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INSTITUTO DE SISTEMAS E ROBÓTICA
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Biosignal-driven Machine Agents and Reinforcement Learning

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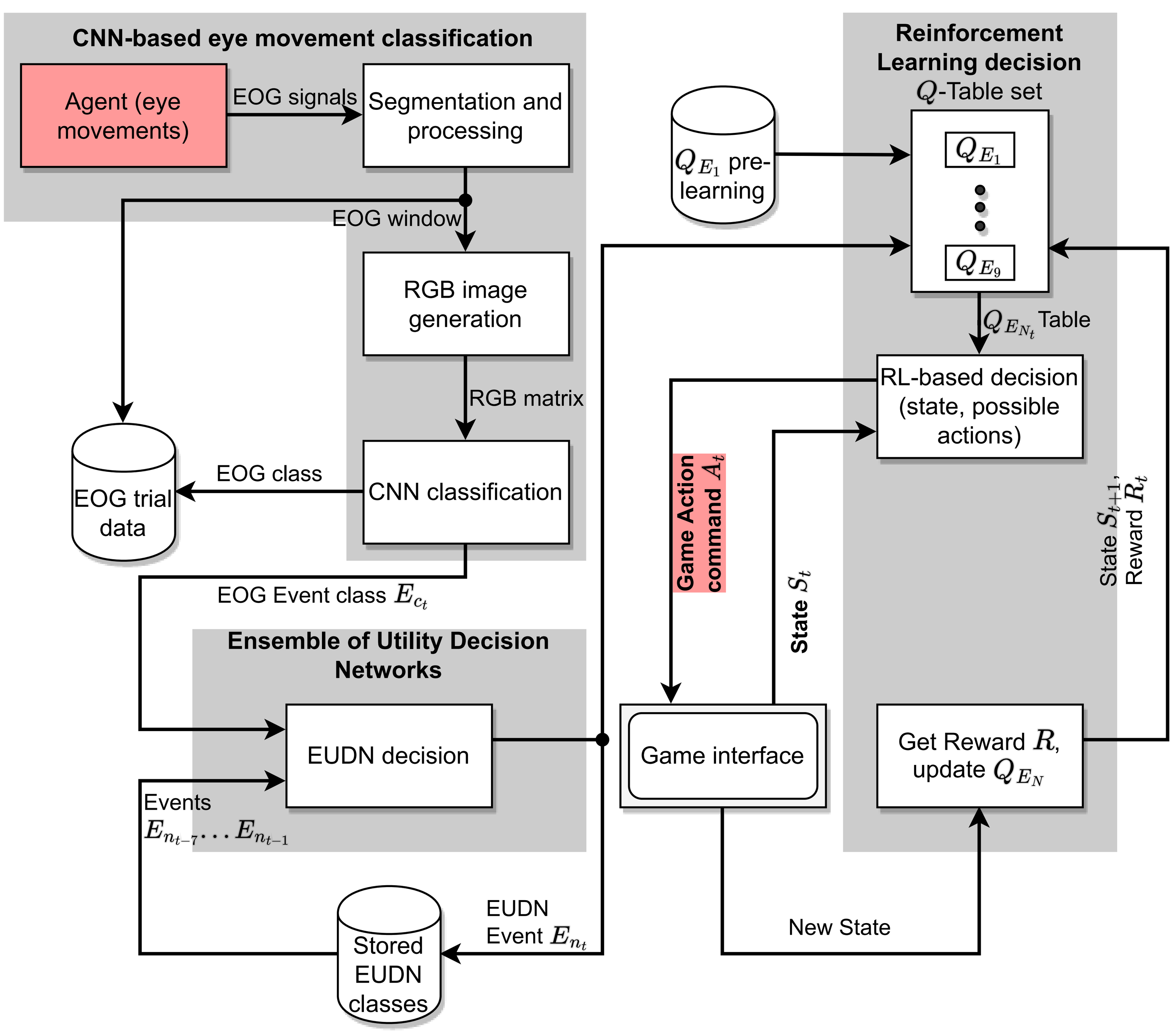
Introduction and challenges

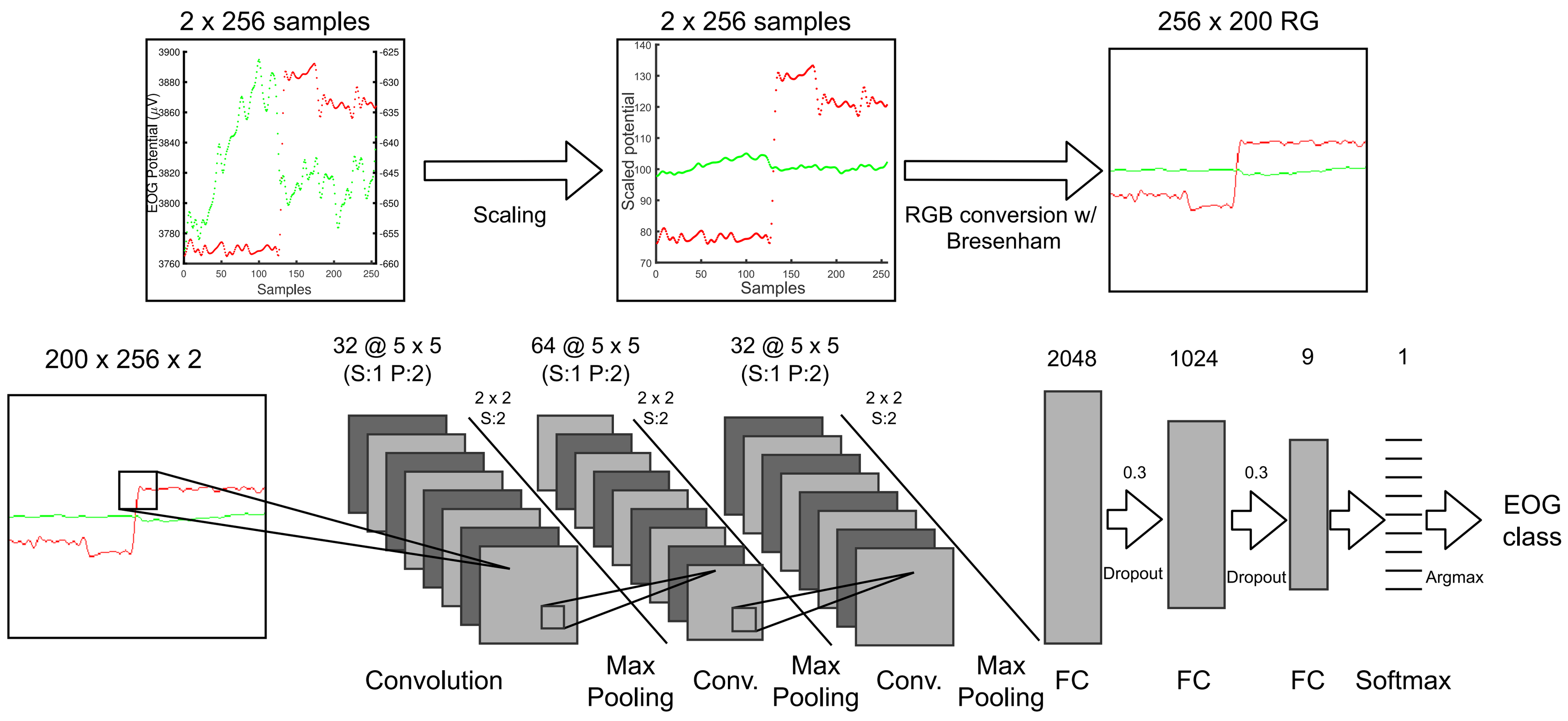
- If Human-Machine Interfaces are ever to become useful to people with motion impairments, they must allow hands-free control, and preferably learn from being used, i.e. adapt their behavior to their user.
- In **Electrooculography-based interfaces**, commands may be issued with eye movements, but there may be difficulty in classifying/making decisions regarding overlapping ocular movements. Muscular movement artifacts are also problematic (most paradigms require user to not move its head).
- On **Electroencephalography-based interfaces**, commands can be issued, for example, by using stimuli provoking P300 responses. Ocular artifacts are the greatest problem, but one must also keep the user engaged and try to eliminate signal artifacts related to distraction and movement.

Training a Machine Agent with eye movements [1]

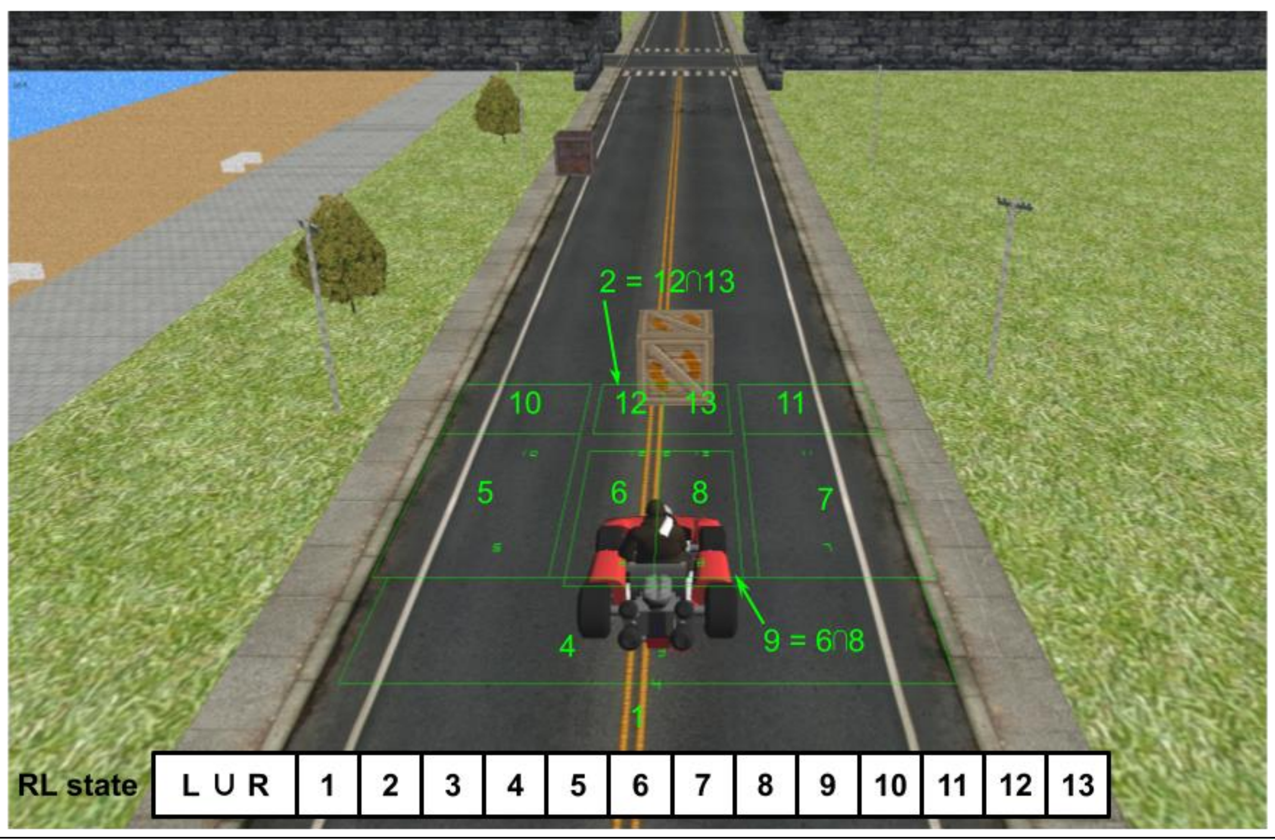
- **Problem:** teach a Machine Agent using biosignal-driven commands.
- A game interface was used so a Machine Agent can learn a non-collision from moderated bio-signal input (Electrooculographic signals - EOG) within a Q-Learning RL framework.
  - User's goal is to avoid collisions on a kart driving game.
  - Classify EOG signals using <u>generalized</u> CNN weights for all participants.
  - Moderate impact of deviant eye movements using an Ensemble of Utility Decision Networks (EUDN).
  - Train a Machine Agent using a modified Q-Learning approach
- Three training modes: inactive RL (learning mode, RL_0), and passive (RL_1) or active (RL_2) assistance from the MA.
- Learning is discrete for each positional state of the obstacles (see figure on the right).
- Results have shown this HMI was capable of effectively training a RL agent.



Full view of the decision pipeline, with all the steps between a user's eye movement and a game command



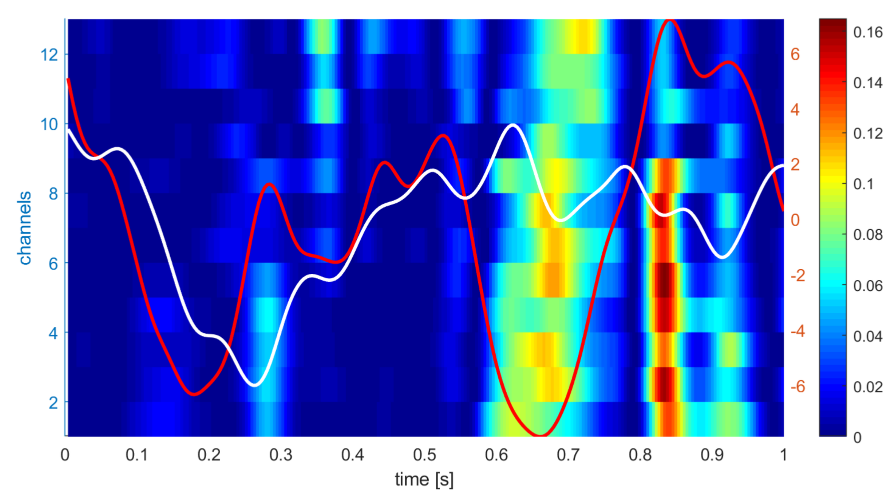
Scaling, conversion and CNN classification of EOG signals take place before the class is inputted to the EUDN, the precursor to the RL pipeline



Depending on the outcome of a user command, the modified Q-Learning algorithm will adjust Q-values for the state the kart was in

Error potential-based learning

- A game interface (checkers game) is being tested in which a Machine Agent is capable of learning a more complex set of rules through a person <u>observing</u> the gameplay.
  - Observable game interface (non-actionable)
  - EEG (Electroencephalographic) error potentials
- A more thorough strategy is being developed to tackle the problem of artifacts.
  - ICA-assisted Deep Learning-based cleanup



On this BCI, error potential viability is first assessed comparing R2 values for GAs from legal (white) and illegal (red) moves when a move is announced

References

1. PERDIZ, João, et al. A Reinforcement Learning Assisted Eye-Driven Computer Game Employing a Decision Tree-Based Approach and CNN Classification. IEEE Access, 2021, 9: 46011-46021.

Acknowledgments

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