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Prediction of Motor-Imagery-BCI performance using Median Nerve Stimulation

Sébastien Rimbert¹, Valérie Marissens Cueva^{1,2}, Laurent Bougrain² and Fabien Lotte¹

Abstract—Motor Imagery-based Brain-Computer Interfaces (MI-BCIs) have grown significantly in recent years and have successfully overcome several challenges in rehabilitation, control, communication, artistic creation, etc. However, not everyone can use MI-BCI, and there are large variations between users in performance. Thus, predicting a user’s future MI-BCI performance is now a critical issue that could enable the BCI system to be adapted as effectively as possible to each user, thereby improving its efficiency. However, few methods exist that can currently predict performance prior to a BCI session. In fact, both neurophysiological markers and questionnaires have been shown to be insufficient as predictive tools. Interestingly, it has previously been shown that painless and passive median nerve stimulation can generate well-known motor patterns of Event-Related Desynchronization (ERD) and Event-Related Synchronization (ERS). In this paper, we propose to use these post-stimulation motor patterns to predict the future performance of an MI-BCI user. Our results show that the ERD after stimulation of the median nerve in the beta frequency band is correlated with the BCI performance of the subjects ($\rho = -0.58$; p -value < 0.05) and that the ERD in the mu band correlates very strongly with BCI performance in this specific frequency band ($\rho = -0.87$; p -value < 0.001). These promising results suggest that there is a strong neural predisposition to perform well with MI-BCI and that median nerve stimulation may be an easy-to-install, fast and highly effective technique for detecting it.

Index Terms—Brain-Computer Interface; Median Nerve Stimulation; Motor Imagery; MI-BCI performances; Electrophysiology; ERD; ERS.

I. INTRODUCTION

Motor Imagery (MI) is a major paradigm in Brain-Computer Interfaces (BCI). MI-BCI have successfully been used in a wide range of applications for rehabilitation, control, communication, artistic creation, and so on. Nevertheless, challenges remain to ensure widespread adoption. The main hurdle is the transition from controlled experimental laboratory settings, where classifiers may lack precision and require extended training, to real-world scenarios where BCIs should offer seamless, user-friendly operation without lengthy training, while maintaining high levels of accuracy. In particular, even in controlled laboratory settings, the current state of BCI detection accuracy remains suboptimal, i.e., about 30% of users cannot use a MI-BCI [1], which is often called BCI illiteracy or deficiency. Moreover, the practical performance remains insufficient, typically below 75-80% for two MI

classes [2] with a high variability of performance within and between individuals.

Therefore, it will be useful to develop tools that allow experimenters to determine, prior to an MI-BCI session, whether a subject will perform well or not. Such tools could help researchers adapting the BCI parameters proactively to maintain high levels of motivation in subject [3]. Another interesting application could be the introduction of a subject selection step prior to an experiment, for example to harmonize the study population in terms of BCI performance, or to select the best BCI paradigm for each user. More importantly, in the specific case of BCI-based rehabilitation, the prediction of MI-BCI performance could support the development of tailored therapeutic MI-BCI protocols to help post-stroke patients regain limb control [4]. In this particular case, the sensitivity of the BCI performance predictor is critical. Indeed, a false negative will deny a patient the opportunity to benefit from MI-BCI-based care. Consequently, identifying whether a subject will perform well or not can save valuable time for researchers and clinicians while improving users experience. Finally, identifying a reliable predictor of MI-BCI performance could also provide a better understanding of why some users are inherently better. It is likely that certain neurophysiological differences associated with motor cortex activation could explain such variabilities [5], even if we do not understand them yet.

Predicting a MI-BCI users’ future performance is an active research question that is still open [6]. Subjective questionnaires (MIQ-RS, KVIQ, 16PF5) have been proposed to predict performance with a MI-BCI, but unfortunately the results are not consistent. A first study concluded that the Kinesthetics MI (KMI) scores obtained from the KVIQ can predict MI-BCI performance of healthy subjects [7]. A second study found that the representation of subjective behaviour calculated with the MIQ-RS and BCI control performance seem strongly related [8]. However, a third study showed that the MIQ-RS questionnaire cannot be used as a predictor of MI-BCI performance based on the distinction between a resting state and a right hand MI task [9]. Finally, a recent study showed for the first time an association between ERD, BCI performance and self-control from the 16PF5 questionnaire, but correlations remain low [10]. Another way of predicting a user’s performance is to use neurophysiological signals such as the mu peak during an eyes-open and/or eyes-closed baseline [11], [12]. Nevertheless, the results obtained are still insufficient to accurately predict whether a user will perform well with a MI-BCI.

Currently, such MI-BCI exploit the modulation of Senso-

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riMotor Rhythms (SMR) over the motor cortex [13], respectively known as Event-Related Desynchronization (ERD) and Event-Related Synchronization (ERS), coming from the mu (7-13 Hz) and beta (15-30 Hz) frequency bands [14]. As a reminder, typically, motor imagery is preceded by an ERD in the mu and beta frequency bands. This gradual decrease in power starts in the preparatory phase of the motor task and reaches a maximum during its imagery [13]. After the motor imagery, an ERS, also called post-movement beta rebound, occurs mainly in the beta frequency band while the ERD in the mu band slowly returns to the baseline [15].

Interestingly, electrical stimulation of the median nerve also induces changes in the cortical activity, which are visible in the EEG signal and similar in the shape but faster than for an intention of movement [16]–[18]. Our hypothesis is that such a Median Nerve Stimulation (MNS) could be a predictor of motor cortex activation underlying performance of the MI task. Indeed, MNS would appear to have all the qualities needed to predict MI-BCI performance: (i) by producing ERD/ERS patterns similar to those generally obtained during MI, (ii) by being passive for the user and therefore independent of how the subject performs or perceives the MI task, and finally (iii), by being easy to set up (i.e. in terms of time) before a BCI session. In this paper, we thus propose to study the use of MNS to predict future MI-BCI performance.

II. MATERIAL AND METHODS

A. Participants

20 right-handed healthy subjects (males; aged 26.2 years old; $STD = 10.42$) were recruited for this study. The subjects had no medical history that could have influenced the task (i.e., diabetes, antidepressant treatment, or neurological disorders). The experiment follows the statements of the WMA declaration of Helsinki on ethical principles for medical research involving human subjects [19] and the participants signed an informed consent approved by the local ethical committee of Inria (COERLE, approval number: 2016-011/01).

B. Motor tasks

Two conditions were performed in this study: a kinesthetic motor imagination and a passive median nerve stimulation. For each motor condition, the first 15 subjects performed 51 trials, and the last 5 subjects performed 64 trials. Because this experiment was originally designed to investigate the impact of general anaesthetic conditions on the EEG (see [20], [21] for more details), the subjects were lying on a comfortable bed with their eyes closed. Their right forearm was put on a cushion to prevent any movement. The order of the two conditions were randomized between subjects.

1) *Condition 1: motor imagery*: For the MI condition (C1), subjects had to imagine a movement between the thumb and index finger, i.e. they had to try to imagine a maximum of sensations that would be caused by a real movement, but without any movement. A low frequency beep indicated when the subject had to start the motor imagery, the grasping MI was maintained during 2 seconds, then a second beep indicated

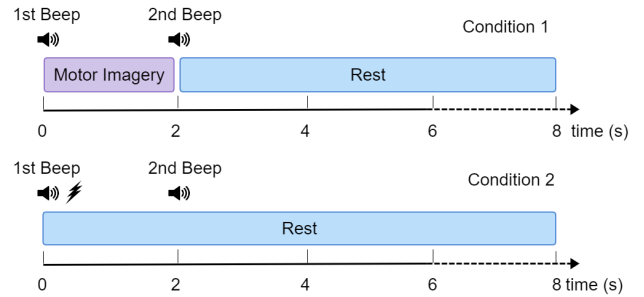


Fig. 1: Timing schemes of a trial for Condition 1 (Motor Imagery task) and Condition 2 (MNS). A first beep indicated the start of the motor task, a second beep the end of the motor task. After the second beep, the participant remains at rest for 6 to 8 seconds (random duration changed at each trial).

the end of the imagined task. Prior to the study, the subject learned to perform the MI task progressively (for more details, see [22]).

2) *Condition 2: median nerve stimulation only*: The MNS only condition (C2) consisted of a series of passive stimulations of the median nerve during resting state. We placed the two electrodes of stimulation on the wrist according to the standards [23], [24], so that stimulation generates a slight movement between the thumb and index. The stimulation intensity was previously adapted for each subject and varied between 8 and 15 mA.

C. Electrophysiological recordings

EEG signals were recorded through the OpenViBE software platform with a Biosemi Active Two 128-channel EEG system, sampled at 2048 Hz. In accordance with the ABC layout, the EEG was recorded from 128 sites. An external electromyogram (EMG) electrode was used for all conditions in order to verify that there was no movement during the MI task. Impedance was kept below 10 k Ω for all electrodes to ensure that the background noise in the acquired signal was low.

D. Time-Frequency Analysis

To analyze the differences between both conditions (MI and MNS alone) and choose the best time window for correlation analysis between the post-MNS and post-MI ERDs, we performed an event-related spectral perturbation (ERSP) between 8-30 Hz. We computed the ERSPs using the gain model approach [25] which is equivalent to the *band power method* [13]. We used a 256 point sliding fast Fourier transform (FFT) window with a padratio of 4, and computed the mean ERSP 2 seconds before the start beep to 5 seconds after it.

E. ERD/ERS modulations

In order to predict BCI performance from MNS-induced motor patterns, we quantified the ERD and ERS resulting from MNS. In particular, we computed the ERD/ERS% using the *band power method* [13] with a Matlab script. First, the EEG signal was filtered in the mu band (7-13 Hz), mu and beta (8-30 Hz) or in the beta band (15-30 Hz) for all subjects using

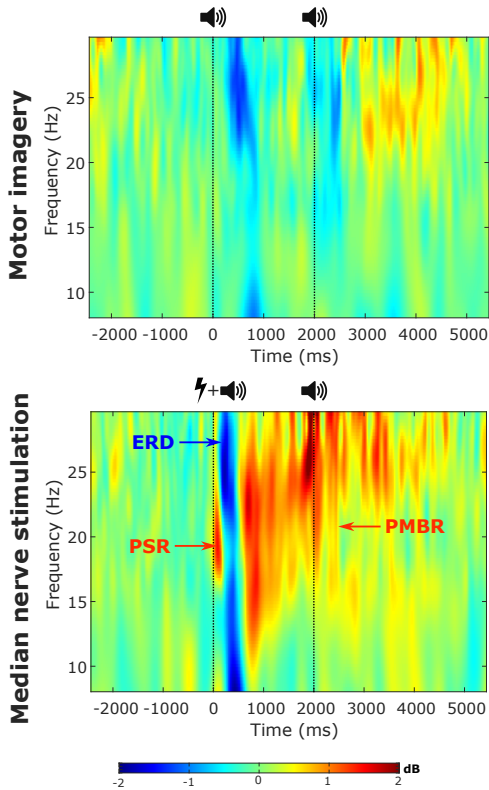


Fig. 2: Event-related spectral perturbation (ERSP) time-frequency average analysis for the Motor Imagery (MI) and Median Nerve Stimulation (MNS) conditions, for electrode C3. The dashed lines indicate when the MI started and finished, and the flash icon when the MNS started. For the MNS condition, a post-stimulation rebound (PSR) appears, then an ERD, followed by a post-movement beta rebound (PMBR).

a 4th-order Butterworth band-pass filter. Then, the signal was squared for each trial and averaged over trials. Next, it was smoothed using a 1-second sliding window with a 100 ms shifting step. We chose a sliding window because the nature of the motor imagery task, as well as the components ERD/ERS that underline them, required a short window. Finally, we subtracted the average power from the baseline to the average power computed for each window, and then divided the result by the same baseline power. This baseline corresponded to the window $[-3; -0.5]$ s, where 0 s is the beginning of each trial. The resulting value was multiplied by 100 to obtain percentages. This process can be summarized by the following equation:

$$ERD/ERS\% = \frac{\overline{x^2} - \overline{BL^2}}{\overline{BL^2}} \times 100, \quad (1)$$

where $\overline{x^2}$ is the average of the squared signal over the sliding window of interest, $\overline{BL^2}$ is the mean of a baseline segment taken at the beginning of the corresponding trial, and ERD/ERS% is the percentage of ERD/ERS estimated for

each step of the sliding window. It was done for all channels separately.

F. Offline BCI performances

We computed offline BCI performances by classifying EEG signals of a resting state versus EEG signals of right-hand KMI. Classifications were performed using the MNE [26], Scikit-learn [27] and pyriemann [28] packages in Python 3.10. These performance metrics were estimated offline by first downsampling EEG signals to 128 Hz, band-pass filtering in 7-13, 8-30 or 15-30 Hz, and then extracting 2.5 seconds long MI and rest epochs from each trial. The rest and MI periods correspond respectively to $[-3; -0.5]$ s and $[0.5; 3]$ s, with a baseline in $[-1.5, -0.5]$ s. Only 40 motor electrodes were used for the classification.

We used a Riemannian classifier, the current state-of-the-art EEG classifiers for BCI [29]. More precisely, we first estimated the EEG covariance matrices of each trial, then projected them in the Tangent Space (at the global training data Riemannian mean) where a Logistic Regression (TSLR) classifier was trained to separate the covariance matrices of MI and rest trials. This TSLR classifier was trained with the first 70% trials (between 35 and 44 trials, depending on subjects) and tested on the rest (between 15 and 19 trials).

G. Correlations between post-ERD MNS, ERD during MI and MI-BCI performances

The originality of this study is to combine the investigation of ERD modulations from MNS, ERD modulations during the MI task and MI-BCI offline performances. In particular, we want to investigate how the strength of the ERD induced by MNS is related to the strength of the ERD during MI, and to BCI performances (here classification accuracy). Thus, we analyzed the ERD modulations of all subjects on the contralateral electrode C3, for both MI and MNS conditions. The time window between 100 and 500 ms after the first beep was selected using the time-frequency analysis, where the ERD for the MNS condition is stronger. The minimum ERD value was then computed in this time window and the corresponding frequency band (7-13, 8-30 or 15-30 Hz), for each MI and MNS condition. This ERD-MNS-related variable was correlated with the ERD-MI variable in the same frequency band, as well as with users' offline performances in a MI vs rest task obtained by the TSLR classifier, where the MI data was filtered in a particular band (see Table I). Due to the large number of correlation tests performed ($n=12$), the significance level α was adjusted at ($p < 0.001$ and $p < 0.05$) for multiple comparisons using the Benjamini-Hochberg procedure [30].

III. RESULTS

A. ERD/ERS modulations for Motor imagery and Median Nerve Stimulation

The analysis of ERD/ERS modulations provides us with a better understanding of the contralateral activation of the motor cortex during the motor imagery and median nerve stimulation

(Fig. 2). During the MI (condition 1), we observed two distinct ERDs that mainly occurred in the beta frequency band (15-30 Hz). The first ERD starts approximately 500 ms after the start beep and switches to an ERS 1 s later. The second ERD appears after the end-of-task beep and disappears 750 ms later, while the mu frequency band seems less affected due to the limited presence of the ERD during the MI task. Finally, a post-movement beta rebound (PMBR) arises mainly in the beta band approximately 1.5 s after the end of the MI. In the case of MNS during rest state (condition 2), a powerful and robust ERS appears immediately (0-250 ms) after the stimulation in low beta (15-22 Hz). For the rest of this article, this very first ERS will be named post-stimulation rebound (PSR). Then, the MNS generates an ERD (in high beta but also in the mu band) lasting 500 ms, followed by a second rebound in both bands. It should be noted that the second rebound for the MNS condition is very wide and also affects both frequency bands.

B. BCI performances

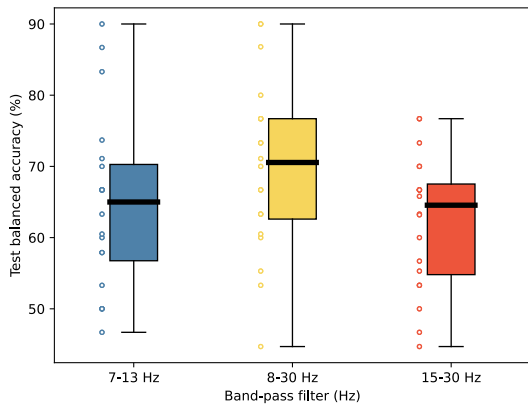


Fig. 3: Boxplots showing the average accuracies ($n = 20$ subjects) for MI vs Rest classification, where the EEG signals were filtered in a particular frequency band: mu (7-13 Hz), mu+beta (8-30 Hz) and beta (15-30 Hz).

Regarding classification performances, Figure 3 shows that the average accuracy is 70% for a classification based on MI vs rest in the 8-30 Hz frequency band. Classification using

TABLE I: Spearman’s correlation coefficient between minimum value of ERD of the MNS condition, in the time window [100; 500] ms, and (i) the minimum value of ERD during MI in the same time window and frequency band, and (ii) users’ offline BCI performance in a MI vs rest task obtained by the TSLR classifier, where the EEG signals were filtered in a particular frequency band.

		ERD-MNS		
		mu	mu+beta	beta
ERD-MI	same freq. band	0.38	0.15	0.47
	mu	-0.87***	-0.82***	-0.47
BCI performance	mu+beta	-0.49	-0.53	-0.58*
	beta	0.23	0.16	-0.28

* $p < 0.05$, *** $p < 0.001$

only the mu or beta frequency band shows lower accuracies (i.e., 65% and 62% respectively). These results show that the extended band between 8-30 Hz gives the best results, which is consistent with the BCI literature. The level of performance of the classifier ($<75\%$) can be explained by the fact that the motor imagery performed engages only the thumb and index finger, and not the whole hand, which is visible in the time-frequency maps, but also by the fact that the number of training trials is low (≤ 44 , see section II-F).

C. Correlation between MNS stimulations and BCI performances

The ERD generated by the MNS is present both in the mu and beta frequency bands (Fig. 2). And therefore, we chose to analyze the correlations (see Table I) between the ERD of the MNS in the three frequency bands (mu, beta and mu+beta) and the BCI performances associated. Our results show that the minimal value of the MNS ERD in the beta band is significantly correlated with the best BCI performance obtained using the standard mu+beta (8-30 Hz) band ($\rho = -0.58$; p -value < 0.05). This means that the MNS predictor in beta frequency band explained as much as 33.6% of the variance in BCI accuracy. We also noted that the post-MNS ERD in the mu or mu+beta frequency band is very strongly correlated with the mu-specific BCI performance ($\rho = -0.87$; p -value < 0.001), which suggests that the mu frequency band would be very predictive of user performance. This means that the MNS predictor in mu band explained as much 75.6% of the variance in BCI accuracy. Finally, we also analyzed correlations between post-MNS ERD and ERD during the motor imagery task and we only found a positive correlation in the beta frequency band ($\rho = 0.47$; p -value < 0.05), which is quite understandable because ERD during MI mainly affects this frequency band (see Fig. 2).

IV. DISCUSSION

In this article, we have described the modulations of ERD/ERS during the MNS and MI conditions and then analyzed the correlations with BCI performance. Regarding ERD/ERS modulations, the results obtained are quite similar to other studies: a median nerve stimulation generates a first ERS (called PSR), then a rapid ERD in the mu and beta frequency bands, followed by a classical ERS (called PMBR) lasting several seconds, mainly in the beta frequency band [16], [17]. Given their high correlation score and significance, these results are particularly promising. In particular, the ERD of the MNS correlates strongly with BCI performance, considering only the contralateral electrode (C3).

A. Future analysis

Although our promising results showed a significant correlation between post-stimulation ERD in the mu and beta frequency band and BCI performance (see Table I), several analyses would be necessary before using MNS as a BCI performance predictor. For instance, these correlations resulted from the analysis of all the MNS stimulations ($n > 50$ trials)

whereas to use MNS as a practical prediction tool, it will be important to perform future analysis to determine a minimum number of stimuli required. Complementary analyses should also be performed from the temporal perspective (study other time windows, e.g. with the PMBR), spatial perspective (determine the electrodes of interest) and frequency perspective (the frequency bands of interest may be different depending on the user). In addition, we could check whether other ERD/ERS modulations present at each stimulation (PSR or PMBR, for example) could also serve as predictors of BCI performance. The predictability of MI-BCI performances with ERD/ERS MNS-related variables could also be tested by using a regression model. Several variables could serve as input vector (e.g. minimum ERD amplitude, mean ERD/ERS, maximum ERS in a particular time-window and frequency band), and the output would be a prediction of the future BCI performance.

B. Relevance of the mu frequency band for BCI performance prediction

Our results showed a strong correlation between post-stimulation ERD in the mu frequency band and the BCI performance associated with this oscillatory rhythm. Furthermore, while the correlation between post-stimulation ERD and BCI performance is well established, the correlation between post-stimulation ERD and ERD during MI is low (Table I). Altogether, these results clearly show that the modulation in the mu frequency band appears to be particularly useful for predicting BCI performance, which had already been shown in other studies [11], [12], [31]. Because the user had his eyes closed during the experiment, this could explain the low presence of ERDs during the motor imagery task in the mu frequency band (Fig. 2), because the power in the mu frequency band is higher in the baseline in this specific condition [32] but also that this frequency band is more predictive of BCI performance.

C. Implications for MI-BCI domain

Our results suggest that there may be a (neuro)physiological and/or anatomical predisposition to using MI-BCIs. Indeed, if we can precisely predict whether a user can or cannot use a BCI by passively stimulating their median nerve, then it implies inherent differences between users. For example, there may be differences in the organization of pyramidal neurons in the motor cortex, affecting the EEG system's ability to detect cerebral activity. Alternatively, differences may lie in the activation level of the motor cortex and its capacity to generate sufficient activation for detection. In both scenarios, the significance of our results legitimately raises questions about determinism in MI-BCI usage. One of the most promising applications would be to forecast in advance whether a user would struggle with MI-BCI, thereby preventing BCI illiteracy. In this specific case, investigating the stability of the ERDs generated by median nerve stimulation is crucial. The correlation obtained in this article might be influenced by the user's learning curve or the duration of MI-BCI usage.

Several studies indicated that repetition and mastery of the MI task result in neural efficiency, characterized by a decrease in ERD amplitude with a focus on this pattern [33], [34]. Hence, it is essential to ensure that MNS remains a reliable predictor despite this phenomenon.

D. Dual benefits of using median nerve stimulation for BCI

Because electrical stimulation of the median nerve also induces changes in the cortical activity, which are visible in the EEG and similar to a MI, it is possible to design a BCI based on the MNS. Interestingly, our previous studies suggest that when an intention or imagination to move a hand coincides with MNS, the ERD/ERS cortical signature of MNS is considerably reduced and can be detected better by machine learning techniques [16]. We showed that MNS can improve MI classification accuracy (up to +15%) and recall/precision scores (up to +20%) [16], [20]. This opens up the possibility of designing a high-performance, asynchronous BCI with enhanced usability, since the user would be passively stimulated, while his/her brain activity would be monitored via a BCI to deduce if MI was performed or not. MNS is thus a promising paradigm for MI-BCI design. In this paper, we have also shown that MNS alone could be used as a prediction tool, to possibly identify users likely to have good MI-BCI performances or those that are likely not to be able to use such BCI. There thus seems to be a dual benefit in using MNS in BCI, both to predict the proficiency of a given user with MI-BCI, before they use an MI-BCI, and as a stimulation tool to enhance MI-BCI classification performances. In the future, it would also be interesting to explore whether MNS-induced ERD/ERS could be predictive of other subject-related information. For instance, it could be interesting to explore whether the strength of MNS-induced ERD/ERS are influenced by users' states such as fatigue or mental workload. If that is the case, MNS might also be used as a more general mental monitoring BCI tool.

V. CONCLUSION

In this paper, a new predictor of MI-BCI performance based on median nerve stimulation was discovered. This predictor corresponds to the minimal ERD value between 100 and 500 ms after median nerve stimulation. Indeed, a significant correlation was observed between this minimum post-MNS ERD value, prefiltered in either the 7-13 Hz or 8-30 Hz frequency band, and BCI performances obtained from EEG signals filtered in the 7-13 Hz band. Additionally, there is a significant correlation between post-stimulation ERD in the beta frequency band and BCI performance in the 8-30 Hz range. These results are particularly promising due to their high correlation score and significance ($\rho = -0.87$, $p\text{-value} < 0.001$), especially considering that the MNS feature was computed using only one contralateral electrode (C3). These promising results suggest that there might be (neuro)physiological and/or anatomical predispositions to successfully using MI-BCIs, and that median nerve stimulation may be an easily implementable, rapid, and highly effective technique for detecting them.

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