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Extraction of Hidden Features using Preprocessing Techniques and Texture analysis for Face Recognition

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***Abstract*: face recognition is the one of the robust technology compared to other biometric technologies. It has a lot of applications such as remote sensing, access control, surveillance systems etc, but it is difficult task under difficult lighting conditions which is frequently occurred. To avoid this problem, extract the hidden features. In this paper make three contributions.1.different normalization techniques used to eliminate the different lighting changes.2.local texture patterns used for robust feature extraction.3.nearest neighbourhood classifier used to measure features similarity. These methods performed on Extended Yale data set to analyse the different normalization techniques to avoiding lighting changes and improving face recognition accuracy.**

Key words: Face recognition, different lighting condition, Normalization, local texture patterns, nearest neighborhood classifier.

I. INTRODUCTION

Face recognition is the most successful biometric technology compared to other technologies, which are fingerprint, iris, retina, voice recognition so on, because of their advantages. for example ,iris, retina, fingerprint analysis, these methods depends on the cooperation of the participants, whereas a face recognition system based on analysis of frontal or profile images of the face is often effective without participant's cooperation. Face recognition can be used lot of areas such as in entertainment, smartcards, Law enforcement, surveillance Systems and Information security, etc .even though most successful technology, not many solutions have proven very efficient. Because it has a lot of problems when photos are taken in uncontrolled environment such as different lighting changes, pose, expression, aging etc.

Among these problems different Illumination is one of the frequently occurred problems when photos are taken in uncontrolled environment. This problem is basically the variability of an object's appearance from one image to another with slight changes in lighting conditions. Psychophysical experiments demonstrate that the human visual system can identify faces of the same person from new images although considerable changes in illumination [1].Lighting changes is a demanding problem in a facial recognition research, it is one of the most challenging problems for robust face recognition [2] [3].The six different persons, with the same facial expressions and different varying lighting conditions of each person, wich having hidden features as shown in Figure 1. Varying in illumination conditions produce a substantial diminish of recognition performances. A face recognition system, based on computing the distance between non processed images, will fail to recognize all the faces in the database and will confuse the faces.

Fig1:Extraction of hidden features on face

Different methods have been proposed to deal with the illumination invariant face recognition technique. Some methods are elastic bunch graph matching (EBGM) [4] principal component analysis (PCA)[5,6,7,8,9], Kernel principal component analysis [10], linear discriminate analysis (LDA)and independent component analysis (ICA),these techniques are also called holistic approaches.
The main shortcoming of holistic approaches is that they assume that any given pel in the image corresponds to the same position in the person's face. Therefore, they are suitable scenarios where the faces image have the same illumination conditions, same pose, and the same expression and are well aligned. Yet small violations of these circumstances dramatically reduce performance.

In this paper we propose different illumination normalization techniques such as Weberfaces, wavelet denoising and gradient faces and compare them and also propose local approaches instead of holistic approaches for robust feature extraction and nearest neighbhourhood classifier used for efficient face recognition.

2. ILLUMINATION NORMALIZATION METHODS

Illumination Normalization is an efficient approach in eliminating illumination changes before face recognition.
In this paper Weberfaces, wavelet denoising, gradient faces techniques are explained below.

2.1weberface normalization technique

Ernst Weber, experimental studied that the ratio of the increment threshold to the background intensity is a constant [11]. This relationship, Known since as Weber's Law. This can be mathematically represented as

$$\frac{\Delta I}{I} = K \qquad (1)$$

Where Δ*I* represents the increment *I* represents the initial stimulus intensity and *k* represents the left side of equation is remains constant despite of changes in the *I* term. The fraction Δ*I*/*I* are known as the Weber fraction. The Weber's Law descriptor (WLD) represents an image as a histogram of differential excitations and gradient orientations, and has several motivating properties like robustness to noise and lighting changes, well-designed detection of edges and dominant image representation. WLD descriptor is based on Weber's Law. According to this law the ratio of the increment threshold to the background intensity is constant. The computation of WLD descriptor involves three steps i.e. finding differential excitations, gradient orientations and building the histogram. An each granule will be separated into overlapping blocks to evaluate the differential excitation with current coefficient and neighbourhood matrix.

2.2Wavelet Denoising

An image is often corrupted by noise during its acquisition or transmission. Image denoising is used to remove the additive noise while retaining as much as possible the important image features. Wavelet denoising attempts to remove the noise present in the signal while preserving the signal charecteristics, regardless of the frequency content. The wavelet based methods mainly rely on thresholding the discrete wavelet transform coefficients [13], which have been affected by Additive White Gaussian Noise. Thresholding is a simple non linear technique which operates on one wavelet coefficients at a time. In its most basis form, each coefficients thresholding by comparing against the, threshold .if the coefficient is smaller than threshold, it is set to zero, otherwise the coefficient is kept or modified. Wavelet based denoising is widely popular due to properties such as a sparsity and multi resolution structure

Denoising by thresholding in wavelet domain was developed by Donoho.In wavelet domain, the large coefficients correspond the signal, and small one represent mostly noise. Wavelet based denoising involves three steps. Linear wavelet transform, nonlinear thresholding step and a linear inverse wavelet transform.

2.3 Gradient faces normalization techniques

A gradient is a two dimensional vector that points to the direction in which the image intensity grows fastest.The gradient operator Δ is given by

$$\Delta = \begin{pmatrix} \frac{\partial}{\partial x} \\ \frac{\partial}{\partial y} \end{pmatrix} \qquad (2)$$

If the operator applied to the 2-dimensional function f(x,y) also known as image

$$\Delta f = \begin{pmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{pmatrix} \qquad (3)$$

The two functions that can be represented in terms of the directional derivatives are the gradient magnitude and the gradient orientation. It is possible to compute the magnitude $\|\Delta f\|$ of the gradient and the orientation $\emptyset(\Delta f)$ .The gradient magnitude gives the amount of the difference between pixels in the neighbourhood which gives the strength of the edge. The gradient magnitude is defined by

$$|\Delta f| = \left|\begin{pmatrix} G_x \\ G_y \end{pmatrix}\right| = \left|\begin{pmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{pmatrix}\right| = \left[G_x^2 + G_y^2\right]^{1/2} \qquad (4)$$

The magnitude of the gradient gives the maximum rate of increase of f(x,y) per unit distance in the gradient orientation of $|\Delta f|$. The function Δf is an image of the same size as the original, created when x and y are allowed to vary over all pixels locations in f.it s also known as gradient image.The gradient orientation gives the direction of the greatest change, which presumably is the direction across the edge. The gradient orientation is given by

$$\emptyset(\Delta f) = tan^{-1}\left(\frac{G_y}{G_x}\right) \qquad (5)$$

3. FEATURE EXTRACTION

3.1Local Binary patterns:

Local binary pattern is an image operator which based on texture description of face. This can be describing the surroundings of pels by generating a bit code also called pattern from the binary derivatives of a pels. These patterns are used for face recognition, movement detection and pattern recognition. The operator is generally applied to gray scale intensity image.The Original LBP operator introduced by ojala [14] takes the 3X3 neighbhourhood of pixels and generates a binary pattern. The LBP operator generates a binary 1 if the surrounding of center pels has larger value than the center pel. The operator generates a binary 0 if the surrounding pels is less than the center. The eight surrounding pels of the center can be represented with 8 bit number, making it is very compact description of image. Uniform patterns are a based on important observations of the LBP code in natural image.The observation is that the majority of LBP codes only contains, at most, two transitions from one to zero or zero to one in a circular defined code. In other words all the binary ones and zeros are connected in the code if it is defined circular. A circularly defined code means also that the last and first bit is connected. Simple algorithm for measuring the uniformity of a LBP code is to summarize the absolute value of the difference between the code and the code circularly shifted one bit. This is defined in equation below

$$U(G_p) = |S(X_{P-1} - X_c) - S(X_0 - X_c)| + \sum_{p=1}^{P-1} |S(X_p - X_c) - S(X_{p-1} - X_c)| \leq 2 \qquad (6)$$

A code that has the value equal or less than 2 are considered uniform. In practice this can be done with the binary XOR function between the codes. The number of possible codes by only using uniform codes reduced to P (P+1)/2, where p is the number of points of the neighbourhood. In addition to number of possible codes, a code could be used to represent codes not designated uniform. In the 3X3 case that means that the code is reduced from 256 to 58, making feature vectors much smaller and also reducing the number of codes inflected by high frequency noise.

3.2 Local Ternary pattern:

LBP is a 2-valued code that is successfully used in lot of applications .The LBP operator is based on just two bit values either 1 or 0. This basis does not tolerate the LBP operator to discriminate between patterns. The drawbacks of Local binary patterns are mainly ,which are: The LBP operator cannot differentiate between two pels values if the first pel is near the central pel but a little bit below that pel and the second undistinguishable one is extreme below the center pel value [15]. LBP operator cannot be suitable for analyzing flat image areas, because in flat image areas, where all pixels nearly have the same gray value, if a slight amount of noise were added to these areas the LBP operator will give some bits the value 0 and others the value 1. So the LBP feature will be unstable and thus the LBP operator will not be suitable for analyzing these areas [16].

To solve these problems a new 3-valued texture operator, Local Ternary Patterns (LTP) that can be considered as an extension to LBP was introduced recently. Instead of a thresholding that is based only on the central pixel value of the neighborhood, the user will define a threshold say *k* and any pixel value within the interval of –*k* and +*k*, thus assigns the value 0 to that pixel, while the user assigns the value 1 to that pixel if it is above this threshold and a value -1 if it is below it when compared to the central pixel value so LTP codes are more resistant to noise, but no longer strictly invariant to gray-level transformations. The following equation shows how to compute the LTP operator: Considering k as the threshold constant, c as the value of the center pixel, a neighboring pixel p, the result of threshold is

$$F(p, c, k) = \begin{cases} 1 & if\ p > c + k \\ 0 & if\ p > c - k\ and\ p < c + k \\ -1 & if\ p < c - k \end{cases} \qquad (7)$$

In this way, each threshold pixel has one of the three values. Neighboring pixels are combined after thresholding into a ternary pattern. Computing a histogram of these ternary values will result in a large range, so the ternary pattern is split into two binary patterns. Histograms are concatenated to generate a descriptor double the size of LBP.

31	19	46
27	25	72
16	29	52

Fig2: 3x3digital image

Positive pattern

1	0	1
1		0
0	0	1

1	-1	1
1		0
-1	0	1

Pattern: 10101001

Pattern: 0100010

0	1	0
0		0
1	0	0

Negative pattern

Fig3: splitting the spectral features

The ternary decision leads to two separate histograms, one representing the distribution of the patterns resulting in a, the other representing the distribution of the patterns resulting in b. Two separate histograms are computed

$$H_{I,lower}(i) = \sum_{x,y}(LBP_{r,p}(x,y) = -i$$

$$i=0, 1……,2^{p}-1 \qquad (8)$$

$$H_{I,lower}(i) = \sum_{x,y}(LBP_{r,p}(x,y) = i)$$

$$i=0, 1… 2^{p-1} \qquad (9)$$

The neighbor information of pixels that lie within the threshold is encoded implicitly by this splitting. Finally, both histograms are concatenated and treated as a single histogram, also called as feature vector.

4. Feature vector Comparison

After construction of feature vector from the query image. These feature vectors compare with the images in the training database. In this work used nearest neighbhourhood classifier for feature vector comparison. For example, the distance can be defined as in which X and ε are the normalized enhanced histograms to be compared, indices i and j refer to i[th] bin in histogram corresponding to the j local region and is the weight for region.

$$X_w^2(x,\varepsilon) = \sum_{j,i} w_j \frac{(x_{i,j}-\varepsilon_{i,j})^2}{x_{i,j}+\varepsilon_{i,j}} \qquad (10)$$

.

5. METHODOLOGY

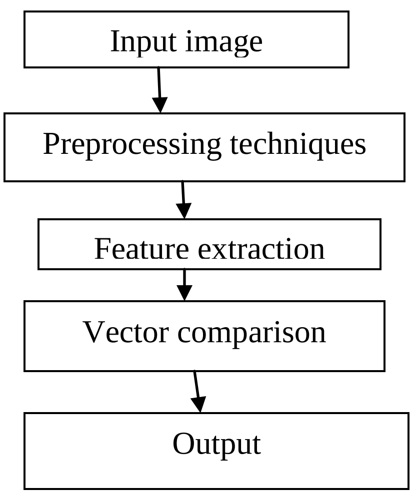

Fig4: Methodology

In this paper, the work consists of 5 steps as mentioned above those are 1.image is given as a input 2.preprocessing techniques 3.feature extraction 4.vector comparision,these all are explained above.

6. RESULTS AND DISCUSSION

In this paper above mentioned methods performed on extended Yale data base which contain 2414 images of size 32X32. Devide this database into two sets,which are train set contain 1140 images and test set ,which contain 1274 images. the experimental results as shown below, which having a few images of train set and test set.

Train set

Fig5:Trainset

weber faces normalization on Trainset

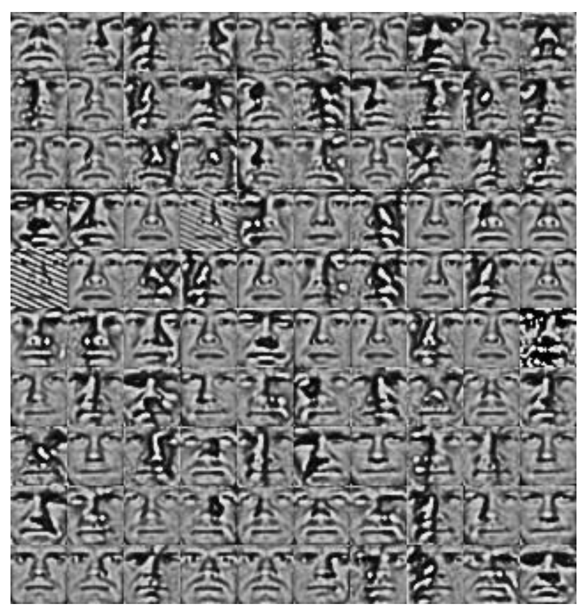

Fig6:weber faces on trainset

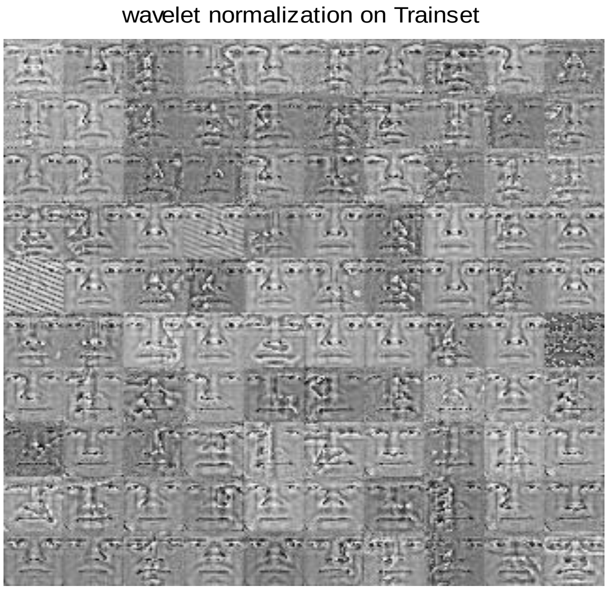

Fig7:wavelet normalization on trainset

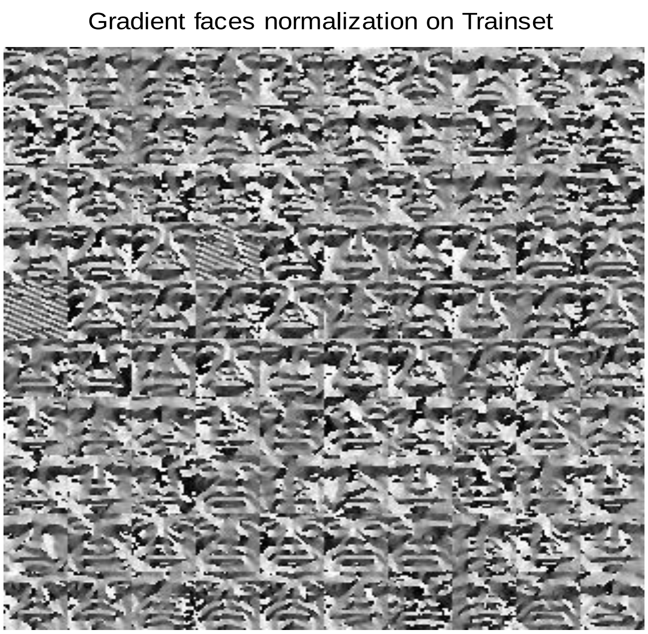

Fig8:Gradient faces on Trainset

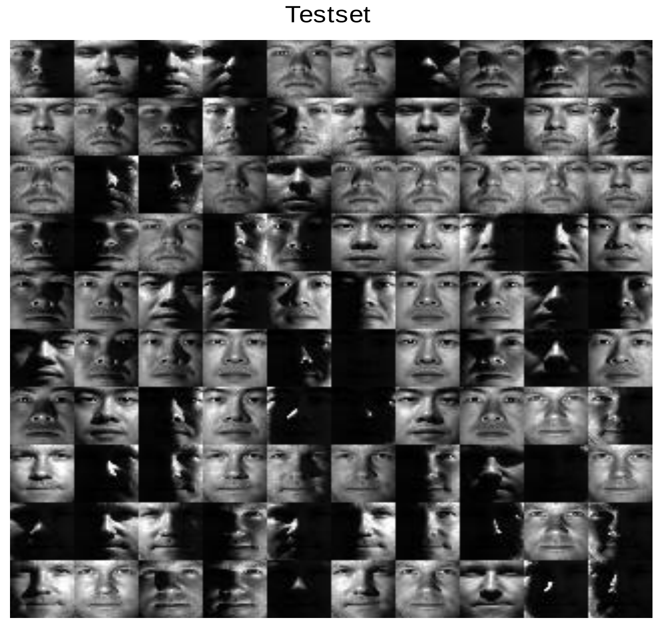

Fig9:Testset

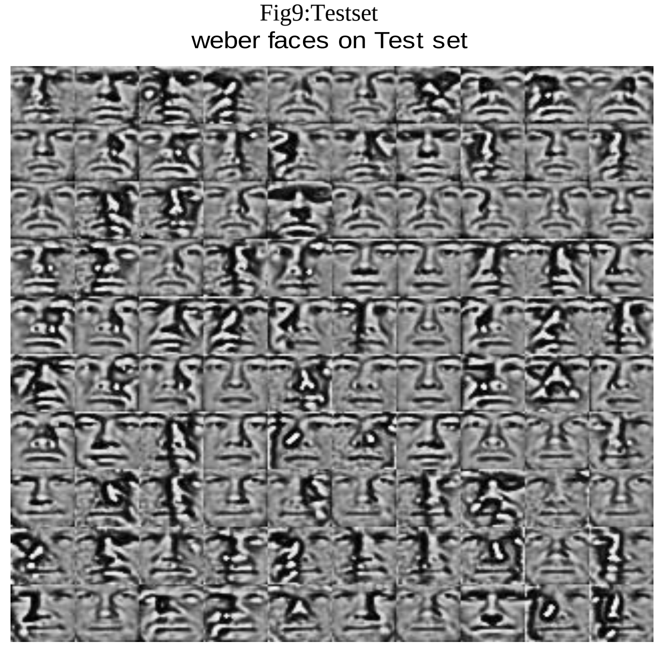

Fig10:weber faces on Testset

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wavelet normalization on Testset

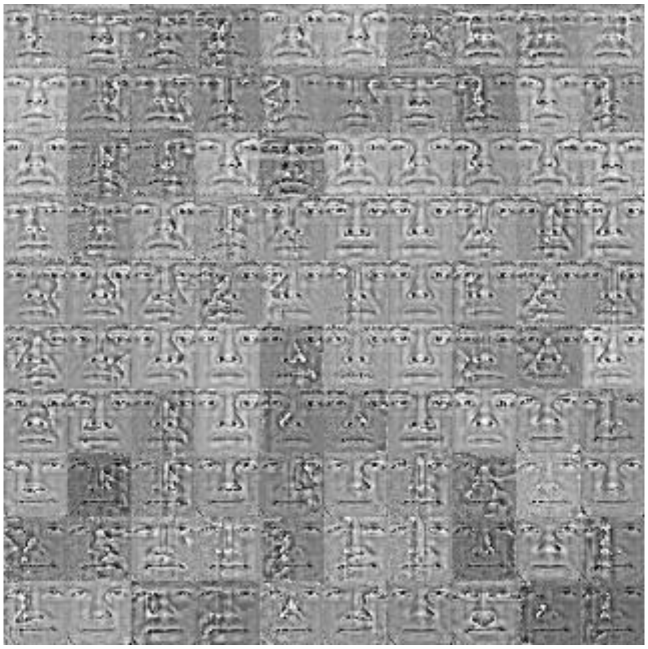

Fig11:wavelet normalization on Testset

Gradient faces normalization on Test set

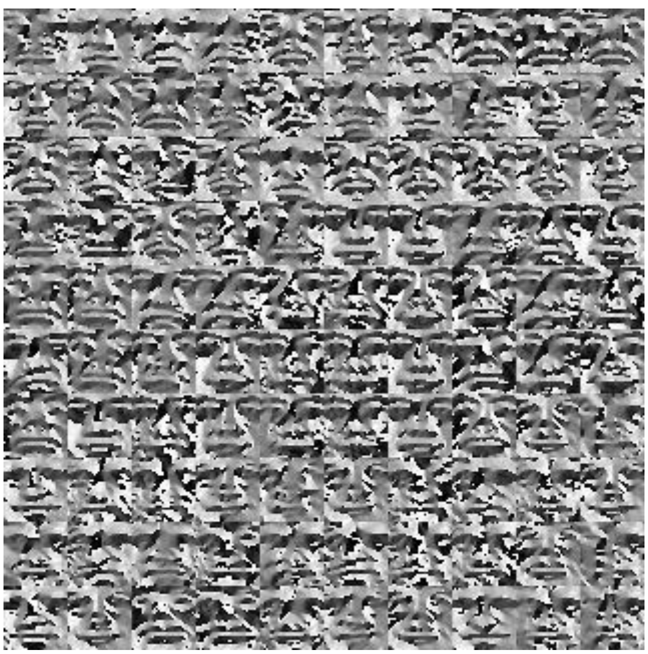

Fig12:Gradient faces on Testset

MEHTOD	Total number of images	Total number of recognized images	Recognition rate
	NO processed		
LBP/NNC	1247	850	66.7248
LTP/NNC	1247	869	69.7434
	Weberfaces normalization		
LBP/NNC	1247	1096	86.0283
LTP/NNC	1247	1126	88.4376
	Wavelet denoising		
LBP/NNC	1247	1136	89.168
LTP/NNC	1247	1155	90.7326
	Gradient faces		
LBP/NNC	1247	1157	90.8163
LTP/NNC	1247	1176	92.3256

Table13:comparision of recognition rate for different normalization techniques

The recognition rate of different normalization technques as shown Table 13.Compare to no processed images processed images achieved a better recogntion rate .The graphical representation of recogntion rate as shown figure 14.

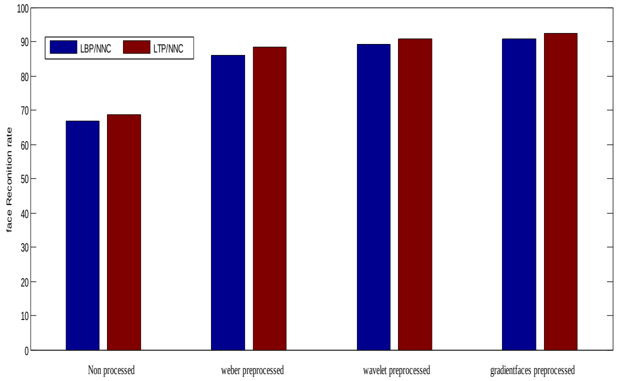

Fig14:recognition rate of different normalization techniques

CONCLUSION

In this paper evaluated the recognition rate of different normalization techniques using texture features and neighborhood classifier. The experimental results shown that Gradient faces normalization techniques achieved better recognition rate compared to different normalization techniques as mentioned above .This experimental results are showing that Local ternary pattern achieved good recognition rate than that of Local binary patterns. In feature scope can extended it to fusion of multiple normalization techniques for better recognition rate.

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