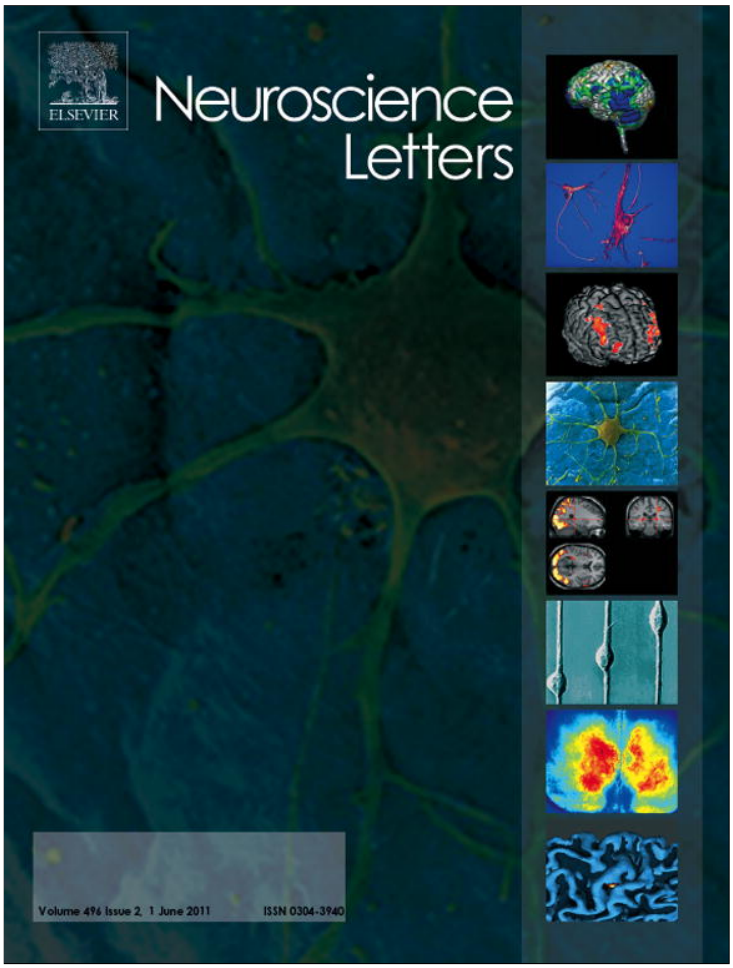

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Event-related potentials in a moving matrix modification of the P300 brain–computer interface paradigm

Sergei L. Shishkin[a,b,*], Ilya P. Ganin[a,b], Alexander Ya. Kaplan[a,b]

[a] Lomonosov Moscow State University, Faculty of Biology, Laboratory for Neurophysiology and Neuro-Computer Interfaces, 1/12 Leninskie Gory, Moscow 119991, Russia
[b] National Research Nuclear University MEPhI, Department of Biophysics, Radiation Physics and Ecology, 31 Kashirskoye Shosse, Moscow 115409, Russia

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ABSTRACT

In the standard design of the brain–computer interfaces (BCI) based on the P300 component of the event-related potentials (ERP), target and non-target stimuli are presented at fixed positions in a motionless matrix. Can we let this matrix be moving (e.g., if attached to a robot) without loosing the efficiency of BCI? We assessed changes of the positive peak at Pz in the time interval 300–500 ms after the stimulus onset (P300) and the negative peak at the occipital electrodes in the range 140–240 ms (N1), both important for the operation of the P300 BCI, during fixating a target cell of a moving matrix in healthy participants ($n = 12$). N1 amplitude in the difference (target – non-target) waveforms decreased with the velocity, although remained high ($M = -4.3$, SD = 2.1) even at highest velocity (20°/s). In general, the amplitudes and latencies of these ERP components were remarkably stable in studied types of matrix movement and all velocities of horizontal movement (5, 10 and 20°/s) comparing to matrix in fixed position. These data suggest that, for the users controlling their gaze, the P300 BCI design can be extended to modifications requiring stimuli matrix motion.

Brain–computer interface (BCI) or a brain–machine interface (BMI) is a technology enabling an individual sending messages or commands to the external world not through the brain's normal output pathways of peripheral nerves and muscles, but directly from the brain, using the electroencephalographic or other signals [28]. One of the most popular BCIs, the P300 Speller, or the P300 BCI, was proposed [5] as a variation of the 'oddball paradigm', a two stimulus discrimination task well known for eliciting the P300 wave of the event-related potentials (ERP). In the P300 BCI, the difference between the P300 wave in responses to flashes presented at the attended and unattended cells of a matrix is a key for detecting the attended cell. Unlike other BCIs, this BCI design enables the user to choose, in one step, one of tens of options, corresponding to the matrix cells (e.g., letters of the whole alphabet, digits, other symbols and command names), while only a short calibration (e.g., 5 min [7]) is needed to start using the interface for a naive user. The P300 BCI performance can remain stable during its long and extensive use (as in an ALS locked-in patient overseen for 2.5 year [22]).

The P300 BCI was originally designed as a static interface, where the stimuli positions in a matrix and the matrix itself are not moving. Currently, attempts are made to integrate BCIs, including the P300 BCI, into non-static devices or environment, such as wheelchairs [19], robots [1] and video games [18]. Combining the P300 BCI with the mu rhythm BCI (which usually has moving elements) in a hybrid interface [14] may also lead to the use of the P300 BCI design together with moving visual elements.

Perception of moving objects and attention to them have been little studied yet [16,20]. The P300 wave was employed by investigators aiming to assess the workload in complex visumotor tracking tasks [10], even with stimuli flashing at moving objects [11], but the effects of movement were not studied by them. The ERP to moving modifications of the stimuli in the P300 BCI design were studied [8], but with stimuli presented at fixed positions. Effects of the P300 BCI stimuli matrix movement on the ERPs have never been investigated.

For the simplicity, we will consider only a situation where the stimuli position are fixed within the P300 BCI matrix, the background is stable, but the matrix is moving. We will also assume that the BCI user controls his/her gaze well and uses smooth pursuit eye tracking and saccades whenever the stimuli matrix move. This situation may appear in the use of robotic devices with control panels fixed on them, in videogames or when a P300 BCI matrix is used as a sophisticated cursor moving on the screen. The moving stimuli matrix can be also useful in studying the basic attention and perception mechanisms as a model of a moving object perceived

* Corresponding author at: Lomonosov Moscow State University, Faculty of Biology, Laboratory for Neurophysiology and Neuro-Computer Interfaces, Leninskie Gory 1/12, 119991 Moscow, Russia. Tel.: +7 495 939 13 73; fax: +7 495 939 13 73.
E-mail address: sergshishkin@mail.ru (S.L. Shishkin).

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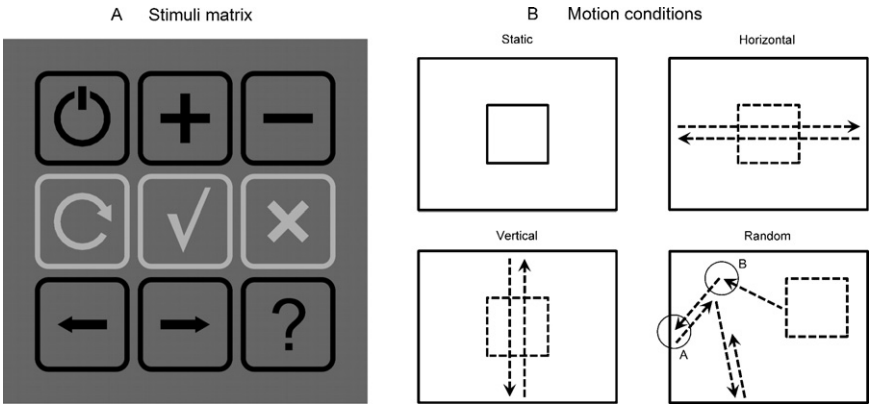

Fig. 1. (A) Stimuli matrix. The rows and columns were flashing in a pseudorandom order (here, the middle row is shown flashing). (B) Motion conditions. In Random condition, "A" is an example of changing the direction when approaching the margin, and "B" is an example of random change of direction.

not as a single moving point in space, but as a spatially extended subscene.

The P300 amplitude and latency depend on many factors related to the cognitive 'load' and the use of attentional resources [10]. Attentional resources are heavily involved into initiation and maintenance of pursuit eye movements [13,15,26]. A common selective attention control mechanism may exist for pursuing and perception of the pursued object [9]. Cognitive resources are needed for predicting the movement trajectory in the nearest time moments and for correction of pursuing performance using visual feedback [13]. Little is known yet about the spatial allocation of attention during pursuit [15]; evidence exists that attention allocation is biased during the smooth pursuit toward an area in front of the pursuit stimulus [26]. Saccades also influence attention [4]. Thus, various factors may interfere with the use of attention in the BCI and affect the P300 wave when the stimuli matrix moves. Both smooth pursuit [20] and saccades [3] are known to change contrast sensitivity, thus they also may modulate ERPs.

Current P300 BCIs may gain from using, together with the P300, the first large occipital negative wave peaking near 200 ms from the stimulus onset [2,12,21,24,25]. This component was observed in the P300 BCI but not in the standard visual oddball paradigm and thus may be related to spatial attention, which is possibly the main factor differentiating the P300 BCI and the oddball paradigm [24]. (Note that the positions of stimuli cells but not, like in the oddball paradigm, their content differentiates targets and non-targets in the P300 BCI paradigm.) Similar latency and localization is specific to one of the visual ERP components currently called N1 in studies of spatial attention [16,17,27]. N1 has been shown recently to be dependent on coding of an object's spatial position relative to the positions of other objects [27]. It seems not unlikely that the movement may affect this component due to changes of spatial positions of the stimuli, in addition to possible influence via the same factors as those listed for the for the P300.

This study was designed to test the hypothesis that the N1 and P300 components in the P300 BCI paradigm – more specifically, their difference in ERP to attended and non-attended stimuli, important for the P300 BCI operation – may be substantially modified when the stimuli matrix moves and is pursued by gaze. We investigated N1 and P300 in relatively "tough" conditions: small spaces between matrix cells (tracking errors could lead to "loosing" the target cell and fixating or attending one of the non-target cells); relatively high matrix movement velocities; abrupt changes of direction. Although factors working in these conditions are evidently a small portion of factors which may influence ERP in various modifications of the P300 BCI paradigm with moving stimuli matrix, we hoped that the extent of changes in N1 and P300 in our study would be somewhat indicative of what could be expected at least in similar modifications of the P300 BCI design. Peak amplitudes and latencies of the occipital N1 and P300 components in the difference waveforms, as well as ERP classification accuracy, were compared between these conditions and the standard condition, i.e., stable position of the matrix.

Twelve healthy volunteers (age 21–22 years, four males; all but one had previous experience with the P300 BCI) with normal or corrected to normal vision participated in the study after signing informed consent. The experiments were run in accordance with institutional guidelines and Declaration of Helsinki. Their protocol was approved by the Bioethics Commission of the Faculty of Biology, Lomonosov Moscow State University.

The participants viewed a 3×3 matrix with pictorial symbols (Fig. 1) presented on a 17-in. CRT monitor with 100 Hz refresh rate at approximately 80 cm distance from their eyes. The matrix was adopted from a BCI "game" [23], where it was optimized for increasing the "distracting power" of flashes in neighboring cells. In the current study, the distance between the cells was 0.2°, the size of each cell was $2.2^\circ \times 2.2^\circ$, and the whole matrix subtended 7.4°H $\times$ 7.4°W. Black color (luminance near 0 cd/m^2) was used for the symbols and cell borders, and gray (3 cd/m^2) for the background. Stimulation ("flashing") was made by setting the color of the symbols and the cell borders to light gray (10 cd/m^2).

Following the standard P300 Speller protocol [5], the stimuli were flashes (125 ms duration, 2 flashes/s) of a column or row in the matrix organized in "sequences", each consisting of all columns and rows presented once in a random order. Given a 3×3 matrix, sequence length was 6 stimuli (3 columns + 3 rows). From 15 to 18 sequences of flashes was presented per run, four consequent runs formed one block. Each block corresponded to one condition and was preceded by a practice run in the same condition. The order of conditions was random.

The matrix was positioned in the center of the screen in Static condition. In other conditions, it moved linearly at a constant speed within a $20.7^\circ \times 15.7^\circ$ field (the whole screen minus small margins). In Vertical 5°/s and Horizontal 5°/s conditions it moved in corresponding direction, abruptly changed by 180° at the screen margin. In Random 5°/s condition it moved in randomly chosen direction, changed at random intervals (duration 5–10 s) and, independently, when approached the screen margin (again by 180°, but not in a mirror-like fashion, to make pursuing more difficult). In all these "5°/s" conditions the velocity was 5°/s. Two conditions with higher velocities, 10°/s (Horizontal 10°/s) and 20°/s (Horizontal 20°/s), were also used.

The participants were instructed to fixate at the target cell, carefully pursue it by gaze (but avoiding head movements), count

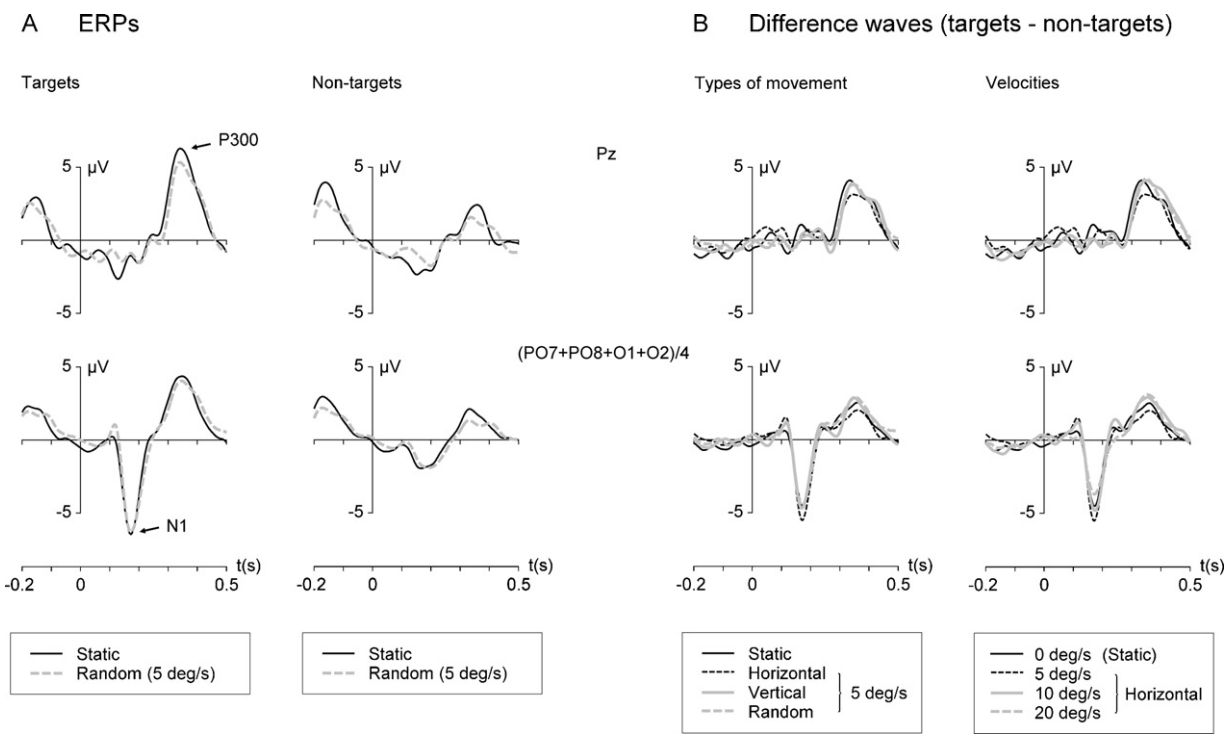

Fig. 2. Grand average ($n = 12$) ERPs (A) and difference curves (B) for Pz and averaged occipital channels. The beginning of stimulus corresponds to 0 at the time axes.

silently the number of flashes in it and report this number when the run ended.

EEG was recorded with NVX-52 amplifier/ADC (MCS, Russia) and CONAN-NVX program (InCo, Russia) from Ag/AgCl electrodes positioned at Cz, Pz, PO7, PO8, O1 and O2 locations, with joined reference at earlobes and ground at Fpz. Vertical and horizontal EOGs were recorded with bipolar electrodes. The EEG and EOG signals were bandpass filtered in the range of 0.05–32 Hz and sampled at 250 Hz.

For ERP analysis, epochs containing artifacts were rejected by a semiautomatic procedure. The percentage of the rejected epochs per participant and condition ranged from 0 to 18%, leaving 86–120 epochs for targets and 209–240 epochs for non-targets (the difference in all pairs of conditions was not significant: $p > 0.1$, uncorrected, Wilcoxon and Student paired tests). Before extracting epochs used for averaging and for evaluating the classification accuracy, EEG was additionally filtered with second order zero phase shift Butterworth filter in 0.5–20 Hz range. To obtain more stable estimate of N1 peak, the mean of PO7, PO8, O1 and O2 channels was computed. For this 'virtual' channel and for Pz, the target and non-target epochs were averaged separately. The N1 amplitude was estimated as the most negative value in the 140–240 ms window relative to the stimulus onset for the difference waveforms (target – non-target) of the averaged 'virtual' channel epochs. The time of this peak provided the N1 latency. The maximum positive value in Pz difference waveforms within the 300–500 ms window gave the P300 amplitude and latency. It was impossible to use baseline correction due to the strong overlap with the response to previous stimulus; however, this contribution was already low after the beginning of the new stimulus in the difference waveforms, according to visual screening (slower components were mainly removed by filtering and subtracting the non-target activity).

To compute offline classification accuracy, amplitudes within 600 ms after each stimulus onset where averaged in 48 ms windows, these values were concatenated for all EEG channels and formed a feature vector. Fisher linear discriminant analysis (FDA) was applied for these vectors separately for each condition. A leave-one-out validation was used, i.e., the classifier was tested at one epoch after training on all other epochs from the same condition; the procedure was repeated for all epochs and the accuracy was estimated as the percentage of correctly classified epochs. The stimulus class information was recorded only as "target"/"non-target", therefore, only binary classification of single trial epochs was possible.

To examine the effects of movement type and velocity on ERP components and on classification accuracy, we used multivariate analyses of variance (MANOVA). Tukey HSD post hoc tests were run whenever factor effect was significant. Wilcoxon matched pairs test was used to compare the number of counting errors between conditions.

The majority of the participants reported boredom, decreased attention and, in some cases, sleepiness in Horizontal 5°/s (but not in other) condition. Error rate, defined as the number of runs in which the number of target flashes was reported incorrectly, per four runs made in one condition, was highest in Random 5°/s condition ($M = 1.6$, SD = 1.6, max = 4) and lowest in Horizontal 20°/s condition ($M = 0.5$, SD = 0.7, max = 2), where the matrix velocity was highest among all conditions. Wilcoxon matched pairs test applied to all pairs of condition showed significant difference only for Random 5°/s condition vs. three others (Static, Horizontal 5°/s, Horizontal 20°/s; $p < 0.05$, uncorrected). Runs for which the target flashes count reported by the participant differed from the actually presented number by 3 or more were excluded from ERP analysis. Over the whole group, there were only 8 such runs, no more than two in one condition.

Grand average target and non-target ERPs are shown in Fig. 2A for Static and Random 5°/s conditions, the latter representing the most complicated type of movement. The N1 component in these grand averages showed no difference between these conditions. In both conditions, N1 and P300 had much higher amplitude in the target comparing to non-target ERPs.

More detailed analysis of difference (targets – non-targets) waveformes (Fig. 2B and Table 1) revealed some effects of conditions on the N1 and P300. Repeated measures 1-way MANOVA with

Table 1
Group ($n = 12$) mean amplitudes and latencies measured in difference curves and mean binary (target or non-target) single trial classification accuracy (random level: 0.5), as a function of condition. Standard deviation values are given in parentheses.

Condition	N1 ((PO7 + PO8 + O1 + O2)/4)		P300 (Pz)		Classification accuracy
	Amplitude (μV)	Latency (ms)	Amplitude (μV)	Latency (ms)	
Static	−5.0 (2.4)	178 (11)	5.5 (2.0)	376 (56)	0.79 (0.05)
Random 5°/s	−5.1 (1.8)	177 (11)	5.0 (2.0)	372 (33)	0.76 (0.04)
Vertical 5°/s	−5.1 (1.9)	174 (9)	4.7 (2.2)	375 (41)	0.78 (0.06)
Horizontal 5°/s	−6.0 (2.0)	176 (10)	4.4 (2.0)	355 (28)	0.78 (0.06)
Horizontal 10°/s	−5.3 (1.9)	176 (12)	5.0 (1.9)	381 (30)	0.78 (0.06)
Horizontal 20°/s	−4.3 (2.1)	184 (16)	4.9 (2.1)	364 (21)	0.70 (0.06)

4 levels (Static, Random 5°/s, Vertical 5°/s and Horizontal 5°/s; *Type of Movement* factor) revealed significant effect for P300 amplitude ($\lambda(3,9) = 0.40$, $p = 0.03$), while the effect for N1 amplitude was not significant ($\lambda(3,9) = 0.61$, $p = 0.19$). Effect for P300 seemed to be primarily driven by 1.2 μV decrease in Horizontal 5°/s relative to Static (marginally significant, according to post hoc test, $p = 0.06$; for other pairs of conditions, $p > 0.25$). A repeated measures 1-way MANOVA was performed with 3 levels of *Velocity* factor corresponding to Horizontal conditions with velocities 5, 10 and 20°/s, separately for N1 and P300 amplitudes. This factor's effect was significant for N1 but not for P300 ($\lambda(2,10) = 0.50$, $p = 0.03$, and $\lambda(2,10) = 0.82$, $p = 0.37$, respectively). N1 mean amplitude decreased: by 0.7 μV in 10°/s comparing to 5°/s condition (according to post hoc test, the effect was not significant, $p = 0.29$); by 1.0 μV in 20°/s comparing to 10°/s (not significantly, $p = 0.11$); and by 1.6 μV in 20°/s comparing to 5°/s (this effect was significant, $p = 0.004$).

When applied to N1 and P300 *latency* data, 1-way MANOVA for the same factors revealed no significant effects. Corresponding test statistics and p-values were $\lambda(3,9) = 0.70$, $p = 0.34$, and $\lambda(3,9) = 0.64$, $p = 0.24$ (*Type of Movement* factor, for N1 and P300, respectively), $\lambda(2,10) = 0.78$, $p = 0.29$, and $\lambda(2,10) = 0.70$, $p = 0.17$ (*Velocity* factor, for N1 and P300, respectively).

The classification accuracy (Table 1) was not affected by the *Type of Movement* factor ($\lambda(3,9) = 0.52$, $p = 0.10$), but the effect of *Velocity* was significant ($\lambda(2,10) = 0.17$, $p = 0.0001$). Post hoc test showed that this effect was driven by the decrease of accuracy at 20°/s velocity ($p = 0.0001$ for both pairs including this condition; $p > 0.9$ for comparing 5°/s and 10°/s).

Our study, for the first time, assessed the effects of stimuli matrix movement in the P300 BCI paradigm on the ERP.

The target minus non-target difference responses were, in general, little affected in 5°/s movement conditions, comparing to static position of the matrix. For example, although P300 amplitude seemed to decrease in target and non-target responses in Random 5°/s condition, the difference waveform remained remarkably similar to what was observed in Static condition, despite of the difficulty of the Random 5°/s condition for participants, indicated by the highest number of counting errors. Only in Horizontal 5°/s condition, a significant decrease of P300 (but not N1) amplitude in the difference waveforms was observed, but it probably reflected decreased general attention specific to this condition. Reallocation of attentional resources was unlikely responsible for the variation of the P300 difference amplitude with the type of movement, otherwise not this but Random 5°/s condition would be the most affected one.

Visual examination of the ERPs suggested that the N1 amplitude decrease at highest velocity (20°/s) could be likely due both to decrease of N1 to targets and its increase to non-targets. It is known that visual acuity during smooth pursuit of slowly moving targets is close to visual acuity for stationary targets, and it declines with increasing objects speed, probably due to increasing eye movement error [20]. The N1 effect we observed could be, thus, related to a loss of precision in differentiating the target and non-target locations. However, it may have a more complicated nature. Ref. [6] did not found high amplitude N1 (defined as N200 there) in responses to flashes that were counted in a P300 BCI matrix's cell different from the cell fixated by a participant, while P300 amplitude remained high. In contrast, N1 but not P300 was observed after the flashes in the fixated cell. One may hypothesize that pursuing the matrix at high velocities could be more stable if not the attended (target) cell is fixated but some other cell which is, for some reasons, easier to pursue, or if the matrix is pursued as a single object. In these cases, the target minus non-target difference responses, as in our experiment, would demonstrate same P300 amplitude but lower N1 amplitude. Testing this hypothesis requires eye tracking, not employed in our work.

As gaze control is often impaired in the heavily paralyzed patients [2], the moving matrix modifications can be used only in other target BCI groups, such as patients with lower degree of paralysis, videogame players, etc. However, it is the users with intact eye movements who may take the full advantage of the P300 BCI, as only they likely can use the large N1 component, which was not found under conditions without fixating the target cells [2,6,25].

In general, N1 and P300 amplitudes and latencies in the difference waveforms, as well as the classification accuracy, were little affected by the movement of the stimuli matrix (Table 1), in contrast to what was expected. This fact implies that the P300 BCI with moving matrix can, in principle, work well in practical situations. Nevertheless, for specific moving modifications of the P300 BCI, or specific settings where they will be used, or specific groups of users (e.g., patients with at least partly impaired gaze control), additional ERP or at least BCI performance studies will be needed to confirm that the target/non-target difference remains sufficiently stable to enable efficient discrimination of the brain responses.

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