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Research Article

Epileptic Seizure Detection in EEG using Support Vector Machines and Statistical Analysis

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Abstract: In this study, we introduce a novel automated system for the detection and prediction of epileptic seizures. Statistical features are extracted from the EEG signal and are passed to a modified Support Vector Machine (SVM) algorithm for classification. Epilepsy is one of the most commonly encountered neurological disorders. Epilepsy is associated with unpredictable seizures. The cause of these seizures is usually unknown. Seizures are embedded in the Electroencephalogram (EEG) signal which represents the brain's electrical activities. The EEG signal can be recorded either from the scalp or invasively from the cortex using intracranial electrodes. This study reveals that the standard deviation and mean of the input EEG signal form discriminative features. Testing the performance of the proposed system on a publicly available epilepsy dataset provided by the University of Bonn, achieved 100% accuracy. The proposed system requires up to 83% fewer clock cycles than the lift algorithm and 88% fewer clock cycles than the convolution-based algorithm.

Keywords: Epilepsy, Electroencephalogram (EEG), seizure detection, statistical moments, Support Vector Machine (SVM), time complexity

INTRODUCTION

The Epilepsy or seizure disorder is one of the most common neurological disorders (NINDS, 2017). About 2% of the world's population are affected by epilepsy (Bromfield *et al*., 2006). Epilepsy is characterized by unforeseeable seizures. The cause of these seizures may be related to a family trend or a brain injury but is often totally unknown (Kammerman and Wasserman, 2001). If a person has one or more seizures, then that person is diagnosed with epilepsy unless the seizures are caused by some known medical conditions (Fisher *et al*., 2005). In other words, if a person has a seizure, it does not necessarily mean that he or she has epilepsy. Non-epileptic seizures may happen because of several reasons including brain tumors, stroke, head injury and birth defects (Chadwick, 2012).

The electrical events that produce the symptoms of a seizure occur in the brain. Specifically, an excessive neuronal discharge and an unanticipated electrical disturbance of the brain cause the seizures (Kramer and Cash, 2012). The unpredictable nature of seizures will have a tremendous impact on the patient's quality of life (Choi-Kwon *et al*., 2003; Kanner, 2005). Consequently, early detection of pre-seizure is a very important demand as it may allow the patient to take appropriate and in some cases life-saving precautions (Fisher *et al*., 2000).

Electrical activities of the brain can be seen by the Electroencephalogram (EEG) (Niedermeyer and Lopes da Silva, 2005; Darvas *et al*., 2004). In addition to its various applications in the medical fields, the EEG is considered the most useful and significant test for checking if someone has epilepsy (Acharya *et al*., 2013).

Recording of the EEG signal can be done either invasively or non-invasively (Ball *et al*., 2009). In the non-invasive method, the EEG is directly recorded from the scalp. Here multiple-channel EEG signals are recorded simultaneously with electrodes placed on the scalp (Yao, 2001). A gel is often applied in order to decrease the electrical resistance between the electrodes and the skin. Usually, 19 electrodes in addition to system reference and a ground are attached to the scalp and arranged in a specific order following the International 10-20 system (Homan *et al*., 1987). Figure 1 depicts the electrode locations of the International 10-20 system for EEG recording. Fewer electrodes are used when recording the EEG signal for a neonate.

The other type of EEG recording known as Intracranial Electroencephalography (iEEG), is invasive and is often captured during a surgery (Pollo *et al*., 2012). Here, electrodes are implanted on the exposed surface of the brain to record the EEG signal directly from the cerebral cortex. Most of the research work in the field of seizure analysis is based on the scalp EEG recording method.

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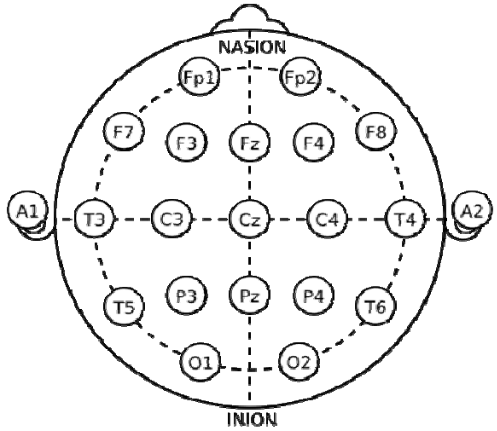


Fig. 1: Electrode locations of International 10-20 system for EEG recording (Wiki, 2017)

In the seizure analysis problem of epilepsy patients, the EEG signal is studied for the purpose of classifying the seizure and for the purpose of predicting epileptic activities before they occur. Visual inspection of EEG signals is a time-consuming process and is subject to a human interpretation which may lead to incorrect diagnosis due to various human-related factors such as fatigue.

In this study, we propose a novel automated epilepsy detection system. Specifically, we use statistical moments to infer discriminatory information about the input EEG signal which hopefully forms a valid representative feature vector. The input feature vector is then passed to Support Vector Machines (SVMs) for classification and labeling (epileptic or not epileptic). Testing the proposed system on an epilepsy dataset, obtained from the University of Bonn (Andrzejak *et al*., 2001), achieved a 100% success rate. To prove the validity and robustness of the proposed scheme, a review of the accuracy rates of various methods employed in the literature is provided in this study.

The proposed system is proved through mathematical analysis to have a very low time complexity compared to the state-of-the-art methods in epilepsy detection.

THE STATE OF THE ART IN THE CLASSIFICATION OF EPILEPTIC SEIZURES

Classification of EEG signals or any signal in general consists of two major functions: feature extraction and class-labeling. The purpose of the feature extraction stage is to obtain finite characteristics that are representative of the input signal. This process often involves compression and redundancy removal. In the class-labeling stage, a classifier is used to operate on the extracted features of the input signal and assign the input to a particular class. Classification methods can be categorized into four kinds: machine learning techniques such as Fuzzy Network, SVM and Artificial Neural Network (ANN); statistical methods such as Bayesian classification; logic-based techniques such as Decision Trees (DT); and instance-based methods such as the K-Nearest Neighbor (KNN) algorithm.

In the following survey, we aim to explore the various feature extraction and classification methods that are found in the literature of seizure detection. A recent review of signal processing techniques and classification methods in seizure analysis was performed by Bou Assi *et al*. (2017). Alotaiby *et al*. (2014) categorized the EEG analysis methods into time-domain and frequency domain methods and provided a valuable survey of the EEG seizure detection and prediction algorithms. Wei *et al*. (2017) used a time-domain method (shape similarity) for feature generation and the Hausdorff distance as a classifier to recognize epileptic discharges in EEG. Patidar and Panigrahi (2017) worked on the diagnosis of epilepsy by extracting features using Kraskov entropy derived from Tunable Q-Factor Wavelet Transform (TQWT) and evaluated the system performance as a function of Q. Jaiswal and Banka (2017) used the Local Neighbor Descriptive Pattern (LNDP) and the One-dimensional Local Gradient Pattern (1D-LGP) techniques for feature extraction and passed the extracted features to an ANN classifier (Li *et al*., 2017) used the Dual-Tree Complex Wavelet Transform (DT-CWT) for feature extraction and SVM for classification. Ekong *et al*. (2016) used a fuzzy SVM in the classification of epilepsy seizures. Satapathy *et al*. (2017) used the Radial Basis Function Neural Network (RBFNN) for epilepsy classification and the Daubechies wavelet at level four for extraction. Riaz *et al*. (2016) employed the Empirical Mode Decomposition (EMD) for extracting features from EEG signals and used SVM for the classification phase.

A Body-Senor Network (BSN) that used signal statistics such the mean, variance, zero-crossing rate and entropy; was developed by Dalton *et al*. (2012) to monitor and detect epileptic seizures. The use of the Principal Component Analysis (PCA) in the Wavelet domain was adopted by Xie and Krishnan (2011) for de-noising and feature extraction. A review of wavelet techniques for computer-aided seizure detection and epilepsy diagnosis was developed by Faust *et al*. (2015). Feature extraction using approximate entropy on DWT coefficients was used by Ocak (2009) and by Guo *et al*. (2010a). Chiu *et al*. (2005) extracted features from the EEG signal using Wavelet energy. Line length feature was adopted by Guo *et al*. (2010b). Subasi and Gursoy (2010) extracted features by employing the PCA, Independent- Component Analysis (ICA) and Linear Discriminant Analysis (LDA) on DWT coefficients.

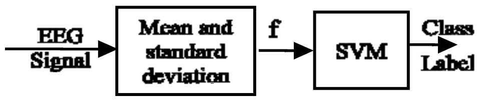


Fig. 2: Block diagram of the proposed system

MATERIALS AND METHODS

A block diagram illustrating the stages of the proposed system is depicted in Fig. 2.

EEG database: The raw EEG dataset used in this study is obtained from Bonn University and is publicly available for free download (The Bonn EEG database, 2017). The entire database is composed of five sets, each of which contains 100 single-channel surface EEG signals of 23.6s. In our dataset, we adopted one healthy set (seizure-free recorded extra cranially with eyes open) and one set containing ictal or seizure activity, recorded intracranially from a volunteer patient. Hence our dataset is composed of 200 samples. Figure 3 shows samples from the used dataset of an epileptic and a seizure free recordings.

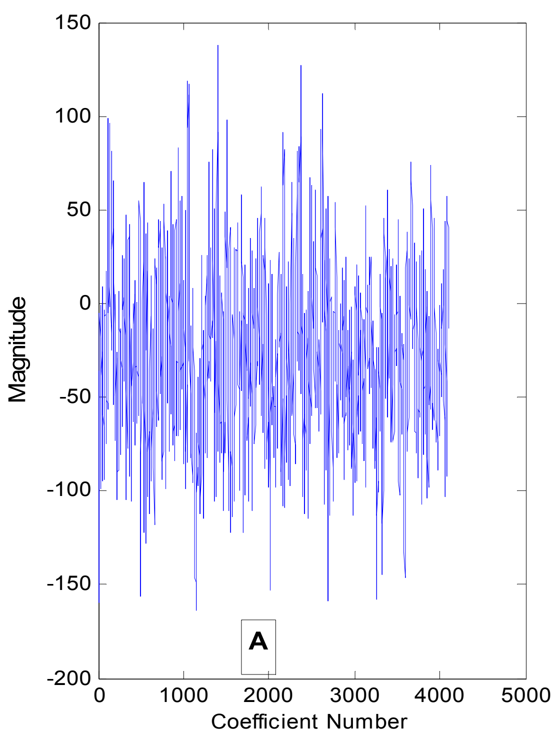
The x-axis and the y-axis in Fig. 3 represent the time period [0 to 23.6s] and the EEG signal value in microvolts, respectively. The raw EEG signals were recorded using a 128-channel amplifier system, band-pass filtered using a band-pass of [0.53-40] Hz and then sampled at a rate of 173.61 Hz. As commonly practiced in supervised machine-learning models, we used the Holdout Sample method for cross-validation. Specifically, the EEG data was randomly split into a training set and a testing set.

Support vector machines: The statistical features (mean and standard deviation) extracted from the input EEG signal are fed directly to an SVM classifier. SVMs are supervised learning algorithms that are commonly used for classification and regression applications. A SVM, devised by Cortes and Vapnik (1995) is a wo-group classifier that has been used in recent years to efficiently solve linear and non-linear classification (Sarhan, 2010). Although SVMs can be modified to handle multiclass problems (Crammer and Singer, 2001), they were originally designed to classify data composed of exactly two classes. In our application, A SVMis used to classify the EEG signal into either healthy or epileptic. As depicted in Fig. 4, a SVM classifies data by determining the best hyperplane that isolates the data points of the two classes. In other words, an SVM tries to find the widest possible margin that separates the two classes and has no interior data points.

The SVM algorithm implemented here uses the Gaussian kernel defined by:

$$k(x, y) = \exp\left(-\frac{\|x-y\|^2}{2\sigma^2}\right), \tag{1}$$

where, σ is a user-defined variance parameter.



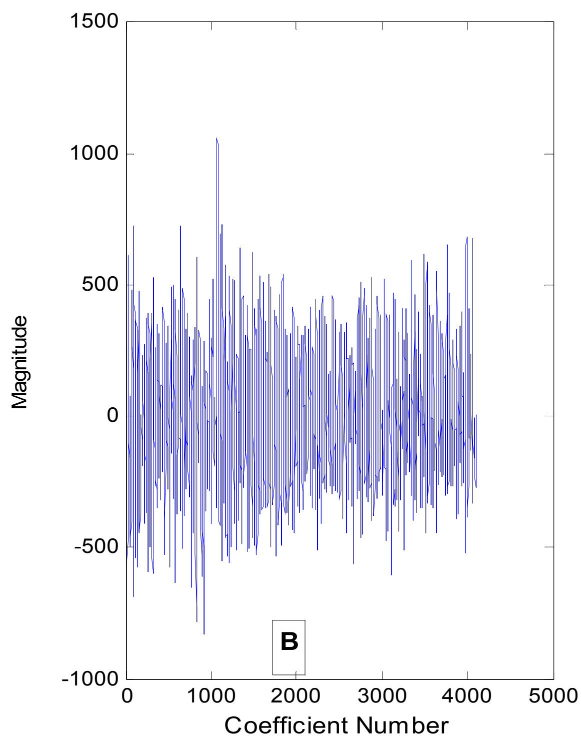


Fig. 3: Examples of raw EEG recordings for (A): seizure-free and (B): seizure phases

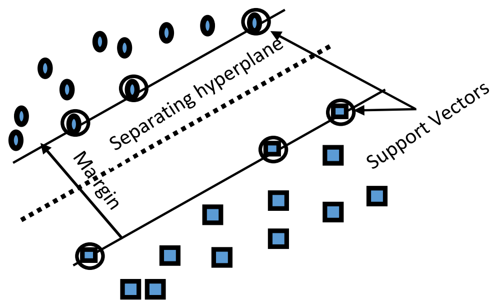


Fig. 4: Support Vector Machine

RESULTS AND DISCUSSION

Statistical analysis: As illustrated in Fig. 3, the normal and seizure EEG samples exhibit different statistical characteristics. For example, the mean and standard deviation of the normal (healthy) sample is negative 28.4 and 42.1, respectively whereas the mean and standard deviation of the epileptic sample is 3.3 and 259.9, respectively. This acute variation in statistical properties is a prominent factor in the motivation to employ statistical moments to obtain distinctive features from the input EEG signal.

In this study, we explore the use of moments as valid features representing the input EEG signals. Moments are statistical measures that describe signal characteristics (Chonavel, 2002). The first two moments in statistics are the mean and the variance which is the square of the standard deviation. These two moments are by far the most commonly used moments. The third and fourth moments are the skewness and the kurtosis, respectively. Higher-order moments (above the 4^{th} moment) are not easily described or estimated (Nikias and Nikias, 1993). Moments have found several practical applications in the field of digital signal processing (DSP) including pattern recognition, image encoding and pose estimation. Sarhan and Al-Helalat (2007) have used the standard deviation measure in the Arabic character recognition application. Amr *et al.* (2010) have employed the moments in an image retrieval application. Boveiri (2010) has discussed the use of statistical moments in pattern classifications. Teh and Chin (1988) have applied the moments in image analysis.

Let the input EEG signal x be defined as a Discrete-Time (DT) sequence of real numbers, such that:

$$x = \{x1, x2, x3, \ldots\ldots\ldots\ldots\ldots xm\} \quad (2)$$

- The first moment or the sample mean is widely used as a measure of central tendency and is affected by every sample in the signal. The mean is given by the following expression:

$$\bar{x} = \frac{\sum x_i}{m} \quad (3)$$

- The Sample Variance measures the variability and is given by

$$s^2 = \frac{\sum (x_i - \bar{x})^2}{m-1} \quad (4)$$

- The sample Standard Deviation is defined as the square root of the variance or s = $\sqrt{s^2}$
- The Sample Standard Deviation is also given by the following expression:

$$s = \sqrt{\frac{\sum x_i^2 - \frac{\left(\sum x_i\right)^2}{m}}{m-1}} \quad (5)$$

SIMULATION RESULTS

When using only the standard deviation and the mean of the input signal as features, the proposed system produces a zero error rate. In the following experiment, we explore the performance of the system when the input EEG is contaminated with additive white Gaussian noise of zero mean. Depicted in Fig. 5 is the error rate of the proposed system as a function of the standard deviation of the noise. Figure 5 clearly illustrates that the proposed system is robust and produces a zero error rate for low levels of additive

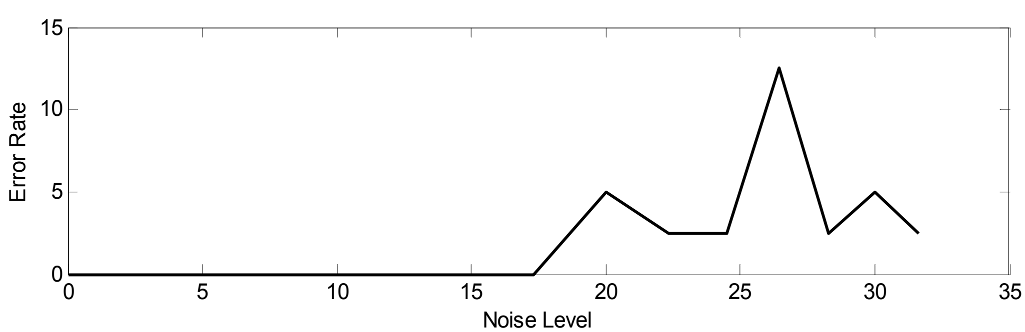


Fig. 5: Error rate of the proposed system as a function of the noise standard deviation

Table 1: Accuracies of seizure classification methods proposed in the literature

Methods	Authors	% Accuracy
K-NN classifier and Wavelet features	Orhan *et al.*(2011)	97
K-NN classifier and Genetic Programming	Guo *et al.*(2011)	93
ANN and PCA	Ghosh-Dastidar *et al.* (2008)	99
Expert model and Wavelet transform	Ubeyli (2008)	95
Histograms and SVM	Runarsson and Sigurdsson (2005)	90
Gaussian mixture model and Wavelets	Chua *et al* (2008)	93
linear least squares models	Roshan (2016)	100
wavelet based and statistical features	Ahammad (2014)	84
PCA and ANN	Tzallas *et al.* (2009)	89
Phase Space Representation (PSR) for feature extraction and Least squares SVM for classification	Sharma and Pachori (2015)	95
LDA and SVM classifier	Bashar *et al.*(2016)	79.2
Wavelets and nearest neighbor classifier	Chen *et al.* (2017)	100

white Gaussian noise. Even for high levels of additive noise, the system's error rate is less than 12.5%.

Compared to the state-of-the-art methods in epilepsy detection which were reviewed in this study, the proposed system is superior in terms of two main merits, accuracy rate and complexities. First, the accuracy rate achieved by the proposed system is100%.Consequently, this accuracy must be greater than or at least equal to the accuracy rates obtained in the literature. The accuracy rates of some of the well-known methods introduced in the literature are shown in Table 1.

Time complexity analysis: We provide here a time complexity analysis of the feature extraction stage for the proposed system and for prominent methods introduced in the literature and demonstrate that the proposed system has a lower time complexity. Since Wavelets is the most commonly used technique in the feature extraction stage of epilepsy analysis and is widely considered the state-of-the-art approach in this field, we compare the time complexity of the proposed system with the complexity of the Wavelet algorithm. First, we note that one disadvantage of using the Wavelet Transform (WT) to perform compression is that it has a higher numerical cost compared to the other transforms such as the Discrete Cosine Transform (DCT) and the Fourier Transform (FT) (Cooklev, 2006; Ortega *et al*., 1999).

There are two approaches for evaluating algorithm complexities (Papadimitriou, 2003). The first method is based on analyzing the written algorithm to count the main operations (Goldreich, 2008). The second method is based on running the algorithm on a PC to measure the time and memory costs. Of course, the latter method is not widely used as it is platform-dependent and the result will vary when the algorithm is run across different platforms.

The calculation cost in the feature extraction stage of the proposed system depends only on calculating the mean and the standard deviation of the input sequence.

Postulate 1: The time complexity Tm[n] for computing the mean function Eq. (3) is given by:

$$Tm[n] = n+1 = O(n) \quad (6)$$

where, n is the length of the 1-D input sequence.

To calculate the time complexity Ts[n] for evaluating the standard deviation function, rewrite Eq. (4) as:

$$s^2 = \frac{\sum(x_i - \bar{x})^2}{m-1} = \sum(x_i)^2 + \sum(\bar{x})^2 - \sum 2(x_i \bar{x})$$

where, the constant 1/(m-1) has been neglected

Postulate 2: The time complexity Ts[n] for computing the variance function Eq. (4) is given by:

$$Ts[n] = n^2 + n^2 + 2n = 2n^2 + 2n = O(n^2) \quad (7)$$

Thus the total time complexity of the proposed systems is:

$$T[n] = Ts[n] + Tm[n] = 2n^2 + 2n + n + 1$$
$$T[n] = 2n^2 + 3n + 1 = O(n^2) + O(n) + O(1) = O(n^2) \quad (8)$$

To provide a clock cycle cost analysis, we assume that the input samples are stored as 16-bit fixed point numbers. Therefore, when the algorithms are implemented on a DSP microcontroller, the cycles per instruction costs are listed in Table 2:

It is known that the discrete wavelet transform of an input vector of length m returns a vector of length m, the same length as the input. It can be deduced from Eq. (8) that the proposed system will require the following operations to process an m-sample signal:

Postulate 3: The number of operations required by the proposed system to process an input sequence of length m:

Total operations = m multiplications + 2 m multiplication by a constant + 3 m additions (9)

Table 2: Cycles per operation for a 16-bit fixed point number

Operation	Number of cycles
Subtraction/addition	1 clock cycle
Multiplication by 2	1 clock cycle
Multiplication	10 clock cycles

Table 3: Number of operations required to compute the Wavelet Transform

Algorithm	Multiplication	Multiplication by 2	Subtraction/addition
Lift-based	8	0	6
Convolution-based	12	0	10

Using Eq. (9) and Table 1, the number of clock cycles required by the proposed system is:

C[m] = 10 m +2 m +3 m cycles. Thus the number of cycles required by the proposed system to process an m-sample input sequence is given by:

C[m] = 15 m clock cycles for an input sequence of m samples (10)

The WT is normally computed using lift algorithms (Daubechies and Sweldens, 1996; Olkkonen *et al.*, 2005) or convolution-based algorithms (Uzun and Amira, 2005). Next, we provide the number of operations (additions, subtractions and multiplications) that are needed by the lift and convolution-based algorithms to calculate the Daubechies (DB) WT. We examine the lift and convolution-based algorithms in calculating a single step of DB-WT. A single step refers here to the calculation of two output samples of a Wavelet transform based on two input samples. Table 3 depicts the required operations of the lift-based and convolution-based algorithms, for evaluating the DB-WT (Lipinski and Yatsymirskyy, 2009).

It can be seen from Table 3 that the lift and convolution-based algorithms, when transforming an m-sample sequence, require the following operations:
Lift-based algorithm = 8 m multiplications and 6 m additions (11)

Convolution-based algorithm = 12 m multiplications and 10 m additions (12)

Using Table 2, the clock cycle costs of the Lift-based and Convolution-based algorithms are:

C[m] = 86 clock cycles Lift-based algorithm (13)
C[m] = 130 clock cycles convolution-based algorithm (13)

Consequently, when using 16-bit integer values, the proposed system requires up to 83% fewer clock cycles than lift algorithms and 88% fewer clock cycles than convolution-based algorithms.

CONCLUSION

Epilepsy is characterized by seizures and is highly unpredictable. Seizure may be epileptic or non-epileptic. EEG signal analysis is considered the standard approach used in the detection and prediction of epileptic seizures. Manually determining the location of the seizure period in EEG signals is a tedious, time consuming and difficult challenge. Consequently, there is a strong need for an automatic system for the detection and prediction of seizures in EEG recordings.

A novel approach to the detection of epileptic seizures in EEG signals is introduced in this study. The system is based on extracting statistical features from the EEG signal and applying the features to an SVM for classification. Experimental tests show that the standard deviation and mean values of the input EEG signal form robust features. Simulations illustrate that the proposed system achieved 0% error rate. The experiments also reveal that when EEG signals are corrupted with a high-level white Gaussian noise, the proposed system still achieves a small error rate of about 15%.

The main merits of the proposed systems is its low complexities and high accuracy compared to the state-of-the-art methods in seizure detection which were reviewed in this study. Assuming 16-bit integer values, the proposed system requires up to 83% fewer clock cycles than lift algorithm and 88% fewer clock cycles than convolution-based algorithm.

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