

# The SVM-Based Feature Reduction in Vocal Fold Pathology Diagnosis

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## **Abstract**

*Acoustic analysis is a proper method in vocal fold pathology diagnosis so that it can complement and in some cases replace the other invasive, based on direct vocal fold observation, methods. There are different approaches and algorithms for vocal fold pathology diagnosis. These algorithms usually have three stages which are Feature Extraction, Feature Reduction and Classification. While the third stage implies a choice of a variety of machine learning methods (Support Vector Machines, Artificial Neural Networks, etc), the first and second stages play a critical role in performance and accuracy of the classification system. In this paper we present initial study of feature extraction and feature reduction in the task of vocal fold pathology diagnosis. A new type of feature vector, based on wavelet packet decomposition and Mel-Frequency-Cepstral-Coefficients (MFCCs), is proposed. Also a new SVM-Based method for feature reduction stage is proposed and compared with conventional methods such as Principal Component Analysis (PCA). Support vector machine is used as a classifier for evaluating the performance of the proposed method. The results show the priority of the proposed method in comparison with current methods.*

**Keywords:** *Vocal Fold Pathology Diagnosis; Wavelet Packet Decomposition; Mel-Frequency-Cepstral-Coefficient (MFCC); Principal Component Analysis (PCA); SVM-Based Feature Reduction; Support Vector Machine (SVM)*

## **1. Introduction**

Voice signal information often plays an important role for specialists to understand the process of vocal fold pathology formation. In some cases vocal signal analysis can be the only way to analyze the state of vocal folds. Nowadays diverse medical techniques exist for direct examination and diagnose of pathologies. Laryngoscopy, glottography, stroboscopy, electromyography, videokimography are most frequently used by medical specialists. But these methods possess a number of disadvantages. Human vocal tract is hardly-accessible for visual examination during phonation process and that makes it more problematic to identify a pathology. Moreover, these diagnostic means may cause patients much discomfort and distort the actual signal, that may lead to incorrect diagnosis as well [1-4].

Acoustic analysis as a diagnostic method has no drawbacks, peculiar to the above mentioned methods. It possesses a number of advantages. First of all, acoustic analysis is a non-invasive diagnostic technique that allows pathologists to examine many people in short time period with minimal discomfort. It also allows pathologists to reveal the pathologies on early stages of their origin. This method can be of great interest for medical institutions. In recent years a number of methods were developed for segmentation and classification of speech signals with pathology.

Different parameters for feature extraction are used. Traditionally, one deals with such parameters like pitch, jitter, shimmer, amplitude perturbation, pitch perturbation, signal to noise ratio, normalized noise energy [5] and others [6-9]. Feature extraction, using the above mentioned parameters, has shown its efficiency for a number of practical tasks [8]. These parameters are frequently used in systems for automatic vocal fold pathology diagnosis, in speaker identification systems or in multimedia database indexing systems. In the proposed method, the Mel-Frequency-Cepstral-Coefficients (MFCCs), Energy and Shannon Entropy parameters have been used for creating the features vector.

Also different approaches for feature reduction are used such as Principal Component Analysis (PCA) [10-13] and Linear Discriminant Analysis (LDA) [14]. In the proposed method, the SVM-based feature reduction has been used and the results of experiments show its better performance in comparison with the PCA.

Finally, the reduced features are used for speech classification into the healthy and pathological class. Different machine learning methods such as Support Vector Machines [10], Artificial Neural Networks [15], Hidden Markov Model [9], *etc.* can be used as a classifier. In the proposed method, the SVM has been used for the classification purpose. In Table 1, some pervious methods in the vocal fold pathology diagnosis are summarized.

**Table 1. The Summary of Some Previous Works**

Reference	Feature set	Feature Reduction Method	Classifier
[10]	25 Acoustic parameters given by MDVP	PCA	Support Vector Machine
[11]	Spectral perturbation	PCA	K-Means clustering
[12]	Acoustic feature, noise	PCA	Threshold
[13]	Linear prediction coefficients	PCA	K-nearest Neighbours
[14]	Mel-frequency-cepstral-coefficients	LDA	Gaussian Mixture Model
[15]	Spectral	-	Artificial Neural Network

## 2. Methodology

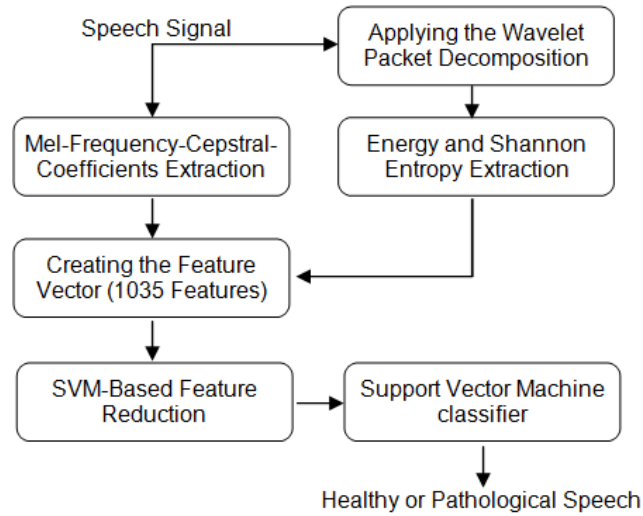
The Block diagram of the proposed method is illustrated in Figure 1. In the first stage, by the use of MFCC and Wavelet Packet Decomposition, feature vector containing 1035 features is made. In the second stage, by the use of the proposed SVM-Based feature reduction method, the dimension of feature vector is reduced. In the last stage, by the use of Support Vector Machines (SVM), the speech signal classified into two classes: pathological or healthy.

### 2.1. Feature Extraction

As it is shown in Figure 1, first, by the use of cepstral representation of input signal, 13 Mel-Frequency-Cepstral-Coefficients (MFCC) are extracted. Then the wavelet packet decomposition in 8 levels is applied on the input signal to make the wavelet packet tree. Then, from the nodes of resulting wavelet packet tree, 511 energy features along with 511 Shannon entropy features are extracted. Finally, by the combination of these features, the initial feature vector with the length of 1035 features is created.

**2.1.1. Mel-Frequency-Cepstral-Coefficients (MFCCs):** MFCCs are widely used features to characterize a voice signal and can be estimated by using a parametric approach derived from linear prediction coefficients (LPC), or by the non-parametric discrete fast Fourier transform (FFT), which typically encodes more information than the LPC method. The signal is windowed with a Hamming window in the time domain and converted into the frequency domain by FFT, which gives the magnitude of the FFT. Then the FFT data is converted into

filter bank outputs and the cosine transform is found to reduce dimensionality. The filter bank is constructed using 13 linearly-spaced filters (133.33Hz between center frequencies,) followed by 27 log-spaced filters (separated by a factor of 1.0711703 in frequency.) Each filter is constructed by combining the amplitude of FFT bin. The Matlab code to calculate the MFCC features was adapted from the Auditory Toolbox (Malcolm Slaney). The MFCCs are used as features in [14] to classify the speech into pathology and healthy class. The MFCC information has been reduced by averaging the sample's value of each coefficient.



**Figure 1. The Scheme of the Proposed Method for Detection of Vocal Fold Pathology**

**2.1.2. Wavelet Packet Decomposition:** Recently, wavelet packets (WPs) have been widely used by many researchers to analyze voice and speech signals. There are many out-standing properties of wavelet packets which encourage researchers to employ them in widespread fields. The most important, multi resolution property of WPs is helpful in voice signal synthesis [16-17].

The hierarchical WP transform uses a family of wavelet functions and their associated scaling functions to decompose the original signal into subsequent sub-bands. The decomposition process is recursively applied to both the low and high frequency sub-bands to generate the next level of the hierarchy. WPs can be described by the following collection of basic functions:

$$W_{2^n}(2^{p-1}x-1) = \sqrt{2^{1-p}} \sum_m h(m-2l) \sqrt{2^p} W_n(2^p x - m) \quad (1)$$

$$W_{2^{n+1}}(2^{p-1}x-1) = \sqrt{2^{1-p}} \sum_m g(m-2l) \sqrt{2^p} W_n(2^p x - m) \quad (2)$$

where  $p$  is scale index,  $l$  the translation index,  $h$  the low-pass filter and  $g$  the high-pass filter with

$$g(k) = (-1)^k h(1-k) \quad (3)$$

the WP coefficients at different scales and positions of a discrete signal can be computed as follows:

$$C_{n,k}^p = \sqrt{2^p} \sum_{m=-\infty}^{\infty} f(m)W_n(2^p m - k) \quad (4)$$

$$C_{2n,l}^{p-1} = \sum_m h(m-2l)C_{n,m}^p \quad (5)$$

$$C_{2n+1,l}^{p-1} = \sum_m g(m-2l)C_{n,m}^p \quad (6)$$

for a group of wavelet packet coefficients, energy feature in its corresponding sub-band is computed as

$$Energy_n = \frac{1}{N^2} \sum_{k=1}^n |C_{n,k}^p|^2 \quad (7)$$

The entropy evaluates the rate of information which is produced by the pathogens factors as a measure of abnormality in pathological speech. Also, the measure of Shannon entropy can be computed using the extracted wavelet-packet coefficients, through the following formula

$$Entropy_n = -\sum_{k=1}^n |C_{n,k}^p|^2 \log |C_{n,k}^p|^2 \quad (8)$$

In this study, mother wavelet function of the tenth order Daubechies has been chosen and the signals have been decomposed to 8 levels. The mother wavelet used in this study is reported to be effective in voice signal analysis [18-19] and is being widely used in many pathological voice analyses [17]. Due to the noise-like effect of irregularities in the vibration pattern of damaged vocal folds, the distribution manner of such variations within the whole frequency range of pathological speech signals is not clearly known. Therefore, it seems reasonable to use WP rather than DWT or CWT to have more detail sub-bands.

## 2.2. Feature Reduction

Using every feature for classification process is not good idea and it may be causes to the increasing the rate of misclassification. Therefore, it is better to choose the proper features from the whole features. This process is called as “Feature Reduction”. In other words, the goal is to reduce the dimension of the data by finding a small set of important features which can give good classification performance. One way for feature reduction is Principal Component Analysis (PCA) which is used frequently in pervious works such as [10-13]. In this section also a novel approach, the SVM-based Feature Reduction, is proposed for the feature reduction.

**2.2.1. Principal Component Analysis:** This method searches a mapping to find the best representation for distribution of data. Therefore, it uses a signal-representation criterion to perform dimension reduction while preserving much of the randomness or variance in the high-dimensional space as possible [20]. The first principal component accounts for as much of the variability in the data as possible, and each succeeding component accounts for as much of the remaining variability as possible. PCA involves the calculation of the

eigenvalues decomposition of a data covariance matrix or singular value decomposition of a data matrix, usually after mean centering the data for each attribute. PCA is mathematically defined as an orthogonal linear transformation that transforms the data to a new coordinate system such that the greatest variance by any projection of the data comes to lie on the first coordinate, called the first principal component, the second greatest variance on the second coordinate, and so on. The principal component  $W_1$  of a dataset  $X$  can be defined as:

$$W_1 = \arg_{\|w\|=1} \max \text{var}\{W^T X\} = \arg_{\|w\|=1} \max E\{(W^T X)^2\} \quad (9)$$

With the first  $K-1$  components, the  $K^{\text{th}}$  component can be found by subtracting the first  $K-1$  principal components from  $X$ :

$$\widehat{X}_{k-1} = X - \sum_{i=1}^{k-1} W_i W_i^T X \quad (10)$$

and by substituting this as the new data set to find a principal component in,

$$W_k = \arg_{\|w\|=1} \max E\{(W^T \widehat{X}_{k-1})^2\} \quad (11)$$

The Karhunen Leove transform is therefore equivalent to finding the singular value decomposition of the data matrix,  $X$ .

$$X = W \sum V^T \quad (12)$$

and then obtaining the reduced-space data matrix by  $Y$  projecting  $X$  down into the reduced space defined by only the first  $L$  singular vectors,  $W_L$ :

$$Y = W_L^T X = \sum V_L^T \quad (13)$$

The matrix  $W$  of singular vectors of  $X$  is equivalently the matrix  $W$  of eigenvectors of the matrix of observed co-variances,  $C = XX^T$ ,

$$XX^T = W \sum \sum W^T \quad (14)$$

In PCA, the optimal approximation of a random vector  $X \in R^N$  in  $N$ -dimensional space by a linear combination of  $M$  ( $M < N$ ) independent vectors is obtained by projecting the random vector  $X$  into the eigenvectors corresponding to the largest eigenvalues of the covariance matrix of vector  $X$ . The main limitation of PCA is that it does not consider class separately, since it does not take into account the class label of the feature vectors.

**2.2.2. SVM-Based Feature Reduction:** As it is mentioned before, the main limitation of PCA is that it does not take into account the class labels and it just focus on the sample's value. In other words, the PCA searches for the features which their sample's value have bigger variance in comparison with others and it does not collaborate with the classifier. So, for overcoming this disadvantage, the SVM-based method is proposed. For this purpose, a distance criterion is defined which shows the distance between the results of classifier and the real classes of speeches in train set. A result vector, which is empty initially, also is defined. The aim of the SVM-based method is to add the specified number of features from initial feature vector into the result vector so that the distance criterion is minimized. Of course this process is repeated and tested for possible situations till the finding desirable solution. The formula (9) has declared the distance criterion. The aim of the SVM-based method is the finding the subset of features so that they minimize the *dist*. The  $a_i$  is the result of classifier

and the  $r_i$  is the real class for  $i^{th}$  speech signal. The  $n$  is the number of speech files in the “train” group.

$$dist = \sum_{i=1}^n |a_i - r_i| \quad (15)$$

### 2.3. Support Vector Machines

For classification, a statistical learning algorithm called support vector machine (SVM) is used. SVMs which were proposed by Vapnik [21], have become an acknowledged classification method in the task of musical genre recognition. Their usage in this task was already justified by works of Li, *et al.*, [22]. The basic theory of SVM is considered below.

Given a set of training vectors belonging to two separate classes,  $(x_1, y_1), \dots, (x_l, y_l)$ , where  $x_i \in \mathbb{R}^N$  and  $y_i \in \{-1, \dots, 1\}$ , one wants to find a hyper-plane  $w \cdot x + b = 0$  to separate the data. In fact, there are many possible hyper-planes, but there is only one that maximizes the margin (the distance between the hyper-plane and the nearest data point of each class). The solution to the optimization problem of SVM is given by the saddle point of the Lagrange functional

$$L(w, b, \alpha) = \frac{1}{2} \|w\|^2 - \sum_{i=1}^l \alpha_i \{y_i [(w \cdot x_i) + b] - 1\} \quad (16)$$

where  $\alpha_i$  are the Lagrange multipliers. Classical Lagrangian duality enables the primal problem (16) to be transformed to its dual problem, which is easier to solve. The solution is given by

$$\bar{w} = \sum_{i=1}^l \bar{\alpha}_i y_i x_i \quad (17)$$

$$\bar{b} = -\frac{1}{2} \bar{w} \cdot [x_r + x_s] \quad (18)$$

where  $x_r$  and  $x_s$  are any two support vectors with  $\bar{\alpha}_i, \bar{\alpha}_s > 0$ ,  $y_r = 1$ ,  $y_s = -1$ .

To solve the non-separable problem slack variables  $\xi_i > 0$  and a penalty function,  $f(\xi_i) = \sum_i \xi_i$ , where the  $\xi_i$  are measures of the misclassification error. The solution is identical to the separable case except for a modification of the Lagrange multipliers as  $0 \leq \alpha_i \leq C$ ,  $i = 1, \dots, l$ . The choice of  $C$  is not strict in practice.

The SVM can realize nonlinear discrimination by kernel mapping, when the samples in the input space cannot be separated by any linear hyper-plane, but can be linearly separated in the nonlinear mapped feature space. There are four typical kernel functions for the nonlinear mapping: polynomial function, Gaussian radial basis function, multilayer perception and Exponential radial basis function. In the proposed method, linear function is used as the kernel function of the SVM.

### 3. Experiments and Results

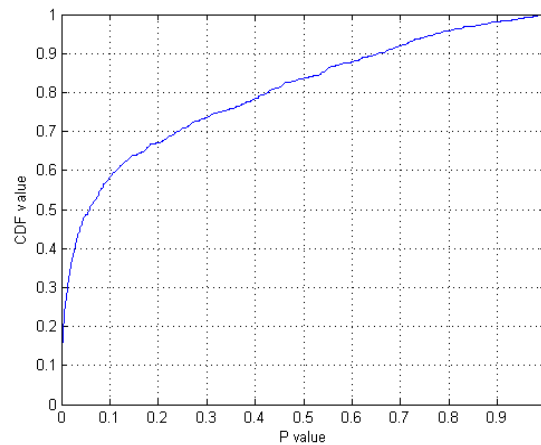
In this section, three experiments have been designed. These experiments are simulated in the Matlab 7.11.0. The whole scheme of the proposed method is illustrated in Figure 1. We have adopted a cross-validation scheme [23, chapter 9] to assess the generalization capabilities of the system in our experiments.

### 3.1. Dataset Description

The dataset was created by specialists from the Belarusian Republican Center of Speech, Voice and Hearing Pathologies. We have selected 40 pathological speeches and 40 healthy speeches randomly which are related to sustained vowel “a”. All the records are wave files in the PCM format. The dataset is divided into the training set with 60 records and the test set with 20 records.

### 3.2. Results

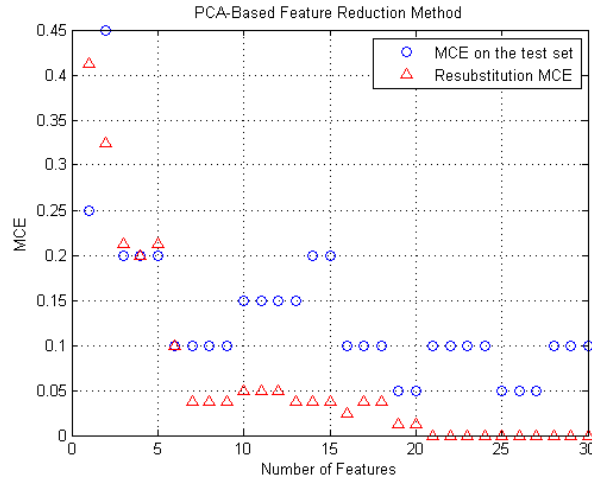
In first experiment, we apply the t-test on each feature and compare p-value for each feature as a measure of how effective it is at separating groups. The result is shown in Figure 2. There are about 20% of features having p-values close to zero and 50% of features having p-values smaller than 0.05, means that there are about 517 features among the original 1035 features which have strong discrimination power. One can sort these features according to their p-values (or the absolute values of the t-statistic) and select some features from the sorted list. However, it is usually difficult to decide how many features are needed unless one has some domain knowledge or the maximum number of features that can be considered has been dictated in advance based on outside constraints.



**Figure 2. The P-value for Features**

One quick way to decide the number of needed features is to plot the MCE (misclassification error, *i.e.*, the number of misclassified observations divided by the number of observations) on the test set as a function of the number of features.

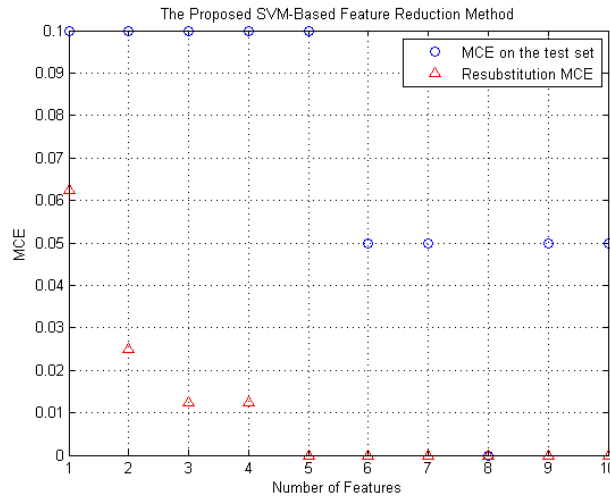
In second experiment, the PCA approach is applied for the feature reduction. Since the total number of our observations is 80, so it is better to use the lower number of features for our classification’s purpose. Therefore, the MCE has computed for various numbers of features between 1 and 30. The result is shown in Figure 3. In order to reasonably estimate the performance of the selected approach, it is important to use the 60 training samples to fit the PCA-Based approach and compute the MCE on the remaining 20 test observations (blue circular marks in the Figure 3). To illustrate why resubstitution error is not a good error estimate of the test error, we also show the resubstitution MCE by using red triangular marks.



**Figure 3. The Obtained MCE by Means of the PCA-Based Feature Reduction Method**

In third experiments, the proposed SVM-Based method is applied for the feature reduction. The MCE has computed for various numbers of features between 1 and 10. The result is shown in Figure 4. In order to reasonably estimate the performance of the selected approach, it is important to use the 60 training samples to fit the PCA-Based approach and compute the MCE on the remaining 20 test observations (blue circular marks in the Figure 4). To illustrate why resubstitution error is not a good error estimate of the test error, we also show the resubstitution MCE by using red triangular marks.

As it is obvious in Figure 3 and Figure 4, from the MCE point of view, the performance of the proposed SVM-Based approach is better than the PCA-Based approach. In the best cases, the PCA-Based method leads to 95% of accuracy with 19 selected features while the SVM-Based method leads to 100% of accuracy with just 8 selected features. The selected features by means of these methods are shown in Table 2.



**Figure 4. The Obtained MCE by Means of the SVM-Based Feature Reduction Method**



**Table 2. The Selected Features for the Construction of Feature Vector**

Feature Reduction Method	The selected features	Accuracy (%)
The Proposed SVM-Based (feature vector length=8)	The 1 <sup>st</sup> , 2 <sup>nd</sup> , 3 <sup>rd</sup> , 4 <sup>th</sup> , 5 <sup>th</sup> , 6 <sup>th</sup> and 7 <sup>th</sup> coefficient of MFCCs. Energy at the 9 <sup>th</sup> node of WP Tree.	100
PCA-Based (feature vector length=19)	Energy at the 17 <sup>th</sup> , 65 <sup>th</sup> , 66 <sup>th</sup> , 67 <sup>th</sup> , 134 <sup>th</sup> , 256 <sup>th</sup> , 257 <sup>th</sup> , 259 <sup>th</sup> , 260 <sup>th</sup> , 261 <sup>th</sup> , 263 <sup>th</sup> and 270 <sup>th</sup> nodes of WP Tree. Entropy at the 16 <sup>th</sup> , 67 <sup>th</sup> , 129 <sup>th</sup> , 256 <sup>th</sup> , 257 <sup>th</sup> , 259 <sup>th</sup> and 268 <sup>th</sup> nodes of WP Tree.	95

### 3.3. Discussion

In the first experiment, it is shown that about 50% of initial features (1035 features) are not strong for the classification purpose. So, feature reduction phase is necessary and important. Feature reduction algorithms can be roughly grouped into two categories: filter methods and wrapper methods. Filter methods rely on general characteristics of the data to evaluate and to select the feature subsets without involving the chosen learning algorithm. Wrapper methods use the performance of the chosen learning algorithm to evaluate each candidate feature subset. Wrapper methods search for features better fit for the chosen learning algorithm, but they can be significantly slower than filter methods if the learning algorithm takes a long time to run. The concepts of "filters" and "wrappers" are described in [24].

In this article, the SVM-Based method for the feature reduction stage has been proposed which belongs to the wrapper methods. On the other side, the Principal Component Analysis (PCA) as the one of famous filter methods has been used which is used frequently in previous works such as [10-13].

In the experiments 2 and 3, the performances of the proposed method as a wrapper method and the PCA-based method as a filter method have been compared. In the Figure 3 and Figure 4, it is clear that the proposed method has better performance in comparison with the PCA-based method. This better performance is due to take into consideration of the SVM classifier in the feature reduction phase. In other words, the proposed method tries to reduce the initial feature vector with the aim of increasing the SVM classifier accuracy. But the PCA-based method just focuses on the data without any attention on the classifier accuracy.

### 4. Conclusion

In this article, it is shown that features based on wavelet transformation have potential for detection of vocal fold pathology. So, in the proposed scheme, Mel-Frequency-Cepstral-Coefficients (MFCC) along with the wavelet packet decomposition are used for the feature extraction phase.

Also a novel approach for the feature reduction phase in the vocal fold pathology diagnosis is proposed. Three experiments are designed to investigate the efficiency of the proposed SVM-Based method. The results of experiments show the priority of the SVM-Based method in comparison with the conventional PCA-Based method.

Although it may be possible to try to build a complete multiclass classification system with a hierarchy of support vector machines so that detection of different type of pathological speech will be possible. For this propose, we suppose that further research on more sophisticated feature extraction phase.

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