysis (ICA) to remove blinks.
  3. Kalman smoother to predict the state of dynamic linear structures.
- Calculation of power spectral density (PSD) and obtaining five frequency bands: Delta, theta, alpha, beta, and gamma.

Statistical Analysis

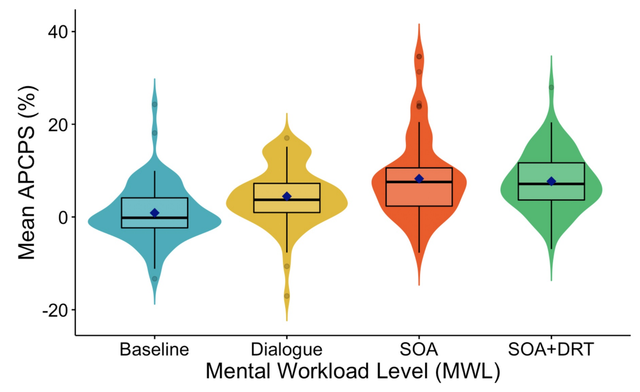
- **Pupillometry:**
  1. Average PCPS (APCPS) signal has a stable pattern during Level 0.
  2. Distinctive patterns of APCPS are observed during Level 1, Level 2, and Level 3.
  3. Level 0, Level 1, and Level 2/Level 3 can be differentiated.
- **EEG:**
  1. Only alpha and beta waves can differentiate just Levels 0-2 and 0-3.
  2. Any of the EEG frequency bands can classify the levels 0-1, 1-2, 1-3, and 2-3.

$\longrightarrow$ Pupillometry is a better physiological signal modality compared to EEG in differentiating different pairs of cognitive levels.

–**The variation in mean APCPS over all samples for four workload levels:**



–**Violin plot of mean APCPS over all events for different cognitive workload levels:**



–**p-values from Benjamini & Hochberg multiple pairwise test performed on APCPS signal obtained from pupillometry for different pairs of cognitive workload levels:**

	Level 0	Level 1	Level 2
Level 1	8.5×10^{-4}	-	-
Level 2	3.1×10^{-8}	0.002	-
Level 3	1.1×10^{-9}	0.002	0.648

–**p-values from Tukey HSD multiple pairwise test performed on five frequency bands obtained from PSD of EEG for different pairs of cognitive workload levels:**

Workload Level	Delta	Theta	Alpha	Beta	Gamma
Level 1-Level 0	0.23	0.47	0.14	0.18	0.30
Level 2-Level 0	0.97	0.99	3×10^{-3}	0.03	0.12
Level 3-Level 0	0.36	0.92	4×10^{-4}	0.01	0.13
Level 2-Level 1	0.49	0.58	0.59	0.89	0.96
Level 3-Level 1	0.99	0.85	0.26	0.70	0.98
Level 3-Level 2	0.65	0.96	0.94	0.98	0.99

Classification Results

- PCPS outperforms other physiological signals regardless of learning models.
- The highest accuracy is achieved by using only pupil diameter for all classification tasks.
- Combining the extracted features of EEG and pupil diameter does not improve the quality of workload prediction.

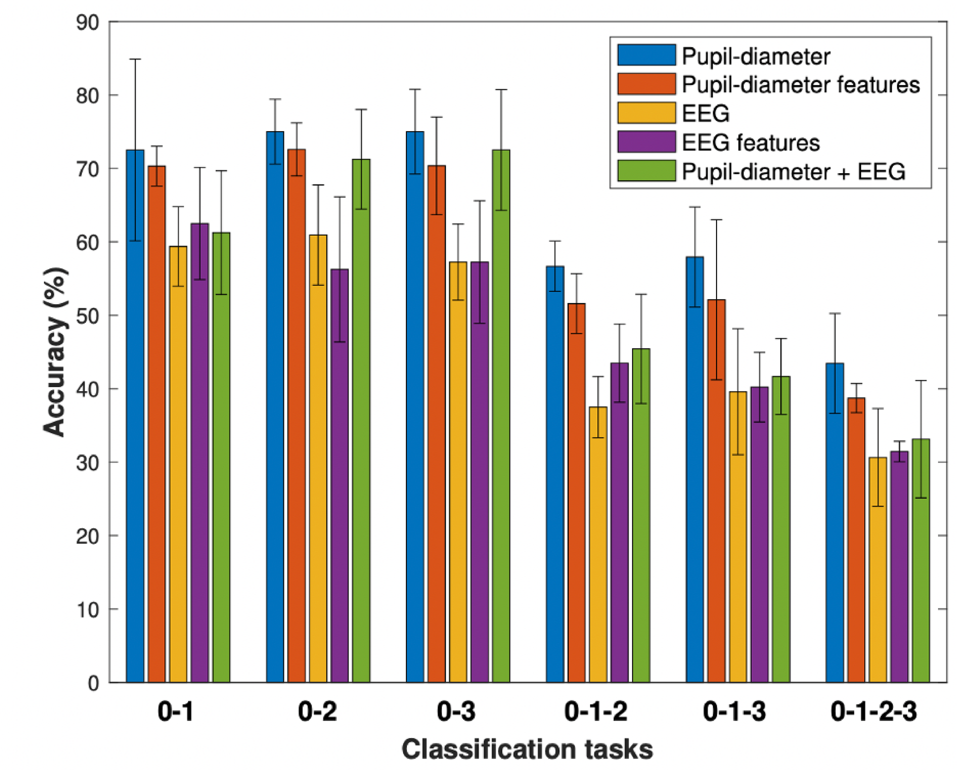


Figure 2: Summary of Classification Efficiency.

Conclusion

- The aim of this study was to investigate the potential of multiple physiological signals such as EEG and pupillometry, alone or combined, for assessing human cognitive workload in interactive, multi-modal, multi-task settings.
- The results indicate that pupil diameter is the most effective physiological parameter in assessing different cognitive workload levels.
- There is no fusion model of extracted features acquired from EEG and pupillometry could improve the prediction accuracy than just using pupillometry alone in our workload classification tasks.
- Given that eye gaze signal is easy to collect and process compared to other physiological sensing modalities, it can be evaluated as important modality for future efforts in improving the team performance of autonomous multimodal human-robot interactive systems.

Please see our latest work titled "Investigating Methods for Cognitive Workload Estimation for Assistive Robots" as follows: