Machine Learning for BCI and Games

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Abstract

BCI gaming is a very young field; most games are proof-of-concepts. Work that compares BCIs in a game environments with traditional BCIs indicates no negative effects, or even a positive effect of the rich visual environments on the performance. The low transfer-rate of current games poses a problem for control of a game. This is often solved by changing the goal of the game. Multi-modal input with BCI forms an promising solution, as does assigning more meaningful functionality to BCI control.

1. State of the Art

Work	Type	Para.	Sens.	NS	NC	A	b/min
Wang et al. [2007]	Game	?	E				
Sobell and Trivich [1989]	Vis.	F	E				
Nelson et al. [1997]	Game	F	E, M				
Allanson and Mariani [1999]	Game	F	E				
Cho et al. [2002]	VR	F	E	3	2		
Tschuor [2002]	Vis.	F	E	32	2	85%	7.9
Hjelm [2003], Hjelm et al. [2000]	Game	F	E				
Palke [2004]	Game	F	E	1			
Mingyu et al. [2005]	Game	F	E	3	1D		
Kaul [2006]	Vis.	F	E, M, O	3			
Lin and John [2006]	Game	F	E	1			
Shim et al. [2007]	Game	F	E	4	2		
Bayliss and Ballard [2000]	VR	P300	E		2	85%	
Bayliss [2003]	VR	P300	E	5	2		
Bayliss et al. [2004]	VR	P300	E	7	2	85%	23.4
Vidal [1977]	Game	VEP	E	5	5	80%	180.0
Middendorf et al. [2000]	Game	VEP	E	2	3	88%	36.7
Lalor et al. [2005, 2004]	Game	VEP	E	2	2	80%	5.5
Martinez et al. [2007]	Game	VEP	E	6	5	96%	34.9
Pineda et al. [2003]	Game	M	E	3	1D		
Leeb et al. [2004]	VR	M	E	4	2	98%	6.1
Leeb and Pfurtscheller [2004]	VR	M	E		2		
Mason et al. [2004]	Game	M	E	12	2	97%	14.0
Leeb et al. [2005]	VR	M	E	6	2	92%	4.1
Kayagil et al. [2007]	Game	M	E	1	4	77%	6.5
Krepki et al. [2007]	Game	M	E	128	2	100%	30.0
Bussink [2008]	Game	M	E	32	4	45%	
Lehtonen et al. [2008]	Game	M	E	6	2	74%	5.2
Oude Bos and Reuderink [2008]	Game	M	E	32	3		

Table 1: *Overview of BCI games*

2. Conclusions

From describing the existing BCI games it becomes clear that the field of BCI and gaming is just starting to define itself. It is a bit disappointing that the oldest BCI game [Vidal, 1977] obtained the highest reported transfer rate. However, there are some promising observations to be made. Middendorf et al. [2000] report that users intensified the SSVEP by looking away slightly from the stimulus center. For the P300 response, types of stimuli presentation that are possibly more suitable for games are being explored by Bießmann [2006]. This seems to indicate that there is still room to improve stimulus presentation in ERP-BCI based games. With a few exceptions such as Brainball and the modulated Playstation$^{\mathrm{TM}}$ controller, BCI is used in a straight-forward way. In future games, BCI can be used to control extraordinary abilities of the avatars in the game; such as flying, psychokinesis, self healing or extra power [Fairclough, 2008]. Another way to make the BCI interact more with the game is by monitoring experience. Many people describe a certain video game experiences as "Flow" or a "Zen"-like experience (Pope and Palsson [2004], Chen [2007]). A brain-computer interfaced game can possibly interact more directly with this experience and improve the experience directly.

Abstract

When we want to use brain-computer interfaces (BCI) as an input modality for gaming, the setup procedure needs to be short. Therefore the user model has to be learned using small training sets. In this work we investigate how the common spatial patterns (CSP) algorithm, that is often used for imagined movement classification, generalizes for small training sets, how the performance changes over time, and how well CSP generalizes over persons.

3. Generalization of CSP

CSP finds a matrix W, satisfying Eq. 1.

$$\mathrm{Cov}(WX_1) = D \quad \text{and} \quad \mathrm{Cov}(WX_1) + \mathrm{Cov}(WX_2) = I \qquad (1)$$

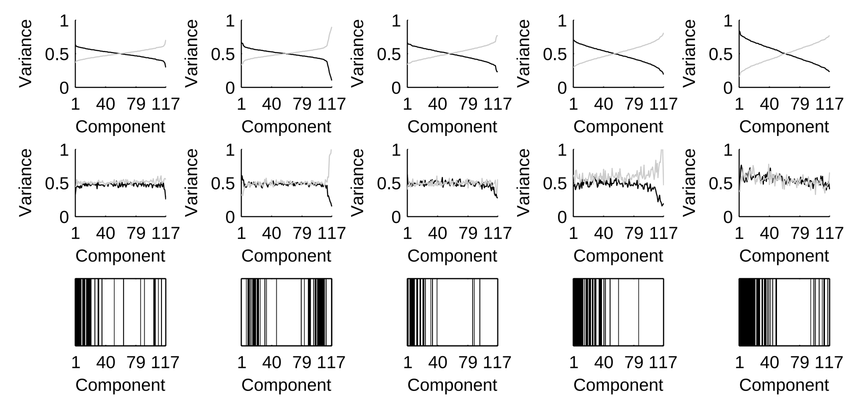

Figure 1: *Variances on the training set (first row), the test set (second row), and the generalization error (last row) for each subject. Black represents trials of the class "right hand", gray represents trials of the class "foot". When there is a significant difference between the component variances on the training and test set, a black bar is drawn for that component in the last row.*

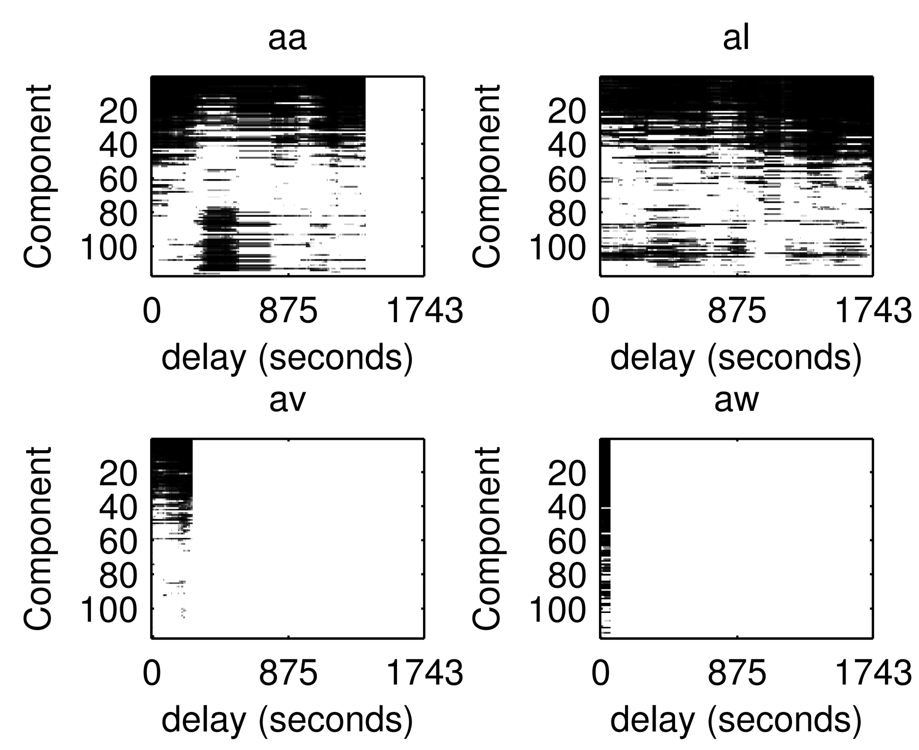

Figure 2: *Mean generalization error depending on the number of trials in the training set. In order to compare the performance of different subjects, all errors are plotted using the same time scale, which explains the white areas for all subjects except "al".*

4. Conclusions

Our first experiment showed that the CSP algorithm does overfit severely on small training sets. As expected, the generalization performance of the CSP algorithm improved when more trials were used in the training set.
The results of the second experiment show us that the variance of the CSP components are not stationary. There is no clear evidence of drifting; the performance does not constantly degrade over time, which we did expect.
Our third experiment shows that current generalization over subjects does not work very well. The most likely cause is the magnitude variations in the EEG that exist between individuals. Normalization could be used to improve the generalization over subjects.
For a convenient BCI, short training times are required. From our second experiment we know that variations in the variance of the CSP do occur. It is therefore unlikely that a short training period contains enough information to generalize over these variances. For future work we would recommend investigating the source of this drifting over time, perhaps the users change their imagery of the motor task, or the pattern changes in a way for which the CSP is not invariant. As the first and last components often seem to overfit on small training sets, we would recommend the use of feature selection to select discriminatory, generalizing features for classification.

Abstract

Brain-computer interaction (BCI) is starting to focus on healthy subjects. This research addresses the affects of using this novel input modality to control a simple game, and also looks into the beneficial effects of bringing game elements into BCI experiments. A BCI simple game has been developed and evaluated with fifteen subjects using the Game Experience Questionnaire (GEQ) developed at the Eindhoven Game Experience Lab. The game was developed by Danny Oude Bos, the online EEG-classifier was developed by Boris Reuderink.

5. BrainBasher

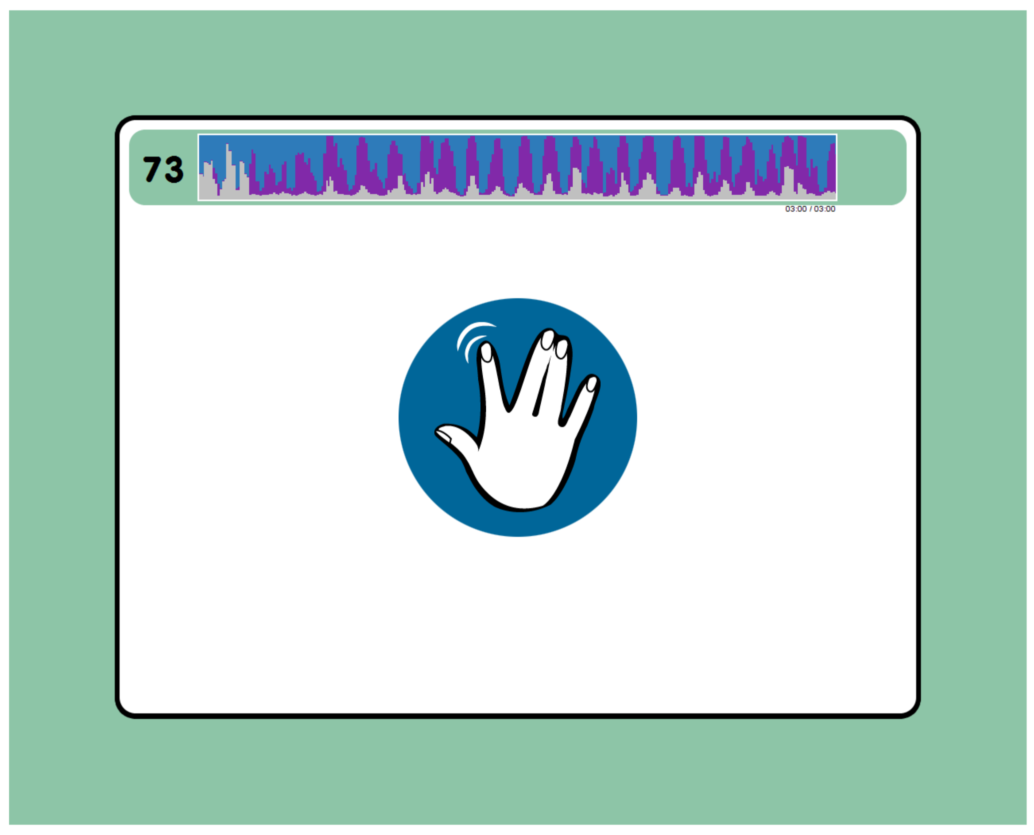

Figure 3: *Screenshot from the online BrainBasher game. The colorful bar shows the history of the classifiers predictions. Each colum represents the class-probabilities; purple represents the left hand, blue the right hand, and no action is represented by gray.*

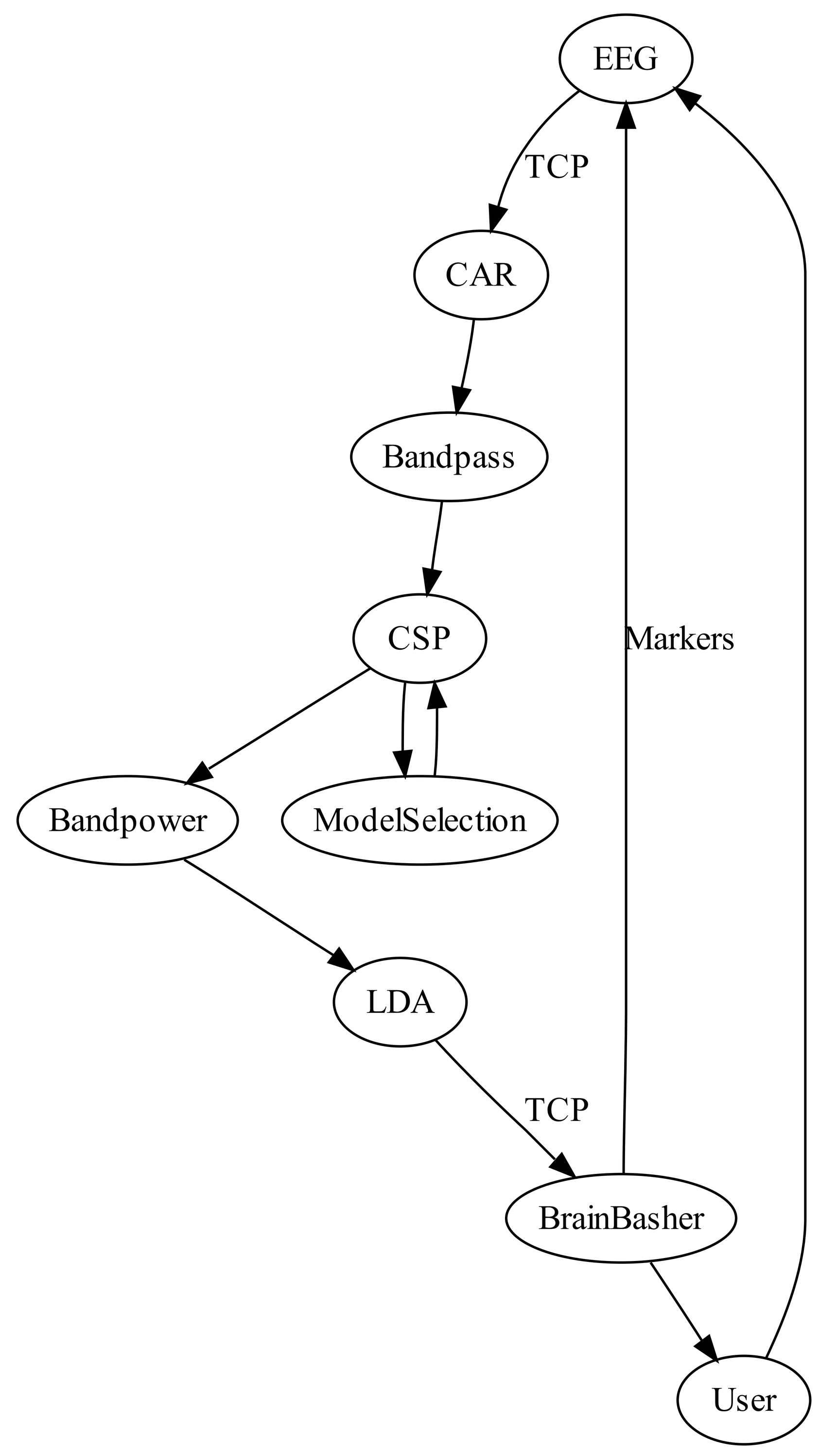

Figure 4: *The online BCI-pipeline*

6. Conclusions

We have a working BCI game. Future work should focus on making the classification more robust to artifacts and outliers.