Using OpenViBE to Test a Brain-Computer Interface Based on Motor Imagery

Mobility Semester Project Report
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Abstract

This study tested a brain-computer interface (BCI) based on motor imagery using the open-source software platform OpenViBE with the aim of future application to robot-assisted motor-neurorehabilitation of stroke patients. Two subjects were measured over eight weeks using 10-channel EEG performing kinesthetic motor imagery of index finger tapping, plus a third subject once. Each recording session was comprised of initial signal acquisition for classifier training followed by online training with neurofeedback. Individual baseline powers of two subjects as well as power spectrum comparisons in stimulus-sensitive recordings showed lateralized desynchronization of the mu-rhythm typically associated with motor imagery during the respective condition. Average motor imagery performances defined as classifier accuracies of 78 EEG recordings are presented and analyzed in terms of sensitivity to temporal and spatial filters, trial number, training progress, handedness, and neurofeedback. Finally, analysis results, a problem with CSP spatial filter, and further potential performance-influencing factors are discussed.

Keywords: *motor imagery, brain-computer interface, BCI, EEG, OpenViBE, neurofeedback, CSP*

Introduction

Motor cognition drawing on mirror neurons allows humans to rehearse motor acts without overt movements by muscular activity. This mental simulation, called *motor imagery*, “is assumed to involve to a large extent the same cortical areas that are activated during actual motor preparation and execution” (Neuper et al. 2009, p. 240). In particular, motor imagery is neurally represented as a desynchronization of the mu-rhythm (8-12 Hz) in EEG over motor cortical areas (Pfurtscheller et al. 2006).

Among its broad variety of application, motor imagery has proved to be an effective tool for neurological motor rehabilitation in stroke patients (Zimmermann-Schlatter et al. 2008, Vries & Mulder 2007, Silvoni 2011, Sharma et al. 2006).

This finding motivated an interdisciplinary group of researchers to launch a project under the title "Brain-computer interface with robot-assisted training for rehabilitation" (Rosipal 2012). Its ultimate goal is to facilitate the neurorehabilitation of stroke patients suffering from motor impairment in their arm by means of a robot-assisted system based on motor imagery.

One step towards this objective consists in building an interface that loads the mental effort of using one's imagination to simulate a particular motor act into software scenarios that read, translate, filter, process, and classify the incoming EEG data on brain activity. The real-time neurofeedback provided by this brain-computer interface (BCI) might then be used by motor-impaired stroke patients to cortically control an external device (a robotic arm) by performing motor imagery of arm motion, thus enabling robot-assisted physical therapy.

In the present study, the open-source software platform OpenViBE (Renard et al. 2010) was used to design and test such a BCI based on motor imagery.

The remainder of this paper is structured as follows. First, applied OpenViBE software scenarios and EEG recording procedures are described. Second, experimental data on motor imagery performance is presented and analyzed in terms of a two-dimensional classification. Lastly, I will discuss the results and potential performance-influencing factors.

METHODS

Two left-handed male subjects (age 25 and 47) were measured on a weekly basis using the EEG device g.USBamp 3.0 (g.tec) to record cortical brain activity through 10 electrodes placed on the scalp at areas FC3, C1, C3, C5, CP3, FC4, C2, C4, C6, and CP4 (plus two electrodes for ground and reference). Additionally on one day, a right-handed female subject (Subject 3, age 32) was measured. The EEG signal was fed into OpenViBE 0.18.0 where it was processed, classified, and used for real-time neurofeedback. The goal of these experimental recording sessions was to explore and fine-tune configurations of OpenViBE scenarios for motor imagery and to accumulate data on classification and motor imagery performance in order to maximize performance and classifier accuracies.

In the OpenViBE Acquisition Server, three configurations were found to be crucial: (1) "Sampling frequency" was set to 512 hertz because lower frequencies produced invalid signal data, (2) relevant channels were named and option "Select only named channels" checked, and (3) "Impedance Check" was unchecked as, in OpenViBE version 0.18.0, it interferes with the signal incoming from g.USBamp.

OpenViBE Designer comes with three basic BCI example scenarios for motor imagery, which constituted the structure of our experimental sessions: (1) signal acquisition, (2) classifier trainer (plus filter trainer when using CSP spatial filter), and (3) online measuring. In the latter two scenarios the "Reference Channel" box was omitted because the reference was calculated on the hardware side. Other than that, the structure of all three scenarios was kept unaltered (see Appendix A for a closer description).

The stimuli produced by Graz Motor Imagery BCI Stimulator (Pfurtscheller & Neuper

2001) were red arrows on a green cross pointing to the left or right (as well as a blue feedback bar in online training). The experimental task was to either physically tap or mentally simulate tapping the left or right index finger upon one stimulus type, and to relax upon the other. Mental simulation was done from the inside, i.e. kinesthetically, rather than visual imagery of finger tapping because the latter was found to impair BCI control performance (Neuper et al. 2005).

To analyze performances and calculate individual baseline powers, a further scenario was designed (see Fig. 1) that reads and processes a recorded EEG signal to store average power spectra in CSV files, which were then analyzed in Microsoft Excel and SPSS.

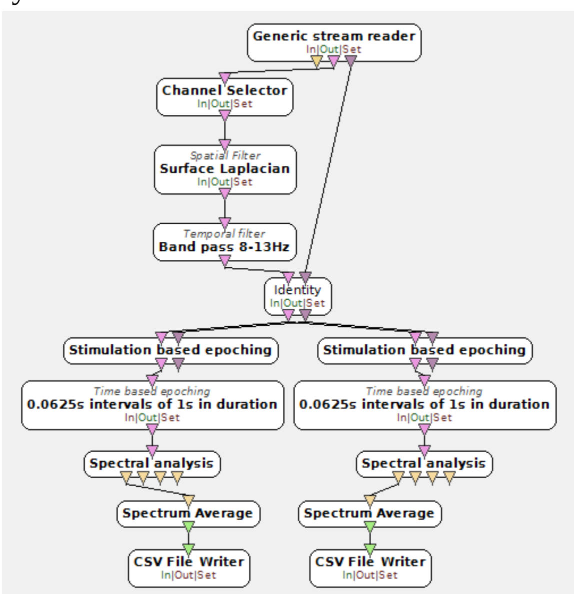


Figure 1. *OpenViBE scenario for power spectrum analysis of recorded EEG data.*

RESULTS

Individual baseline powers were tested by mentally simulating finger tapping on four trials followed by relaxing on four further trials while altogether ignoring the stimulus type. As motor imagery is “associated with a desynchronization of the *mu*-rhythm (8-12 Hz) in EEG over motor cortical areas” (Rosipal 2012, p. 7), we would expect decreased lateralized cortical power during the mental simulation of index finger tapping. Fig. 2 shows that each subject’s left finger tapping motor imagery was indeed associated with right-hemisphere lateralized mu-rhythm desynchronization. Although the same desynchronization graphically seems to be present in the relax condition as well, t-tests assured that “Motor Imagery right” (n = 196; Subject 1: M = 9.68, SD = 2.16; Subject 2: M = 8.59, SD = 2.12) differed significantly from “Relax right” (n = 196; Subject 1: M = 11.89, SD = 3.02; Subject 2: 11.81, SD = 4.09): $t(390) = -8.335$, $p < 0.001$ for Subject 1; $t(390) = -9.813$, $p < 0.001$ for Subject 2.

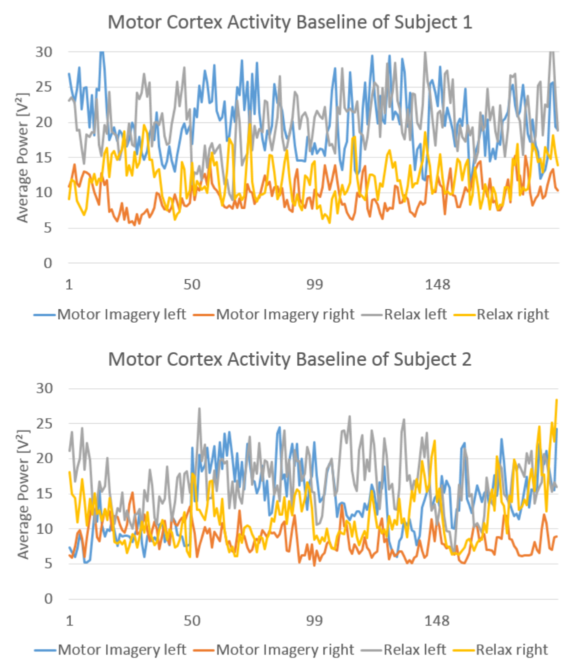


Figure 2. *Baselines of motor cortex activity for relaxing and left finger tapping motor imagery. X axis values denote the beginning of each trial consisting of 49 epochs, 4x49 in total for each condition. “Left/right” stands for the respective brain hemisphere.*

Power spectrum comparisons in stimulus-sensitive recordings confirm this lateralized desynchronization (see Fig. 3).

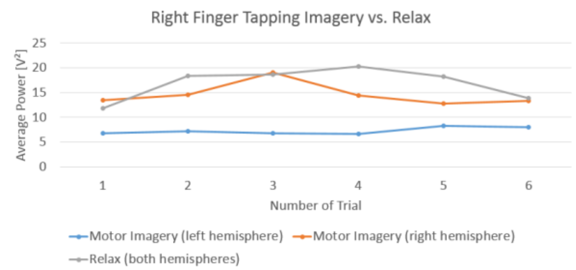


Figure 3. *Power spectrum analysis of an EEG recording on Subject 2 yielding 94.5% classifier accuracy with Laplacian spatial filter and band pass temporal filter (7.5-13.5 Hz). This measurement was done over 6 trials for each stimulus type: relaxing for arrows pointing to the left, right finger tapping imagery for arrows to the right, 12 trials in total. For "Relax" the average of both brain hemispheres was calculated because the respective power values were similar.*

Stimulus-sensitive classification was also reflected in an analysis of the logarithmic band powers of all processed signal blocks that were, after feature aggregation, fed to the classifier trainer module (see Fig. 4).

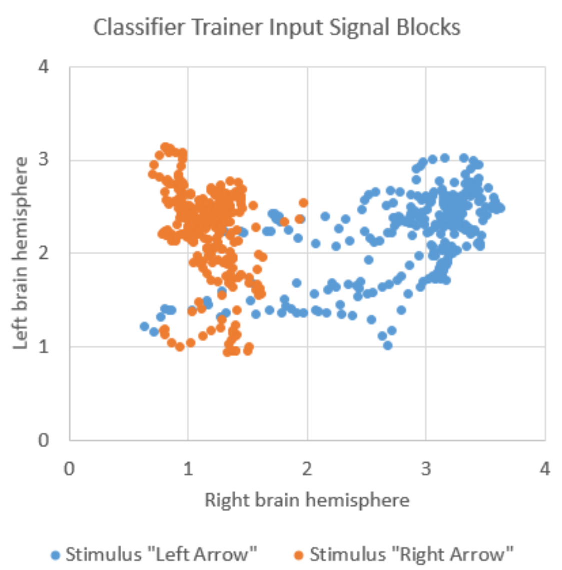


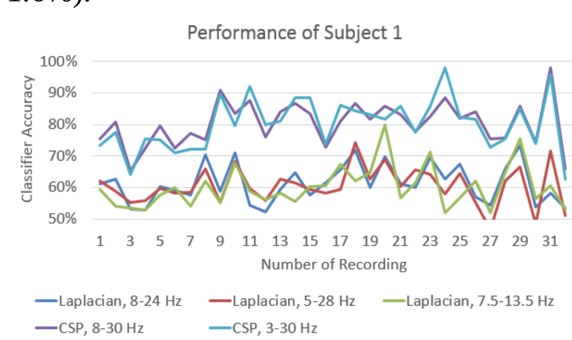
Figure 4. *Processed blocks of filtered signal as input to the classifier trainer module in an EEG recording over 2x6 trials yielding 94.5% classifier accuracy with Laplacian spatial filter and band pass temporal filter (8-13 Hz) showing two separated groups associated with two stimulus types: "left arrow" for relaxing, "right arrow" for right index finger tapping imagery. Logarithmic band powers of the left brain hemisphere are on the x axis, the y axis is for the right hemisphere.*

Overall, 78 recordings were taken: 32 on Subject 1, 39 on Subject 2, 7 on Subject 3 (see Appendix B for performances). Average classifier accuracies are presented in Table 1.

Classifier Accuracy	Laplacian & 8-24 Hz Band Pass Filter	CSP & 8-30 Hz Band Pass Filter
Subject 1	61.3%	80.4%
Subject 2	75.2%	90.3%
Subject 3	58.3%	86.2%

Table 1. *Average classifier accuracies (n = 78) in relation to different spatial and temporal filters as resulted from the OpenViBE classifier trainer scenario.*

Classifier accuracies were tested with two different spatial filters varying over, in total, five temporal filters (see Fig. 5). Although the choice of spatial filter had a crucial impact on classifier accuracy (19.1% mean difference for Subject 1, 15.1% for Subject 2, 27.9% for Subject 3), the mean differences resulting from changing the band pass temporal filter frequency range were insignificant (0.2-1.6%).



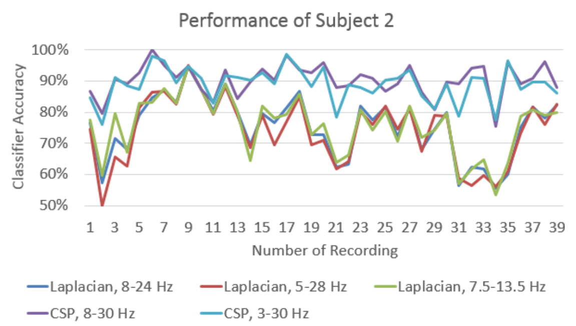


Figure 5. *Classifier performance accuracies in relation to different spatial and temporal filters as resulted from the OpenViBE classifier trainer scenario over 71 (32+39) recordings.*

Performance-dependent classifier accuracy was also found to be a function of trial number per recording: the lower the number of trials, the better the mean performance (see Fig. 6). Linear regression analysis showed that there was a significant decline in classifier accuracy as the number of trials increased: $F = 26.25$, $\beta = -0.683$, $t = -5.12$, $p < 0.001$ for Subject 1 using CSP filter; $F = 15.93$, $\beta = -0.565$, $t = -3.99$, $p < 0.001$ for Subject 2 using CSP filter; $F = 7.04$, $\beta = -0.310$, $t = -2.65$, $p = 0.01$ for Subject 1+2 using Laplacian filter.

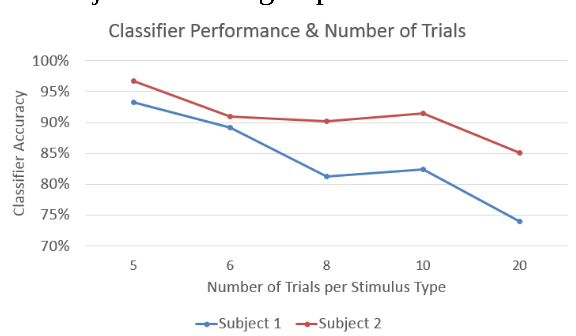


Figure 6. *Mean classifier performance accuracy using CSP spatial filter in relation to number of stimulus pairs per recording.*

Another linear regression analysis showed that there was no significant increase in performance over eight weeks of recording ($p > 0.05$ for Subject 1 and 2), no matter which data block was being looked at (all data vs. data from specific number of trials).

Independent samples t-tests comparing left against right finger motor imagery in terms of classifier accuracy produced insignificant results as well: $t(30) = -0.67$, $p = 0.51$ for Subject 1; $t(37) = -0.46$, $p = 0.65$ for Subject 2.

Lastly, t-tests comparing signal acquisition with online training trials in terms of classifier accuracy were also non-significant.

Discussion

This experiment cannot fully endorse the utility of the motor imagery scenarios in OpenViBE as a valuable tool for the use of a brain-computer interface based on the kinesthetic mental simulation of motor acts. On the one hand, power spectrum analysis results were congruent with the theory of lateralized mu-rhythm desynchronization. On the other hand, only two of three subjects received reliable neurofeedback during online training.

It was found that optimal BCI control performances expressed as classifier accuracies were reached when a CSP spatial filter was used to train the LDA classifier, whereas changing the band pass filter frequency range only had a minor impact.

In one control trial, Subject 1 kept relaxing over all trials while ignoring the stimuli. Training the classifier with this data set amounted to an expected accuracy of < 65% using Laplacian filter but surprising 79.72% using CSP filter. This incredible result, which has yet to be explained, does reflect subjective experiences of unreliable behavior of the Graz feedback bar despite high classifier accuracies with CSP filter.

Furthermore, the results suggest that keeping the number of trials per recording at a minimum maximizes BCI control performance, although too few (< 5-8) trials may not always suffice to train the classifier in the first place.

In contrast to other studies (Guger et al. 2000, Hwang et al. 2009), no significant improvement in performance of either subject was found over eight days of weekly recording. It remains an open question whether consecutive days of training would have had another effect and what individual factors might have inhibited gradual improvement.

The insignificant results of independent samples t-tests indicate that subjects' handedness was irrelevant and suggest that the neurofeedback received during online sessions may have neither been helpful for improving performance nor distracting.

BCI control performance might, however, be influenced by external factors such as mental fatigue, environmental conditions (e.g. ambient light), time of the day, mood, psychoactive drug (e.g., caffeine) intake, motor pattern rehearsal right before recording, et cetera. Yet none of those effects was researched systematically in this study.

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Appendix A: Motor Imagery BCI in OpenViBE

0) Signal Monitoring. This scenario should be used prior to the initial data acquisition as well as in the background during, or between, online sessions.

Its goal is to check the signal quality of the acquisition device by spotting eye blinks & jaw clenches (see Fig. I).

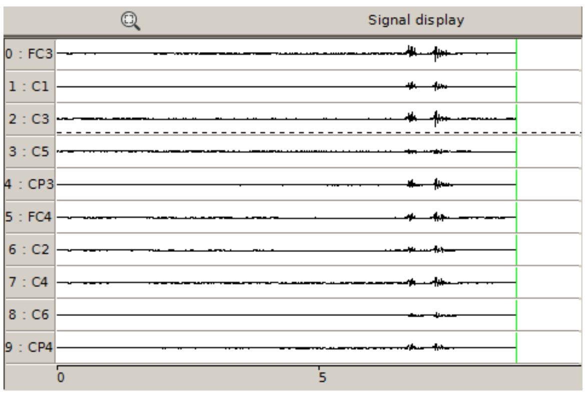

Figure I. *Jaw clenching in signal display of OpenViBE signal monitoring scenario.*

The input is an EEG signal from the Acquisition client (configure *hostname* & *port*).

The output is a display of two different EEG signal streams: (A) Filtered signals (configure *scaling* & *scan/scroll display*), (B) Raw signals (configure *scaling* & *scan/scroll display*).

The signal processing consists of: (A) Temporal filter to reduce the noise and filter out frequencies we're not interested in; configuration: (1) "Butterworth" *filter method* to get as flat a frequency response as possible, (2) "band-pass" *filter type* to limit passing frequencies within a certain range (defined by *low cut frequency* & *high cut frequency*), (3) *filter order* "4" to get a roll-off rate of 80dB/decade (24dB/octave), (4) *pass band ripple* of "0.5dB" to allow the gain in the pass-band to vary slightly from unity, (B) Identity to forward the signal by duplicating input on its output (the only difference to not using this box is that the two output signals appear, when displayed, together in a single window).

1) Initial Data Acquisition. The goal of this scenario is to collect some data for training the classifier.

The input is: (A) Acquisition client to forward the EEG signal (incl. experiment information) from the acquisition device (configure *hostname* & *port*), (B) Graz Motor Imagery BCI Stimulator to load an lua script for producing visual stimuli; configuration: set path to the directory of the *lua script*, set *number of trials for each class*, label the two classes (*first class*, *second class*), *baseline duration* defines the time before the first cue appears (e.g., "20" means that the first cue appears after 30 (= 20+10) seconds), time specifications for *Beep*, *Cue*, *Feedback*, *End of Trial*, etc.

The output is: (A) Graz visualization to display the visual stimuli generated by the Graz Motor Imagery BCI Stimulator on the monitor (configure display of *instruction* & *feedback*): green cross directs attention, red arrows pointing left or right dictate which motor action/imagery to perform, (B) Player Controller to enable termination of the experiment (configure *stimulation name* & *action to perform* (e.g., "Stop")), (C) Generic stream writer to store the EEG signal (incl. experiment information) plus BCI stimulations in an ov file (configure *filename* & *compression*)

The signal processing part consists only of Identity to forward the signal by duplicating input on its output, thus making the scenario structure more lucid.

2) Classifier Training. The goal of this scenario is to use the so far collected data for training a classifier to detect—real-time in a later given online EEG signal stream—two different types of movement (e.g., left vs. right hand movement, or finger movement vs. relaxing). At the end of training, the estimated classifier performance will be printed in the console: if it is below 65%, repeat scenarios 1 and 2.

The input is GENERIC STREAM READER to load the ov file created in the previous scenario (configure *filename*) and output the EEG signal plus BCI stimulations.

The output is PLAYER CONTROLLER ending the scenario once the classifier has been trained (configure *stimulation name* & *action to perform* (e.g., “Stop”)).

The signal processing consists of: (I) preprocessing: (A) REFERENCE CHANNEL to subtract the value of the reference channel from all other channels; configuration: *channel* name (e.g., “Nz”—the channel located on the nose/ear), *channel matching method*: “Smart” by default (“Name” has, at least in this scenario, the exact same effect, but with “Index” no channel is displayed anymore), (B) CHANNEL SELECTOR to select the channels that are to be classified; configuration: *channel list* (e.g., all channels over the motor cortex), *action*: “Select”, not “Reject”, *channel matching method*: same as with Reference Channel, (C) SURFACE LAPLACIAN: a spatial filter that maps all selected channels (*number of input channels*) to “2” output channels (*number of output channels*) representing the two brain hemispheres by multiplying each input vector with a matrix consisting, here, of 20 values (*spatial filter coefficients*), (D) TEMPORAL FILTER to reduce the noise and filter out frequencies we’re not interested in (configuration as in scenario 0); (II) feature extraction (in this part, all boxes are set twice, once for each type of stimuli): (A) STIMULATION BASED EPOCHING to forward EEG epochs dependent on the instructions given, i.e., one box forwards “4” seconds of signal after an arrow pointing to the left was shown, whereas the other box forwards epochs related to arrows to the right (configure *epoch duration*, *epoch offset* & *stimulation* type), (B) TIME BASED EPOCHING to split the epochs into one-second blocks 16 times per second, (C) SIMPLE DSP to apply a mathematical formula (*equation*) for squaring every incoming signal block (“x*x”), (D) SIGNAL AVERAGE to compute the average of every incoming sample buffer, (E) SIMPLE DSP to apply a mathematical formula (*equation*) for the third and final step of computing the logarithmic band power of every incoming signal block in order to better identify power variations, (F) FEATURE AGGREGATOR to convert every incoming matrix into a feature vector that can be used for classification (it merely shifts all values into one column); (III) the CLASSIFIER TRAINER produces—from the BCI stimulations and the two feature vector inputs (one for each class)—a cfg (configuration) file which will be used in the next scenario (online session); configuration: choose *strategy to apply*: “Native” means that all data is passed to a single classifier trainer without a pairwise strategy (see OpenViBE online documentation for more info), choose *algorithm to use*: e.g., “Linear Discriminant Analysis (LDA)”, define *filename to save configuration to*, specify the stimulation that triggers the training process (*train trigger*), set *number of partitions for k-fold test* that estimates the accuracy of the learned classifier (see OpenViBE online documentation for further description), specify a *reject class label* for a stimulation reflecting that the feature vector could not be classified, label the two classes (*Class 1 label*, *Class 2 label*).

3) Online Session. The goal of this scenario is to use the trained classifier and an online EEG signal for providing real-time visual feedback and for acquiring experimental data on motor imagery.

The input is the same as in scenario 1.

The output is: (A) GENERIC STREAM WRITER to store the EEG signal (incl. experiment information) plus BCI stimulations in an ov file (configure *filename* & *compression*), (B) GRAZ VISUALIZATION to display the visual stimuli generated by the BCI Stimulator (see scenario 1) including blue, length-changing bars (left or right) for real-time feedback provided by the Classifier Processor as a streamed matrix.

The signal processing consists of: (I) preprocessing: same as in scenario 2, (II) feature extraction: same as in scenario 2 yet without Stimulation based epoching because the signal need not be split up in terms of stimuli type, (III) the CLASSIFIER PROCESSOR classifies the incoming feature vector and outputs a streamed matrix (a positive value for one class and a negative value for the other class) for visual feedback through Graz visualization, (IV) SIMPLE DSP: this box is redundant as long as we use the LDA classifier—if we used a SVM classifier instead, we would need (to modify) this box to shift the values received from the Classifier processor by -0.5.

4) Replay. The goal of this scenario is to quickly replay an online session recorded file.

The input is a GENERIC STREAM READER that loads the ov file created in the previous scenario (configure *filename*) and outputs the EEG signal plus BCI stimulations.

The output is GRAZ VISUALIZATION (see scenario 3).

The signal processing is the same as in scenario 3.

APPENDIX B: LIST OF CLASSIFIER ACCURACIES [%] OF ALL MEASUREMENTS

10-Channel EEG Recordings	**Laplacian Filter**			**CSP Filter**	
(Online_)Condition_StimulusResponse_Subjectname_Trial#-[Date-Time]	**8-24Hz**	**5-28Hz**	**7.5-13.5Hz**	**8-30Hz**	**3-30Hz**
tapping_leftrelax_Igor_all-[2014.12.18-16.17.12].ov	61.22	61.94	59.44	75.41	73.21
online_tapping_leftrelax_Igor_all-[2014.12.18-16.28.40].ov	62.65	58.67	54.13	80.61	77.60
imagery_leftrelax_Igor_all-[2014.12.18-16.41.43].ov	53.11	55.10	53.47	65.20	64.23
online_imagery_leftrelax_Igor_all-[2014.12.18-16.41.43].ov	52.96	55.97	53.01	72.55	75.31
tapping_leftrelax_Igor_all-[2015.01.08-16.18.02].ov	60.36	59.69	57.65	79.59	75.26
imagery_leftrelax_Igor_all-[2015.01.08-16.26.37].ov	59.13	58.21	60	72.5	70.87
online_tapping_leftrelax_Igor_all-[2015.01.08-16.37.54].ov	57.7	58.37	54.13	77.09	72.19
online_imagery_leftrelax_Igor_all-[2015.01.08-16.46.39].ov	70.46	66.02	61.94	75.15	72.19
tapping_leftrelax_Igor_6trials-[2015.01.20-14.18.00].ov	58.84	55.27	55.16	90.82	89.63
imagery_leftrelax_Igor_8trials-[2015.01.20-14.28.18].ov	71.09	68.2	67.69	83.5	79.59
online_imagery_leftrelax_Igor_6trials-[2015.01.20-14.28.18].ov	54.25	59.56	58.84	87.59	92.01
imagery_leftrelax_Igor_8trials-[2015.01.20-14.42.36].ov	52.3	55.88	56.12	76.15	79.97
imagery_leftrelax_Igor_10trials-[2015.01.20-14.49.23].ov	59.29	62.65	58.16	84.08	81.02
imagery_leftrelax_Igor_8trials-[2015.01.20-15.00.08].ov	64.67	61.61	55.48	86.74	88.52
tapping_leftrelax_Igor_8trials-[2015.01.27-16.31.18].ov	57.65	59.44	60.33	83.55	88.52
imagery_relaxright_Igor_8trials-[2015.01.27-16.42.10].ov	61.48	58.16	60.71	72.7	73.6
tapping_relaxright_Igor_8trials-[2015.01.27-16.47.01].ov	65.56	59.31	67.47	80.99	86.22
imagery_leftrelax_Igor_8trials-[2015.02.03-12.45.00].ov	71.81	74.11	62.12	86.61	84.44
imagery_leftrelax_Igor_8trials-[2015.02.03-12.50.21].ov	60.08	62.75	64.8	81.51	83.04
imagery_relaxright_Igor_8trials-[2015.02.03-12.58.38].ov	69.77	68.75	79.77	85.84	81.76
online_imagery_relaxright_Igor_8trials-[2015.02.03-13.12.42].ov	61.22	60.2	56.76	83.16	85.84
imagery_leftrelax_Igor_8trials-[2015.02.03-13.18.29].ov	60.08	65.64	61.48	77.93	77.55
imagery_relaxright_Igor_8trials-[2015.02.12-15.27.38].ov	69.39	64.16	71.17	82.53	85.84
online_imagery_relaxright_Igor_5trials-[2015.02.12-15.33.13].ov	62.65	57.96	52.04	88.57	97.96
online_imagery_relaxright_Igor_8trials-[2015.02.12-15.38.44].ov	67.47	64.54	56.76	82.02	82.14
online_imagery_relaxright_Igor_10trials-[2015.02.12-15.46.08].ov	57.14	55.2	61.94	83.98	81.73
online_imagery_relaxright_Igor_20trials-[2015.02.12-15.53.03].ov	54.39	46.79	51.94	75.46	72.81
imagery_leftrelax_Igor_10trials-[2015.02.19-16.07.08].ov	66.02	61.94	64.69	75.61	75.31
imagery_leftrelax_Igor_10trials-[2015.02.19-16.13.45].ov	73.27	66.43	75.31	85.92	85
online_imagery_leftrelax_Igor_8trials-[2015.02.19-16.20.24].ov	53.83	48.34	56.38	74.23	73.98
online_imagery_leftrelax_Igor_5trials-[2015.02.19-16.27.00].ov	58.16	71.43	60.61	97.96	95.92
online_imagery_leftrelax_Igor_20trials-[2015.02.19-16.35.05].ov	53.32	50.97	53.11	66.02	62.76
tapping_leftrelax_Dominic_all-[2015.01.08-15.15.36].ov	76.48	74.39	77.5	86.58	84.54
imagery_leftrelax_Dominic_all-[2015.01.08-15.24.43].ov	57.4	50	59.75	79.69	75.97
online_imagery_leftrelax_Dominic_all-[2015.01.08-15.39.13].ov	71.68	65.56	79.54	90.66	91.02
online_tapping_leftrelax_Dominic_all-[2015.01.08-15.49.14].ov	67.91	62.7	67.04	89.08	88.37
imagery_relaxright_Dominic_only10trials-[2015.01.13-14.56.13]	78.95	81.42	82.81	92.48	87.33
imagery_relaxright_Dominic_only5trials-[2015.01.13-15.21.23]	84.69	86.33	83.06	100	97.96

imagery_relaxright_Dominic_6trials-[2015.01.13-15.40.54]	86.9	86.73	87.56	94.9	96.6
imagery_relaxright_Dominic_10trials-[2015.01.13-15.45.29]	83.16	82.45	82.76	91.23	89.49
online_imagery_relaxright_Dominic_6trials-[2015.01.13-16.04.49]	94.56	94.9	94.56	94.56	94.73
online_imagery_relaxright_Dominic_6trials-[2015.01.13-16.09.11]	87.42	87.25	87.25	87.42	90.82
online_imagery_relaxright_Dominic_10ch_20trials-[2015.01.13-16.13.40]	80.31	79.18	79.49	83.01	82.7
online_imagery_relaxright_Dominic_10ch_6trials-[2015.01.13-16.30.49]	88.95	88.27	88.95	93.54	91.84
online_imagery_relaxright_Dominic_10ch_6trials-[2015.01.13-16.42.14]	80.27	78.91	80.27	84.18	90.99
online_imagery_relaxright_Dominic_10ch_6trials-[2015.01.20-15.22.21].ov	69.56	68.71	64.29	89.63	90.14
online_imagery_relaxright_Dominic_10ch_6trials-[2015.01.20-15.27.27].ov	79.59	79.08	81.97	93.71	92.52
online_imagery_relaxright_Dominic_10ch_6trials-[2015.01.20-15.32.26].ov	76.53	69.39	78.06	90.31	89.12
imagery_leftrelax_Dominic_7trials-[2015.01.20-15.41.28].ov	81.2	76.97	79.15	98.25	98.4
imagery_leftrelax_Dominic_7trials-[2015.01.20-15.41.28].ov	86.73	84.99	85.71	93.59	93.88
online_imagery_leftrelax_Dominic_10ch_7trials-[2015.01.20-15.56.22].ov	72.74	69.39	72.74	92.57	88.19
tapping_leftrelax_Dominic_8trials-[2015.01.27-15.39.19].ov	72.7	71.05	76.4	95.92	94.52
imagery_leftrelax_Dominic_8trials-[2015.01.27-15.44.52].ov	62.24	61.73	63.9	87.88	78.44
imagery_relaxright_Dominic_8trials-[2015.01.27-15.50.20].ov	63.25	64.03	66.2	88.39	88.78
tapping_relaxright_Dominic_8trials-[2015.01.27-15.55.33].ov	82.02	80.1	80.61	92.09	87.88
imagery_relaxright_Dominic_8trials-[2015.01.27-16.01.08].ov	77.55	76.15	74.11	90.69	85.97
online_tapping_relaxright_Dominic_8trials-[2015.01.27-16.12.04].ov	81.63	81.89	80.23	86.73	90.31
online_imagery_relaxright_Dominic_8trials-[2015.01.27-16.18.47].ov	72.19	74.45	70.54	89.16	90.69
imagery_leftrelax_Dominic_8trials-[2015.02.03-10.46.57].ov	81.76	80.99	81.89	95.03	93.37
online_imagery_leftrelax_Dominic_20trials-[2015.02.03-10.55.52].ov	68.06	67.45	71.84	86.35	85.2
online_imagery_leftrelax_Dominic_8trials-[2015.02.03-11.10.46].ov	74.62	78.95	74.36	80.61	81.12
online_imagery_leftrelax_Dominic_8trials-[2015.02.03-11.27.28].ov	79.72	78.57	79.46	89.54	89.16
imagery_leftrelax_Dominic_10trials-[2015.02.12-13.29.45].ov	56.43	58.67	57.14	89.08	78.78
imagery_leftrelax_Dominic_5trials-[2015.02.12-13.36.00].ov	62.45	56.53	61.63	94.08	91.02
online_imagery_leftrelax_Dominic_8trials-[2015.02.12-13.41.45].ov	61.86	59.82	64.67	94.64	90.94
online_imagery_leftrelax_Dominic_20trials-[2015.02.12-13.56.27].ov	55.51	56.22	53.42	75.46	77.55
online_imagery_leftrelax_Dominic_10trials-[2015.02.12-14.13.01].ov	60.1	60.92	63.47	95.92	96.43
imagery_leftrelax_Dominic_10trials-[2015.02.19-15.20.23].ov	75	73.37	78.57	88.98	87.24
online_imagery_leftrelax_Dominic_8trials-[2015.02.19-15.29.51].ov	81.76	81.51	80.87	90.94	89.67
online_imagery_leftrelax_Dominic_5trials-[2015.02.19-15.35.46].ov	78.16	76.12	78.98	96.12	89.59
online_imagery_leftrelax_Dominic_20trials-[2015.02.19-15.39.55].ov	82.09	82.55	79.8	87.86	85.97
tapping_relaxright_Barbora_8trials-[2015.02.12-12.22.27].ov	55.23	56.25	51.53	74.62	80.99
imagery_relaxright_Barbora_8trials-[2015.02.12-12.29.40].ov	61.48	62.12	64.8	91.96	90.69
online_imagery_relaxright_Barbora_8trials-[2015.02.12-12.38.43].ov	52.42	59.18	52.17	87.12	89.54
online_imagery_relaxright_Barbora_5trials-[2015.02.12-12.44.44].ov	66.12	61.02	52.65	93.88	95.71
online_imagery_relaxright_Barbora_20trials-[2015.02.12-12.53.41].ov	60.41	55.51	57.86	84.8	80.46
online_imagery_relaxright_Barbora_6trials-[2015.02.12-13.03.39].ov	55.95	57.31	50.85	79.59	84.18
online_imagery_relaxright_Barbora_10trials-[2015.02.12-13.08.31].ov	56.53	54.08	50.92	91.73	88.98