

EEG Eye Blink Artifact Removal by EOG Modeling and Kalman Filter

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Abstract— We present a novel method to remove eye blink artifacts from the electroencephalogram (EEG) signals, without using electro-oculogram (EOG) reference electrodes. We first model EEG activity by an autoregressive model and eye blink by an output-error model, and then use Kalman filter to estimate the true EEG based on integrating two models. The performance of the proposed method is evaluated based on two different metrics by using Dataset IIa of BCI competition 2008. For RLS algorithm, artifact removal and EEG distortion metrics are 7.35 and 0.79, while for our proposed method these metrics are 9.53 and 0.84, respectively. The results show that our proposed method removes the EOG artifact more efficiently than RLS algorithm. However, the RLS algorithm causes a little less EEG signal distortion.

Index Terms— Ocular artifact, Eye blink, Kalman filter, EOG modeling, Electroencephalography.

I. INTRODUCTION

Electroencephalogram (EEG) signals provide a valuable source of information for comprehending neural activity. Eye movement and blinking can change the electrical field near the eye and produce a signal known as electro-oculogram (EOG). The recorded EEG signals, specifically those from electrodes located near the eyes, are contaminated by EOG (known as artifact in EEG studies). EOG artifacts have mainly high amplitude and low frequency components and their effects appear usually in the low frequency band of EEG spectrum [1]. Since clean EEG is essential for efficient signal processing and feature extraction, it is necessary to remove EOG artifacts from EEG. So far, many methods have been developed for removing the ocular artifact from EEG. These methods are mainly divided into two groups; those that use only EEG for the correction process, e.g. independent component analysis (ICA), and those that utilize EOG channels for eliminating the artifacts, e.g. regression-based techniques and adaptive filters. ICA classifies the signals into different components with each belonging to an independent source. This method requires large databases and is not suitable for real-time applications [2]. Regression-based techniques assume that the recorded EEG is a combination of true EEG and a proportion of EOG. Limitations of these methods include their dependence on initial calibration and determination of transfer coefficients between each EOG reference and EEG channels [3]. He *et al.*

introduced an adaptive filter with RLS algorithm to correct EEG signals [4]. They used vertical and horizontal EOG channels to represent the input reference and demonstrated that their method can be used in online tasks. A disadvantage of the latter approach is its need of EOG channels, since it is not convenient to place electrodes near eyes in a routine practice. Recently eye tracker is developed for ocular artifact correction along with employing Kalman filter [5] or measuring the EOG reference signal when it is needed [6]. Although the correction ability of these new methods has been proved, using an extra instrument is still a serious disadvantage. Professional image processing algorithms are also required for these methods.

Validation of ocular artifact removal algorithms is important. Since clean EEG is not available during real data acquisition, the performance of different methods applied to real data, is usually assessed only by visual inspection [2]. However there are metrics that can evaluate the efficacy of these methods, including the ratio of the power of the removed artifacts to the power of the estimated EEG signal [1], or the ratio of the power of the removed artifacts to the power of the contaminated EEG [2]. Furthermore, a decrease in the power of low frequency components of the estimated signal in comparison to the contaminated signal may be another measure for evaluation of different methods. Applying the algorithm to simulated data can have a merit for better metrics such as SNR [7], [8]. However generating simulated data in a manner that completely mimics EOG contaminated signal is the main pitfall of this method.

In this paper we use Kalman filter to eliminate ocular artifacts. Since blinking is the major involuntary movement of eyes, we only considered blinking artifacts and focused on those segments contaminated only by such artifacts. Our proposed approach is a modified version of the technique introduced by Morbidi *et al.* [9], which utilized Kalman filter to remove the transcranial magnetic stimulation (TMS)-induced artifacts from EEG recordings. Our method does not need EOG reference electrodes or extra instruments and can work in real-time applications. To demonstrate the performance of our method, we compare the obtained results with those derived from applying RLS algorithm as described by He [4], by means of available metrics for real data.

II. METHODS

In dealing with real data we only have contaminated EEG, that is a combination of true EEG and ocular artifact. Therefore we may suppose that,

$$eeg_c(n) = eeg_t(n) + eog(n) \quad (1)$$

where $eeg_c(n)$ and $eeg_t(n)$ are contaminated and true EEG signals, respectively. $eog(n)$ represents the portion of eye blink signal that appears in EEG. We also suppose that $eeg_t(n)$ and $eog(n)$ are uncorrelated. These assumptions are valid for all EEG channels. Since we do not use EOG reference electrodes and the precise nature of the modeled system is unknown, Kalman filter can be a proper technique for estimating each part of the measured signal. The state-space form of a Kalman filter is,

$$\begin{cases} \mathbf{x}(n) = \mathbf{A} \mathbf{x}(n-1) + \mathbf{B} u(n-1) + \mathbf{C} w(n-1) \\ z(n) = \mathbf{H} \mathbf{x}(n) + v(n) \end{cases} \quad (2)$$

in which $z(n)$ is the measured signal and $\mathbf{x}(n)$ is the state vector. \mathbf{A} , \mathbf{B} , \mathbf{C} , and \mathbf{H} are constant matrices which will be obtained by modeling different parts of the measured signal, $u(n)$ is the input signal, and $w(n)$ and $v(n)$ represent the process and measurement noise, respectively, and their covariance matrices are \mathbf{Q} and \mathbf{R} [10], [11]. Note that in this manuscript capital and bold letters represent matrices and bold lower case letters are used for vectors.

According to previous studies [12], Autoregressive model is a suitable choice for modeling the EEG signal, therefore

$$eeg_t(n) = \frac{1}{A(q)} w_E(n-1) \quad (3)$$

where $w_E(n)$ is a white noise of variance σ_E^2 and $A(q) = 1 + a_1 q^{-1} + a_2 q^{-2} + \dots + a_{N_a} q^{-N_a}$ in which q^{-1} is a unit shift in discrete time and N_a is the order of model. Since Kalman filter is defined in state-space, we change (3) into

$$\begin{cases} \mathbf{x}_E(n) = \mathbf{A}_E \mathbf{x}_E(n-1) + \mathbf{C}_E w_E(n-1) \\ eeg_t(n) = \mathbf{H}_E \mathbf{x}_E(n) \end{cases} \quad (4)$$

in which

$$\begin{aligned} \{\mathbf{x}_E(n)\}_{N_a \times 1} &= [x_E(n) \ x_E(n-1) \ \dots \ x_E(n-N_a+1)]^T \\ \{\mathbf{A}_E\}_{N_a} &= \begin{bmatrix} -a_1 & -a_2 & \dots & -a_{N_a-1} & -a_{N_a} \\ 1 & 0 & \dots & 0 & 0 \\ 0 & 1 & \dots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \dots & 1 & 0 \end{bmatrix} \\ \{\mathbf{C}_E\}_{N_a \times 1} &= [1 \ 0 \ \dots \ 0 \ 0]^T \\ \{\mathbf{H}_E\}_{1 \times N_a} &= [1 \ 0 \ \dots \ 0 \ 0] \end{aligned}$$

$x_E(n)$ represents the true EEG.

The next step is modeling the eye blink artifact. Figure 1 shows an eye blink signal recorded by vertical EOG channels. We model this signal with an Output-error (OE) model [9].

$$eog(n) = \frac{B(q)}{F(q)} u(n-1) + e(n) \quad (5)$$

where

$$\begin{aligned} B(q) &= b_1 q^{-1} + b_2 q^{-2} + \dots + b_{n_b} q^{-n_b} \\ F(q) &= 1 + f_1 q^{-1} + f_2 q^{-2} + \dots + f_{n_f} q^{-n_f} \end{aligned}$$

are polynomials with different orders and $e(n)$, which represents the measurement noise, is a zero-mean white noise of variance of σ_R^2 [10]. Defining the input signal, $u(n)$, is the main part of modeling. An eye blink signal in Fig. 1 can be divided into three parts: ascending, descending and ascending again. Therefore we suppose,

$$u(n) = \begin{cases} e^{\alpha_s(n-n_m)} & n_s \leq n \leq n_m \\ e^{-\alpha_m(n-n_m)} & n_m < n \leq n_l \\ e^{\alpha_l(n-n_e)} & n_l < n \leq n_e \end{cases}$$

where n_s and n_m are the start and peak time of the eye blink signal respectively, n_l refers to the time of negative peak, and n_e is the time of signal return to its baseline. α_s , α_m and α_l are coefficients obtained through EOG modeling. Similar to the previous part we may show the model in state-space form,

$$\begin{cases} \mathbf{x}_B(n) = \mathbf{A}_B \mathbf{x}_B(n-1) + \mathbf{B}_B u(n-1) \\ eog(n) = \mathbf{H}_B \mathbf{x}_B(n) + e(n) \end{cases} \quad (6)$$

in which

$$\begin{aligned} \{\mathbf{x}_B(n)\}_{r \times 1} &= [x_B(n) \ x_B(n-1) \ \dots \ x_B(n-r+1)]^T \\ \{\mathbf{A}_B\}_r &= \begin{bmatrix} -f_1 & -f_2 & \dots & -f_{r-1} & -f_r \\ 1 & 0 & \dots & 0 & 0 \\ 0 & 1 & \dots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \dots & 1 & 0 \end{bmatrix} \\ \{\mathbf{B}_B\}_{r \times 1} &= [b_1 \ b_2 \ \dots \ b_{r-1} \ b_r]^T \\ \{\mathbf{H}_B\}_{1 \times r} &= [1 \ 0 \ \dots \ 0 \ 0] \end{aligned}$$

and $x_B(n)$ represents the part of eye blink which appears in the EEG signal. Here for simplicity we choose $r = \max(n_b, n_f)$ to express matrices.

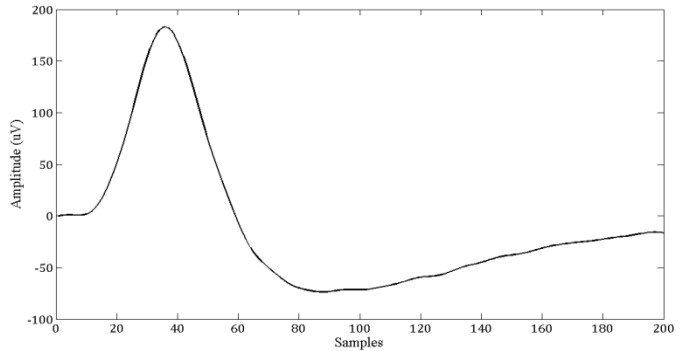


Fig. 1. A sample eye blink signal.

By combining (4) and (6) we can build the Kalman filter state-space form,

$$\begin{cases} \mathbf{x}(n) = \mathbf{A} \mathbf{x}(n-1) + \mathbf{B} u(n-1) + \mathbf{C} w_E(n-1) \\ eeg_i(n) + eog(n) = \mathbf{H} \mathbf{x}(n) + e(n) \end{cases} \quad (7)$$

where

$$\mathbf{x}(n) = [\mathbf{x}_E(n)^T \quad \mathbf{x}_B(n)^T]^T, \quad \mathbf{A} = \begin{bmatrix} \mathbf{A}_E & \mathbf{0}_{N_a \times r} \\ \mathbf{0}_{r \times N_a} & \mathbf{A}_B \end{bmatrix}$$

$$\mathbf{B} = \begin{bmatrix} \mathbf{0}_{N_a \times 1} \\ \mathbf{B}_B \end{bmatrix}, \quad \mathbf{C} = \begin{bmatrix} \mathbf{C}_E \\ \mathbf{0}_{r \times 1} \end{bmatrix}, \quad \mathbf{H} = [\mathbf{H}_E \quad \mathbf{H}_B]$$

We consider the Non-stationary components of EEG and EOG signals by changing the process and measurement noise and defining the time-variant covariance matrices [9]. We change the process noise during times that eye blink artifact appears. Therefore we have,

$$\mathbf{w}(n) = [w_E(n) \quad w_B(n)^T]^T$$

$\mathbf{Q}(n)$ is the covariance matrix of $\mathbf{w}(n)$ and is described as follows,

$$\mathbf{Q}(n) = \begin{bmatrix} \sigma_E^2 & \mathbf{0}_{1 \times r} \\ \mathbf{0}_{r \times 1} & \mathbf{Q}_B(n) \end{bmatrix}$$

where

$$\mathbf{Q}_B(n) = \begin{cases} \sigma_B^2 \mathbf{I}_r & n_s \leq n \leq n_m \\ \mathbf{0}_r & \text{otherwise.} \end{cases}$$

We also replace $e(n)$ with $v(n)$ with its variance changing with time:

$$R(n) = \text{var}\{v(n)\} = \begin{cases} \sigma_R^2 & n_s \leq n \leq n_l \\ 0 & \text{otherwise.} \end{cases}$$

Noise variances σ_E^2 , σ_B^2 and σ_R^2 will be determined by applying the algorithm. By these assumptions we construct the final state-space form of Kalman filter as follows,

$$\begin{cases} \mathbf{x}(n) = \mathbf{A} \mathbf{x}(n-1) + \mathbf{B} u(n-1) + \mathbf{C}_K \mathbf{w}(n-1) \\ eeg_i(n) + eog(n) = \mathbf{H} \mathbf{x}(n) + v(n) \end{cases} \quad (8)$$

where

$$\mathbf{C}_K = \begin{bmatrix} \mathbf{C}_E & \mathbf{0}_{N_a \times r} \\ \mathbf{0}_{r \times 1} & \mathbf{I}_r \end{bmatrix}$$

By comparing (2) and (8) we find the measurement signal, $z(n)$:

$$z(n) = eeg_i(n) + eog(n) = eeg_c(n) \quad (9)$$

After estimating the EEG and EOG signals and finding the matrices we apply the Kalman filter to (8). The Algorithm consists of two steps: prediction step and update step. In prediction step we produce an uncertain estimation of state variables,

$$\hat{\mathbf{x}}_n^- = \mathbf{A} \hat{\mathbf{x}}_{n-1} + \mathbf{B} u_{n-1}$$

$$\mathbf{P}_n^- = \mathbf{A} \mathbf{P}_{n-1} \mathbf{A}^T + \mathbf{C}_K \mathbf{Q}_n \mathbf{C}_K^T$$

and in update step we compare the previous estimation with measurement signal, and generate $\hat{\mathbf{x}}_n$ which is an improved estimation of state variables,

$$\mathbf{K}_n = \mathbf{P}_n^- \mathbf{H}^T (\mathbf{H} \mathbf{P}_n^- \mathbf{H}^T + R_n)^{-1}$$

$$\hat{\mathbf{x}}_n = \hat{\mathbf{x}}_n^- + \mathbf{K}_n (z_n - \mathbf{H} \hat{\mathbf{x}}_n^-)$$

also we calculate \mathbf{P}_n for the next timestep,

$$\mathbf{P}_n = (\mathbf{I} - \mathbf{K}_n \mathbf{H}) \mathbf{P}_n^-$$

Since $\hat{\mathbf{x}}_n = [\hat{\mathbf{x}}_E(n)^T \quad \hat{\mathbf{x}}_B(n)^T]^T$, we can have an estimate of the true EEG utilizing Kalman filter:

$$\widehat{eeg}_i(n) = \mathbf{H}_E \hat{\mathbf{x}}_E(n)$$

III. EXPERIMENTAL RESULTS

A. Database

The database we used to test the effectiveness of our method was Dataset IIa of BCI competition 2008 [13]. This dataset consists of 22 EEG and 3 EOG monopolar channels. All signals were sampled with 250Hz and band-pass filtered between 0.5 Hz and 100Hz. Also a 50Hz notch filter was applied to the dataset. This dataset consists of EEG data from 9 subjects in two sessions. In the beginning of each session there are 3 tasks: eyes open, eyes closed and eye movements [13]. Position of EOG electrodes in this dataset differed from what was purposed by Croft [3]. Since we noticed that the second EOG channel can properly represent the vertical EOG, specifically eye blinks that we were interested to remove from EEG, we used this channel for our work. Furthermore we applied an additional 45Hz low-pass filter to all EEG segments. Since the EOG channel may be contaminated by the EEG signal [14], we filtered the EOG signals by a 20Hz low-pass filter.

B. EEG and EOG modeling

The modeling section was done by the System Identification Toolbox in MATLAB. For EEG modeling we needed the relax state without any eye movement artifact, therefore we selected the first part of EEG segments in the dataset. Since EEG is stationary in limited times [11], we used 500 samples (2 seconds) for modeling. Autoregressive model with different orders was tested and finally AR(5) was chosen based on its simplicity and performance: 87% accuracy in fitting. The most important part of our method was eye blink modeling. For each subject we generated a sample eye blink artifact by combining 5 different eye blinks of that specific person. We only used the second EOG channel once for building a basic eye blink artifact for each person and the modeled artifact is later utilized in the processing steps. Several simulations revealed that OE(5,5) has the best performance for Kalman filter with an accuracy of 98% in fitting.

C. Kalman filter Tuning and Results

After modeling the two parts of our signal (i.e. true EEG and EOG) and finding the state-space matrices, we applied Kalman filter to our dataset. The noise variances play an important role in stability and efficacy of the Kalman filter.

We chose the following values based on the experiments performed with different values of variances on different EEG segments obtained from all subjects,

$$\sigma_E^2 = 1 \times 10^{-6}$$

$$\sigma_B^2 = 6 \times 10^{-4}$$

$$\sigma_R^2 = 5 \times 10^{-7}$$

Figure 2 represents the real EEG ($ee_g(n)$) and true EEG estimated by Kalman filter ($\widehat{ee}_{g_t}(n)$) for one participant. It is evident that eye blink artifacts were removed efficiently.

Next we validate our method by means of available metrics. These metrics have no meaning singularly, however the results of several methods can be compared by these metrics. We compared the results obtained from the proposed algorithm with those derived from simulating the RLS algorithm [6] ($M=12$ and $\lambda=0.999$). The first metric is the ratio of the power of the removed artifacts to the power of the true EEG estimated by Kalman filter [1],

$$R = \frac{\sum_{n=1}^N (ee_g(n) - \widehat{ee}_{g_t}(n))^2}{\sum_{n=1}^N (\widehat{ee}_{g_t}(n))^2} \quad (10)$$

where N represents the number of samples. High values of R are due to considerable removal of artifact. However removing the artifact may distort the original signal. Therefore, we also utilized another metric introduced by Nouredin *et al.* [2] for evaluating the distortion of EEG signal. This metric is calculated as ratio of the power of the removed artifacts to the power of the real EEG:

$$\hat{R} = \frac{\sum_{n=1}^N (ee_g(n) - \widehat{ee}_{g_t}(n))^2}{\sum_{n=1}^N (ee_g(n))^2} \quad (11)$$

Lower values of \hat{R} represent less distortion of the EEG signal. We calculate these two metrics for our proposed method and compare them with those obtained by applying the RLS algorithm. We test our method for all subjects in the dataset. We first build models (EEG model and EOG model) for each person at the beginning of examination and then apply the algorithm to EEG segments contaminated by eye blink artifacts. Table I illustrates the average values of R and \hat{R} for segments containing eye blink artifacts, for 9 subjects. Total duration of EEG segments was about 1 minute for each person and we implement our method on FC1 electrode.

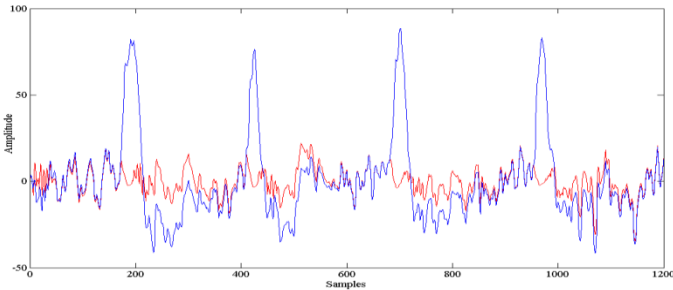


Fig. 2. Real EEG (blue) and true EEG estimated by Kalman filter (red).

It is evident that higher values of R result in higher values of \hat{R} . In other words, there is a tradeoff between how much an algorithm removes the artifact and how much it distorts the EEG signal [2]. Our method has better performance in removing artifacts, although the EEG signal is more distorted in some cases. By tuning the Kalman filter parameters, we may reach the \hat{R} value of RLS algorithm, as demonstrated for subject 5. However, the benefit of not using EOG electrodes in our method outweighs a bit more signal distortion. Variant values of R and \hat{R} for different subjects, is the consequence of different amplitudes and number of eye blink artifacts in each case. Meanwhile, the average values of all participants are shown in the last row of Table I.

We also used the power spectral density (PSD) for assessment of our method. Figure 3 shows the PSD of real EEG and true EEG estimated by Kalman filter. Since eye blink artifacts usually have low frequency components, a decrease in the power of low frequencies in estimated EEG in comparison with real EEG can demonstrate the effectiveness of our algorithm. Since the frequency components of the real EEG and true EEG, estimated by Kalman filter, are almost the same for frequencies higher than 20 Hz, we may conclude that these frequencies were left intact. Although we express our algorithm for one EEG channel, same procedure may be developed for other EEG channels. Finally we apply our algorithm to other EEG channels; those were affected more by eye blink signals. Figure 4 reveals that the proposed method eliminates the eye blink artifacts on other EEG channels as well.

TABLE I. COMPARISON OF RLS ALGORITHM WITH KALMAN FILTER

Subject Number	Number of Eye Blinks	RLS Algorithm		Kalman Filter	
		R	\hat{R}	R	\hat{R}
Subject 1	31	4.04	0.80	10.87	0.95
Subject 2	28	2.09	0.66	2.78	0.72
Subject 3	29	3.20	0.75	3.37	0.79
Subject 4	22	16.47	0.94	17.86	0.95
Subject 5	23	5.14	0.85	5.36	0.85
Subject 6	27	1.23	0.54	2.46	0.70
Subject 7	20	24.11	0.95	27.73	0.97
Subject 8	23	3.14	0.73	3.37	0.75
Subject 9	26	6.70	0.85	11.94	0.92
Mean of All Subjects	25	7.35	0.79	9.53	0.84

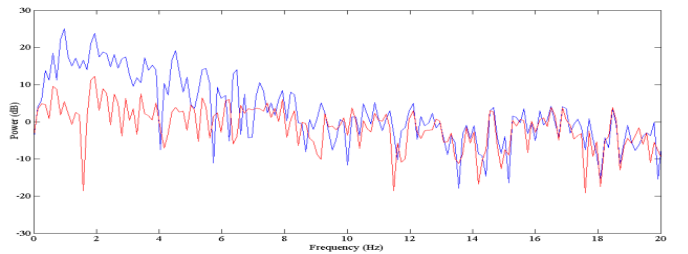


Fig. 3. Power spectral density (PSD) of real EEG (blue) and true EEG estimated by Kalman filter (red).

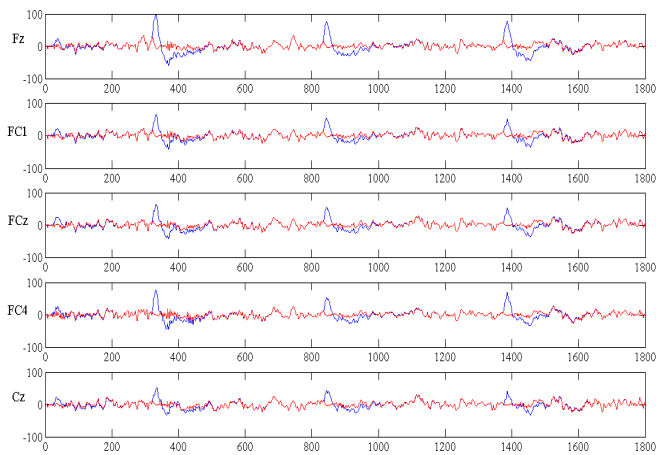


Fig. 4. Applying the Kalman filter to five EEG channels.

IV. CONCLUSION AND DISCUSSION

In this paper we introduced a novel method for correcting EEG signals which were contaminated by eye blink artifacts. The proposed method is based on signal modeling, time variant covariance matrices and Kalman filter. Unlike the other adaptive algorithms that need EOG reference electrodes during all the processing time, we used one EOG channel only once for each person to create an eye blink model. 5% more EEG distortion in the proposed method (see last row of Table I) is the cost of not using EOG reference electrodes, which has the benefits of more Eye blink artifact removal and conventional use in routine practice. Several simulations have demonstrated that our method can suitably adapt to narrow, wide, high and low amplitude eye blink artifacts. Note that in our proposed method we selected the maximum length of eye blink artifacts manually, however the artifacts can be extracted automatically by different signal processing techniques as described in [15].

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