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Andrea Finke, Yaochu Jin, Helge Ritter

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A P300-Based Brain-Robot Interface for Shaping Human-Robot Interaction (Supplementary Materials)

Andrea Finke, Yaochu Jin, Helge Ritter

Motivations

Brain-computer interfaces (BCI) based on the P300 event-related potential (ERP) have been studied widely in the past decade. These BCIs exploit stimuli, called oddballs, which are presented on a computer screen in an arbitrary fashion to implement a binary selection mechanism. The P300 potential has been linked to human surprise (Duncan-Johnson and Donchin, 1977), meaning that P300 potentials can be triggered by unexpected events. This hypothesis is the basis of the oddball paradigm Lenhardt et al. (2008); Bell et al. (2008). In this work, we go beyond the standard paradigm and exploit the P300 in a more natural fashion for shaping human-robot interaction (HRI).

A P300-Based Human-Robot Interaction System

The the proposed framework is illustrated in Fig. 1. It consists of the following core modules: (1) a *P300 spotter* that analyzes the incoming preprocessed data stream for identifying P300 potentials on a single-trial basis and (2) a *translation module* that translates the detected P300s into appropriate feedback signals to the robot.

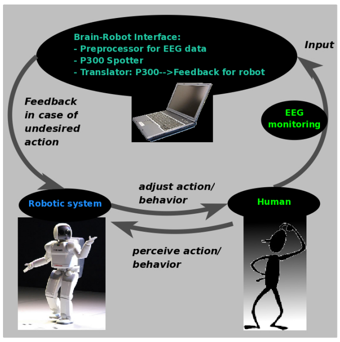


Figure 1: A diagram of the P300-based HRI system.

Methods

The classification uses a supervised machine learning algorithm that requires labeled training data. The pseudocode of the classification algorithm is presented in Algorithm 1. The data for off-line training must be collected subject-wise to account for the high inter-subject variances typically found in EEG data, as shown in Fig. 2. The off-line training needs to be carried out only once prior to using the interface. The trained classifier is then employed for on-line detection of P300 signals.

Algorithm 1 Online classification and feedback generation.

Initialize $t \leftarrow 0$, $w \leftarrow W$ {W is the window size parameter}
Load pre-trained classifier Φ
Buffer data until t=w
for t = w+1 to T **do**
  Create vector $\vec{y}_t = (y_t^1, ..., y_t^n)^T$
  Create window matrix $\vec{x}_t = (\vec{y}_{t-W+1}, ..., \vec{y}_t)$
  Preprocess $\vec{x}_t$
  Feature extraction: obtain $\hat{\vec{x}}_t$
  Classify $\hat{\vec{x}}_t$
  if $\Phi(\hat{\vec{x}}_t) > \theta$ **then**
    Generate feedback
  end if
  $t \leftarrow t + 1$
end for

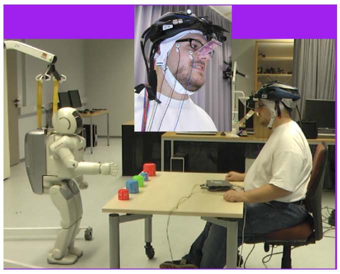
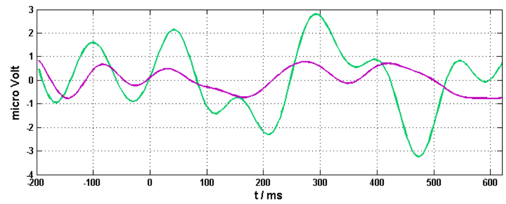


Figure 2: A scene from experiments on P300-based HRI using ASIMO.

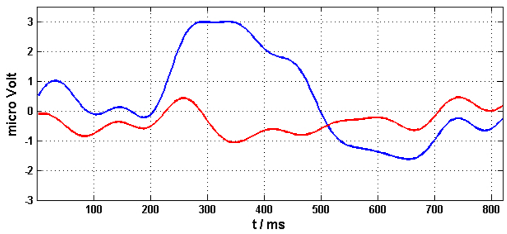
Results and Conclusions

We developed an interaction paradigm to evaluate the proposed framework using Honda's humanoid robot ASIMO, refer to Fig. 2. This paradigm is suited for eliciting P300 events in a controlled experimental environment without neglecting the constraints of real robots. We recorded EEG data during interaction with ASIMO and applied our method off-line. As a proof of concept we show that we are able to elicit P300 potentials in the real-world scenario with our approach. Fig. 3(a) shows the averaged signals for target vs. non-target trials while Fig. 3(b) shows the average from a standard oddball task for comparison. We are able to show that single-trial classification is feasible though the accuracies stay currently below those achieved in a standard P300-based BCI.

In the future we plan to extend our system to a fully on-line operation mode.



(a)



(b)

Figure 3: (a) Averaged signals for target vs. non-target trials in HRI paradigm. The continuous data stream was segmented according to ASIMO's movement onsets. (b) Averaged signals for target vs. non-target trials in standard oddball paradigm.

References

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