A NOVEL FACE RECOGNITION APPROACH USING A MULTIMODAL FEATURE VECTOR

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ABSTRACT
This paper proposes a face recognition technique using a composite framework consisting of a number of parameters for facial feature extraction and matching. Recognition of a known face often becomes an intricate task due to the presence of lighting variations, viewpoint changes, facial expression variations and presence of occlusions like spectacles or beard. Often the recognition system may be required to function in the presence of a very small training set; even a single training image in many situations. The feature extraction technique should thus have the potential to extract maximum information from the existing training set and also prove to be resilient in any varying conditions. The basic idea of the multimodal framework stems out from the fact that using an integrated framework can reduce the multiple false alarms or wrong identification obtained while depending on a single feature. The framework mainly aims in giving a computationally inexpensive, consistent and reliable detection rate which can be robust against any variations (such as pose, orientation) and environmental conditions (lighting, surroundings) and can be applied for tasks ranging from object matching to face, gesture recognition and medical imaging applications. Experimental results with a set of images from the PIE database demonstrate the effectiveness of the approach in giving a good recognition rate even in the presence of huge variations between the training and test set images. The framework is also tested with the plastic surgery face database where a post surgery face needs to be identified from a single pre-surgery training image .The paper also uses an efficient feature dimension reduction technique which improves the overall performance of the feature extractors in the framework.

KEYWORDS: *face recognition, feature extraction, gabor filter, wavelet, local binary pattern.*

I. INTRODUCTION

The need for secure, safe and accurate authentication system is increasing with the huge demand in online transactions. The biometric system such as face, iris, fingerprint, gait for example, has already replaced the existing manual inspection process and surveillance systems in many disciplines. Amongst all these biometrics, face is more attractive as it provides information such as identity, expression, gender, ethnicity and age of an individual. This led to the demand of a robust face recognition system that is resilient to the face lighting conditions and different variations like pose, facial expression or occlusions like spectacles or beard. Facial aging and plastic surgery [1], [2] are yet two other challenges that have not received substantial attention compared to other facial variations. Figure 1 displays an example of face images subject to lighting, pose or expression variations. An efficient recognition system should have the capability to match two faces even when they are subject to these variations. A lot of work has been carried out in this field over the years, each being an improvement over the other. One of the most common method used for face recognition is Principal Component Analysis (PCA) done by Turk and Pentland in 1991 [3] .The Linear Discriminant Analysis (LDA) [4] ,[5] ,[6] is an improvement over the PCA as it works by maximizing the between class scatter matrix and minimizing the within class scatter matrix instead of finding the variation among the entire data set, irrespective of class membership. Following this there are various other methods used for face recognition such as Independent Component Analysis (ICA)

[7] , Neural Network [8], Geometric matching [9], Template matching [10], Hidden Markov model (HMM) [11], Support Vector Machine (SVM) [12] [13] [14].These techniques however gives a poor recognition rate in presence of huge illumination and pose variations. Their performance was further improved by using distinct image features instead of using the intensity images directly. Popular feature extraction techniques like Gabor wavelet , Active Appearance Models (AAM) [15], and Local Binary Pattern were used for this purpose. Shape, size, color, texture, position and orientation parameters form different discriminative features from a face image. LBP and Gabor wavelet features extract local shape and texture information while AAM provides better global shape information. Different color spaces were also used to obtain distinct facial features from various color planes [16].

Figure 1: Images of the same person at varying light, pose and expressions.

This paper uses a multimodal feature vector, which represents an object in a multidimensional feature space for feature extraction. The feature vector is basically a framework with a composite representation of various features like shape, size, color, texture, position and orientation .The basic idea stems out from the fact that if a large number of parameters are used instead of one then the detection rate increases considerably. Limitations of certain parameters in particular situations can then be conveniently addressed by the remaining set thus making the framework resilient to any environmental conditions. Failures of many face recognition algorithms, mainly due to view point variations, lighting conditions, occlusion and influence of other factors like facial expressions can also be successfully resolved by this framework. The framework uses four different features (CGABOR, LSBH, Edge components

and Local Energy and Entropy

) to represent the face image .The CGabor and LSBH are variations of the Gabor and LBP operators and are used to extract the salient texture features, the edge component gives the global shape of the face pattern while the local energy-entropy feature provides unique local features. This paper is organized in the following manner. Section I discuss the basic background of the problem. Section II provides details about the feature extraction technique, the experimental results of recognition using the proposed technique and its comparison with other existing methods. Finally, discussion and conclusion is presented in section III.

II. FEATURE EXTRACTION FRAMEWORK

The basic idea of the framework is to represent the total feature set **x** in terms of a multimodal probability distribution in a multidimensional feature space, mathematically expressed as

$$x = \{x_1, x_2, ... x_n\} \quad (1)$$

where $\mathbf{x}_i$ (i=1...n) denote distinguishable features like color, texture, energy, shape, size etc. Some of these features may be orthogonal to the other. Any number of features may be used in the framework depending on the application requirements and available computational resources. For any object to be represented in this framework it should have more than one feature like color, texture, energy, shape etc. The classification of the object of interest (face for this particular case) is done using the combined distance metrics using all the feature parameters. The combined distance metrics is calculated from the distance metrics of the individual feature parameters obtained using the mahalanobis distance classifier. The parameter estimation θ ($\theta = \{\mu,\sigma^2\}$) (required for calculating the mahalanobis distance between the distributions) of the sample's distribution is done using the

maximum likelihood estimator (MLE) as it is known to give a consistent, convergent unbiased and minimum variance estimate for gaussian distributions, provided such an estimate can be determined for a particular sample. It can be proved that using a multimodal probability distribution , the distance metrics σ_{comb} obtained by combining all the variables is less than the individual distance metrics $\sigma_1,\sigma_2,\sigma_3$ for each of the variables $\mathbf{x}_1$, $\mathbf{x}_2$, $\mathbf{x}_3$ (Lemma 1).It is known that for a multiparametric search space the combined deviation is given by equation 2.Lemma 1 can be proved easily from this identity using proof by contradiction.

$$\frac{1}{\sigma_{comb}} = \frac{1}{\sigma_1} + \frac{1}{\sigma_2} + \frac{1}{\sigma_3} + \ldots\ldots \frac{1}{\sigma_n} \tag{2}$$

It is assumed that $\sigma_{comb} > \sigma_1$. Thus

$$\frac{1}{\frac{1}{\sigma_1} + \frac{1}{\sigma_2} + \frac{1}{\sigma_3} + \ldots\ldots \frac{1}{\sigma_n}} > \sigma_1 \quad , \quad \Leftrightarrow \frac{1}{\sigma_1} > \frac{1}{\sigma_1} + \frac{1}{\sigma_2} + \frac{1}{\sigma_3} + \ldots\ldots \frac{1}{\sigma_n} \tag{3}$$

The above identity is wrong for all values of σ_1 as σ_1 is a square root of a squared term and hence is always positive. Thus the above assumption is wrong and it can be stated that $\sigma_{comb} < \sigma_1$. σ_{comb} is similarly less than σ_2, σ_3,. …etc. Hence it is seen that σ_{comb} is less than the standard deviations of all the variables and also decreases with the increase in the number of variables. The efficiency of the multiparametric method over other single parameter based methods is thus established. In the present work the framework includes texture, edge components, and energy-entropy features. The superiority of the framework over other conventional approaches is two-fold. Firstly it encapsulates all the distinct features of the object; secondly the classification approach allows the intraclass variations to a great extent. The feature extraction procedure is further explained in the subsequent subsections.

2.1. Texture

Among the various texture modeling techniques like Gray-Level Co-occurrence Matrices (GLCM's), Local Binary Pattern (LBP), Law's texture , autocorrelation based, primitive length based and edge feature based methods, the Gabor filters [17] and Local Binary Pattern [18] [19] are two notable texture analysis methods which are mostly used at present. Gabor filter extracts large amount of discriminating local features due to its ability to operate in selective scales and orientations thus capturing the spacial locality and quadrature phase relationships. Two types of texture descriptors named CGABOR and LSBH are used in the framework.

2.1.1. Compressed Gabor: CGABOR

Usually the gabor kernel $\psi_{\gamma,\nu}$ is constructed using five scales ν =0,1,2,3,4 and eight orientations γ=0,1….7 , hence resulting in a very high dimensional representation.

$$\psi_{\gamma,\nu}(z) = \frac{\left\| k_{\gamma,\nu} \right\|}{\delta^2} e^{-\frac{\left\| k_{\gamma,\nu} \right\|^2 \|z\|^2}{2\delta^2}} [e^{ik_{\gamma,\nu} z} - e^{\frac{\delta^2}{2}}] \tag{4}$$

where $k_{\gamma,\nu} = k_\nu e^{i\phi_\gamma}$, $\delta = 2\pi$, $k_\nu = k_{\max} / f^\nu$, $f = \sqrt{2}$, $k_{\max} = \pi/2, \phi_\gamma = \pi\gamma/8, z = (r,c)$ and $\| \ \|$ denotes the norm operation. Although PCA or LDA is applied for dimension reduction of the gabor convolved image $O_{\gamma,\nu}(z)$ it still takes a huge time for computation. Also, there is a decrease in the performance for ignoring some of the principal components. Thus it is essential to reduce the feature dimension in an optimal way without hampering the recognition accuracy.

$$O_{\gamma,\nu}(z) = \Im^{-1}\left[\Im[\mathrm{Im}(z)]\Im\left[\psi_{\gamma,\nu}(z)\right]\right] \tag{5}$$

A possible alternative can be to reduce the image size by down sampling the image. In the present approach the gabor filter is applied on a compressed version $\overline{\mathrm{Im}(r,c)}$ of the original image *Im(r,c)* .This is basically a low pass filtered image which can be obtained from a wavelet decomposed image as shown in Figure 2.A sampling technique is then used to select the maximum gabor coefficients from a *3 X 3* sliding window for each of the *40* (*8* orientations X *5* scales) filtered images as shown in Figure 4 .Thus the dimension is almost reduced to more than $1/100^{th}$ of the original size. For example if gabor filter is applied over a *150 X 130* image the total vector size prior to PCA will be *7,80,000* (*150 X 130 X 40*).However for the present case it will be *53040* (*39 X 34 X 40*) after applying gabor filter on the compressed image and *5893* after sampling.

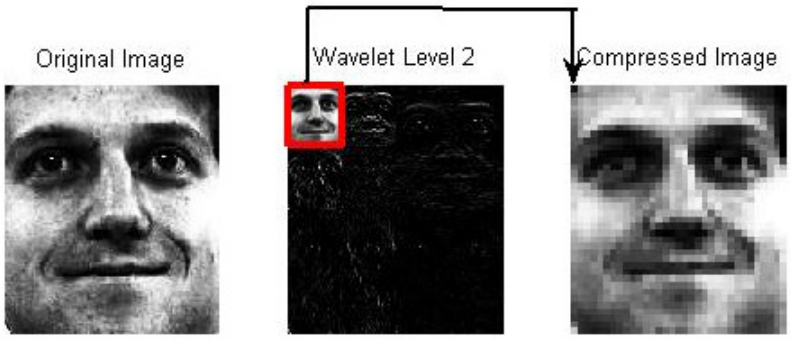

Figure 2: The approximate coefficients of the wavelet decomposition gives the compressed image which is used to extract gabor features

The wavelet function used for compression is selected experimentally .The recognition accuracy increases with the increase in the number of components used but at the cost of computation. Thus the selection needs to be done by keeping a balance between the computational complexity and recognition accuracy. Table 1 shows a list of the number of components for a sampled gabor coefficient vector for each wavelet function at different levels. A computation up to *7000* components may be supported. Thus level *1* wavelet decomposition or level *2* wavelet decomposition for db6 and db8 are not used. A comparison between the second, third and fourth level decomposition using db2 and db4 wavelet as shown in Figure 3 shows that the second level wavelet decomposition gives a better result and is hence chosen. In this case, PCA is applied to the sampled vector $\overline{O_{\gamma,\nu}(z)}$ for transforming the vector to the eigen space rather than reducing its dimensionality. It is observed that this approach not only performs faster than the conventional Gabor-PCA or Gabor-LDA,but also gives a steady hike in its recognition rate. The gabor feature vector is formed using the magnitude value of the gabor coefficients as it is seen to give better accuracy when compared to real,complex or angle value of the coefficients as shown in Table 2.The results of Figure 3 and Table 2 uses the PIE face database with a set of *980* images (*35* different individuals with *28* images each).For all the cases *15* out of the *28* images were used for training.

$$F_{cgabor} = \overline{O_{\gamma,\nu}(z)} \quad (6)$$

Table 1: Sampled Gabor dimension for different Wavelet functions at different levels using an image dimension of 150 X 130 pixels

Wavelet Type	db2	db4	db6	db8
Level 1	22293	23573	24888	26240
Level 2	5893	6906	8000	9173
Level 3	1680	2346	3111	3995
Level 4	533	933	1520	2248

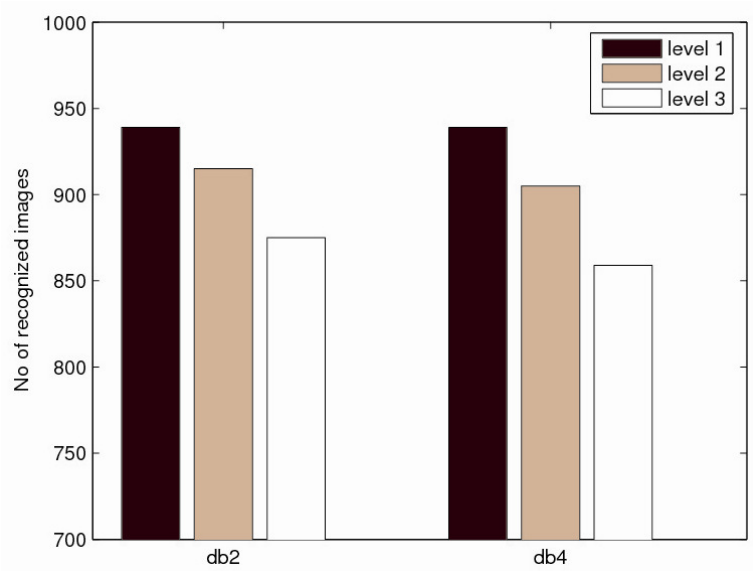

Figure 3: Comparison performance of gabor features using different wavelet functions .

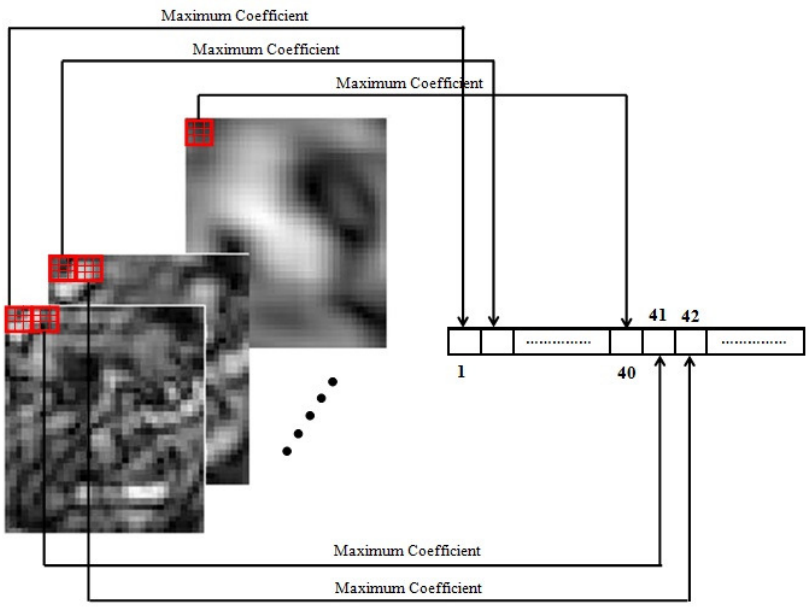

Figure 4: The maximum coefficient is selected from each 3 X 3 sliding window for all the 40 gabor filtered images.

Table 2: Performance Comparisons using the complex, real, magnitude, log magnitude and angular value of the gabor coefficients

Type	Complex	Real	Mag	Log Mag	Angle
No. of Recognized images	907	903	915	915	720

2.1.2. Local Sign Binary Histogram: LSBH

The LBP code of a given pixel f_c is computed by finding its local difference with its neighbours f_p and generating the binary code c_s as shown in equation 7.The LSBH operator is a variation of the LBP

operator where the histogram of the sign components computed for each *3 X 3* window of a block is updated as shown in equation 8 .From the equation it is clear that only the histogram bins which are a power of *2* are considered. Thus instead of a *255* component code for normal LBP, an *8* component code for each block n is obtained hence resulting in a much shorter feature vector. For example, for an image of size *150 X 130* pixels, LBP feature extraction with a block size of *12 X 12* pixels gives a vector size of approximately *30,000*.The LSBH operator on the contrary gives a vector size of *1000* for the same case, thus reducing the computation complexity to a great extent.

$$c_s = \sum_{p=0}^{7} 2^p s_p \qquad \text{where} \quad s_p = \begin{cases} 1 & (f_p - f_c) > 0 \\ 0 & (f_p - f_c) < 0 \end{cases} \tag{7}$$

$$H_n(2^p) = H_n(2^p) + 2^{ps^p}, \ \forall\, p = 0.....7 \tag{8}$$

The final vector F_{lsbh} is thus formed by concatenating the histogram H_n of all the *b* blocks .

$$F_{lsbh} = [H_1 \quad H_2 \quad H_3 \quad ... \quad H_b] \tag{9}$$

2.2. Edge components

The edge features are obtained using a kirsch operator over the original image. Generally a kirsch operator gives the edge coefficients in eight directions by *8* consecutive *45* degree rotations of the kernel k_1. Here the horizontal, vertical and diagonal edge elements are calculated by combining the *2* horizontal and *2* vertical components and the *4* diagonal components as shown in equation 10.The low pass filtered image and the components are shown in Figure 5 .

Figure 5: The lowpass filtered image along with the horizontal, vertical and diagonal edge components.

$$k_1 = \begin{pmatrix} 5 & 5 & 5 \\ -3 & 0 & -3 \\ -3 & -3 & -3 \end{pmatrix}$$

Imn edge_comp = Im ⊗ kn

Im(z)edge = maxn=1:8 Im(z)n edge_comp

flpf(τ) = Im- Imedge

$$fh(\tau) = \sum_{n=1,5} \text{Imn edge\_comp}, \quad fd(\tau) = \sum_{n=3,7} \text{Imn edge\_comp}, \quad fv(\tau) = \sum_{n=2,4,6,8} \text{Imn edge\_comp}$$

$$f(\tau)=[\, f_{lpf}(\tau) \quad f_h(\tau) \quad f_v(\tau) \quad f_d(\tau)] \tag{10}$$

It is observed that using both the low pass filtered image along with the edge components gives a better recognition rate than the one achieved using only the edge components. To reduce the dimensionality the component matrix is sampled by selecting the maximum coefficient value in each *3 X 3* sliding window and the sampled vector $\overline{f}(\tau)$ is generated. It can be verified from Table 3 that the above mention procedure gives a better recognition rate than normal sampling. Feature size can be varied as required by altering the sliding window size or using a downsampled image to calculate the edge components.

Table 3: Comparison of performance using normal sampling and maximum selection

Normal Sampling	897
Maximum Selection	913

$F_{edge}= \overline{f}(\tau)$

2.3. Local Energy and Entropy

Energy entropy parameters are rich in information and are often used for object pattern identification purposes. Cunjian chen [20] calculated the energy and entropy from the approximate coefficients of a wavelet decomposed image and used it for face recognition. In the present approach the face image is divided into equal block sizes as shown in Figure 6 and the energy and entropy for each block *n* is calculated as shown in equation 11. The performance of the recognition algorithm using the energy entropy feature depends on the block size. A performance variation with different block sizes is shown in Table 4 .It is observed that a block size of *15 X 15* gives the best performance when experimented on an image of *150 X 130* pixels. This observation was obtained using images of size *150 X 130* pixels from the PIE and ORL databases. The performance variations with the block size using the ORL database with a set of *80* images is given in Table 4.

$$energy_n = \sum_{I=0}^{255} P(I)^2, entropy_n = \sum_{I=0}^{255} P(I)\log_2 P(I) \tag{11}$$

where *P(I)* denotes the probability density function of intensity level *I*. The final vector $F_{energy\text{-}entropy}$ is thus formed by concatenating the energy and entropy of all the *b* blocks .

$F_{energy\text{-}entropy}$ =[$energy_1$ $entropy_1$ $energy_2$ $entropy_2$..... $energy_b$ $entropy_b$]

Figure 6: Face partitioned in equal sized blocks and energy entropy vector is obtained by computing the energy and entropy parameter of each block.

Table 4: Effect of block sizes on the recognition rate

Block Size	No. of Recognized images
40 x 40	65
35 x 35	66
25 x 25	68

20 x 20	74
15 x 15	79
12 x 12	76
10 x 10	71
5 x 5	58

The total feature vector $\mathbf{x}^j$ of a face image *Im(r,c)* can thus be represented by

$$\mathbf{x}^j = \{F_{cgabor}, F_{lsbh}, F_{edge}, F_{energy\text{-}entropy}\} \quad (12)$$

Each feature $\mathbf{x_i}$ in the feature vector is further transformed in the eigen space using equations 13 to 16.

The mean vector of each feature is calculated using equation 13.

$$\mu_i = \sum_{j=1}^{m} x_i^j \quad (13)$$

The covariance $\mathbf{C}_i$ of the feature *i* in the training set is calculated using the mean adjusted data φ_i

$$\varphi_i = \mathbf{x_i} - \mu_i \quad , \quad \mathbf{C}_i = 1/m\, \varphi_i^{\,T} \varphi_i \quad (14)$$

The feature is then transformed to the eigen space using the eigen vectors ω_i of the covariance matrix $\mathbf{C}_i$ as shown in equation 15.

$$\Omega_i = \omega_i^T \varphi_i^{\,T} \quad (15)$$

For any test image the transformed vector in the eigen space is calculated from the feature vector $\mathbf{x}^k$ using equation 16.

$$\Omega_i^k = \omega_i^T (\varphi_i^k)^T \quad \text{where} \quad \varphi_i^k = \mathbf{x_i^k} - \mu_i \quad (16)$$

The distance matrix σ_i is calculated by finding the distance between each training image principal component vector Ω_i^j and test image principal component vector Ω_i^k . σ_{comb} is then computed using equation 2 and the best match is mapped to the jth image such that the minimum value of σ_{comb} corresponds to σ_{comb}^j.

2.4. Experimental Results

The performance analysis of the feature extraction technique is carried out using the PIE face database with a set of *980* images (*35* different individuals with *28* images each). For all the cases *15* out of the *28* images were used for training. The face images were normalized to a dimension of *150 x 130* pixels before use. The performance comparison of the proposed technique and conventional gabor-pca, lbp-pca and wavelet decomposition techniques is presented in Table 5.The gabor features are computed using the image compressed with db4, level *2* wavelets while the edge features are computed using a downsampled image. Block size for energy entropy parameter is taken as *15* as these give the best results as seen from Figure 3 and Table 4.

Table 5: Recognition results with PIE face database

Methods	Test + Training (in %)	Test (in %)
LBP	88.87	76.04
Gabor	80.41	57.8
Wavelet	88.27	74.73
Feature Vector	95.92	91.43

The results of applying the framework on the plastic surgery face database is given in Table 6.The database consists of a pre-surgery and post-surgery image of *250* individuals. It is seen that the framework gives a better performance when compared to the other existing approaches.

Table 6: Recognition results with Plastic surgery Face Database

Methods	Test (in %)
LBP	60
Gabor	54

Wavelet	48
Feature Vector	72

III. DISCUSSIONS AND CONCLUSIONS

The experimental results verify that the proposed feature matching technique gives a better recognition rate than the conventional gabor, lbp and wavelet feature extraction techniques. It is observed that the energy-entropy parameter and edge component (not commonly applied for face recognition applications) used in the framework gives a high recognition rate (about *88%*) thus increasing the overall performance. It is also seen that applying gabor filter over a compressed image and using the local maximum coefficients is far more efficient in terms of both accuracy and computational complexity than the general gabor-PCA or gabor-LDA approach used so far as using the entire feature set of a compressed image (even $1/4^{th}$ of the original size) gives a better recognition rate than considering a certain percentage of the feature set calculated from the original image. Similar technique of compression when applied before LBP feature extraction also shows considerable hike in performance. This performance can also be achieved using the LSBH operator, which gives a reduced feature size on the original image itself. As a matter of fact, it is noted that the LSBH operator outperforms the traditional LBP operator in terms of speed as well as accuracy. Work is being carried out to further test the performance of the feature extractor on facial age modelling.

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