Classification method
for Brain-Computer Interface

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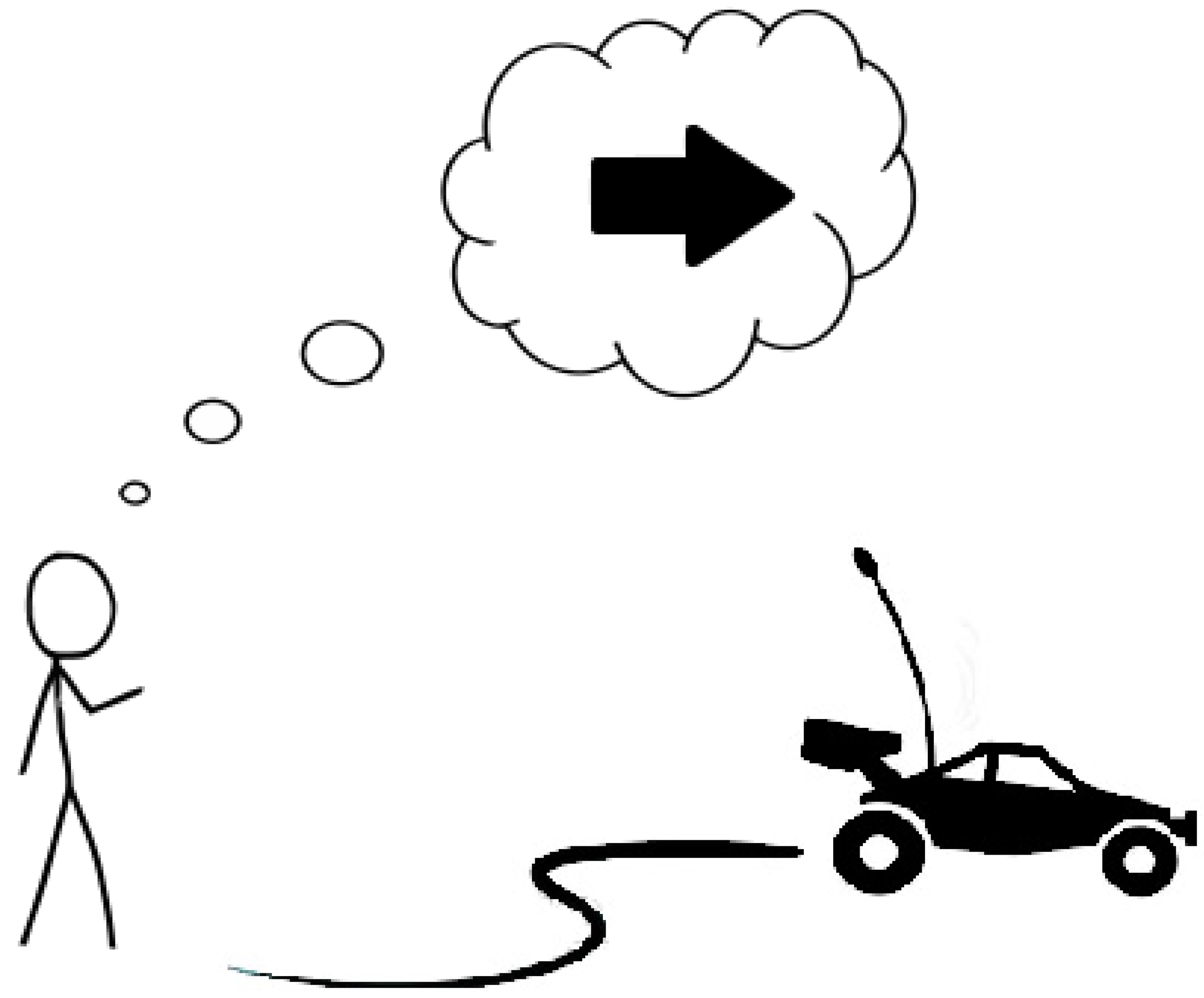
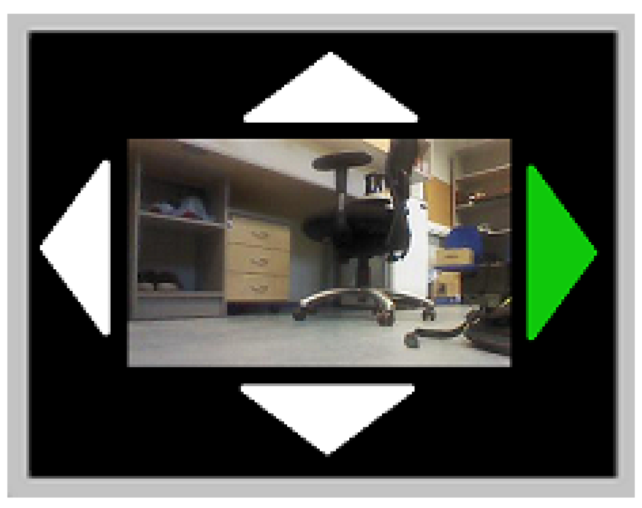
BRAIN-COMPUTER INTERFACE



In this project, a classification method for brain-computer interface (BCI) was proposed. BCI is a direct communication channel between the brain and an external device, which does not rely on standard input methods like pushing buttons. Instead, the commands are read out directly from the user's brain. Reliable BCIs would be particularly beneficial for severely disabled people who could use them to control electric wheelchairs or other devices.

STEADY-STATE VISUAL EVOKED POTENTIAL

The classification method proposed in this work is for steady-state visual evoked potential (SSVEP) based BCIs. SSVEP-based BCIs work by displaying visual stimuli that are called targets on a computer screen and tries to detect which of the targets the user is looking at. Each target corresponds to different command that the user can send to the device. In the figure below there is an example of how a BCI could present visual stimuli on a computer screen along with a video stream from the device can be seen (right) and an example of brain consumer-grade brain imaging device Emotiv EPOC that can be used in SSVEP-based BCIs (left).



FEATURE EXTRACTION

To detect the brain's response to different stimuli, feature extraction methods are used. The BCI implemented as a practical part of this work has five feature extraction methods: power spectral density analysis, canonical correlation analysis, continuous wavelet transform, likelihood ratio test and minimum energy combination.

The features extracted by these methods are used by the proposed classifier. Each method extracts a feature for each target and larger feature value for a target means that the target is more likely to be the users choice.

PROPOSED CLASSIFICATION RULE

Notation:

- n classes $\{1, 2, \ldots, n\}$,
- n features $\{f_1, f_2, \ldots, f_n\}$,
- n thresholds $\{t_1, t_2, \ldots, t_n\}$.

A sample is classified as class k if $f_k \geq t_k$ and $f_j < t_j$ for $j \in \{1, \ldots, n\} \setminus k$.

PERFORMANCE MEASURE

In the proposed classification method, the thresholds t_k are chosen so that they maximise a performance measure of the BCI. The proposed method requires estimating online mean detection time (MDT) of the BCI which is estimated using the proportion of predictions made to all samples on training set p, the window length w and time step between consecutive feature extractions s

$$\mathrm{MDT} = w + \left(\frac{1}{p} - 1\right) \cdot s.$$

Amount of information transferred with one prediction can be calculated using mutual information between the correct class C and predicted class P, both of which are random variables

$$I(P, C) = \sum_{i=1}^{n} \sum_{j=1}^{n} \mathbf{P}(P_i \cap C_j) \log_2 \left(\frac{\mathbf{P}(P_i \cap C_j)}{\mathbf{P}(P_i) \cdot \mathbf{P}(C_j)} \right),$$

where P_i and C_j denote the events that predicted class is i and correct class is j respectively. Finally, the thresholds are chosen so that they maximise the performance measure

$$\mathrm{ITR} = I(P, C) \cdot \frac{60}{\mathrm{MDT}}.$$

MAXIMISING THE PERFORMANCE MEASURE

By making assumptions on the distribution of features, the mutual information $I(P, C)$ can be calculated using the cumulative distribution functions (CDFs) of their distributions and the proportions of correct classes. Therefore, the performance measure ITR can be represented as a function of thresholds t_k and finding optimal thresholds can be represented as maximisation task

$$\arg\max_{\vec{t}} \mathrm{ITR}(\vec{t})$$

where $\vec{t} = (t_1, \ldots, t_n)$. This maximisation task was solved using gradient descent in this work, which also requires calculating the gradient of $\mathrm{ITR}(\vec{t})$.

RESULTS AND CONCLUSION

The proposed method was tested using publicly available SSVEP dataset by Bakardjian *et al.* [1]. The results can be directly compared to two other articles where the same dataset was used and where the classifier was able to not make predictions for some samples. See the table below.

	Classes	**Window length (s)**	**MDT (s)**	**Accuracy**	**ITR**
This work	3	1	1.5	83%	37.82
[2]	3	N/A	8.4	88%	8.15
[3]	2	1	N/A	74%	16

In this work a classification method for SSVEP-based BCI was proposed that uses threshold for classification, which are chosen so that they maximise a performance measure. The method shows good results when comparing to previously reported results. For future work, the classifier should be also tested online because in this work only offline testing was performed.

[1] H. Bakardjian, T. Tanaka, and A. Cichocki. Optimization of SSVEP brain responses with application to eight-command Brain-Computer Interface. Neuroscience Letters, 469(1):3438, 2010. http://www.bakardjian.com/work/ssvep_data_Bakardjian.html. (24.04.2017).
[2] A. F. Demir, H. Arslan, and I. Uysal. Bio-inspired Filter Banks for SSVEP-based Brain-computer Interfaces. In 2016 IEEE International Conference on Biomedical and Health Informatics (BHI), Las Vegas, NV, USA, 2016.
[3] M. Jukiewicz and A. Cysewska-Sobusiak. Implementation of Bilinear Separation algorithm as a classification method for SSVEP-based brain-computer interface. Measurement Automation Monitoring, 61(2):5153, 2015
Emotiv EPOC picture: http://www.arts-numeriques.info/emotiv-epoc/
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