# Transfer approach for the detection of missed task-relevant events in P300-based brain-computer interfaces

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*Abstract*— **Detection of human cognitive states using biosignals such as the electroencephalogram (EEG) is gaining relevance in different application areas, e.g., teleoperation, human-robot collaboration, and rehabilitation. Especially, the P300, which is evoked as an event-related potential (ERP), when humans perceive task-relevant infrequent events among task-irrelevant frequent events, is widely used in brain-computer interfaces (BCIs). P300 detection has been used as an indicator that a human perceives task-relevant events or detects the occurrence of task-relevant or important events. In this paper, we focus on not only perceived task-relevant events but also not-perceived task-relevant events (i.e., missed events). In fact, a human can miss task-relevant events for different reasons, e.g., reduced attention level or increased workload level during parallel task-processing situations among others. Moreover, a human can also intentionally ignore task-relevant events to manage several simultaneous tasks. However, such missed events do not often occur in real-world applications. In this paper, we propose a transfer approach to handle insufficient number of events for training a classifier. For example, task-irrelevant infrequent events are used for training of classifier to detect missed task-relevant events. We evaluated our approach in different settings of training and testing a classifier with and without classifier transfer.**

## I. INTRODUCTION

Brain-computer interface (BCI) applications [1], [2] are making use of the electroencephalogram (EEG) to control PC programs, devices or to communicate [3], [4], [5], [6]. Either changes in the time domain or frequency domain or a combination of both are used. In our study, changes in the time domain, i.e., event-related potentials (ERPs) were investigated. Different types of ERPs, i.e., EEG correlates of different cognitive processes (e.g., attention, workload, motion planing, recognition of errors, etc.) have been used in various application areas, e.g., rehabilitation, robotics, gaming areas, etc. [7], [8], [9], [10].

While in some BCI applications there might not necessarily be a natural link between observed changes in the EEG and control commands since these changes are purposely evoked, e.g., by thinking of a hand movement to guide a cursor to the right or left, some BCI applications were developed to detect human cognitive states and to make use of them without attentional control of the user. For example, in embedded brain reading (eBR) [11], detected ERPs are not explicitly used for system control. Instead, human intention and human implicit feedback are used for optimizing human-robot(machine) interactions, e.g., optimization of system behavior, of behavior strategy of a robot, of an interface between human and machine, etc. [12], [13]. Changes in cognitive states that are detected within eBR applications are often accompanied by specific ERPs.

The most widespread ERP used for BCI applications is the P300, which is elicited when recognizing task-relevant infrequent events among task-irrelevant frequent events. Such task schema is called an *oddball discrimination task* [14]. P300 is a well-known ERP and has been investigated in different modes (auditory/visual) and under different task conditions (single task/dual task) in numerous studies (see for review [15]). In classical P300-based BCI applications, task-relevant events are detected to decode the user's brain signal for explicit control of a PC or device [5], [4]. For example, in the classical BCI-speller paradigm, a matrix is consisting of various characters that are aligned in columns and rows. These columns and rows are flashed in random order. When the user explicitly selects one specific character in mind and focuses attention to the selected character, the chosen character is then a task-relevant event (*target*) among other task-irrelevant characters (*standards*). This task-relevant event (*target*) elicits a P300 when the column or row containing this character flashes up. The elicited P300 can be detected in the EEG using machine learning technique.

In our previous studies and applications, we used the occurrence of P300 to estimate cognitive state changes to optimize interaction, i.e., the interface between human and machine to be better suited for the current cognitive state (e.g., current levels of workload) of the user. For this purpose the P300 must be detected online and in single-trial (see for discussion [11]). When the user's workload is increased and his/her attention's level is reduced, it can occur that the user does not recognize task-relevant events (*targets*). Such reduction of the user's attention level can be caused by fatigue or excessive demands due to multi-tasking (e.g., control of several robots and several task managements). On the other hand, ignoring task-relevant events (*targets*) can be intended by the user, i.e., it can be a strategy to manage several simultaneous tasks. In any case, reduction of cognitive resources, attentional deficits or other forms of distraction will diminish P300 expression or will even result in absence of P300 [16], [17], [18], [19]. To detect

*This work was funded by the Federal Ministry of Economics and Technology (grant no. FKZ 50RA1011, FKZ 50RA1012, and grant FKZ 50RA1301) and the Federal Ministry for Education and Science (grant no. 01IW07003).

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such events, i.e., reduced or absent P300 (*missed targets*), is an important information to adapt an interface, e.g. to repeat relevant information or to increase or decrease the time interval between two targets such that the interacting person is neither bored nor overstrained.

Given the above mentioned example, in real-world applications, it can be especially relevant to detect *missed targets*. However, *missed targets* do not often occur compared to correctly perceiving task-relevant events or irrelevant stimuli. Hence, it is not always easy to collect a sufficient amount of training data containing *missed targets* within a reasonable time. Here, we assume that *missed targets* can be more similar to task-irrelevant events (*standards*) compared to task-relevant events (*targets*). In general, collection of training data containing task-irrelevant events (*standards*) is less time-consuming in real-world applications compared to data collection of *missed targets*. Hence, we aimed to investigate whether a classifier trained on task-irrelevant frequent events (*standards*) with task-relevant events (*targets*) can be used to classify *missed targets*. Further, we investigate whether classification can be improved when EEG data evoked by task-irrelevant infrequent events (*deviants*) is used as training data instead of missed targets or standards. The idea behind this is the assumption that target events might not only be missed completely but miss-interpreted as task-irrelevant events. Hence, missed target events might evoke ERP activity similar to task-irrelevant events (deviants). In this paper, different settings of classifier transfer were evaluated on a dataset containing task-irrelevant frequent events (*standards*), task-irrelevant infrequent events (*deviants*), and task-relevant infrequent events (*targets*). The dataset was collected from 13 subjects who performed multi-tasking, i.e., performed an oddball task and played a labyrinth game.

## II. METHODS

### A. Data acquisition and experimental setup

Thirteen subjects (2 female, 11 male; age between 27 and 39 years; right- handed; normal or corrected-to-normal vision) participated in the presented study, which was conducted in accordance with the Declaration of Helsinki and approved by the ethics committee of the University of Bremen. Written informed consent was obtained from all participants that volunteered to perform the experiments. Written informed consent for publication of identifying information/images was also obtained from all participants.

EEGs were recorded with 62 active electrodes (extended 10-20 actiCap system) and amplified by two 32-channel BrainAmp DC amplifiers [Brain Products GmbH, Munich, Germany]. Electrodes were referenced to electrode FCz. Impedance was kept below 5 kΩ. Sampling rate was set to 2500 Hz and data was band-pass filtered between 0.1 Hz to 1000 Hz.

Fig. 1 shows the experimental setup. Subjects performed the oddball task and played the labyrinth game at the same time. Three stimulus types were displayed to subjects: task-irrelevant frequent stimuli (*standards*, N=720), task-irrelevant infrequent stimuli (*deviants*, N=60), and task-relevant infrequent stimuli (*targets*, N=60). Each stimulus was displayed for 100 ms on a monitor that was placed directly behind the labyrinth game. *Targets* were randomly mixed among *standards* and *deviants* with a ratio of 1:12:1 and displayed with an Inter-Stimulus Interval (ISI) of 900 and 1100 ms. *Standards* (white-colored words, e.g., *speed 17 kn*) provided no task-relevant information. *Deviants* (orange-colored word *press SOON*) contained no task-relevant information, but were infrequently displayed to subjects. *Targets* (red-colored word *PRESS*) provided task-relevant information and only in this case the subject was instructed to press a buzzer which was located approximately 30 cm away from the left side corner of the game board. More detailed information about experimental scenario and task descriptions is given in our previous study [20].

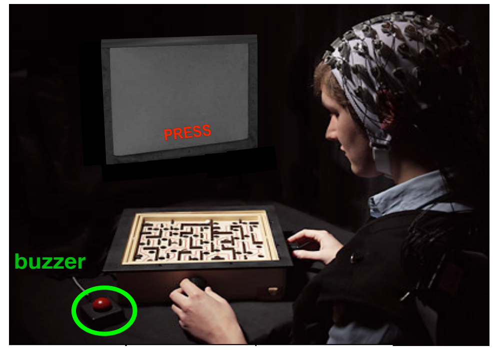

Fig. 1. Experimental setup. The subject who is shown in this figure has given written informed consent to publish this image.

### B. Preprocessing and classification

One dataset was collected per subject within two sessions. We obtained 13 datasets (1×13 subjects) in total. Segments containing artifacts were rejected semi-automatically (amplitude $> 100$ and $< -100\,\mu$V, gradient $> 75\mu$V). We merged 13 datasets across all subjects for our evaluation, since the amount of artifact-free data per subject was very different and the amount of training examples was not sufficient for training a classifier for some subjects, when using only artifact free data as it was required for our former study [20]. In this way, we obtained sufficient training and testing instances for classification. Further, this procedure reduces subject-specific effects on classification performance. After merging all datasets, we obtained one dataset.

We segmented the continuous EEG signal into epochs from 0 to 1 s after each stimulus type (standard/deviant/target). Here, we labeled only target stimuli as target class for classifier, when subjects responded on target stimuli. Otherwise, we labeled target stimuli as *missed targets*. As stated above, we used only artifacts-free trials for our evaluation. After artifacts-rejection, we obtained 6226 standards, 524 deviants, 360 targets, and 42 missed targets. All epochs were normalized to zero mean for each channel, decimated to 25 Hz, and bandpass filtered between 0.1 and 4 Hz. The low-pass filter was used to assure that the classifier could only make use of data in the frequency range of mainly ERP activity. The xDAWN [21] was used as a spatial filter to enhance the signal-to-signal plus noise ratio. By applying the xDAWN algorithm, 62 physical channels were reduced to 8 pseudo channels. We used data points in the time domain as features. We extracted features from 0.4 to 0.8 s and obtained 88 features (8 channels $\times$ 11 data points = 88). The extracted features were normalized over all trials and used to train a classifier.

We used a linear support vector machine (SVM) [22] to classify different types of class pairs: standards vs. deviants, standards vs. targets, targets vs. deviants, targets vs. missed targets, deviants vs. missed targets. Under classifier transfer condition, a classifier was trained on one class pair and tested on another class pair. For parameter optimization of the SVM, the cost parameter of the SVM (i.e., regularization constant [23]) was optimized with a stratified five-fold cross validation using a grid search among the predetermined values [$10^0$, $10^{-1}$, ... , $10^{-6}$]. As performance metric, we used balanced accuracy (bACC), i.e., an arithmetic mean of true positive rate (TRP) and true negative rate (TNR) [(TPR + TNR)/2]), where the class of detected ERP refers to positive class (details for bACC, see [24]).

We designed different settings of classifier transfer. Here, different types of class pairs were used for training and testing a classifier (see Tab. I). We detected three ERP correlates of targets, missed targets, and deviants. For target detection (test case), we used three kinds of class pairs as test data: (a) standards and targets, (b) missed targets and targets, and (c) deviants and targets. For detection of missed targets (test case), we used two kinds of class pairs as test data: (a) targets and missed targets and (b) deviants and missed targets. Finally, three kinds of class pairs were used as test data for deviant detection (test case): (a) standards and deviants, (b) missed targets and deviants and (c) targets and deviants. Different combinations of class pairs were used to build training data for detection of targets, missed targets, and deviants. Note that 10$\times$10 cross validation was performed for evaluation of none-transfer cases (i.e., the same class was used for training and testing).

TABLE I

PERFORMANCE FOR DIFFERENT TRANSFER CASES (ST: STANDARDS, T: TARGETS, D: DEVIANTS, MT: MISSED TARGETS, BL: BASELINE)

| transfer case | training data | test data | detected ERP | classification performance |
|---|---|---|---|---|
| detection of target (t) | | | | |
| 1 (bl) | st, t | st, t | t | 0.96 |
| 2 | mt, t | st, t | t | 0.94 |
| 3 | d, t | st, t | t | 0.92 |
| 4 | st, d | st, t | t | 0.71 |
| 5 (bl) | mt, t | mt, t | t | 0.91 |
| 6 | st, t | mt, t | t | 0.90 |
| 7 | d, t | mt, t | t | 0.85 |
| 8 | mt, d | mt, t | t | 0.73 |
| 9 | st, d | mt, t | t | 0.67 |
| 10 (bl) | d, t | d, t | t | 0.86 |
| 11 | st, t | d, t | t | 0.79 |
| 12 | mt, t | d, t | t | 0.79 |
| detection of missed target (mt) | | | | |
| 1 (bl) | mt, t | t, mt | mt | 0.85 |
| 2 | st, t | t, mt | mt | 0.84 |
| 3 | mt, d | t, mt | mt | 0.80 |
| 4 | d, t | t, mt | mt | 0.75 |
| 5 | st, d | t, mt | mt | 0.64 |
| 6 (bl) | mt, d | d, mt | mt | 0.82 |
| 7 | mt, t | d, mt | mt | 0.80 |
| 8 | st, t | d, mt | mt | 0.61 |
| detection of deviant (d) | | | | |
| 1 (bl) | st, d | st, d | d | 0.62 |
| 2 | mt, d | st, d | d | 0.64 |
| 3 | st, t | st, d | d | 0.66 |
| 4 (bl) | mt, d | mt, d | d | 0.71 |
| 5 | mt, t | mt, d | d | 0.61 |
| 6 | st, t | mt, d | d | 0.60 |
| 7 (bl) | d, t | t, d | d | 0.66 |

## III. RESULTS

Table I and Figure 2 show classification performance detection of detection of targets, missed targets, and deviants.

### A. Target detection

Table I shows classification performance for target detection in 11 transfer cases and one case of no transfer (baseline). Three different settings of test data were constructed for target detection: standards and targets; missed targets and targets; deviants and targets. For each setting of test data, we set a baseline (bl): the same class pair was used for training and testing a classifier, i.e., no transfer case. As expected, the best performance of target detection was achieved in case of baseline, e.g., a classifier which was trained on standards and targets was tested on data containing standards and targets (see *bl* in Tab. I). An overview of results on different settings of training data and test data is illustrated in Figure 2.

*a) Test data: standards and targets:* We used four training data settings for evaluation on data containing standards and targets (transfer case 1, 2, 3, 4, see Tab. I). Target detection performance was not substantially reduced when missed targets (instead of standards) were used for training a classifier (transfer case 1 vs. 2: 0.96 vs. 0.94 bACC). A high classification performance was still achieved when we used deviants (instead of standards) for training a classifier (transfer case 3: 0.92 bACC). However, the classification performance was reduced when using deviants (instead of targets) as training examples (transfer case 4: 0.71 bACC).

*b) Test data: missed targets and targets:* We did not use standards as test data for target detection. Instead, missed targets were used as test data. Again, we used different training data settings for evaluation on data containing standards and targets (transfer case 5, 6, 7, 8, 9, see Tab. I). The classification performance was slightly reduced in general, when we used missed targets (instead of standards) as test data for target detection. However, the classification performance was still high, when missed targets or standards were used as training examples (transfer case 5, and 6: 0.91 and 0.90 bACC).

*c) Test data: deviants and targets:* The classification performance was reduced when we used deviants as test data irrespective of which training data setting was used (transfer case: 10, 11, 12, see Tab. I). As expected, the usage of the same data for training and testing led to the best performance (transfer case 10: 0.86 bACC).

### B. Detection of missed targets

Table I shows classification performance for the detection of missed targets. Here, we evaluated 7 transfer cases and one case of no transfer (bl). Two settings of test data were constructed for the detection of missed targets: targets and missed targets and deviants and missed targets. We used different settings of training data for both settings of test data. Again, we used no transfer case, i.e., same class pair was used for training and testing a classifier as baseline (see *bl* in Tab. I). An overview of results on different settings of training data and test data is illustrated in Figure 2.

*a) Test data: targets and missed targets:* In the first setting of test data, targets and missed targets were used for evaluation. As expected, we obtained the best performance in no transfer case, i.e., missed targets and targets were used for training and testing. An interesting finding is that a high performance was achieved although standards were used as test data for the detection of missed targets (transfer case 1 vs. 2: 0.85 vs. 0.84). The classification performance was reduced when using deviants as training example (transfer case 4 and 5), but the performance was not reduced when training data contained missed target (transfer case 3).

*b) Test data: deviants and missed targets:* In the second setting of test data, we used deviants (instead of targets) as test data. Here, we still obtained a high performance as long as missed targets were used as training example (transfer case 6 and 7).

### C. Deviant detection

Table I shows classification performance of deviant detection for 6 transfer cases and one case of no transfer (bl). Three different settings of test data were constructed for target detection: standards and deviants; missed targets and deviants; targets and deviants. We used different settings of training data for both settings of test data. Again, we used no transfer case, i.e., the same class pair was used for training and testing a classifier as baseline (see *bl* in Tab. I). An overview of results on different settings of training data and test data is illustrated in Figure 2.

*a) Test data: standards and deviants:* Deviant detection performance was lower compared to detection of targets and missed targets in general.

*b) Test data: missed targets and deviants:* When using missed targets for training and testing a classifier, the classification performance was higher compared to the use of standards as training and test data.

*c) Test data: targets and deviants:* The use of deviants and targets as training and test data led to the same classification performance when using standards and deviants for training and testing a classifier.

## IV. DISCUSSION AND CONCLUSION

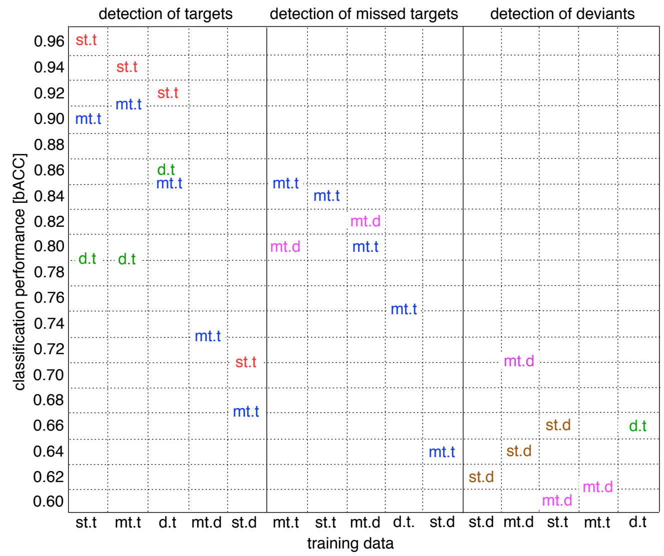


Fig. 2. Classification performance in single-trial detection of targets, missed targets, and deviants (st: standards, t: targets, d: deviants, mt: missed targets).

In this study, we could show that it is possible to use a classifier trained on *standards* and targets to distinguish between *missed targets* and targets. For this transfer case, we obtained a high classification performance for the detection of *missed targets* (0.84 bACC), which was not essentially different from the case of no transfer, i.e., *missed targets* and targets were used for both training and testing a classifier (detection of missed targets: 0.85 bACC). These findings support our assumption that the EEG pattern evoked by missed targets is similar to the pattern evoked by standards. Furthermore, such transfer was successful not only for the detection of missed targets but also for target detection (0.90 bACC). Moreover a reversed transfer case, i.e., the use of a classifier trained on *missed targets* and targets for distinguishing between *standards* and targets, was also successful for target detection (0.94 bACC). These results also support our assumption. Finally, the obtained results are relevant for applications, since it is not always easy to collect a sufficient amount of missed targets in real-world applications within a reasonable time.

The use of deviants as training examples was less successful for the detection of missed targets (0.75 bACC) compared to the use of standards as training examples (0.84 bACC). This finding indicates that the use of standards as training examples is more effective for detection of missed targets. Additionally, this finding suggests that in our experimental setting, subjects did likely miss target events, since missed target events were more similar to standards than to deviants. Correspondingly, we obtained a high performance when using deviants as test examples for detection of missed targets irrespective of whether target or deviant was used as training examples (deviants used for training: 0.82 bACC; targets used for training: 0.80). These results suggest that under our experimental setup it is possible to distinguish between EEG activity evoked by missed targets and deviants. In future work, it would be interesting to evaluate the same transfer cases when subjects have to actively decide not to respond to target events due to task load. Under such a condition it might be possible that EEG activity evoked by missed events (consciously not responded events) might be more similar to EEG activity evoked by task-irrelevant infrequent events (*deviants*).

In summary, we showed that missed task-relevant events (*missed targets*) can successfully be detected applying classifier transfer. Classification performance was close to baseline condition when an appropriate transfer case was chosen. The dependency of appropriateness of a specific transfer case for different experimental conditions (missing target events versus ignoring target events) must still be investigated in future work.

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