2014 5th IEEE RAS & EMBS International Conference on
Biomedical Robotics and Biomechatronics (BioRob)
August 12-15, 2014. São Paulo, Brazil

The effect of feedback presentation on motor imagery performance during BCI-teleoperation of a humanlike robot

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Abstract— **Users of a brain-computer interface (BCI) learn to co-adapt with the system through the feedback they receive. Particularly in case of motor imagery BCIs, feedback design can play an important role in the course of motor imagery training. In this paper we investigated the effect of biased visual feedback on performance and motor imagery skills of users during BCI control of a pair of humanlike robotic hands. Although the subject specific classifier, which was set up at the beginning of experiment, detected no significant change in the subjects' online performance, evaluation of brain activity patterns revealed that subjects' self-regulation of motor imagery features improved due to a positive bias of feedback. We discuss how this effect could be possibly due to the humanlike design of feedback and occurrence of body ownership illusion. Our findings suggest that in general training protocols for BCIs, realistic feedback design and subject's self-evaluation of performance can play an important role in the optimization of motor imagery skills.**

I. Introduction

Brain computer interfaces (BCIs) provide a direct communication channel between a human brain and a computer. Subjects can learn to intentionally modulate their brain activities in order to translate their intention into meaningful commands for an external machine. Motor imagery, is one of the most commonly employed methods for BCI motion control [1]. Subjects imagine the movement of a part of their own body and the BCI detects the corresponding changes in mu and beta rhythms over sensorimotor cortex. Since the movement imagination without execution is an unfamiliar experience to most people, motor imagery task requires relatively long training sessions for novice BCI users.

As in any form of training paradigm, users of BCIs improve their skills in motor imagery task through the feedback they receive of their performance. Therefore feedback design is particularly influential in the process of motor imagery learning and performance improvement. While the importance of BCI feedback design is well recognized, very few studies have challenged new training paradigms that can facilitate the learning process for subjects [2]. Standard BCI protocols typically provide online visual feedback in the form of a moving cursor or target on the computer screen. Neuper et. al [3] compared realistic presentation of feedback, in form of a grasping hand, vs abstract feedback, in form of an extending bar, on a computer screen. However, they found no evidence of a significant difference between the performances of two feedback groups. In other study, authors biased the feedback accuracy and investigated the influence of motivation on BCI performance [4]. The results indicated that subjects with poor performance benefitted from positive biasing while those with better performance were impeded by inaccurate feedback. Similarly, Gonzalez-Franco et. al [5] provided subjects fake negative and positive feedback of their performance and reported that negative feedback had a greater learning effect on motor imagery BMIs.

Although in the above works, the effect of feedback presentation and accuracy has been probed, none of them has actually discussed the direct interaction between subject and BCI system. When performing a motor imagery task, subjects are asked to imagine their own body movements while the output is fed back in the form of movement for objects other than their own body. This mismatch and dissociation between subject's life experience and BCI task can in fact interfere with the imagination and impair the performance of motor imagery especially for novice users.

The goal of the present study is to explore the influence of feedback design on enhancement of user's performance and interaction with a BCI system. We previously showed that BCI-control of a pair of humanlike robotic hands along with real time first-person perspective visual feedback of robot's motions could arouse an illusion of embodiment in the operators [6]. Subjects reported a sense of owning the robot's hands after a certain amount of BCI-operation, and showed physiological reaction when robot's hands were threatened. In the following, we call this feeling of embodiment "body ownership illusion". Our results also revealed that the intensity of the body ownership illusion was associated with feedback presentation and subjects' performance during BCI motion control. We hypothesized that inducement of such feeling of owning robot's body and the sense of agency driven toward the seen motions may have a positive loop effect on execution of motor imagery during BCI-operation. In other words, we speculated that once the thought of "I am the one moving the hands" raises the feeling of "These hands are mine", the illusion of owning hands enhances the imagery ability in subjects and boosts the inverse thought of "These are my hands so I can move them".

To that end, in this study we used the same BCI-teleoperation paradigm while exposed naïve subjects to

*This research was partially supported by JSPS KAKENHI Grant Number 2522004 and 24650114.

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different feedback conditions in order to probe the relationship between subject's experience of BOT and BCI-performance. Two experiments are presented. In the first experiment, by manipulating the presentation of misperformance, we surveyed how subjects' perception of their own performance could affect the intensity of BOT. In the second experiment, we then examined how this effect can be influential on subjects' real performance and trend of motor imagery learning.

II. Method

A. Participants

Sixteen healthy subjects (6 male and 10 female, age M=21.1, SD=1.4) participated in this experiment. 15 participants were right-handed and one left-handed. All participants were naive to research topic and received explanation prior to the experiment.

B. EEG recording

Brain signals were recorded by g.USBamp biosignal amplifiers (Guger Technologies) from 27 EEG electrodes that were placed over primary sensori-motor cortex according to the international 10-20 system (FT7, FC5, FC3, FC1, FCz, FC2, FC4, FC6, FT8, T7, C5, C3, C1, Cz, C2, C4, C6, T8, TP7, CP5, CP3, CP1, CPz, CP2, CP4, CP6, TP8). A reference electrode was mounted on the right ear and a ground electrode on the forehead.

C. Experimental paradigm

Participants sat in a comfortable chair and the experimenter placed the EEG electrodes. In an initial training session, they practiced a motor imagery task by extending a feedback bar to the left or right side on a 15-inch laptop computer screen. A visual cue in form of a horizontal pointing arrow specified the timing and the hand they were supposed to hold image for. Each trial lasted 7.5 seconds and started with the presentation of a fixation cross on the display. After 2 seconds, an acoustic warning was given in form of a "beep". From second 3 to 4.25, an arrow pointing to the left or right side randomly was displayed. Participants were instructed to perform motor imagery depending on the arrow's direction. After the arrow disappeared continued the imagery task until the fixation cross was erased. After a short pause the next trial started. The first run consisting of 40 trials (20 trials per class left/right presented in a randomized order) was conducted without feedback. The recorded brain activities in this initial non-feedback run were used to set up a subject specific classifier for the classification in the following feedback runs (See details in section II-D). In the following feedback runs, participants performed similar trials, however received online feedback of their performance in form of a horizontal feedback bar on the screen that extended to right or left side based on the classification results. Subject's task was to extend the feedback bar in the correct direction.

Following to the training sessions, experiment was continued to the main test sessions, in which subjects wore a head mounted display (Sony HMZ-T1) and tele-operated robot's hands using the same BCI system and paradigm. They performed a motor imagery task for their right or left hand

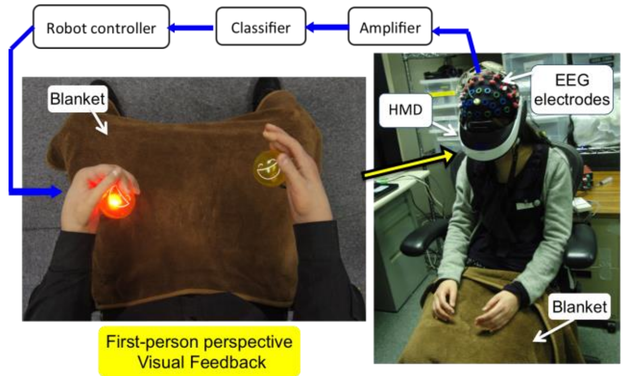

Fig. 1. EEG electrodes placed on subject's sensorimotor cortex recorded brain activities during a motor imagery task. Subjects watched first-person images of robot's through a head mounted display. A lighting ball in front of robot's hands gave motor imagery cue and subjects held images of a grasp for their own corresponding hand. Classifier detected two classes of results (right or left) and sent a motion command to robot's hand.

while they watched first-person perspective images of robot's hands performing the motions respectively (Fig. 1). Two LED-embedded balls were installed in robot's grasp and gave motor imagery cue by randomly lighting. During experiment subjects were told to keep a looking down posture as if they were looking at their own hands. Identical blankets were laid on both robot's and participants' legs to give similar view of one's own body. Participants placed their arms in the similar position and orientation of robot's arms. They performed 4 experimental sessions each consisting of 40 imagery trials. The first half of each session (20 trials) was randomly conditioned as below:

(1) Raw: Participants' performance was not biased. Robot's hands grasped the ball according to the classification result.
(2) Match: Participants' performance was not biased. However robot's hands only grasped the lit ball when the classification results matched the cue.
(3) Positive Feedback (Fake-P): Participants' performance was biased positively. Robot's hands grasped the lit ball correctly in 90% of trials regardless of subject's real performance.
(4) Negative Feedback (Fake-N): Participants' performance was biased negatively. Robot's hands grasped the lit ball correctly only in 20% of trials regardless of subject's real performance.

In the first two conditions, Raw and Match, subject's performance was not biased however the presentation of mistaken trials were different –one with execution of wrong hand motion and one without robot motion. In Fake-P and Fake-N conditions the visual feedback of performance was biased regardless of subjects' real performance accuracy in order to deliberately enhance or decrease their self-evaluation. Subjects were unaware of the condition setups. In all sessions they were told that accurate execution of motor imagery task would produce a robot motion.

In the second half of all sessions subjects received feedback of their real performance in the same presentation of Raw condition. The goal was to seek changes in BCI-performance and motor imagery skills in the second half of each session due to the manipulation or bias of visual feedback.

Moreover at the end of each session the following question regarding subjects' experience of BOT was asked: Q) Throughout the entire session while you were operating the robot's hands, did it feel as if robot's hands were your own hands? Participants scored Q based on the seven-point Likert Scale, where 1 denoted, "Didn't feel such thing at all" and 7 denoted, "Felt it very strongly".

D. Online classification

Recorded brain signals were processed under Simulink/MATLAB (Mathworks) for both online and offline parameter extractions. The data in the first calibration session were used to train the classifier. This process included bandpass filtering between 0.5 and 30 Hz, sampling at 128 Hz, cutting off artifacts by notch filter at 60 Hz, and adopting Common Spatial Pattern (CSP) algorithm for discrimination of Event Related Desynchronization (ERD) and Event Related Synchronization (ERS) patterns associated with motor imagery task [7]. CSP found weight vectors that weighed each electrode based on its importance for the discrimination task. The spatial filters were designed such that the resulting signal had maximum variance for left trials and minimum variance for right trials. Therefore the difference between left and right populations was maximized to show where the EEG variance fluctuated the most. After computing feature vectors by averaging the variance and calculating the logarithm, Fisher's linear discriminant analysis (LDA) was applied for distinction of left versus right hand trials. The signals recorded in the first non-feedback session were used to set up the decision border for a subject specific classifier. In the feedback sessions the system used the individual classier of each participant to discriminate between left and right imaginations. The results of classifier were then outputted as a linear array signal in the range of [-1,1], where -1 denotes the extreme left and 1 denotes the extreme right. Negative values were then translated as grasp motions for robot's left hand and positive values were commanded as grasp motions for robot's right hand.

E. Offline classification

Since the classifier does not use a learning algorithm, once the classification boundary for two classes "Right" and "Left" is defined within the feature space in the initial recording session, the same classifier and parameters are used to the end of the experiment. On the other hand, we speculated that by receiving biased feedback or experiencing body ownership illusion, subjects would consciously or unconsciously modify the generation of their brain activity patterns during motor imagery. However an initially set classifier may not detect this optimization of brain patterns accurately. Therefore, we used the original brain signals and extracted class features of right and left motor imagery through offline processing to observe the distribution and separability of motor imagery features in the feature space.

After artifact removal and temporal filtering [7], the features used for classification were obtained by the method of CSP. Having N channels of EEG for each left and right trial $\mathbf{X}$, the CSP builds an N × N projection matrix $\mathbf{W}$. With the projection matrix $\mathbf{W}$, the mapping of a trial is given as

$$\mathbf{Z} = \mathbf{WX} \tag{1}$$

The columns of $\mathbf{W}^{-1}$ are the common spatial patterns and can be seen as time-invariant EEG source distribution vectors. By construction the variance for left movement imagination is largest in the first row of $\mathbf{Z}$ and decreases with the increasing number of subsequent rows. To obtain reliable features, it is not necessary to calculate the variances of all N time series. The optimal number of common spatial patterns used to build the feature vector is four [8]. Therefore, only the first and last two rows (p = 4) of $\mathbf{W}$ were used to filter data $\mathbf{X}$ and build new signal $\mathbf{Z}_p$ (p = 1… 4). The variance of the resulting four time series is obtained for a time window $T = (t_0, t_1)$

$$\mathrm{var}_p = \sum_{t=t_0}^{t_1} (\mathbf{Z}_{p(t)})^2 \tag{2}$$

where window length was set 1s, starting 1500ms after the presentation of the cue [9]. Feature vectors were obtained after normalizing and log-transforming as following:

$$\mathbf{f}_p = \log\left(\mathrm{var}\left(\mathbf{Z}_p\right) / \sum_{i=1}^{p} \mathrm{var}\left(\mathbf{Z}_p\right)\right) \tag{3}$$

The online classifier uses each trial's feature vector $\mathbf{f}_p$ to categorize it into two classes of right and left. In order to evaluate the goodness of this classification, we used the following discriminant criterion measures (measures of class separability) in the discriminant analysis [10] to observe the distribution of two classes (Right and Left) feature vectors in a 4-dimential space:

$$J = \delta_B^2 / \delta_W^2 \tag{4}$$

where

$$\delta_B^2 = \omega_R \omega_L (\tilde{\mu}_R - \tilde{\mu}_L)^2 \tag{5}$$

$$\delta_W^2 = \omega_R \tilde{s}_R^2 + \omega_L \tilde{s}_L^2 \tag{6}$$

are the between-class scatter and within-class scatter respectively. ω_R and ω_L denote the probabilities of class occurrence, and $\tilde{\mu}_R$ and $\tilde{\mu}_L$ are the class means respectively. The quantity $|\tilde{\mu}_R - \tilde{\mu}_L|^2$ is the distance between two classes' means. For each class, $\tilde{s}_R^2$ and $\tilde{s}_L^2$ are class variances, obtained by

$$\tilde{s}_i^2 = \sum_{x \epsilon \mathbf{f}_i} (x - \tilde{\mu}_i)^2 \quad (7)$$

When performing motor imagery a larger J corresponds to closer dispersion of feature vectors per each class and further distance between two class means, which represents better feature distribution for classification and therefore better execution of motor imagery task (Fig. 2).

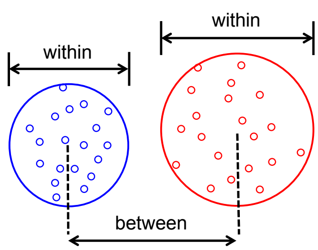

Fig. 2. J parameter, a measure of class separation, is obtained as a ratio of between-class variance to within-class variance. A larger J indicates a better separability of feature sets regarding right and left classes, which corresponds to the subject's skill in generating distinct brain features during a right or left motor imagery task.

F. Evaluation

We examined the effect of feedback conditioning on the trend of learning by two measurement methods; 1) subjects' online performance in the second half of sessions and 2) time-variant distribution of EEG features regarding right and left hand imagery between first and second halves of each session.

III. Results

Results were obtained from the online measurements of subjects' BCI performance and offline analysis of their recorded EEG signals. The offline analysis was performed in order to find the changes in subjects' motor imagery patterns that the classifier failed to detect. Similar to most of BCI paradigms, the classifier used in this experiment employed the subject specific discriminative parameters that were set in the initial calibration session. However this type of classifier can perform poorly as subjects' ability in generating motor imagery patterns is expected to improve due to both successive sessions and feedback bias. Therefore, in addition to subjects' online performance, we sought a pattern transformation in the original motor imagery features.

A. Online performance

Performances of 16 subjects in the second half of each session were averaged and compared by Tukey-HSD multiple comparison method. The term performance refers to the percentage of successful trials among the post 20 trials. Fake-P (M=60.78, SD=10.24) showed the highest performance compared to Raw (M=49.22, SD=9.07), Match (M=54.37, SD=10.89) and Fake-P (M=50.47, SD=10.58). However no significant difference was found between these sessions.

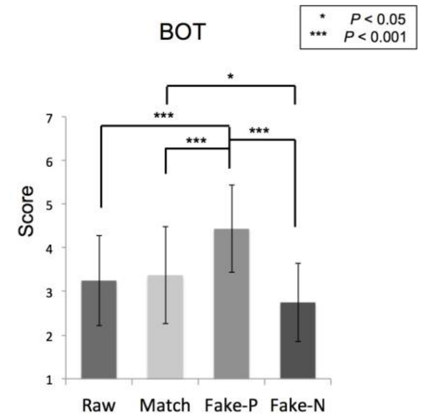

Fig 3. Subjects reported significantly higher body ownership illusion in the positively biased condition (Fake-P) compared to other three conditions. Match also revealed a significantly higher BOT score compared to Fake-N condition.

Meanwhile, participants' average scores for body ownership illusion in each condition were averaged and depicted on Fig. 3. Fake-P condition (M=4.44, SD=1.01) showed a significantly higher BOT compared to all other three conditions Raw (M=3.25, SD=1.03), Match (M=3.38, SD=1.11) and Fake-N (M=2.75, SD=0.90); [Fake-P > Raw, Match, Fake-N, $p < 0.001$]. Significant difference was also found between Match and Fake-N; [Match > Fake-N, $p < 0.05$].

B. Offline EEG features

In each session, J parameter for the first 20 conditioned trials (J_1) and for the second 20 test trials (J_2) was calculated. Since subjects' initial skills were diverse, and for every subject the order of sessions was considerable in the amount of motor imagery skills, the ratio $\Delta J = J_2/J_1$ was selected as a measurement of subjects' motor imagery learning in that particular session. We initially calculated ΔJ for all 16 subjects however using interquartile range (IQR) for statistical dispersion in each condition [11], two outliers were detected in Fake-N condition (S2 and S4) and one outlier was detected in Raw condition (S15). The data of these three subjects were discarded from further analysis. The values of ΔJ in each session for the remaining 13 subjects are shown in Fig. 4a. ΔJ for 13 subjects was averaged in each condition and compared by Tukey-HSD multiple comparison method. The mean value was highest in Fake-P condition (M=4.25, SD=2.35) compared to other three conditions Raw (M=2.15, SD=1.50), Match (M=3.74, SD=1.90) and Fake-N (M=2.70, SD=1.68). Significance difference was obtained between Fake-P and Raw; [Fake-P > Raw, $p < 0.05$] and between Match and Raw; [Fake-P > Raw, $p < 0.1$] (Fig. 4b).

S5 showed the highest ΔJ in the Fake-P session. To better display the effect of body ownership illusion on motor imagery learning, the obtained feature vectors for this subject in two halves of Fake-P session are demonstrated in Fig. 4c. We used principle component analysis to reduce the feature space dimensions into a 2D space. As can be seen in this

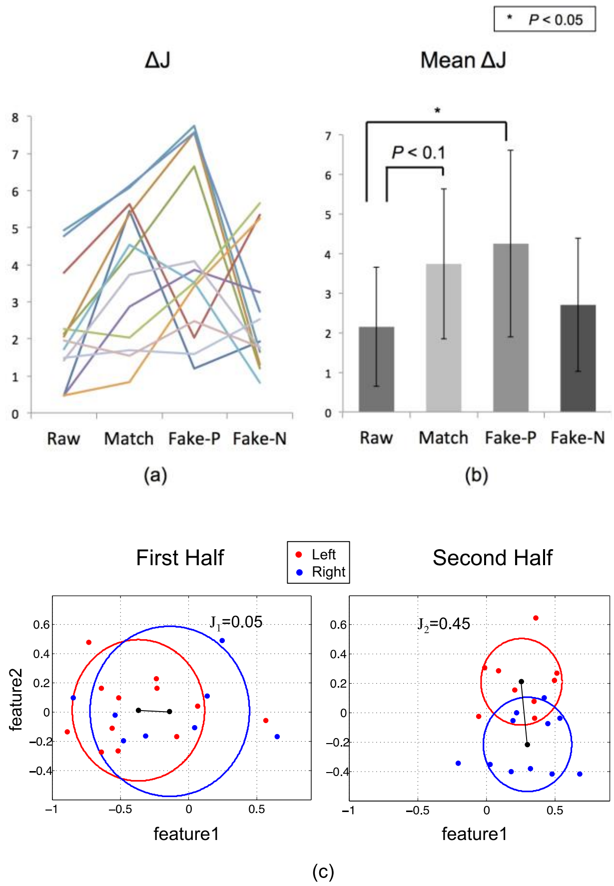

Fig. 4. (a) The trend of motor imagery learning ΔJ in all sessions for 13 subjects (b) Mean value of ΔJ in each session, Fake-P and Match showed a significantly higher mean value compared to Raw at the statistical significance level of 5% and 10% respectively. (c) A 2D distribution of motor imagery features obtained from S5's performance in the first and second half of Fake-P displays a better separation of right and left trials in this session.

figure the separability of right and left hand trials as well as value of parameter J has improved in the second half of the session compared to the first half.

IV. Discussion

Online results confirmed a higher body ownership illusion in positively biased session however no significant changes in the subjects' real time performance was found and the mean value of performance remained in the chance level for all conditions. Assuming the classifier defect in detecting the correct class for each feature vector as the classification parameters were set at the beginning of the experiment, we adopted an offline process of the original brain activities to find changes in the distribution of right and left motor imagery features. Results revealed that the ratio J_2/J_1, an identifier of class separability between two halves of sessions, was significantly higher in Fake-P condition, where subjects' performance was positively biased, than Raw condition, where subjects' real performance was presented without manipulation. This result indicates that subjects could generate motor patterns that were more classifiable by CSP algorithm when they received an enhanced feedback of their operational performance. Using a statistical significance level of 10%, similar relation was confirmed between Match and Raw conditions, indicating that in Match condition where subjects did not receive negative feedback of their failed performance, motor imagery improved and they could produce more separable activity patterns for two imagery tasks of right and left grasp. Both results imply that subjects' positive evaluation of their own performance had enhancing effect on motor imagery learning which is consistent with some previous reports [2]. As we could confirm significantly higher BOT score in the Fake-P condition, we can associate the improvement of motor imagery learning with the inducement of a stronger body ownership illusion due to a biased feedback, which probably facilitated imagination of movement in motor imagery task and eventually enhanced self-regulation of brain patterns in subjects.

Unlike previous reports on biased BCI feedback, no significant improvement [5] or impediment [4] was found in the Fake-N condition compared to other conditions. However, S2 and S4 who were discarded from analysis as outliers showed drastic ΔJ increase in Fake-N condition. Although subjects majorly received enhanced learning in Fake-P condition, results of S2 and S4 could lead us to this assumption that the effect of biasing is closely relevant to the subject's personality and the influence of motivation on different individuals. While there are learners who benefit from encouragement and positive feedback of their performance, there are a few who benefit more from negative feedback. These subjects try harder when the feedback informs them that they are not performing well. In future experiments, personality test could be used in order to categorize subjects into groups, so that results can be analyzed according to stratified personality groups.

Lastly, although in this experiment we hypothetically assumed that enhancement of motor imagery learning due to positive bias of feedback was associated with ownership illusion over controlled robot's hands, further study is required to veritably measure the intensity of illusion. The BOT measured in this experiment indicates the illusion score regarding the whole session, however it was more appropriate to measure the BOT at the end of the conditioned section, the first 20 trials. Despite knowing this fact, in this experiment we were skeptical that by pausing the session in the middle and asking assessment question the illusion would be shattered. In future, comparison between human-like and non human-like visual feedback under biased feedback is necessary to precisely verify weather illusion of body ownership influences the trend of motor imagery learning.

V. Conclusion

User training is one of the primary issues in development and application of motor imagery BCIs. As a result, employing a feedback design that increases the interaction between the user and the interface becomes critical. In this study, we manipulated the visual feedback of performance in a motor imagery BCI-teleoperation system of humanlike robotic hands in order to probe the effect of positive and negative feedback bias on subjects' experience of body ownership illusion and the consequent influence of this illusion on BCI-performance and motor imagery skills. Our results showed that biasing feedback could significantly increase the intensity of body ownership illusion in subjects however it could not immediately boost subjects' performance in the same session. Nevertheless, the analysis of brain patterns revealed improvement in the learning of motor imagery skills when the feedback was positively biased. From these results we conclude that the sense of embodiment and the interaction between the user and BCI could facilitate the motor imagery task and contribute to the learning process.

In terms of feedback design for future BCI systems, it is conceivable that a more realistic feedback presentation can assist novice users to train and adapt to a system faster and more efficiently. Also, BCI users may benefit from positive bias of feedback in training sessions, although their personality should be taken into account. Meanwhile, since subjects' motor imagery skills dynamically change during a session based on their state of mind, further developments of sophisticated classifiers that customize classification parameters in an online session are required.

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