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A submatrix-based P300 brain-computer interface stimulus presentation paradigm*

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Abstract: The P300 event-related potential (ERP), with advantages of high stability and no need for initial training, is one of the most commonly used responses in brain-computer interface (BCI) applications. The row/column paradigm (RCP) that flashes an entire column or row of a visual matrix has been used successfully to help patients to spell words. However, RCP remains subject to errors that slow down communication, such as adjacency-distraction and double-flash errors. In this paper, a new visual stimulus presentation paradigm called the submatrix-based paradigm (SBP) is proposed. SBP divides a 6×6 matrix into several submatrices. Each submatrix flashes in single cell paradigm (SCP) mode and separately performs an ensemble averaging method according to the sequences. The parameter of sequence number is used to improve further the accuracy and information transfer rate (ITR). SBP has advantages of flexibility in division of the matrix and better expansion capability, which were confirmed with different divisions of the 6×6 matrix and expansion to a 6×9 matrix. Stimulation results show that SBP is superior to RCP in performance and user acceptability.

Key words: Brain-computer interface, Event-related potentials, P300 speller, Submatrix-based paradigm
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1 Introduction

A brain-computer interface (BCI) translates a subject's intentions into a control signal for external devices without using the brain's normal output pathways of peripheral nerves and muscles (Wolpaw *et al.*, 2002). Various types of brain activity have been used in BCIs. Some BCIs rely on voluntary changes in endogenous brain rhythms, such as slow cortical potentials and event-related (de)synchronization (ERD/ERS). Others rely on voluntary changes in evoked potentials, usually visual, such as steady-state visual evoked potentials (SSVEPs) and event-related potentials (ERPs) (Jin *et al.*, 2011). The P300, which has been the most popular form of ERP in recent decades, is elicited in the oddball paradigm. In this paradigm, participants are asked to view rare target stimuli in a series of many irrelevant stimuli. Compared with other BCI approaches, P300-based BCI offers an excellent information transfer rate (ITR) and has the advantage of not needing time-consuming training (Jin *et al.*, 2011).

Farwell and Donchin (1988) introduced the first P300-based BCI paradigm. In this paradigm, a computer presents a 6×6 matrix of alphanumeric characters on a screen and participants attend to the item they wish to select. These characters are intensified in rows and columns in a random order. Only flashes of the rows or the columns containing the attended item should elicit a P300 component. The attended item exists at the intersection of the detected row and column. Although the row/column paradigm (RCP) has been most commonly used and tested with various configurations, it remains subject to adjacency-

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distraction and double-flash errors (Townsend *et al.*, 2010).

Many new visual stimulus paradigms have been proposed to overcome these errors. Guan *et al.* (2004) proposed the single cell paradigm (SCP) in which each single character is flashed randomly and individually. SCP elicits a larger P300 component because of the smaller probability of occurrence of a target item (Duncan-Johnson and Donchin, 1977), but accuracy and speed of communication are reported to be lower compared with RCP (Guger *et al.*, 2009). SCP is suitable for small available item paradigms, such as direction control (Pires *et al.*, 2008), virtual hand control (Chen *et al.*, 2010), and Chinese typewriter (Li *et al.*, 2009). Townsend *et al.* (2010) proposed the checkerboard paradigm (CBP) to disassociate the rows and columns and present stimuli in quasi-random flash groups. This paradigm eliminates adjacency-distraction and double-flash errors and achieves a better classification performance than RCP. Also, CBP can cause less visual fatigue and is more acceptable to users. Sellers *et al.* (2011) further examined CBP by suppressing items that surround the target. Fazel-Rezai and Abhari (2009) proposed the region-based paradigm (RBP), in which character recognition is done at two levels. Jin *et al.* (2011) used new flash pattern approaches to improve the accuracy and ITR.

Due to the low signal-to-noise ratio (SNR), each item must be flashed multiple times and ensemble averaging is performed to detect the P300 component. The need for signal averaging results in a tradeoff between speed and accuracy of communication (Mak *et al.*, 2011). Jin *et al.* (2011) described several ways to improve the accuracy and ITR. Decreasing the number of flashes per trial could enhance the single-trial P300 amplitude. However, this may increase the number of trials in one sequence and increase the time for each character selection. Although these new visual stimulus paradigms improve performance by solving adjacency-distraction and double-flash errors, the tradeoff between decreasing the time of an oddball sequence and enhancing the single-trial P300 amplitude restricts the improvement of P300-based BCI systems.

In this paper, a new submatrix-based paradigm (SBP) is proposed. This new visual stimulus paradigm divides the traditional 6×6 matrix of alphanumeric characters into several submatrices. The characters in each submatrix flash randomly and individually, as with SCP. In previous paradigms, the parameter of sequence number is used only for ensemble averaging by simple repetition. Our new paradigm can obtain information from this parameter and further improve the accuracy and ITR. With an increasing number of sequences, SBP can detect the target submatrix and the attended item simultaneously.

2 Submatrix-based P300 stimulus presentation paradigm

According to the oddball condition, a P300 component is elicited by infrequent target stimuli. The P300 amplitude increases as the target probability decreases (Sellers and Donchin, 2006; Sellers *et al.*, 2006). But a lower target probability will lead to a requirement for more trials in an oddball sequence and reduce the ITR. In RCP, the probability of a target being flashed is 1/6, and there are 12 trials in a sequence, including two target stimuli. Most paradigms improve accuracy and ITR by changing the target probability and the number of trials in a sequence. In this paper, the proposed paradigm can obtain information from the sequence number, which is used not only for ensemble averaging but for classification.

2.1 Principle of the submatrix-based P300 stimulus presentation paradigm

Working from the traditional 6×6 matrix of alphanumeric characters, we designed a new visual stimulus presentation paradigm called the submatrix-based paradigm (SBP). In SBP, the 6×6 matrix is divided into four 3×3 submatrices (Fig. 1). Two dashed lines divide the matrix into four parts, and the characters in each submatrix are numbered from 1 to 9. In the upper left submatrix, for example, the three characters of the first row are numbered 1 to 3 in order from left to right, Similarly, characters of the second and the third rows are numbered 4 to 6 and 7 to 9 respectively, in order from left to right. When the computer presents a 6×6 matrix on screen, the dashed lines are invisible. Each submatrix flashes in SCP mode and is independent of other submatrices. In each trial four characters, coming randomly from different submatrices, are intensified. There are nine trials and all characters flash once in an SBP sequence. Therefore, the probability of flashing the target is 1/9.

In SBP, the positions of the flashing items are recorded. For example, Code=4285 means that the four characters in this flashing trial are: the fourth character in the upper left submatrix, G, the second character in the upper right submatrix, E, the eighth character in the lower left submatrix, 6, and the fifth character in the lower right submatrix, 3. The flashing trial is illustrated in Fig. 1. The dashed lines are invisible in experimental presentation.

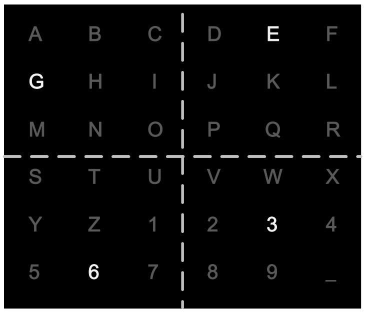

Fig. 1 The submatrix-based paradigm (SBP) with four 3×3 submatrices

There are nine trials in a sequence including one target stimulus. For each submatrix, ensemble averaging according to sequences is performed separately. If a submatrix contains the attended item, ensemble averaging can enhance P300 potential SNR; otherwise, it is ineffective. Take the recognition of a specific character as an example to illustrate the implementation of enhancing the SNR: the target character is E, and therefore, the upper right submatrix is the target submatrix. If the target stimuli in the first sequence are Code=4285 and those in the second sequence are Code=5237, the averaging according to sequences can enhance the P300 potential SNR for the target submatrix. Though target stimuli can elicit P300 potentials for non-target submatrices, P300 potentials are not elicited by the characters themselves from non-target submatrices. Rather, they result from characters in the non-target submatrices flashing at the same time as the target character. After averaging with several sequences, P300 potentials are buried in noise from non-target submatrices. There is a special case in which characters from non-target submatrices flash consistently with the target character. If the target stimulus in the second sequence is Code=42*XX*, where *X* is an integer between 1 and 9, averaging with the first two sequences can enhance P300 potential SNR for the upper left non-target submatrix. Luckily, the probability of this situation is only 1/9, and the probability of enhancing P300 potential SNR for the upper left non-target submatrix is $(1/9)^{N-1}$ after N sequences. Thus, ensemble averaging is ineffective for non-target submatrices due to such low probabilities. The target character cannot be recognized correctly after just one sequence in SBP. There should be at least two sequences, and with increasing numbers of sequences, the classification accuracy of the target submatrix and target character will be improved simultaneously.

SBP has advantages besides eliminating adjacency-distraction and double-flash errors. First, matrix division is flexible. A total of P alphanumeric characters in a matrix can be divided into N submatrices, with M characters per submatrix such that $P=N\cdot M$. There are M trials per sequence including one target stimulus and N flashes per trial. The probability of flashing the target is $1/M$. Since P300 potentials are subject-specific (Mak *et al.*, 2011), the performance of SBP can be improved by proper adjustment of the parameters N and M. Optimal N and M are obtained when the number of sequences is the lowest that is sufficient to detect the target submatrix and target character simultaneously. Second, the expansion of the 6×6 matrix does not increase the recognition time markedly. The number of trials per sequence is determined by the parameter M, and the total recognition time is the product of M and the sequence number. Increasing the number of submatrices will not lead to a prolonged recognition time, but too large a number of submatrices may reduce the detection of the target submatrix. In SBP, the classification accuracy of the target submatrix grows exponentially with the number of sequences. Thus, if a target submatrix is not detected, the required increase in the number of sequences will prolong recognition time only slightly. However, in RCP, the total recognition time grows linearly with the sequence number.

2.2 Experiments and data acquisition

In this experiment, SBP and RCP were used to implement the P300 speller. To illustrate the advantages of our proposed paradigm, an SBP with six 2×3 submatrices and an SBP expansion to a 6×9 matrix with six 3×3 submatrices were compared (Figs. 2a and 2b, respectively). The SBP with four 3×3 submatrices (Fig. 1) is labeled SBP433, and the SBPs in Figs. 2a and 2b are labeled SBP623 and SBP633, respectively.

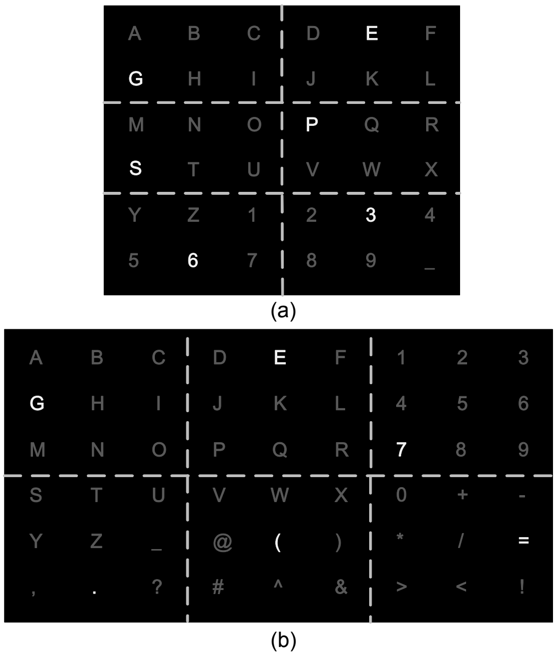

Fig. 2 Submatrix-based paradigm (SBP) with different divisions of the matrix
(a) SBP with six 2×3 submatrices (SBP623); (b) SBP with six 3×3 submatrices (SBP633)

Seven able-bodied subjects, five males and two females, of age range 20–27 years, with no known neurological disorders and with normal or corrected to normal vision, participated in this experiment. All were naive to BCI use. During data acquisition, subjects sat in a comfortable chair about 1 m from a cathode ray tube (CRT) monitor. The general-purpose BCI software platform BCI2000 (Schalk *et al.*, 2004) was used for stimulus presentation and data collection. EEG signals were amplified and digitized by the 64-channel Neuroscan Synamp2 system, band pass filtered between 0.1 and 50 Hz, and sampled at 250 Hz. Previous studies (Vaughan *et al.*, 2006; Hoffmann *et al.*, 2008; Krusienski *et al.*, 2008; Rakotomarnonjy and Guigue, 2008; Mak and Wolpaw, 2009) have shown that P300 is detected mainly over the central and parietal regions of the brain (Picton, 1992; Mak and Wolpaw, 2009). Good results have been reported using eight electrodes, Fz, Cz, P3, Pz, P4, PO7, PO8, and Oz (Vaughan *et al.*, 2006), and two central electrodes C3, C4 (Kaper *et al.*, 2004; Rakotomarnonjy and Guigue, 2008). Therefore, only these 10 electrode positions were used for processing in this study, and all channels were referenced to the left mastoid and grounded to the right mastoid. The subjects were presented with a matrix of characters flashing in RCP and SBPs. Every paradigm was presented in the copy-spelling mode in which subjects had to attend to prescribed characters such that the target character was predefined. Subjects were instructed to count the number of times the target character was flashed.

Each subject completed RCP, SBP433, SBP623, and SBP633 during four experimental sessions on different days within a two-week period. There were five runs in each session and 10 character epochs in each run. For each character epoch, SBP433 was designed as follows: the prescribed character was displayed for 3.48 s to ensure that participants could find the target character in a 6×6 matrix during the allotted time. Then four characters selected randomly from four submatrices flashed for 80 ms, followed by an 80 ms inter-stimulus interval (ISI). Thus, each trial took a total of 160 ms. There were nine trials and all characters could be intensified once in an SBP433 sequence. The sequence was repeated 15 times for each character epoch. Each character epoch was followed by a 0.96 s period, during which the matrix was blank and participants were asked to prepare for the next character epoch. For other paradigms, experimental parameters were set the same as those of SBP433. But for SBP623 and SBP633, six characters were intensified per trial, and the trial number per sequence was six in SBP623 and nine in SBP633. Therefore, the durations of a one-character epoch for RCP, SBP433, SBP623, and SBP633 were 28.8, 21.6, 14.4, and 21.6 s, respectively. After performing these experiments, the participants completed a questionnaire to survey the acceptance of SBP.

3 Data processing and stimulation results

The recorded EEG signals were filtered with an eight-order band pass Chebyshev Type I filter with cut-off frequencies of 0.1 Hz and 12 Hz, and decimated by selecting every tenth sample from the filtered signals. The signals were then corrected using a regression method (Schlogl *et al.*, 2007). For each channel, we extracted all data samples between 0 and 600 ms after the beginning of an intensification for the offline analysis. So, an extracted signal from a single channel was composed of 15 samples.

In the classification stage, support vector machine (SVM) with a polynomial kernel was used for training and classification. For each experimental session, five classifiers were trained by five runs of EEG signals individually in the training phase. Each run was used as test data, classified by the other four classifiers using the ensemble-of-classifiers strategy (Rakotomarnonjy and Guigue, 2008) in the classification phase. The average classification accuracy for 15 sequences with 10 channels is shown in Table 1. The average accuracy was the highest for SBP433 (99.7%), and then SBP623 (99.4%). With increasing numbers of characters in the matrix, the average classification accuracy of SBP633 dropped, but was still higher than that of RCP.

Table 1 The average classification accuracy for 15 sequences with 10 channels

Participant No.	Classification accuracy (%)			
	RCP	SBP433	SBP623	SBP633
1	92	98	100	98
2	100	100	100	100
3	100	100	98	100
4	100	100	100	98
5	98	100	98	98
6	94	100	100	96
7	100	100	100	100
Mean (%)	97.7	99.7	99.4	98.6

Though all the paradigms had the same number of sequences for each character epoch, the execution time was different. It is meaningful to compare the accuracy at the same time, or the speed of communication. ITR or bit rate (McFarland *et al.*, 2003) was calculated as follows:

$$B=\log_2 N+P\log_2 P+(1-P)\log_2[(1-P)/(N-1)], \quad (1)$$

where N is the number of possible targets, and P is the probability that the target is accurately classified. However, bit rate does not account for the fact that every error results in a penalty of two additional selections, and it is much more reasonable to use practical bit rate to estimate the actual speed of communication (Hoffmann *et al.*, 2008; Townsend *et al.*, 2010; Jin *et al.*, 2011). Practical bit rate was calculated as follows:

$$\mathrm{PB}=B(1-2P)/T, \quad (2)$$

where T is the recognition time. In this paper, we tested different electrode configurations, consisting of 4, 6, 8, or 10 electrodes. The simulation results are shown in Fig. 3. The paradigms had the same number

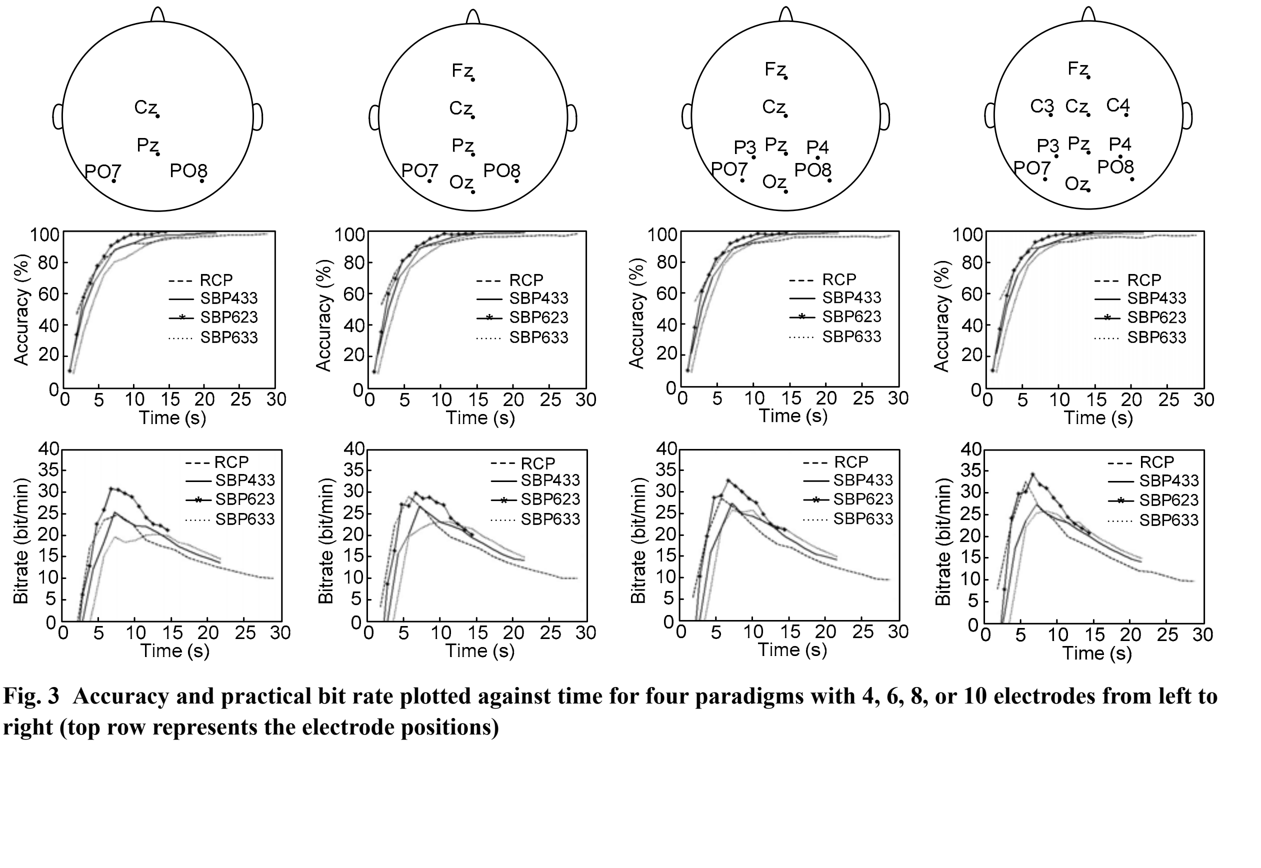

Fig. 3 Accuracy and practical bit rate plotted against time for four paradigms with 4, 6, 8, or 10 electrodes from left to right (top row represents the electrode positions)

of sequences in a character epoch, but the time needed to take a decision was different. The recognition times in a sequence of RCP, SBP433, SBP623, and SBP633 were 1.92, 1.44, 0.96, and 1.44 s, respectively, and the total recognition times in a character epoch were 28.8, 21.6, 14.4, and 21.6 s, respectively. The stimulation results show that the accuracy and practical bit rate can be improved by increasing the number of electrodes, but the improvement is limited by the expense of having more data to process. Fewer electrode channels appear to be more convenient and practical for long-term BCI use.

Fig. 3 illustrates that for RCP the beginning time was the latest to start, but the beginning accuracy and practical bit rate were the highest. The reason is that the target character would be recognized after one sequence for RCP theoretically, but the number of sequences should be greater than two for SBPs. The advantages of SBPs became clear as the number of sequences increased. About 5 s after the beginning of an intensification, i.e., after five SBP623 sequences, SBP623 accuracy was higher than RCP accuracy. After about 8 s, i.e., four RCP sequences, SBP433 accuracy was higher than RCP accuracy. At 14.4 s, the time of the last SBP623 sequence, the average accuracies of RCP, SBP433, SBP623, and SBP633 were 95.2%, 97.9%, 99.3%, and 97.1%, respectively. In the 6×6 matrix condition, SBP433 accuracy was significantly higher than that of RCP (t=2.973, P=0.0035), and SBP623 accuracy was significantly higher than that of RCP (t=4.012, P=0.0001). In comparison with other SBPs, SBP633 accuracy was slightly lower because increasing the number of possible targets may reduce the recognizability of the target submatrix. A few extra sequences will compensate for the loss of accuracy. If the 6×9 matrix was presented in RCP mode, the recognition time would be lengthened by 25%. So, the expansion for SBP does not greatly increase the recognition time.

Practical bit rate takes accuracy, time, and error correction into account and contributes to a better evaluation of system performance. The highest practical bit rate was obtained between 5 and 10 s after the beginning of intensification (Fig. 3). The average practical bit rate of SBP623 was the highest (31.9 bits/min) at about 7 s within different electrode configurations, and the average practical bit rate of RCP (28.8 bits/min) was superior to those of SBP433 and SBP633 (26.8 and 23.8 bits/min, respectively). Through flexible division of the matrix in SBP, we can achieve the highest practical bit rate for a specific subject.

Adjacency-distraction and double-flash errors can be eliminated by proper arrangements of flashing, but the tradeoff between enhancing the single-trial P300 amplitude and increasing the speed of communication restricts the improvement. The CBP, for example, takes longer to present one sequence and the number of selections per minute is not improved significantly. In a CBP study (Townsend *et al.*, 2010), the mean number of RCP sequences was 4.5, that is about 10 s. At this time, SBP is superior to RCP in accuracy and practical bit rate. CBP sequence time changes almost linearly with the number of possible targets. SBP sequence time is determined by the number of targets in a submatrix and is suitable for recognizing large numbers of targets. Compared with other visual stimulus paradigms, SBP can obtain information from the sequence number and improve the overall performance.

According to the questionnaire, most participants (6 out of 7) preferred SBPs to RCP. The reasons given were: fewer characters flashing in a trial, less visual fatigue, easier to focus attention on the target character, and a shorter experiment time. Only one participant preferred RCP because flashing rows or columns helped to focus attention on the target character. In general, SBP was superior to RCP in performance and user acceptability.

4 Conclusions

We propose a new visual stimulus presentation paradigm that divides a 6×6 matrix of alphanumeric characters into four 3×3 submatrices. Each submatrix flashes in SCP mode and separately performs ensemble averaging according to sequences. Compared with RCP, SBP has fewer trials and only one target stimulus in a sequence, leading to less time in a sequence and a larger P300 amplitude. SBP obtains information not only from the target probability and trial number in a sequence, but also from the number of sequences. With an increasing number of sequences, the classification accuracy of the target submatrix and the target character will be improved simultaneously.

SBP eliminates adjacency-distraction and double-flash errors. It also has advantages of flexible division of the matrix and better expansion, which were confirmed with different divisions of the 6×6 matrix and expansion to a 6×9 matrix. The performance of SBP can be improved by subject-specific division. The expansion of an SBP does not increase the recognition time markedly, which makes SBP extremely useful for recognizing large numbers of targets. The results of this research show that SBP is superior to RCP in performance and user acceptability.

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