Spatio-temporal Comparison between ERD/ERS and MRCP-based Movement Prediction

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Abstract: In brain-computer interfaces (BCIs) based on electroencephalography (EEG), two distinct types of EEG patterns related to movement have been used for detecting the brain's preparation for voluntary movements: a) event-related patterns in the time domain named movement related cortical potentials (MRCPs) and b) patterns in the frequency domain named event-related desynchronization/synchronization (ERD/ERS). The applicability of those patterns in BCIs is often evaluated by the classification performance. To this end, the known spatio-temporal differences in EEG activity can be of interest, since they might influence the classification performance of the two different patterns. In this paper, we compared the classification performance based on ERD/ERS and MRCP while varying the time point of prediction as well as the used electrode sites. Empirical results were obtained from eight subjects performing voluntary right arm movements. Results show: a) classification based on MRCP is superior compared to ERD/ERS close to the movement onset whereas the opposite results farther away from the movement onset, b) the performance maximum of MRCP is located at central electrodes whereas it is at fronto-central electrodes for ERD/ERS. In summary, the results contribute to a better insight into the spatial and temporal differences between ERD/ERS and MRCP in terms of prediction performance.

1 INTRODUCTION

In the event-related brain activity, two patterns are commonly associated with movement, the movement related cortical potentials (MRCPs) and the event related desynchronization and synchronization (ERD/ERS) (Pfurtscheller and Lopes da Silva, 1999). Each of these patterns has components in the preparatory phase of movements (Pfurtscheller and Lopes da Silva, 1999; Shibasaki and Hallett, 2006).

The MRCPs are slow changes in the amplitude of the recorded brain activity elicited by movement planning and execution. Among the pre-movement MRCPs several components can be distinguished. The *early readiness potential* (RP) starts about 2-1.5 s before voluntary movement (Stancák et al., 2000; Paradiso et al., 2004; Shibasaki and Hallett, 2006). It is followed by a steep increase in negativity about 500-400 ms before movement onset (Deecke et al., 1976; Stancák et al., 2000; Shibasaki and Hallett, 2006), called *late RP*. The term *pre-motor positivity* (PMP) commonly indicates a positive increase of potential occurring between 100 and 50 ms before movement onset (Deecke et al., 1976; Shibasaki and Hallett, 2006; Santucci and Balconi, 2009), which is between the late RP and the *motor potential* (MP). The latter is a steep increase in negativity starting shortly before movement onset ($\sim$ 50 ms) (Deecke et al., 1976; Stancák et al., 2000).

The ERD/ERSs are the reflection of changes in the oscillatory activity of neural networks in form of an attenuation/increase in the power of specific frequency bands, which correspond to a desynchronization/synchronization of neural populations in response to an event. The brain rhythms commonly associated with movement, including pre-movement components, are the μ (8-13 Hz), β (13-30 Hz) and γ (over 30 Hz) rhythms (Pfurtscheller and Lopes da Silva, 1999; Pfurtscheller, 1981; Pfurtscheller and Neuper, 1992; Pfurtscheller et al., 1993; Bai et al.,

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2005). The μ ERD has been reported having its onset about -2 s with respect to movement onset (Stancák et al., 2000; Shibasaki and Hallett, 2006). The onset of the ERD in the β-band has been reported between 2 and 1 s before movement onset (Stancák et al., 2000; Bai et al., 2005; Shibasaki and Hallett, 2006). Concerning the γ-band a pre-movement ERS has been reported starting about 1 s before movement onset (Pfurtscheller and Lopes da Silva, 1999).

Being able to recognize and correctly classify these pre-movement components allows to predict forthcoming movements. Exploiting the temporal advantage offered by brain signals over normal output pathways can for instance result in an earlier perceived response of brain computer interfaces (BCIs) (Morash et al., 2008), thus making BCIs more user friendly. Furthermore the detection of motor intention may be relevant for neuro-rehabilitation by promoting activity-dependent brain plasticity (Niazi et al., 2011).

Motivated by these possibilities, BCI-researchers often used the two patterns for the classification of movement intention (e.g. Wang et al., 2004; Li et al., 2004; Morash et al., 2008; Bai et al., 2011; Folgheraiter et al., 2011; Lew et al., 2012; Seeland et al., 2013; Ibanez et al., 2014; Jiang et al, 2014). Some studies used MRCP or ERD/ERS separately (e.g. Mller-Gerking et al., 1999; Morash et al., 2008; Wang and Wan, 2009; Bai et al., 2011; Niazi et al., 2011; Lew et al., 2012; Seeland et al., 2013; Jiang et al., 2014), others combined them (e.g. Wang et al., 2004; Li et al., 2004; Ibanez et al., 2014). . However in only a few studies the reasons behind the choice of the applied pattern are discussed—a choice that may rather derive from experience than having a solid theoretical basis. Hence, one aim of this work is to empirically compare the two patterns concerning their efficiency for movement prediction.

For such a comparison the time point of prediction as well as the used electrode sites can be relevant, since one of the most observed differences between the two patterns is their spatio-temporal evolution. The ERD/ERS has a contralateral onset and evolves to a bilateral spread around movement onset (Pfurtscheller and Berghold, 1989; Babiloni et al., 1999; Leocani et al., 2001), while MRCP starts as bilateral spread and shifts to the contralateral hemisphere as the onset of movement approaches (Shibasaki and Hallett, 2006). Our intent was to investigate whether this difference has an impact on the prediction of voluntary movements in order to get a better insight into the two EEG patterns that are commonly applied for movement prediction. Found differences between ERD/ERS and MRCP can be advantageous for the applicability of movement prediction systems. For example they may help in selecting electrode setups or choosing the target pattern for detection, depending on the application at hand.

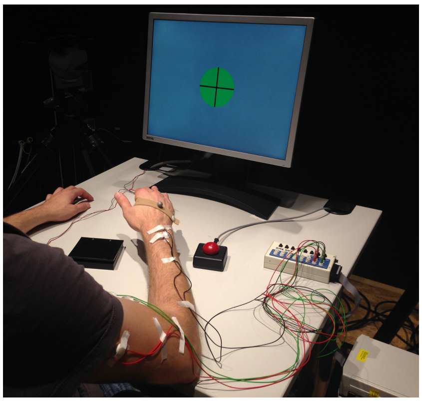

Figure 1: Experimental Setup: During the experiment, subjects performed 120 similar movements with their right arm from a push button to a buzzer.

2 MATERIALS AND METHODS

The comparison of the two signals is based on an empirical analysis of a previously conducted study (Tabie and Kirchner, 2013). Data and methods used in this analysis are described in the following.

2.1 Data Description

EEG data were recorded via 128 electrodes (actiCAP Brain Products GmbH, Munich, Germany) located according to the extended international 10-20 system. The predefinded sampling frequency of the hardware (four BrainAmp DC amplifiers; Brain Products GmbH, Munich, Germany) was 5 kHz. The electrode FCz was used as reference and the data were filtered between 0.1 and 1000 Hz. Simultaneously, eight bipolar channels placed on the right arm of the participant were used to record the electromyogram (EMG) in order to monitor muscular activity (amplified with BrainExG MR; Brain Products GmbH, Munich, Germany). Moreover, a motion capturing system (ProReflex 1000, three cameras; Qualisys AB, Gothenburg, Sweden) was used at 500 Hz to mark the mechanical movement onset in the EEG.

Eight healthy subjects (29.9 ± 3.3 years) participated in the study. Handedness and gender were fixed to right-handed males to avoid an influence of these factors on the experimental results of the rather small number of subjects. Subjects sat comfortably at a table in a shielded room and performed three sessions interleaved with breaks of 10 min. They were instructed to perform voluntary self-paced right arm movements from a push button to a buzzer (see Figure 1). A resting time of 5 s between two consecutive movements had to be maintained for a valid movement. A visual feedback was shown to subjects when the resting time was shorter. Each session was considered as completed when 40 valid movements were performed. For a detailed description of data and paradigm it is referred to (Tabie and Kirchner, 2013).

2.2 Physiological Movement Onset

The point in time when the muscles get the electrical signal to move is defined as physiological movement onset. Commonly in neurobiological studies the physiological movement onset, derived from the EMG, is used to define the timescale, i.e., time point zero corresponds to the point in time when an increase in electric activity is measured at the muscles. Here, in an offline procedure the EMG data of M. biceps brachii and M. brachioradialis, which contained the highest signal-to-noise-ratios, were used to label the physiological movement onset (EMG onset) of each trial. First, each trial was normalized by subtracting the mean and dividing by the standard deviation of the resting period $[-2500, -500\,\text{ms}]$ preceding the release of the push button at 0 ms, respectively. Then, these two normalized EMG channels were averaged. Next, a variance filter (Nikolic and Krarup, 2011; Tabie and Kirchner, 2013) with a window length of 20 ms was applied. Finally, the physiological movement onset was set to the first point in time where the data value exceeded a threshold T for at least 30 ms. This threshold was defined as

$$T = m_{[-2500,-500]} + 5 * s_{[-2500,-500]} \quad (1)$$

with mean m and standard deviation s computed for the resting period from -2500 to -500 ms with respect to the release of the push button.

2.3 Mechanical Movement Onset

The electromechanical delay (Cavanagh and Komi, 1979; Zhou et al., 1995) describes the time between the physiological movement onset and the production of force that yields to an actually visible movement. The latter onset, here named mechanical movement onset, can also be of interest for applications. Hence, its relation to the physiological movement onset shall be given. For that, EEG/EMG and tracking data streams were synchronized. After calculation of the speed per sample from the tracking data, the data were analyzed beginning from the release of the push button backwards in time. Whenever the speed went below a threshold of 0.15 mm/sample, which corresponds to the accuracy of the tracking system, a mechanical movement onset was marked in the EEG.

The median distance between physiological and mechanical movement onset across trials was 70 ms (interquartile range 69 ms).

2.4 EEG Processing

Signal processing and classification of the EEG data were performed with the open source software framework pySPACE (Krell et al., 2013).

Both processing chains, one to detect MRCP and one to detect ERD/ERS, were provided with the same training and testing data. The training data contained supposedly clearly distinguishable instances for the two classes: instances close to or short after the EMG onset for the *movement preparation* class (positive class) and instances far away from the EMG onsets for the *rest* class (negative class). Accordingly, 1 s windows ending at -100 and 50 ms with respect to EMG onset belonged to the *movement preparation* class, and windows of the same length cut every 200 ms, if no movement occurred 3 s before and 2 s after them, belonged to the *rest* class. For the testing data of the *rest* class the same extraction rules were applied, but in order to investigate the temporal evolution of the performance to detect a pre-movement pattern, the testing data for the *movement preparation* class had to be varied (see Section 2.5).

After window extraction the data were standardized channel-wise (subtraction of mean and division by standard deviation). Then, the data were processed differently, depending on the type of patterns (MRCPs or ERD/ERSs) that should be detected. This different processing, including dimensionality reduction and feature extraction, was required due to the different properties of the pattern types.

2.4.1 Processing for MRCP

The processing used to detect MRCP pre-movement components has already be described (Kirchner et al., 2013a; Kirchner et al., 2013b; Seeland et al., 2013). Since the RP is a low-frequency component, a first noise reduction step comprised a decimation of the sampling rate to 20 Hz together with an anti-alias finite impulse response filter. Subsequently, another band pass filter was applied to reduce the frequencies contained in the signal to 0.1-4 Hz. After this preprocessing, the 1 s window was reduced to the last 200 ms. A second noise reduction step was accomplished by training the spatial filtering algorithm xDAWN (Rivet et al., 2009), that is specifically designed to enhance evoked potentials. Then, the amplitude values of four channels retained from xDAWN were extracted as features.

2.4.2 Processing for ERD/ERS

The data were decimated to 125 Hz since higher frequencies are of importance for detection of ERD/ERS. Accordingly, the signal was filtered in the broad band from 8 to 40 Hz, which has been chosen from previous investigations. Broad bands are often employed for ERD/ERS classification in the literature (Wang et al., 2004; Li et al., 2004; Bai et al., 2011). The window was then reduced to the last 800 ms and a common spatial pattern filter (Blankertz et al., 2008) was applied with 16 retained pseudo-channels. The mean and variance of each channel were used as features, which has been suggested before (Liao et al., 2007).

2.4.3 Classification and Postprocessing

Each feature dimension was normalized to have zero mean and a standard deviation of one on the training data, before a linear support vector machine (SVM) was trained on the data (Chang and Lin, 2011). The complexity parameter of the SVM was optimized for each split using a grid search strategy (grid values: $10^0, 10^{-1}, \ldots, 10^{-6}$) together with a nested 5-fold cross validation on the training data. Further, to account for the class imbalance and to emphasize the importance of the *movement preparation* class, the weight parameter of the SVM for the positive class was set to 2. Finally, an optimal decision criterion (threshold), that maximizes the performance on the training data, was determined to assign a class label based on the SVM score.

2.5 Evaluation

For evaluation, the data of each subject (three sessions) were merged and results were obtained with a stratified 10-fold cross-validation. Accordingly, 108 trials labeled as *movement preparation* were used in each cross-validation split for training and 12 trials for testing. The total number of trials for the *rest* class varied across subjects between 140 and 647 since there was no upper limit of the resting time between two consecutive movements. As for the *movement preparation* class, training in each cross-validation split was based on 90 % of the trials and the remaining 10 % were used for evaluation.

The balanced accuracy was used as metric, i.e., the average of true positive and true negative rate ($BA = (TPR + TNR)/2$). The BA compensates for the different unbalanced ratios of the number of trials for the positive and negative class (Straube and Krell, 2014).

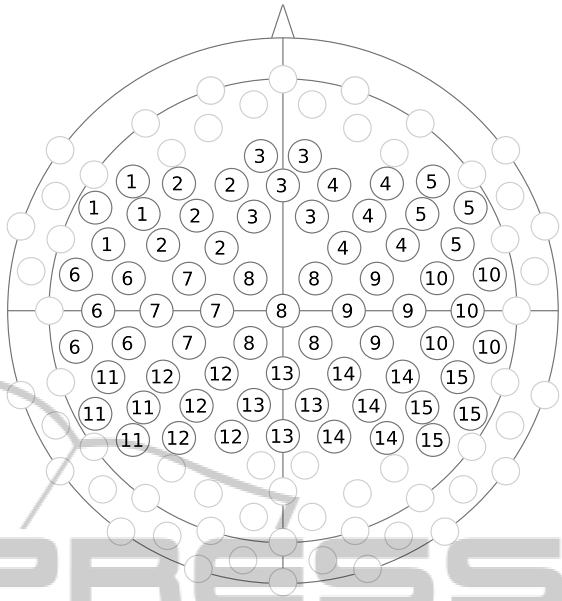

Figure 2: Electrode locations of a 128-channel actiCAP system. Used electrodes in this analysis are numbered. The number denotes the cluster (1–15) to which the electrode was grouped.

To investigate the spatio-temporal differences in performance of the two brain patterns, the end time of the windows for the *movement preparation* class and the electrode locations used for classification were varied. 68 electrodes, that cover a broad area around the motor cortex, were considered in this analysis. Electrodes were grouped into 15 different spatial clusters of four or five electrodes to account for the noisiness of a single EEG channel (Figure 2). In the time dimension, time points from -2.5 to 0.2 s with respect to the EMG onset were analyzed. In addition, the performances based on all 68 channels as well as the performance of a random classifier were computed and served as baselines.

3 RESULTS & DISCUSSION

The results are structured into two parts. First, the movement prediction performance of MRCP and ERD/ERS components was compared in the temporal and spatial domain by analyzing the performance at different electrode groups and time points. However, a suboptimal performance was expected in this analysis since only four or five electrodes were used to train each classifier. Hence, the second part presents a comparison of the two patterns using all electrodes

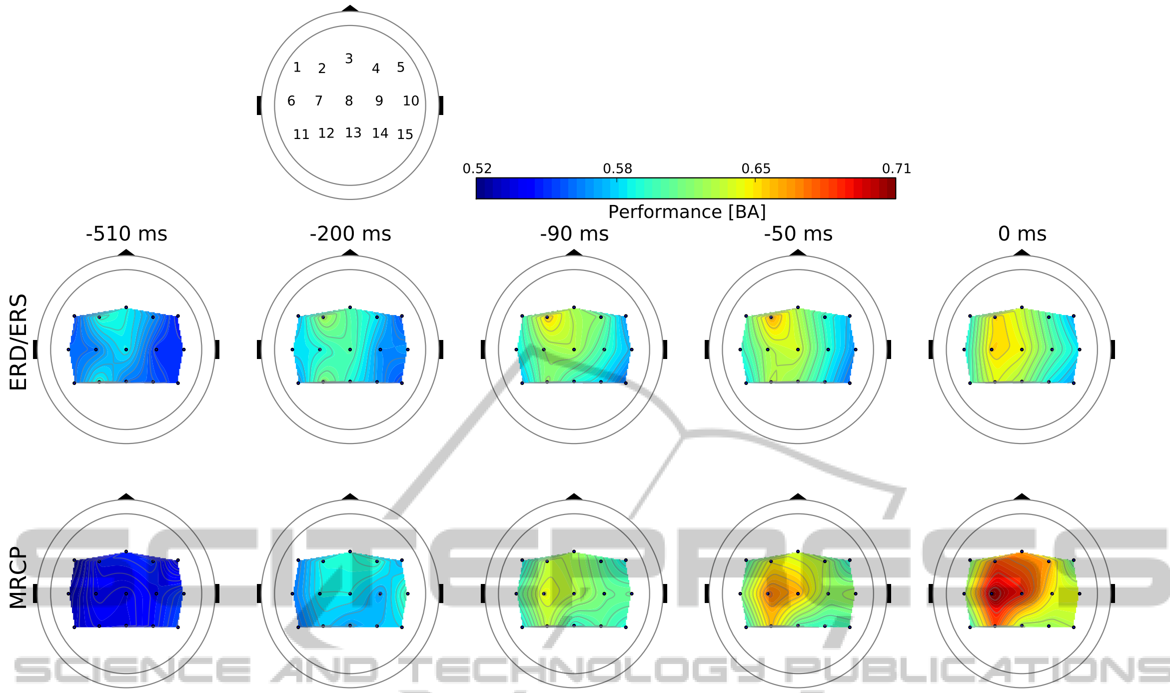

Figure 3: Spatio-temporal evolution of movement prediction performance in terms of averaged balanced accuracy (BA) across splits and subjects based on ERD/ERS (top) and MRCP (bottom). Topologies are displayed for 15 electrode clusters (each black dot indicates the center of a cluster). Time points, relative to the EMG onset at zero, were selected to illustrate exemplarily the different spatial stages for each pattern as well as the main spatial differences.

for training, i.e., only the time dimension is varied. Additionally, this second analysis gives a more application-oriented view, since one common objective in an application is to maximize classification performance.

3.1 Spatio-temporal Comparison

The averaged performance results of MRCP and ERD/ERS showed differences in their spatio-temporal evolution as illustrated for selected time points in Figure 3. The performance of ERD/ERS exceeded the baseline (0.5 BA) earlier than that of MRCP (ERD/ERS at about -1.5 s, MRCP at about -1.0 s).

Furthermore, the performance increase for ERD/ERS emerged as a recurrent process consisting of a local maximum at cluster 2 and partly also cluster 12, as well as a spread of this maximum to surrounding clusters 8, 3 and sometimes 4 and 7. For example, 0.09 s before EMG onset the highest performance is obtained at cluster 2 (Figure 3 third column). On the other hand the stage of a more distributed performance can be seen, e.g., 0.51 s before movement onset (Figure 3 first column). Compared with this, accuracy of MRCP detection increased simultaneously, i.e., being widespread over clusters even 0.46 s before EMG onset. Then, a local maximum emerged at -0.43 s at cluster 2 that spread to clusters 3 and 4 during the following 200 ms. The next increase in performance is obtained at -0.24 s at cluster 4 that spread again widely over clusters 3, 7, 8, and 2 within 0.23 and 0.18 s before movement onset (Figure 3 second column). Finally, a maximum occurred at cluster 7 that expanded to clusters 8 and 12 (Figure 3 at -0.09 and -0.05 s).

Optimal classification accuracies for ERD/ERS and MRCP were observed at time point -0.04 s and zero, respectively, whereby classification of MRCP outperformed detection of ERD/ERS (average BA $\pm$ standard error; ERD/ERS: 0.67 ± 0.01, MRCP: 0.71 ± 0.01).

3.2 Comparison using All Channels

As expected, the overall classification performance increased for both brain signals when all 68 channels were used during training. A possible reason for this increase could be that performance of MRCP and ERD/ERS is at least partly distributed over electrodes, as indicated by the results explained above (Section 3.1 and Figure 3). Thus, adding more electrodes for training might reveal more relevant information for the detection of the specific

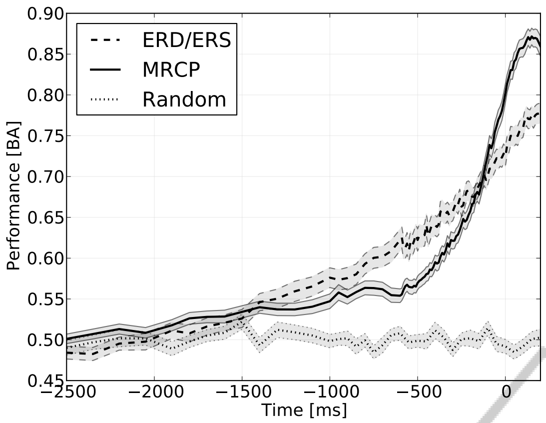

Figure 4: Averaged classification performance across splits and subjects over time for classifiers based on ERD/ERS (dashed line) and MRCP (solid line). As baseline performance of a random classifier is depicted. Shaded area around curves represent the standard error.

brain pattern. The increase was slightly weaker for ERD/ERS than for MRCP, e.g., at EMG onset (ERD/ERS: 0.65 ± 0.014 BA with electrodes in cluster 2 and 0.72 ± 0.012 BA with 68 electrodes, MRCP: 0.71 ± 0.014 BA with electrodes in cluster 7 and 0.8 ± 0.012 BA with 68 electrodes).

Figure 4 shows the time course of performance for the classification of MRCP and ERD/ERS, respectively. In addition, the performance of a classifier that randomly assigns a class label with equal probability is depicted. The classification performance of both, MRCP and ERD/ERS, performed clearly better than random after -1.5 s. Further, both performance curves can be subdivided into three slopes with different timings: For MRCP a slow raise in performance up to -500 ms was observed followed by a steeper increase from -500 to -200 ms, that was even steeper from -200 ms until the movement approached. In comparison, accuracy of ERD/ERS detection also slowly raised up to -900 ms, but already then increased more steeply from -900 to -150 ms, having the strongest increase from -150 ms until movement onset. However, this last slope was weaker than the corresponding one of the MRCP performance curve. Therefore the two curves intersect at around -130 ms.

After EMG onset the raise in performance for both patterns continued, resulting for example at the averaged mechanical movement onset (70 ms after EMG onset) in an accuracy of 0.85 for MRCP and 0.75 for ERD/ERS.

4 CONCLUSION & OUTLOOK

In this work, we compared the classification performance of pre-movement components based on MRCP and ERD/ERS at different time points and different electrode groups. This comparison allows to investigate if the reported neurobiological differences (Pfurtscheller and Berghold, 1989; Leocani et al., 2001; Babiloni et al., 1999; Shibasaki and Hallett, 2006) have an influence on the effectiveness of movement prediction. Indeed, we obtained spatio-temporal differences for ERD/ERS and MRCP in the performances which indicate a higher effectiveness of ERD/ERS far away from the movement onset, whereas MRCP performed better near the movement onset. In the spatial domain, ERD/ERS performance peaked rather locally at fronto-central electrodes (contra-medial to the side of movement). This peak spread to central electrodes. On the contrary, MRCP performance distribution was more widespread, peaking at central electrodes (contra-medial to the movement side). These findings do not map one-to-one to the neurobiological literature, but this is not expected since methodology (average analysis vs. single trial processing) and independent variable (voltages differences vs. classification performance) differed.

As outlined in the introduction, ERD/ERS and MRCP are used separately or sometimes combined. However, there is no consistent opinion in the literature on whether ERD/ERS and MRCP should be combined or not. Some authors are in favor of a combination (Wang et al., 2004; Li et al., 2004) while some others believe that there is no benefit from the extraction of features from both patterns (Wang and Wan, 2009). Our results, i.e., the obtained spatio-temporal differences, indicate that an improvement by combining features from both patterns may also depend on the time point of classification and the used electrode sites. Taking a closer look at these two aspects (time point and sites) may help to resolve existing controversies. Furthermore, knowledge about the spatio-temporal differences can facilitate the design of novel combining strategies.

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