Illumination Invariant Face Recognition Using Photometric Stereo

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SUMMARY  In this paper, we propose an elegant approach for illumination invariant face recognition based on the photometric stereo technique. The basic idea is to reconstruct the surface normal and the albedo of a face using photometric stereo images, and then use them as the illumination independent model of the face. And, we have investigated the optimal light source directions for accurate surface shape reconstruction, and the robust estimation technique for the illumination direction of an input face image. We have tested the proposed algorithm with 125 real face images of 25 persons which are taken under 5 quite different illumination conditions, and achieved the success rate of more than 80%. Comparison results of conventional face recognition methods and the proposed method are also evaluated. These results demonstrate that the proposed technique have a great potential for the robust face recognition even when the lighting condition changes severely.

key words: face recognition, illumination invariance, photometric stereo, 3D reconstruction

1. Introduction

Face recognition is a challenging problem in computer vision because of the sensitivity due to the dramatic variations between images of the same face. For example, facial expression, pose variation, hair style give rise to huge geometrical variations. In addition, illumination, aging, make-up, scale, background variations also make it difficult to recognize the same face. Thus, for real-world applications, the face recognition algorithm must be robust to these image variations. A recent survey [1] presented a detailed overview of more than 20 years of face cognition research done in the fields of psychophysics, neuroscience and engineering. Many psychophysical experiments [2], [3] show that the human visual system can recognize a face against considerable variations among images of the same face. Among many variations, in this research, we mainly focus on the problem of compensating for the changes of illumination direction. Note that even for a human being, it is very difficult to recognize faces correctly when the illumination varies severely, since the same person appears to be dramatically different. Needless to say, the difference induced by illumination is larger than that of individuals.

Since it has been a major issue in computer vision society from the early 1990s, much works have been done for face recognition by lots of researchers. According to the report of FERET contest [4], the eigenface [5] and the elastic bunch graph matching [6] approaches have shown excellent recognition rate with very large face database. Besides, classical classification methods such as the neural network [7] or the deformable template [8] approaches have also found successful applications in some restricted domains. However, most of the researches have focused on face location, feature selection, classifier design for the face images taken under well-controlled environment such as frontal faces, no expression, same illumination condition, and so on.

So far, only few studies have been done on illumination variation problem in face recognition. In [9], the authors describe a comparative study of some face representations that are relatively insensitive to illumination variation. Examples of such representations are edge maps, image intensity derivatives, and 2D Gabor-like filters. [9] reported that the miss percentages were above 50% for most image representations and the lowest miss percentage was 20% with their database constructed by changing illumination direction. Another approach [10] uses the grey level information to extract the three-dimensional shape of the object, namely, a shape from shading. The approach presented in [10] used three face images of doll, each taken under a distinct illumination direction, for photometric alignment scheme. The author suggested a photometric alignment-based face recognition method using the fact that a grey level image of general rigid object could be synthesized by the linear combination of three images taken under different illumination directions and poses. This procedure can reduce the effect of changing illumination in the recognition process without scene information, i.e. surface albedo or surface normal, and the illumination direction. However, this scheme requires at least 4 manually marked correspondence points between the novel image and one of the model images. In [17], the authors proposed an appearance-based method for modeling face images using the illumination cone representation from training images which models the complete set of all images of an Lambertian object under an arbitrary combination of point light sources. To construct illumination
cone representation, a convex Lambertian surface with normals and albedo was estimated by singular value decomposition (SVD). Although it produces much improved results than other existing methods, the convex assumption of faces and the cast shadows problems under extreme illumination conditions still make it far from satisfaction. Vetter et al. [18], [19] has presented a method to synthesize 3D object views using only a single image under the assumption that the linear class property holds, and showed some promising results for the application of the face image synthesis. However, in general faces are not linear class objects, thus infinite number of examples may be required to represent the details of faces. Moreover, since only rigid transformation is considered, variations due to the expression and illumination changing are not covered.

In this paper, we propose an elegant approach for illumination invariant face recognition based on the photometric stereo technique. The basic idea is to describe each model face using illumination invariant primitives; the surface normal and the albedo which are obtained by photometric stereo images of the face. Matching is then accomplished by comparing the input face image and the model images generated with the same illumination direction as the input face image.

In order to reconstruct accurate surface normal and albedo, we have investigated the optimal light source directions for a model face. Moreover, a robust estimation technique for the illumination direction of an input face image is also developed. Unlike the view-based face recognition approaches [10], [17]–[19], the proposed method is a 3D model-based in which explicit 3D shape and reflectance information of each face are reconstructed and used for matching. Thus, by exploiting the complete 3D shape and photometric information of a face directly, we can manage the variability problems due to illumination, pose and expression more easily using the alignment method: Once estimating the light source direction of the input face image, the illumination problem can be solved by aligning the illumination direction of the generated model faces to that of the input face image, and also the pose and expression variation can be normalized by warping after aligning the fiducial points between the input face image and the 3D face model [20].

This paper is organized as follows. In Sect. 2, the overview of our face recognition system that is composed of registration and recognition procedure is introduced. Section 3 describes a face shape reconstruction method using photometric stereo. In Sect. 4, we explain the registration procedures under given image geometry and optimal light direction conditions. In addition, masking and normalization of face are also addressed. The main face recognition algorithm and the experimental results are described in Sect. 5. Sect. 6 respectively. Finally, concluding remarks are given in Sect. 7.

2. Overview of the System

The whole procedure of the proposed face recognition algorithm is illustrated in Fig. 1. The procedure has two phases; registration and recognition. For this task, two different groups of face images are constructed; the training group or gallery, and the testing group or prove. Both phases have the same preprocessing steps. First, an elliptic face region is extracted in each image by locating the positions of two eyes. In this research, since the face detection is beyond the scope of this research, the eye positions are determined manually, and the shape of the ellipse is chosen empirically. Then, geometric and radiometric normalization steps follow to align the photometric stereo images.

In the registration procedure, the shape models extracted from the training group are used to construct the reference database. The construction of model is discussed in more detail in Sect. 4 including preprocessing steps. Once the gallery of the shape models is constructed, a generic face shape model can be obtained by averaging them, which will be used to estimate the light source direction of the input image in recognition procedure.

In the recognition procedure, estimation of the light source direction and matching are the key steps for robust face recognition. Note that with the surface normal and albedo, the face images in gallery illuminated from arbitrary direction can be easily generated. Thus, by synthesizing the gallery face images with the same illumination direction as the input image, we can match faces under the same illumination condition. The main steps are discussed in Sect. 5.
3. Face Shape Reconstruction Using Photometric Stereo

3.1 Illumination Model

Extracting the shape information of an object from its shaded image, known as the shape from shading (SFS) problem, has been one of the fundamental problems in computer vision. Many SFS algorithms using a single image have been developed [11], [12]. However, it is well known that this problem is ill-posed so that the solution may not be reliable. Thus, researchers have also considered the use of multiple images to provide additional information for robust surface reconstruction, which includes the photometric stereo method [13]–[15].

In this research, in order to recover the shape and albedo, which are illumination invariant generic information of a face, we employ the photometric stereo method using three distinct photometric stereo images of the face. The configuration of the imaging system is modeled as shown in Fig. 2, where \( \sigma \) is the slant angle between Z-axis and light source, and \( \tau \) is the tilt angle between X-axis and the projection vector of light source into X-Y plane. To standardize the imaging geometry (with reference to Fig. 2), it is convenient to choose a coordinate system such that the viewing direction is aligned with the Z-axis, and the three light sources are located on a circle with the same slant angle \( \sigma \) and different tilt angle \( \tau \)’s.

3.2 Reflectance Map

Although an ideal image formation process can be modeled by a perspective transformation, if the size of the objects in view is small compared to the viewing distance, then we can approximate the perspective projection as a simple orthographic projection. And, we assume that the face skin is Lambertian which scatters the incident light equally in all directions and appear equally bright from all directions. Then, for a fixed light source and viewing direction, the image intensity corresponding to a Lambertian surface point depends only on the surface normal, and the image formation process can be expressed by the following image irradiance equation.

\[
I(x, y) = R(x, y) = \begin{cases} \rho(x, y) \mathbf{n}^T \mathbf{n}, & \mathbf{n}^T \mathbf{n} \geq 0, \\ 0, & \mathbf{n}^T \mathbf{n} < 0, \end{cases}
\]

(3)

where \( \rho \) is the albedo of the surface point, \( \mathbf{n} = \frac{(-p, -q, 1)^T}{\sqrt{1 + p^2 + q^2}} \) is the surface normal, and

\[
\mathbf{l} = \frac{(-p_s, -q_s, 1)^T}{\sqrt{1 + p_s^2 + q_s^2}} = (\cos \tau \sin \sigma, \sin \tau \sin \sigma, \cos \sigma)^T
\]

(4)

is the unit vector of the illumination direction toward the point light source, and \( p_s \) and \( q_s \) denote the slope of a surface element perpendicular to the illumination direction.

3.3 Photometric Stereo

It is known that three photometric stereo images taken under distinct lighting conditions while maintaining the viewing direction fixed are sufficient to reconstruct the surface normal and the albedo of a Lambertian surface [13], [14].

Suppose that we have three photometric stereo images \( I_1 \), \( I_2 \), and \( I_3 \) obtained with the corresponding light source directions \( \mathbf{l}_1 \), \( \mathbf{l}_2 \), and \( \mathbf{l}_3 \), respectively. Then, we have three independent image irradiance equations for the images, and this can be written in matrix form as

\[
\mathbf{I} = \rho \mathbf{L} \mathbf{n},
\]

(6)

where \( \mathbf{I} = [I_1, I_2, I_3]^T \), and \( \mathbf{L} = [\mathbf{l}_1, \mathbf{l}_2, \mathbf{l}_3]^T \). If \( \mathbf{l}_1 \), \( \mathbf{l}_2 \), and \( \mathbf{l}_3 \) are linearly independent, \( \mathbf{L}^{-1} \) exists. Then by using the fact that \( \mathbf{n} \) is unit normal, we can determine the albedo as

\[
\rho = \frac{1}{\mathbf{n}^T \mathbf{L}^{-1} \mathbf{n}}
\]

(7)

and, in turn, the corresponding unit surface normal by

\[
\mathbf{n} = \frac{1}{\rho} \mathbf{L}^{-1} \mathbf{I}.
\]

(8)
4. Registration Procedure

4.1 Analysis of Light Source Directions

Selecting a set of appropriate photometric stereo images is very important for reconstructing accurate surface shape of a given object. Therefore, in order to choose the best photometric image sets for a face, we first investigate the optimal illumination conditions for the face. In order to analyze the illumination effect exclusively, a plaster statue of ‘Beethoven’ is used as the target face model for this test. There are two reasons why we use a plaster statue: One is that the 3D surface information of the ‘Beethoven’ exhibits the geometric nature of a face sufficiently, and there are no geometrical variations between basis set images so that the correspondence problem become trivial, and the other is that the plaster statue has nearly Lambertian reflectance property and constant albedo. In general, a real human face raises a geometrical variation in some degree even though he makes an effort to keep his expression fixed while taking images.

To examine the optimal illumination directions, ideally all the sets of possible light source directions represented by the points on the illumination sphere (as shown Fig. 2) should be examined. However, since this is impractical and empirically it is shown that due to the smoothness of face surface, a finite samples on the illumination sphere suffice to cover the illumination changes of a face, we have constructed candidate illumination direction sets empirically: For each slant angle of \( \sigma = 30^\circ, 45^\circ, 60^\circ \), by varying the tilt angle of the first light source by the amount of 30\(^\circ\) while maintaining the other light sources to be 120\(^\circ\) apart in azimuth angle from each other, 12 sets of candidate basis images of the statue are obtained.

The surface normal and albedo for each basis image set are determined by Eqs. (7) and (8). Then to measure the reconstruction accuracy of each test set, the MAD (Mean Absolute Difference) error between real images illuminated from different directions and the corresponding synthesized ones are calculated. We use three verifying images illuminated from \((\sigma, \tau) = (15^\circ, 120^\circ), (15^\circ, 90^\circ), \) and \((15^\circ, 60^\circ)\). The results are shown in Fig. 3(a), and an example of verifying image, reconstructed image, and the error image are also shown in Figs. 3(b)–(d), respectively.

In this test, in order to reduce the effect of cast shadow and highlights, we have excluded the points whose albedo values deviate far from the mean. The black pixels in Figs. 3(b)–(d) represent those excluded ones when the threshold value is 50. We have examined the effect of the threshold value on reconstruction error, and the results are shown in Figs. 4 and 5 for the thresholds are 40 and 30, respectively. The percentage of valid region at each Figs. 3–5(a) means the ratio of the area under the threshold within the whole face region. We notice that as the threshold for albedo becomes small, the intensity error tends to decrease.

As shown in Figs. 3–5(a), extensive experimental tests with real plaster statue and synthesized face images reveal that the reconstruction error tends to be smaller when the slant angle \( \sigma \) get closer to the Z-axis and the tilt angle \( \tau \) is arranged symmetrically. Thus, the basis image set, set 4, always gives minimum reconstruction error regardless of the threshold or target images. Thus, in our approach, we choose the optimal light source directions to be \((\sigma, \tau) = (30^\circ, 90^\circ), (30^\circ, 210^\circ), \) and \((30^\circ, 330^\circ)\). We note that since actual human faces are not pure Lambertian, and there are shape and texture variations among them, there may be some differences between the actual optimal light source directions for each individual face and the ones obtained by the empirical test using the particular ‘Beethoven’ statue.

4.2 Face Region Extraction

In general, the locations of two eye points can be provided as a result of face detection algorithm. However, since the face detection problem is out of the scope of this paper, the exact locations of two eye points of each face are given manually. After the eye locations are obtained, in order to consider only the facial region to be examined in a scene, the face region is extracted by an
appropriate face mask which covers all the distinctive facial features. In this research, we employ an elliptic mask to extract the facial area effectively, by using the following elliptic function.

\[
\frac{(x - c_x)^2}{a^2} + \frac{(y - c_y)^2}{b^2} = 1,
\]  

where \( c = (c_x, c_y) \) is the center point between two eye locations and

\[
a = c_1 \cdot d_{eye}, \quad b = c_2 \cdot d_{eye},
\]

where \( d_{eye} \) is the distance between two eye locations, and \( c_1, c_2 \) are constants given empirically. Note that according to human race, the elliptic mask shape may be slightly different. In case of oriental Asian, by setting \( c_1 = 1.00, c_2 = 1.43 \), we can extract face region reliably in a scene.

4.3 Normalization

Note that the photometric stereo method assumes that the correspondence between corresponding pixels in photometric stereo images is established. However, in real situation, although the camera direction is fixed, a face can be move slightly while taking pictures, and this may cause alignment errors and result in inaccurate shape reconstruction. Therefore, it is necessary to normalize the size and adjust the in-plane rotation of a face in each image. This can be accomplished by resizing and rotating the images using the eye positions as the anchor points. In addition, in order to compensate for the difference in illumination conditions among images, we also normalize the intensity so that the maximum intensity value becomes unity for all images.

5. Recognition Procedure

5.1 Estimation of Light Direction

It is very important to estimate the illumination direction of an input face image correctly for an accurate face matching. In this research, by constructing a generic surface model of faces using the models in the gallery DB, and utilizing the surface normal and albedo information of it, we estimate the illumination direction via least squared estimation method. The generic face model can be obtained by averaging the surface normals and albedos of the faces in the gallery DB, which are extracted by the photometric stereo as discussed in Sect. 3. Thus, this generic face model is the mean face of the trained samples and serves as an important role for estimating the light direction of the input image in the recognition procedure. Figure 6 shows how the generic face looks like, in which Figs. 6(a)–(c) represent the synthesized generic face images with the light source directions at \((\sigma, \tau) = (30^\circ, 270^\circ)\), \((\sigma, \tau) = (30^\circ, 180^\circ)\), and \((\sigma, \tau) = (30^\circ, 90^\circ)\), respectively.

For a given input face image, the \( i \)-th pixel has the
Following relation.

\[
E_i = \frac{1}{\rho}I_i = n_i^T l, \tag{10}
\]

where \(E_i\) is the normalized intensity of the \(i\)-th point in the input face image, \(n_i = [n^T_i, n^T_y, n^T_z]T\) is the surface normal of the corresponding point in the generic model, and \(l = [l_x, l_y, l_z]^T\) is the illumination direction vector to be estimated. If we are considering \(m (> 3)\) pixels in the face region, we obtain \(m\) corresponding linearly independent equations of (10), and this overdetermined system can be written in following matrix form as

\[
E = \begin{bmatrix}
E_1, E_2, \ldots, E_{m-1}, E_m
\end{bmatrix}^T
= \begin{bmatrix}
n^1_x & n^1_y & n^1_z \\
n^2_x & n^2_y & n^2_z \\
\vdots & \vdots & \vdots \\
n^m_x & n^m_y & n^m_z
\end{bmatrix} \begin{bmatrix}
l_x \\
l_y \\
l_z
\end{bmatrix} = NL, \tag{11}
\]

where \(E\) is the normalized intensity vector of the input face image, \(N\) is the surface normal matrix of the generic face model. Then the illumination direction can be determined by the least square estimation as

\[
l = (N^T N)^{-1} N^T E \tag{12}
\]

Note that relatively flat face regions such as forehead and inner cheek regions are not sensitive to the variation of the illumination direction, providing not enough information it. Thus, in order to enhance the accuracy of the estimation, we consider only the region around the nose and outer cheek regions where the illumination sensitivity is relatively good, rather than the whole face region in calculating (12).

5.2 Matching

Once the illumination direction of an input face image is estimated, the corresponding face images of the gallery models for the same illumination condition can be synthesized using (3). Then, by measuring the similarity between the input face and the synthesized model face images, illumination invariant face matching can be accomplished. The dissimilarity measure used in this experiment is the MAD of the corresponding intensities of the input and synthesized model face as follows.

\[
D = \frac{1}{N} \sum_{(x, y) \in R} |I_i(x, y) - I_m(x, y)|, \tag{13}
\]

where \(R\) is the face region, \(N\) is the number of pixels within the face region, and \(I_i, I_m\) are the intensities of the input image and a synthesized image, respectively. By ordering the model faces according to the dissimilarity in increasing order, we can establish a registered face list to the given input face. In general, the recognition rate is defined by the percentage that the input face ranks top in the registered face list. However, since this does not represent the potential ability of a recognition scheme well, we employ the cumulative recognition rate [16]. \(P(n)\) defined as follows:

\[
P(n) = \sum_{i=1}^{n} p(i), \tag{14}
\]

where \(n = 1, \ldots, N\), and \(p(i)\) is the probability of the correct face being placed at \(i\)-th position on the registered list. The cumulative recognition rate represents the probability of the input face being matched to the first top \(n\) faces on the registered list.

6. Experimental Results

6.1 Face DB

All face images were acquired in a darkroom so that the influence of unwanted extra light is prevented in the scenes, and halogen lamps are used as the point light sources to make stable and well-controlled illumination condition. Then, 640×480, 8-bit grey level images were taken using 3CCD digital camcorder interfaced to PC.

In this experiment, images of 25 distinct persons, including 20 males and 5 females, have been taken in frontal viewing direction with size variation, and without any restriction about distinctive features such as glasses, make-up, or hair-style. We have constructed two groups of face image DB: One is the training group of the three basis images for each person, 75 images in total, which are taken under the optimal illumination directions discussed in Sect. 4.1. Some example images of training group are shown in Fig. 7. The other is the testing group for evaluating the performance of the proposed algorithm. 5 different images for each person, 125 images in total, taken under very different illumination directions from that of the basis images are used for the test. In addition to the illumination variation, since there are time gap in acquiring the training images and the testing images by about one month, testing group are exposed to other variations such as expressions, pose, cosmetics and adornments. Therefore, even for the same person, the appearances look quite different. Figure 8 shows some face images of the testing group.
6.2 Effect of Light Direction Estimation

In this experiment, firstly, we have examined the error in the light direction estimation and its relation to the performance of the face recognition. To investigate the performance variation due to the accuracy of the illumination direction estimation, the recognition results with the ground truth light source direction and with ones obtained by the two different estimation methods, the whole face region-based and the nose region-based method, respectively, are evaluated. Since all images in the testing group are taken under precisely controlled environment, we know the correct light direction, and thus can measure the estimation error of the light direction for all images in testing group. Table 1 represents the average error of the illumination direction estimation for each method in radian. It shows that more accurate estimation result is obtained when the region around the nose rather than whole face is considered.

Figure 9 shows the resulting cumulative recognition rates for each light direction estimation method. The results show that when the nose region are used exclusively for the estimation, the proposed algorithm can achieve a top 1 recognition rate of 80% even under a severely changing illumination condition as shown in Fig. 8. It also shows that the cumulative recognition rate can increase to 93% as the correct position on the registered list increases up to 10. While, when the whole face region is engaged in estimating the light direction, the recognition rate decreases about 10% and the estimation error also increases by 0.09 radian. Therefore, we can conclude that the selection of effective region for estimating the illumination direction is very critical for accurate face recognition. Note also that if we estimate the illumination direction exactly, the recognition rate will increase up to 87%, and we can achieve potential performance of the excellent cumulative recognition rate of 96%.

6.3 Comparison with Conventional Methods

In this experiment, we have compared the performance of the proposed algorithm with conventional face recognition methods. Among many existing face recognition algorithms, we have considered the PCA-based eigenface method and the Gabor-based elastic bunch graph matching method, since these methods have shown the best performance for the recent FERET tests. The
PCA-based algorithm is the representative method of holistic matching techniques [5], which use the global information of a face for recognition. The basic idea of this approach is to project the whole input face data into the lower-dimensional eigen space and perform matching in this reduced space using the Euclidian distance measure. However, since the PCA-based approach is basically a correlation-based matching, it has some limitations in face recognition, especially when the corresponding faces are not aligned correctly, and when the illumination conditions are quite different. While, the elastic bunch graph matching approach is a hybrid method which utilizes the holistic and local feature information of a face by using the responses of a bunch of Gabor filters known as the Gabor jets [6].

The same face DBs as mentioned in 6.1 are used for the test: A training group of 75 images from 25 persons under optimal illumination direction, and a testing group of 125 images from the same persons with different illumination conditions. For the PCA experiment, the training group is used to construct the scatter covariance matrix [5].

For the Gabor jets experiment, we have predefined 12 fiducial points in a face region, where the Gabor filters are to be convolved. The Gabor jet is the responses of a family of Gabor filters in the shape of plane waves with wave vectors, restricted by a Gaussian envelope function. In this test, we have used a discrete set of 5 different frequencies and 8 orientations. Thus, we obtained a feature vector of 480 dimensional arrays composed of 40 magnitude values at each fiducial point. Recognition is then accomplished by measuring the similarity between corresponding feature vectors [6].

The comparison results of PCA, Gabor jets and the proposed method are shown in Fig. 10. This shows clearly that the recognition rate of the proposed algorithm is much higher than the two existing methods: the top 1 recognition rate of proposed method is 9% higher than the Gabor jet method and 58% higher than the PCA method. Note that the PCA-based method is almost impossible to recognize a face in some extreme illumination conditions, while the Gabor jet method performs rather good, and as the count of ranking increases, the recognition rate reaches to that of the proposed method. Although, generally, Gabor response is known to be robust against local deformation and some illumination variations, it can not compete with the proposed 3D model-based technique especially under the extreme illumination conditions. Therefore, we conclude that the proposed face recognition method is quite robust against even severe illumination change.

7. Conclusions

We have addressed a new approach for illumination invariant face recognition, in which the shape and albedo information of the gallery face are built using the photometric stereo technique, and used as the illumination independent model of the faces. Once estimating the illumination direction of an input face, gallery face images of the same illumination condition are synthesized, and then matching between them are conducted using MAD dissimilarity measure. In this research, the optimal illumination direction for acquiring the three photometric stereo basis images which ensures the accurate face shape reconstruction is also investigated. Moreover, a robust estimation technique for the illumination direction of an input face image is proposed. Experimental results on real face images have demonstrated that the proposed approach has a great potential for the robust face recognition even when the lighting condition changes significantly.

Our further studies will be focused on the following problems.

- How to extend the proposed face recognition approach to overcome the pose and expression variations. This can be done by incorporating the pose estimation technique, 3D facial feature detection and shape deformation technique.
- How to cope with the non Lambertian nature of the face. Actually, a face skin is not pure Lambertian, so more complex reflectance model including specular component might be needed for accurate representation. Also, the non skin areas such as hair, eyebrow, glasses must be carefully treated to reduce the modeling error.
- How to estimate the illumination direction correctly. As shown in the experiment, the overall performance of the face recognition highly depends on the accuracy of the light source direction estimation. Thus, to improve the performance substantially, it is necessary to develop an optimal light source direction estimation technique.

References


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