# Towards Operator Monitoring via Brain Reading - An EEG-based Approach for Space Applications

Elsa Andrea Kirchner[*,**], Hendrik Woehrle[*], Constantin Bergatt[*], Su Kyoung Kim[*,**], Jan Hendrik Metzen[**], David Feess[*], and Frank Kirchner[*,**]

[*]Robotics Innovation Center (RIC),
German Research Center for Artificial Intelligence (DFKI GmbH), Germany

[**]Robotics Lab, University of Bremen, Germany

e-mail: elsa.kirchner@dfki.de

**This is a modified manuscript for publication on the author's website.**

## Abstract

In today's space applications, astronauts have to perform a variety of tasks. An intelligent on-board monitoring system that ensures uninterrupted, on time monitoring of the astronauts would be a great support. In this paper we want to introduce a new approach for the use of single trial analysis of the human electroencephalogram (EEG) that gives insight into the cognitive state of the operator. This passive monitoring is called brain reading (BR). We discuss the suitability of BR for operator support in space applications regarding the achieved kind and effectiveness of assistance. Further on, solutions for method-depending constraints like the acquisition of training data as well as the the need for software and hardware improvements that will allow the integration of BR in real space applications in the future, are explained.

## 1 Introduction

Today's Man Machine Interfaces (MMIs) are widely used in different areas of life. Most MMIs support humans to interact with machines like PCs, robots, or prosthesis. Seldom these interfaces are used to give the machine insight into the human to allow a better understanding of his or her intention. In some cases, this is done in a way that the human has to communicate actively with the machine. This active communication in form of speech, gesticulation, mimic expression, or the use of special input devices demands, inter alia, cognitive resources of the user. Since cognitive capacities are limited it is of high interest to search for new ways for MMIs that allow the machine to get better insight into the human's cognitive state and to understand their demands in certain situations without deploying extra cognitive efforts.

A special form of MMIs are Brain Computer Interfaces (BCIs) [17] that allow the human to control PCs or machines directly by brain activity. BCIs are motivated by the need to enable individuals who cannot use any motor system (e.g. *locked-in* patients) to communicate [3, 4]. For several decades scientists have been working on improving these interfaces regarding speed and accuracy. In BCIs, patients do actively produce certain brain activity that is used as a kind of control signal. The production of this brain activity is, in the majority of BCI applications, not directly linked to the initiated action of the machine. For example, EEG activity induced by the imagination of right and left hand movements could be used as a control signal to open or close a hand prosthesis [6] or choose a certain letter within a spelling device application [11]. Approaches to enhance an astronaut's capabilities in space application by utilizing that kinds of BCIs in space have been discussed [16]. However, regardless of which type of brain activity is used as control signal, it is always directly linked to an action of the machine or computer, which constitutes a problem for the usage of these kinds of BCI systems in critical situations (see also [16]).

In this paper, we discuss BR as a new approach of operator support that is based on the passive monitoring of EEG data. The most critical difference to classical BCI is that in BR, brain activity is no longer directly linked to an action of a machine. Instead, it gives insight into processes that take place unconsciously but can be observed by BR. We will discuss why this, among other differences, makes BR usable for space applications, focussing on questions regarding training data acquisition, transferability of models as well as the dealing with incorrect classification results which are unavoidable in single trial EEG analysis. To integrate BR systems into application scenarios, further software and hardware developments have to be tackled. Methods are introduced that speed up EEG-data single trial analysis, since fast data processing is a prerequisite for EEG-data based predictions regarding the mental or cognitive state of the subject, which could be used for, e.g., subject-centered control decisions like situation-specific operator warnings or general adjustments of the operator support system. Further on we will discuss developments in EEG acquisition and analysis hardware.

## 2 Brain reading

In the following, we introduce BR for the usage of operator support in space applications. After a discussion of the advantages of BR, an example will be given to explain methods and challenges that have to be addressed to make BR usable for space applications.

### 2.1 Advantages of brain reading for MMI

For the use of brain activity in MMI it is fundamental that one can differentiate between states of the subject that are correlated with certain brain activity patterns. Those patterns are quite often overlaid by stronger brain activity that does not correlate with the searched mental or cognitive state of the subject. Besides, even the state-specific brain activity itself is different for different subjects and depends, for example, on the subject's training status or on the stress level in a given situation. Therefore it is not possible to achieve 100 percent correct classification results even by using machine-learning methods combined with certain strategies that do improve adaptability (see, e.g., [1]). Due to this, brain activity cannot always be interpreted correctly. Therefore, classical BCIs that link brain activity directly to actions of a PC or a machine are only of limited suitability for space applications, since a misinterpretation of brain activity leads directly to unwanted action, which could possibly lead to uncontrollable situations (see [16] for a discussion).

However, EEG data could be used in a different way. Instead of using brain activity to directly control machines, one could analyze EEG data in a way that allows insight into the current mental and cognitive state of the subject such as, e.g., in the case of EEG-based lie detectors where brain activity can be used to prove the correctness of statements of subjects in criminal investigations [5]. Here the subject does not produce brain activity for artificially creating a control signal. On the contrary, brain activity is directly correlated with the situation-dependent cognitive state of the subject. However, in this example, misclassifications, which are not avoidable with today's methods for single trial EEG analysis, might still lead to critical wrong decisions. To avoid this, a carefully chosen set of rules has to be defined for each application and has to be implemented into a context-sensitive control system.

Our approach is therefore to analyze brain activity, using the electroencephalogram to obtain insights into cognitive and mental states of a subject, and hence to facilitate a passive monitoring, called brain reading. This passive monitoring does, in comparison with the functionality of, e.g., a lie detector, not even require any active participation and therefore no extra cognitive efforts of the monitored subject. BR integrated into an intelligent support system that acts in the background and is guided by certain situation-specific rules could enable automated assistance. For example, intelligent warning systems could be developed that would allow to warn astronauts only subliminally and in a way that distractions from the main task (e.g. , the manipulation of a robotic device or the performance of an experiment) are minimized. More specifically, if brain activity recorded after the presentation of a warning does show a certain pattern that is typical for the case that a warning was understood, and provided that the required response of the subject is not too urgent, the support system can give the operator more time to react before the warning is repeated. In the opposite case, a warning could be repeated more vividly. Here it is most important to stress that for BR, in contrast to most BCI applications where stimulus repetition is possible, classification must be based on real single trial EEG analysis and has to be fast to be applicable as will be explained later on. Also, since BR is observing processes of the brain that take place unconsciously, it is not possible to apply feed-back sessions [6] for the subject.

### 2.2 Experimental set up for brain reading

To give an illustrative example for BR, we want to introduce an experimental setup that allows to reproduce a situation, during which a subject is performing a manipulation task and is at the same time responding to important messages while ignoring unimportant ones.

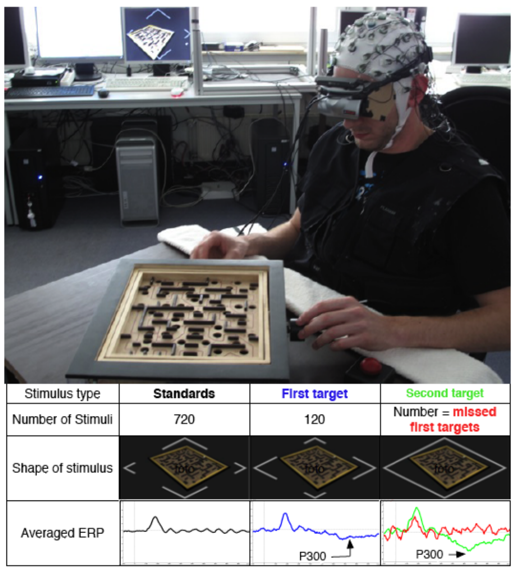


**Figure 1. Experimental setup**

In short, the experimental setup *Labyrinth Oddball paradigm*, as displayed in Figure 1, can be described as follows: A subject plays a virtualized BRIO® labyrinth game and reacts to rare warnings (first and second target stimuli, see Figure 1) by pressing a buzzer. Second targets are presented in case that first targets were missed. Interstimulus interval (ISI) is 1000 ms with a random jitter of ±100 ms. The visual presentation (shape and color) of unimportant stimuli that require no response (standards) and first target stimuli is kept very similar in order to avoid differences in early visual processing and to make sure that differences in the EEG recorded after the presentation of both stimuli types are actually due to higher cognitive processing.

While the subject was performing the task, the EEG was recorded continuously (62 electrodes, extended 10-20 system with reference at FCz), using a 64 channel actiCap system (Brain Products GmbH, Munich, Germany). The two remaining electrodes were used to record EMG (electromyography) signals of muscles of the lower arm. EEG and EMG signals were sampled at 1000 Hz, amplified by two 32 channel BrainAmp DC amplifiers (Brain Products GmbH, Munich, Germany) and filtered with a low cutoff of 0.1 Hz. Impedance was kept below 5 kΩ.

Targets, as opposed to standards or missed targets, evoke the event-related potential P300, a positive fluctuation in the EEG with a maximum amplitude at electrode Pz (see Figure 1). Peak latency of the P300 can range between 300 and 1000 ms. The P300 is evoked by infrequent, important (task-relevant) stimuli that are attended, recognized, and cognitively evaluated by the subject. Thus, P300 can be used as a marker for successful information processing of the user. The actual task for the BR system is to discriminate between the EEG pattern associated with either the correct or with the incorrect cognitive processing of target stimuli. Correct cognitive processing results in the understanding of the stimulus' meaning by the user while incorrect processing leads to misclassification of the stimulus by the brain, meaning that the subject does not recognize the target stimulus. Nonrecognized targets were labeled as *missed targets* (see Figure 1). The task of the BR system was therefore to predict whether the subject processed a target stimulus correctly (and will respond accordingly) or whether the subject processed the target stimulus incorrectly.

Since subjects do not often miss target stimuli, all presented investigations were performed on a similar task, namely to discriminate EEG trials recorded after the presentation of standard stimuli and first target stimuli. This is based on the assumption that EEG patterns induced by the incorrect or incomplete processing of target stimuli are similar to EEG patterns that are induced by unimportant frequent standard stimuli (see discussion in [9] for a justification and Figure 1 for an example).

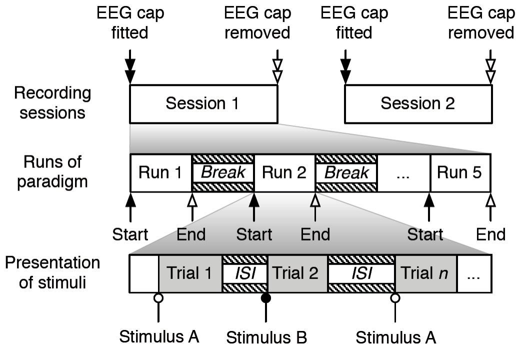


**Figure 2. Structure of the data sets**

### 2.2.1 Data set

The data set used in this paper consists of the labeled EEG data recorded in five sessions from three male subjects who had experience performing the experiment; subject A performed one session and subjects B and C two sessions each. All sessions were recorded on different days. Each of these sessions consists of five repetitions (called *runs*) of the Labyrinth Oddball paradigm intermitted by short breaks of 15 min (see Figure 2). The first run was used for adaption of the subject[1]. Together with the recorded EEG, information about stimulus presentation and response was stored.

### 2.2.2 Single trial data processing

In this section, we present the overall architecture of our software framework for single-trial classification of an operator's mental state. As stated above, in this scenario the single-trial brain reading device has to make a decision whether an operator did perceive an important message or whether he did not. The processing system is structured as follows: (1) EEG data acquisition, (2) windowing, (3) signal preprocessing and feature generation, (4) classification. See Figure 3 for an overview.

**EEG Acquisition** EEG data was recorded with a certified medical device. It is a continuous stream of the raw signal data, to which *markers* were added to label special events, such as the stimulus presentation and subject response.

**Windowing** For each message presented, exactly one decision has to be made. All information that can be used for this decision is usually contained in a certain fixed time range around the message presentation. Here, the decision can be based solely on the EEG recorded in the second after message presentation. The process of extracting this time window is called *windowing*. Windowing simplifies computation, since it allows to work always on instances of the same shape (length of the signal frame).

[1] Initially, standard and target stimuli are all considered to be new and potentially important for the subject such that also standards might result in a P300.

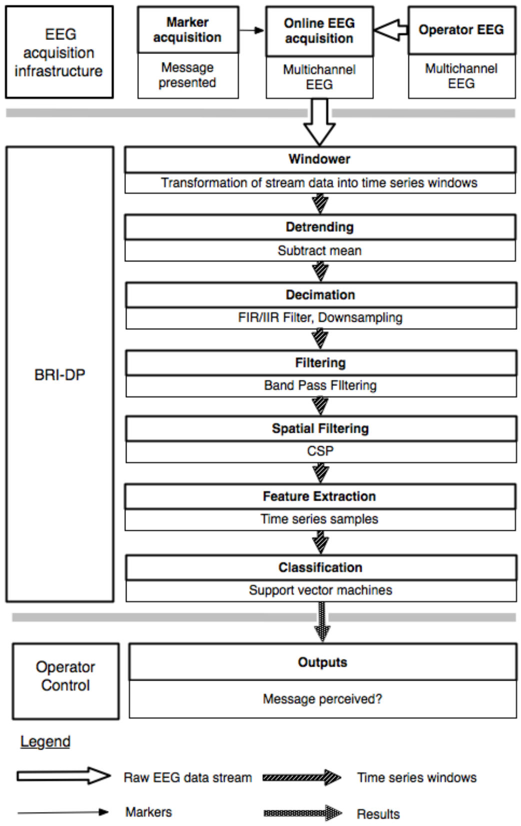


**Figure 3. Data processing scheme**

**Preprocessing and feature generation** Preprocessing refers to operations aimed at increasing the signal-to-noise ratio. Data preprocessing was performed in several steps, see Figure 3. Here, detrending means the channel-wise subtraction of the mean signal value of the given window followed by a decimation with an anti-aliasing filter to reduce the sampling rate of the data from 1000 Hz to 25 Hz. In the next step we applied another band pass filter to remove unwanted frequencies while retaining the sample rate. The spatial filtering step refers to methods that combine information of several channels and create a new (usually smaller) set of pseudo channels to separate channels that contain a high signal content while the noise is more concentrated in the remaining channels. We used a Common Spatial Patterns (CSP) filter [10] in this work.

**Classification** Any kind of classification algorithm suited for binary decision tasks can be used here. We applied support vector machines with a linear kernel.

# 3 BR interfaces in space applications

To integrate BR interfaces into space applications, more general questions have to be addressed as well. As stressed before, it is most important for BR to analyze EEG data in single trial and in real-time. For this purpose, the EEG analysis methods used here have to be optimized regarding their automatic processing by deploying and using adequate software frameworks for training as well as for the real time application (see [9]) and regarding the consumed processing time. Besides, improvements of the EEG recording and analyzing hardware are necessary and will be explained in the following.

## 3.1 Training data acquisition

For applying BR on space missions it is most important to get suitable EEG data in order to train or tune the BR system to the corresponding operator. Ideally, this training data should be recorded while the operator is doing the actual task under realistic conditions like in outer-space, experiencing zero-gravity, and so on. Such data would be nearly impossible and very expensive to acquire in a *real-world* environment before the operator starts his or her mission in outer-space. Additionally, in order to utilize current machine-learning methods that allow real zero-training (see, for example, [1]) it would be necessary to acquire multiple sets of such training data. Beside this, retraining might be needed in case that brain activity changes due to training or other not always foreseeable circumstances.

Therefore, training sessions are needed that produce many training examples in a short training time and that are also similar enough to the real application. For this purpose, our approach is to use a *simulated environment* to acquire the training data. The Labyrinth Oddball paradigm is such an example (see Figure 1). In this scenario, the subject has to react to rare visual target stimuli by pressing a buzzer while playing the simulated game. We use the real BRIO® labyrinth game as an input device for the simulation. Here, the board angles of the game are measured with the help of potentiometers and used to control the board angles of the simulated game. Further, we use a head-mounted display (HMD) for the visualization of the simulated environment and the presentation of the visual stimuli in the current field of view of the subject. In combination with a head tracker to map the movement of the head of the subject to the corresponding movement of the point of view within the simulation, we are able to realize a virtual immersion of the subject.

One of the main advantages of using a simulation is that even complex scenarios (e.g. manipulation with a robotic arm) and extreme environmental conditions like in outer-space (e.g. zero-gravity, temperatures at around 2.7 K, radiation, etc.) can be made available with much less effort than in reality. For example, creating zero-gravity within a simulated environment can be realized by simply setting the corresponding gravitation constant to a value of zero, whereas in reality one has to, e.g., conduct parabola flights, which means one has zero-gravity only for a very limited time and it is very costly to do so.

A side effect of our approach is that the equipment needed for acquiring the training data is much smaller, cheaper, and in addition more portable. For example, all that is needed for acquiring the training data for our exemplary Labyrinth Oddball paradigm would be the BR system itself, a computer with enough computational power to run the simulation, some visualization (e.g. computer screen or HMD), and input devices (e.g. joystick, keyboard, hand or head tracker). Depending on the complexity of the given scenario, the required equipment would be more or less extensive. Thus, the costs for performing even multiple training sessions on earth are kept to a minimum. Optionally, if appropriate devices are available on the used space vehicle, it could be even possible to acquire additional training data in outer-space.

Furthermore, the training of the operator can be seen as a kind of additional fail-safe mechanism. Since in order to acquire the needed EEG data the operator has to execute the given or a very similar task repeatedly and in that sense gets some kind of offline practice, thus reducing the probability of human failure. Also, due to training in simulation a wear out of the real system is avoided.

An important prerequisite in order to use our approach to its fullest extent is that the simulation-reality-gap is reduced to a minimum. Ideally for the operator, both systems should behave the same. This means if both systems are in the same state and the operator issues the same command to both systems, all subsequent states should be identical. Thereby the operator should have no problem switching from the simulated system to the real system and vice versa. Unfortunately, because of noise and error of real components and the inability of simulations to perfectly model reality, there will always be a difference between the real and the simulated system and thus a simulation-reality-gap. But, for example, by optimizing the simulation taking into consideration only very few, targeted and carefully planned interactions with the real system [2] or by adding noise to each simulated component with respect to the behavior of its real counterpart [7], the impact of this gap can be minimized.

## 3.2 Transferability of classifiers

One of the most crucial factors for the applicability of BR in space applications is that the preparation time for the system should be as short as possible. Preparation time is mainly caused by setting the electrodes (the more electrodes the longer, see Section 3.5 for more details on reducing the number of electrodes) and by conducting a calibration procedure with the user during which prototypical data is recorded that allows to adapt the BR system to the specific user. This adaptation is required since brain patterns of different subjects differ and even change over time for the same subject. Adaptation can be achieved by training classifiers, spatial filters, and other adaptable components of the data-processing flow on user- and session-specific data. In this section, we focus on transferability of trained classifiers and investigate to what degree knowledge (namely trained classifiers) deteriorates when transferred to another run within the same session (*intra-session*), to another session of the same user (*inter-session*), and to another user (*inter-subject*) compared to the no-transfer situation (*intra-run*). Furthermore, we investigate how the duration of the calibration procedure (it takes approx. 8 min to acquire 420 training examples inthe given paradigm) influences the performance. For statistical analysis, we performed repeated measures ANOVA with two within-subjects factors: (a) type of transfer levels: intra-run, intra-session, inter-session and inter-subject, and (b) size of the training set for classifier. If needed, the Greenhouse-Geisser correction was applied and the corrected $p$-value was reported. For pairwise comparisons, Bonferroni correction was applied.

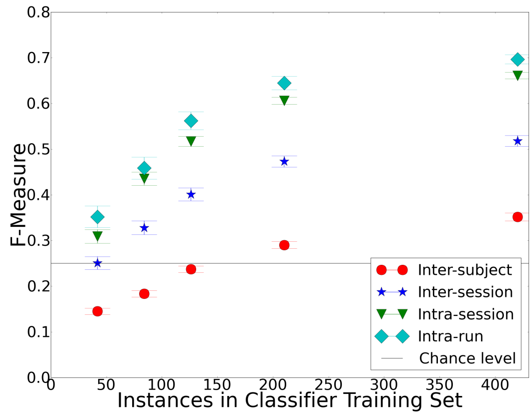


**Figure 4. Effect of transfer type and training set size**

Figure 4 depicts the results of the data processing discussed in Section 2.2.2. Independent of the type of transfer, classifiers trained on larger training sets (corresponding to longer calibration sessions) achieve better results than classifiers trained on smaller training sets [$F(4, 124) = 205.94, p < 0.001$, pairwise comparisons: larger training set vs. small training set: $p < 0.001$ for each transfer type except for inter-subject transfer]. Furthermore, performance deteriorates significantly when classifiers are transferred inter-session or even inter-subject compared to intra-session transfer [$F(3, 93) = 83.30, p < 0.001$, pairwise comparisons: inter-session vs. intra-session: $p < 0.001$, inter-subject vs. intra-session: $p < 0.001$]. In contrast, intra-session does not significantly perform worse than intra-run [pairwise comparisons: intra-session vs. intra-run in all classifier's training sets $p = n.s.$].

These results suggest that the calibration procedure should be performed once at the start of a session since transferring across sessions and subjects deteriorates performance. On the other hand, transferring across sessions achieves a performance significantly above chance level. Thus, it seems to be promising to reuse knowledge from previous sessions to *jump-start* the system and thus to reduce the amount of training data and thereby the duration of the calibration procedure that is required to achieve sufficient performance. Therefore, the acquisition of training data prior to a mission (see Section 3.1) is useful.

### 3.3 Dealing with misclassifications

While in principle it is desirable to avoid misclassification altogether, this can usually not be achieved in classification tasks with noisy data, like BR. Thus, there exists an intrinsic trade-off between the misclassification rates of the two classes: reducing the ratio of wrongly classified instances of the one class typically increases this ratio for the other class. In many applications, it is more harmful to misclassify instances of the one class than those of the other. For instance, it is less harmful to present an important message a second time even though the user has already perceived it at the first presentation (which happens when the system does not correctly detect this perception) than to not repeat the message presentation when the user actually missed it (which happens when the system erroneously detects a perception). These application-specific demands can be formalized by using a cost function as objective function instead of more simple functions like misclassification rates. This allows to specify criteria like "It is X times more costly to misclassify an instance of class A than one of class B" and evaluate the data processing system according to this metric.

Furthermore, by integrating the classification results into a rule-based system, the reliability of the system can be increased. For example, such a rule in the Labyrinth Oddball paradigm could be: "If the BR system supposes that the subject has perceived a warning (first target) but the subject does not respond appropriately within ten seconds, the system should present a more urgent warning (second target)!". Hence, by combining the classification results of the BR system with other relevant information, it is possible to add further safety mechanisms.

### 3.4 Software optimization

The implementation of the data processing system shown in Figure 3 is mainly based on the Modular toolkit for Data Processing [18], which in turn uses NumPy and SciPy [8] to perform the computations. These frameworks consist of C++ implementations of the mentioned algorithms with adapters to Python. Since the actual computationally intensive algorithms are compiled binary code, the performance impairment of a scripting language does not account here significantly.

Real-time processing of the data is essential for the given scenario. Therefore we analyzed the running time

| Type of optimization | Filtering algorithm FIR | FIR×2 | IIR×2 | No |
|---|---|---|---|---|
| F-Measure | | | | |
| Mean | 0.72 | 0.73 | 0.74 | 0.63 |
| SD | 0.073 | 0.081 | 0.062 | 0.076 |
| Running time in ms | | | | |
| Normal | 20.6 | 17.8 | 16.0 | 15.3 |
| Parallel | 16.9 | 17.0 | 15.4 | – |

**Table 1. Running times and F-Measures**

of the data processing. The initial processing time for a window was at about 30 ms, which could be optimized to 20 ms by applying different general optimization techniques like preallocation of buffer variables. A remaining bottleneck was the anti-aliasing lowpass filter in the decimation step. We used different anti-aliasing filters here: a 31 tap finite impulse response (FIR) filter with either one or two decimation steps, an elliptic infinite impulse response (IIR) filter with 8 taps in two decimation steps (with −40 dB stopband attenuation each) or reduction of the sampling frequency without prior filtering. The filters resulted in different F-Measures and runtimes, as shown in Table 1. The F-Measures are the averages of the intra-session F-Measures of a 2-fold cross validation for all sets of the data described in Section 2.2.1. The runtimes are the averages of the wallclock processing times of windows of the first dataset, which was processed as a data stream to reconstruct a realistic situation. We used an Apple Mac Pro with two Intel Quad-Core Xeon processors (resulting in 16 virtual cores due to Hyper-Threading) at 2.66 GHz and 32 GB memory for the time measurements. A channel-wise parallelization of the filtering was performed using OpenMP [12]. Clearly, all filtering methods result in significantly better classification performance than the omission of a filtering step [$F(3, 117) = 67.95, p < 0.001$, pairwise comparisons: No filter vs. 1 step FIR: $p < 0.001$, No filter vs. 2 step FIR: $p < 0.001$, No filter vs. 2 step IIR: $p < 0.001$]. The classification rates of the different filters do not vary significantly [2 step FIR vs. 2 step IIR: $p = n.s.$], apart from the better performance of 2 step IIR filter compared to 1 step FIR filter [2 step IIR vs. 1 step FIR: $p < 0.015$].

The runtimes in Table 1 indicate (1) that real time processing of the EEG data and P300 detection is possible with common hardware if some optimization techniques are applied which do not hamper the classification performance, (2) a considerable speedup of certain algorithms can be achieved already by obvious parallelization techniques. The effect of parallelization grows with increasing sampling rates (e.g. 5000 Hz instead of 1000 Hz) and with the length of the used EEG data windows. Both depends on the used methods. Apart from this it is impracticable

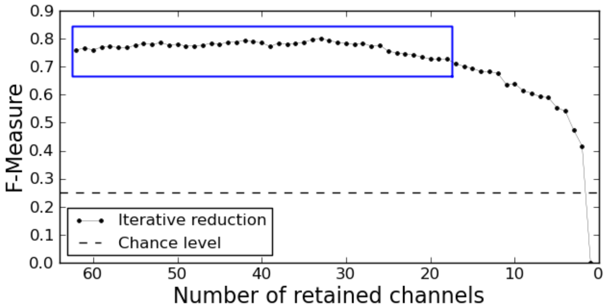


**Figure 5. Effect of the number of EEG channels**

to use multi-core systems in space, particular hardware is needed for the data processing.

### 3.5 Hardware optimization

Since there is a limited ability to communicate with the ground station, the EEG recording and analysis have to be realized in situ, i.e. on board of the space station. The space environment space causes several specific requirements for the BR system. The hardware for BR systems can be divided in two major parts: the EEG acquisition hardware, which in turn consist of electrodes and amplifiers, and the data processing hardware, which is basically a computer with sufficient computing performance to perform the computations. A minimization of the hardware also allows free movements of the operator and thereby reduces possible constraints.

The electrodes measure small variations in the electric field of the brain on the surface of the scalp. A possible problem for the usage of electrodes in space applications is their dependence on conductive gel and sensitiveness to a possibly deficient placement. These difficulties are addressed by gel-free *dry* electrodes. However, the usage of dry electrodes currently results in a lower classification accuracy [14]. Hence, the signal processing algorithms mentioned in Section 2.2.2 have to be adapted. Beside this, dry electrodes are usually used in a much lower number.

A complementary approach and a prerequisite for the use of dry electrodes is to cut down the number of electrodes. In this way, the effort in preparing the EEG system is also reduced. Figure 5 shows the classification performance by means of the F-Measure, based on one session as described in Section 2.2.1, but with different numbers of EEG channels used for classification. In this investigation, both training and classification are performed within individual runs. The reduction of channels was performed in an iterative manner, proceeding from the full set of 62 electrodes. In every iteration, all possible sets with one electrode less were analyzed. The channel whose dismissal led to the least loss in performance was discarded permanently. The classification performance was analyzed by repeated measures ANOVA with the generated constellations as within-subjects factor (62 levels) [effect of number of retained electrodes[2]: $F(59, 1416) = 82.22, p < 0.001$]. No significant decrease is observed until the number of retained electrodes reaches 17 [pairwise comparisons: $p = n.s.$ for 62–17 electrodes, indicated by the box in Figure 5]. Notice that this channel reduction procedure can be performed only subsequent to a measurement with all electrodes. The results, however, indicate a vast potential for the use of EEG caps with sparse electrodes. Further studies will investigate whether EEG cap designs can be found that are robust between different sessions, to different subjects and applications.

The special requirements of the data processing hardware in space applications are, among others, small size, weight and energy consumption, sufficient computing performance of the analysis system, as well as robustness against the environmental conditions (especially radiation). Since the handling of complex tools is hampered in a zero-gravity environment, the usability of the hardware is an important point. There are several promising approaches to achieve a sufficiently high computing performance in small embedded devices, e.g., a power-saving processor in combination with a high-performance dedicated co-processor that accomplishes the compute-intensive operations. For instance, field programmable gate arrays (FPGAs) with additional digital signal processing functionality are characterized by high computing performance and low energy consumption. According to [13], even SRAM-based FPGAs are reliable against radiation if special precautions are taken. FPGAs have been used successfully in specific signal processing of actual BCI systems, see, e.g., [15]. However, a well-known problem of FPGAs is the intricate software development. A related problem to address is the heterogeneity of the necessary algorithms, see Figure 3. On the other hand, graphics processor units have large computing power and are comparably easily programmable with high-level languages, although their enormous energy consumption usually restricts their usage in mobile embedded systems. Nevertheless, the usage of graphics cards for data processing is increasingly popular and worth evaluating.

## 4 Conclusion

Support systems for astronauts are very fundamental to assure the success of outer space missions. We introduced a new kind of those systems that gives insight into the astronaut's brain activity and by this allows to read and understand even processes that happen unconsciously to the human. We discussed that the main power of our attempt is that BR does not use any cognitive resources

[2]The values of last two retained electrodes were excluded since the classification rates were zero.

of the astronaut and that there is no direct link between brain activity and action of a machine. By this and by implementing rules that prohibit critical wrong decisions one can build powerful astronaut support systems based on BR. To bring those systems into space applications, improvements have to be made regarding training, implemented software, structure of the data processing flow as well as hardware for acquisition and analysis of brain activity. We discussed options and presented first results. Still, some aspects were not discussed. For example, improvements in EEG amplifiers and battery packs will be necessary as well. The main goal of this paper was therefore to show a new way for the sensible and practical usage of brain activity in space applications.

## 5 Acknowledgements

This work was supported by the German Bundesministerium für Bildung und Forschung (BMBF, grant FKZ 01IW07003), and the German Bundesministerium für Wirtschaft und Technologie (BMWi, grant FKZ 50 RA 1012).

## References

[1] M. Alamgir, M. Grosse-Wentrup, and Y. Altun, "Multitask learning for Brain-Computer Interfaces", JMLR, Vol. 9 (AISTATS 2010 Proceedings), 2010, pp. 17–24.

[2] C. Bergatt, J.H. Metzen, E.A. Kirchner and F. Kirchner, "Quantification and Minimization of the Simulation-Reality-Gap on a BRIO® Labyrinth Game", Proceedings of the First International Workshop on Learning and Data Mining for Robotics, Slovenia, 2009, pp. 26–38.

[3] N. Birbaumer, A.R. Murguialday, C. Weber, and P. Montoya, "Neurofeedback and Brain-Computer Interface: Clinical Applications", In: Brain Machine Interfaces for Space Applications: enhancing astronaut capabilities, International Review of Neurobiology, Vol. 86, Eds. L. Rossini, D. Izzo, L. Summerer, Academic Press, 2009, pp. 107–117.

[4] L.A. Farwell and E. Donchin, "Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials", Electroencephalogr Clin Neurophysiol, Elsevier, Vol. 70, 1988, pp. 510–523.

[5] L.A. Farwell and E. Donchin, "The Truth Will Out: Interrogative Polygraphy ("Lie Detection") With Event-Related Brain Potentials", Psychophysiology, Wiley, Vol. 28, 1991, pp. 531–547.

[6] C. Guger, W. Harkam, C. Hertnaes and G. Pfurtscheller, "Prosthetic control by an EEG-based Brain-Computer Interface (BCI)", Proceedings of the 5th AAATE Conference, Duesseldorf, Germany, 1999.

[7] N. Jakobi, "Evolutionary robotics and the radical envelope-of-noise hypothesis", Adaptive Behavior, Vol. 6, 1997, pp. 325–368.

[8] E. Jones, T. Oliphant and P. Peterson, "SciPy: Open source scientific tools for Python", http://www.scipy.org/, 2001–2010.

[9] E.A. Kirchner, J.H. Metzen, T. Duchrow, S.K. Kim, and F. Kirchner, "Assisting Telemanipulation Operators via Real-Time Brain Reading", In: Machine Learning in Real-time Applications (MLRTA 09), KI 2009 Workshop, Paderborn, Germany, Lemgoer Schriftenreihe zur industriellen Informationstechnik, Eds. V. Lohweg and O. Niggemann, 2009.

[10] Z.J. Koles, "The quantitative extraction and topographic mapping of the abnormal components in the clinical EEG", Electroenceph Clin Neurophysiol, Elsevier, Vol. 79, 1991, pp. 440–447.

[11] K.R. Müller, M. Tangermann, G. Dornhege, and M. Krauledat, "Machine learning for real-time single-trial EEG-analysis: From brain–computer interfacing to mental state monitoring", J Neurosci Methods, Elsevier, Vol. 167, 2007, pp. 82–90.

[12] OpenMP Architecture Review Board, "Version 3.0 Complete Specifications", http://openmp.org/wp/openmp-specifications/, 2008.

[13] P.S. Ostler, M.P. Caffrey, D.S. Gibelyou, P.S. Grahham, K.S. Morgan, B.H. Pratt, H.M. Quinn, and M.J. Wirthlin, "SRAM FPGA Reliability Analysis for Harsh Radiation Environments", IEEE Transactions on Nuclear Science, Vol. 56, 2009, pp. 3519–3526.

[14] F. Popescu, S. Fazli, Y. Badower, B. Blankertz, K.R. Müller, "Single Trial Classification of Motor Imagination Using 6 Dry EEG Electrodes", PLoS ONE, Vol. 2, 2007.

[15] K.K. Shyu, P.L. Lee, M.H. Lee, M.H. Lin, R.J. Lai, and Y.J. Chiu, "Development of a Low-Cost FPGA-Based SSVEP BCI Multimedia Control System", IEEE Transactions on Biomedical Circuits and Systems, Vol. 4, 2010, pp. 125–132.

[16] L. Summerer, D. Izzo, and L. Rossini, "Brain Machine Interfaces for Space Applications: Enhancing Astronaut Capabilities", Academic Press, 2009.

[17] J.R. Wolpaw, N. Birbaumer, D.J. McFarland, G. Pfurtscheller and T.M. Vaughan, "Brain-computer interfaces for communication and

control", Clin Neurophysiol, Elsevier, Vol. 113, 2002, pp. 767–791.

[18] T. Zito, N. Wilbert, L. Wiskott, P. Berkes, "Modular Toolkit for Data Processing (MDP): A Python Data Processing Framework", Front Neuroinform, Vol. 2, 2008.