Illumination Insensitive Face Recognition Using Gradientfaces

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ABSTRACT
The performance of most existing face recognition methods is highly sensitive to illumination variation. It will be seriously degraded if the training/testing faces under variable lighting. Thus, illumination variation is one of the most significant factor affecting the performance of face recognition and has received much attention in recent years. In this paper we propose a novel method called gradientface for face recognition under varying illumination. When we rarely know the strength, direction or number of light sources. The proposed method has the ability to extract illumination insensitive measure, which is then used for face recognition. The merits of this method is that neither does it require any lighting assumption nor does it need any training images. Gradientface method reaches very high recognition rate of 98.96% in the test on yele B face database. Further more the experimental results on Yale database validate that gradient faces is also insensitive to image noise and object artifacts such as facia;l expression.

Keywords: Face recognition, gradientfaces, gradient domain, illumination insensitive measure.

I. INTRODUCTION

During the past decade, face recognition has drawn significant attention [1][2][3][4] from the perspective of different applications. A general statement of the face recognition problem can be formulated as follows. Given still or video images of a scene, the problem is to identify or verify one or more persons in the scene using a stored database of faces. The environment surrounding a face recognition application can cover a wide spectrum – from a well controlled environment to an uncontrolled one. In a controlled environment, frontal and profile photographs of human faces are taken complete with a uniform background and identical poses among the participants. In the case of uncontrolled environment, recognition of human faces is to be done at different scales, positions, luminance and orientations; facial hair, makeup and turbans etc.

The performance of most existing face recognition methods is highly sensitive to illumination variation. It will be seriously degraded if the training/testing faces under variable lighting. Thus, illumination variation is one of the most significant factor affecting the performance of face recognition and has received much attention in recent years. Many methods have been proposed to handle the illumination problem. In general, these methods can be divided into three main categories. The first approach uses image processing technique/model to normalize face images under different illumination conditions. For instance, histogram equalization (HE)[5] , logarithm transform [6] are widely used for illumination normalization. However, it is difficult for these image processing techniques to account for different lighting conditions. There have been models developed to remove lighting effects from images under illumination conditions. Images under variable illumination and proposed the complexity of ratio of two images as the similarity measures. Introduced the low curvature image simplifier (LCIS) using anisotropic diffusion for eliminating the notorious halo artifacts effect. However, the algorithm is computational intensive and requires manual selection of no less than 8 different parameters.

The second approach, which handles the illumination problem by constructing 3-D face model[7].Face images with fixed pose under varying illumination form a convex cone in the space of images, called illumination cone. It can be approximated well by low-dimensional linear subspace whose basis vectors are estimated from training data using the generative model.

However, it requires multiple face images under different illumination conditions. The spherical harmonic model[8]is applied to represent the low-dimensional subspace of different illumination face images. A segmented linear subspace model is presented generalizes the 3-D illumination subspace model by segmenting the image into regions with similar surface normal. However, these methods based on 3-D model either require the assumptions of light source or need many training samples, which are not practical for real applications. The third approach i,e gradient face attempts to extract illumination invariant features or illumination insensitive measure, which is then used for face recognition.

Methodology

Here we introduce how to extract illumination insensitive measure from face images under lighting conditions.

The gradient domain is very important to image processing. For example, edge detecting is important application of the gradient domain . The gradient domain compositing approach is employed in constructing seamless composites using the gradient domain of images. A general framework for performing constrained mesh deformation tasks with gradient domain techniques.

The authors describe a unified framework for performing these operations on video in the gradient domain. Therefore, there may be more discriminating features in the gradient domain than the pixel domain.

As all we know, the pixel points are not completely independent of each other, there are some relationships between neighboring pixel points. However, the conventional face recognition methods, such as PCA and LDA, which are implemented in pixel domain such that they ignore the underlying relationships between neighboring pixel points. While the gradient domain explicitly considers such relationships between neighboring pixel points such that it is able to reveal underlying inherent structure of image data. Therefore, the gradient domain has more discriminating power to discover key facial features than pixel domain. In order to take advantage of the benefits of the gradient domain, we propose a novel method to extract illumination insensitive measure from gradient domain.

We begin with the analysis of the reflectance model and gradient domain, then Gradientfaces is extracted from gradient domain Finally, we compare Gradientfaces with SQI[3] and LTV[7] method, the comparison analysis show that Gradientfaces is more robust to different illumination.

II. Block Diagram And Its Discription

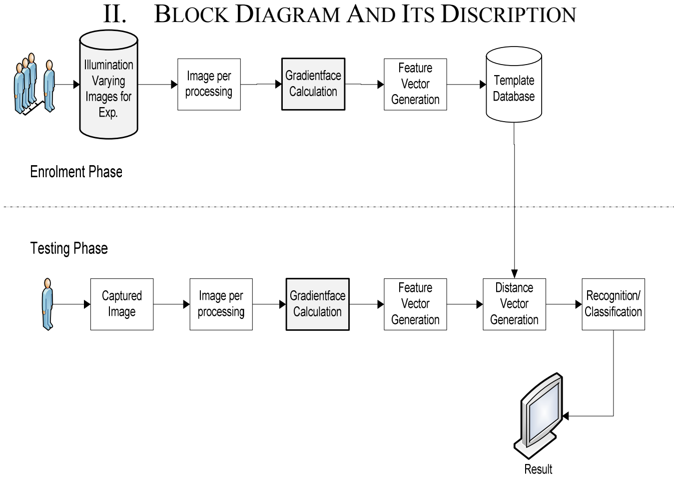

Figure.1 Block diagram of face recognition

In the enrolment phase many persons images is taken with different illumination and different poses. Each and every image is preprocessed then gradientface is calculated for the image then vector is generated of the calculated image and stored in template database.

In the testing phase we give the trained database as input to the system. The trained database consists of various images of faces of different persons taken under various illuminations. Here in this phase the input image is preprocessed then gradientface is calculated for the image then vector is generated of the calculated image and compared with template database to generate distance vector as shown in Fig. 1.

A. Preprocessing

Real-world input data always contains some amount of noise and certain preprocessing is needed to reduce its effect. The term noise is to be understood broadly: anything that hinders a pattern recognition system in fulfilling its commission may be regarded as noise no matter how inherent this "noise" is in the nature of the data. Some desirable properties of the data may also be enhanced with preprocessing before the data is fed further in the recognition system. Preprocessing is normally accomplished by some simple filtering method on the data. In the case of speech recognition, this may mean linear high-pass filtering aimed to remove the base frequency and to enhance the higher frequencies. In image recognition, the image may be median filtered to remove spurious point noise which might hamper the segmentation process. An advantageous preprocessing step for color images is decorrelation of the color components. Such a process transfers an image originally in the RGB (red-green-blue) coordinates linearly to the YIQ (luminosity-inphase-quadrature) system.

B. Gradientface generation

In order to extract illumination insensitive measure from gradient domain, we have the gradientface theorem by studying the relationships between the components of gradient domain which is explained in later sections.

C. Feature extraction

The meaning of the feature extraction phase is most conveniently defined referring to the purpose it serves : feature extraction problem . . . is that of extracting from the raw data the information which is most relevant for classification purposes, in the sense of minimizing the within-class pattern variability while enhancing the between-class pattern variability. During the feature extraction process the dimensionality of data is reduced. This is almost always necessary, due to the technical limits in memory and computation time. A good feature extraction scheme should maintain and enhance those features of the input data which make distinct pattern classes separate from each other. At the same time, the system should be immune to variations produced both by the humans using it and the technical devices used in the data acquisition stage.

Besides savings in memory and time consumptions, there exists another important reason for proper dimensionality reduction in the feature extraction phase. It is due to the phenomenon known as the curse of dimensionality, that increasing the dimensionality of the feature space first enhances the classification accuracy but rapidly leads to sparseness of the training data and poor representation of the vector densities, thereby decreasing classification performance. This happens even though the amount of information present in data is enriched while its dimensionality is increased. The curse thus forces the system designer to balance between the amount of information preserved as the dimensionality of the data, and the amount of density information available as the number of training samples per unit cube in the feature vector space. A classical rule of thumb says that the number of training samples per class should be at least 5-10 times the dimensionality. An issue connected to feature extraction is the choice of metric. The variances of individual features may vary orders of magnitude, which inevitably impairs the classifier. The situation can be eased by applying a suitable linear transform to the components of the feature vector. In that case spectral or linear prediction coefficients can be used as descriptive features. The diverse possibilities for feature extraction in recognition of handwritten characters include features calculated from the outline of the character, the distribution of mass and direction in the character area, etc. Neural networks provide some ways for dimensional reduction and feature extraction.

D. Distance vector generation

We evaluate the performance of face recognition by template matching method, and apply the minimum-distance classifier for its simplicity metric which are discussed in next sections.

By calculating the distance vector between the images of testing and enrollment phase the minimum distance images are taken to give the output.

III. System Implementation

In this section, we introduce how to extract illumination insensitive measure from face images under lighting conditions. We begin with the analysis of the reflectance model and grad -ient domain, then Gradientfaces is extracted from gradient domain.

A. Reflectance Model

The reflectance model used in many cases can expressed as

$$I(x,y) = R(x,y)\, L(x,y) \tag{1}$$

where I(x,y) is image pixel value, R(x,y) is the reflectance and L(x, y) is the illuminance at each point (x,y). Here, the nature of R(x,y) is determined by the lighting source, while R(x,y) is determined by the characteristics of the surface of object. Therefore, R(x,y) which can be regarded as illumination insensitive measure. Unfortunately, separating the reflectance R and the illuminance L from real images is an ill-posed problem. In order to attempt to solve the problem. A "common" assumption is that L varies very slowly while R can change abruptly.

Let us analyze the "common" assumption. Considering two neighbor point (x,y) and (x+Δx,y) of an image I(x,y) taken under lighting, since L(x,y) is determined by the lighting source, then it is reasonable that L(x,y) and L(x+Δx,y) are approximately equal in general when Δx is small. Therefore, L is approximately smooth. This coincides with the "common" assumption[9] (L varies very slowly), which means L is approximately smooth. In fact, the "common" assumption is a widely accepted assumption which has been used in[10]. It should be pointed out that the conclusion (L be approximately smooth) may be violated in shadow boundaries. However, shadow is an open problem in the field of image processing and pattern recognition. To address the issue of shadow boundaries, Gaussian kernel function is introduced to the Gradientfaces in3.2. Furthermore, different from image processing, we ought to be more concerned with recognition performance rather than image itself in face recognition applications.

B. Gradientfaces

In order to extract illumination insensitive measure from gradient domain, we have the following theorem by studying the relationships between the components of gradient domain:

Theorem 1: Given an arbitrary image I(x,y) taken illumination condition, the ratio of Y-gradient of I(x,y) (∂I(x,y)/ ∂y) to X-gradient of I(x,y) (∂I(x,y)/ ∂x) is an illumination insensitive measure.

Proof: Considering two neighboring points (x,y) and (x+Δ,y),according to the illumination model (1), we have

$$I(x,y)=R(x,y)L(x,y) \tag{2}$$

$$I(x+\Delta x,y)=R(x+\Delta x,y)L(x+\Delta x,y) \tag{3}$$

Subtracting (2) from (3) we obtain

$$I(x +\Delta x , y) - I(x , y) = R(x+\Delta x, y) L(x+\Delta x, y) - R(x , y) L(x, y)$$

Based on above common assumption, which means L is approximately smooth thus we have

$$I(x +\Delta X , y) - I (x , y) \approx R(x+\Delta X , y) L(x+\Delta x , y) - R(x , y) L (x , y)$$

$$\approx R(x+\Delta X,y) - R(x , y) L(x , y) \tag{4}$$

Taking the limitations of the above equality (4) we can obtain

$$\frac{\partial I(x,y)}{\partial x} \approx L(x,y)\frac{\partial R(x,y)}{\partial x} \tag{5}$$

Similarly we have

$$\frac{\partial I(x,y)}{\partial y} \approx L(x,y)\frac{\partial R(x,y)}{\partial y} \tag{6}$$

Dividing (6) by (3)

$$\frac{\partial I(x,y)}{\partial y} \Big/ \frac{\partial I(x,y)}{\partial x} \approx \frac{\partial R(x,y)}{\partial y} \Big/ \frac{\partial R(x,y)}{\partial x} \tag{7}$$

Accordingly to illumination model , R can be considered as an illumination insensitive measure. Thus, the ratio of y-gradient of I(x,y) (∂I(x,y)/ ∂y) to x-gradient of I(x,y) (∂I(x,y)/ ∂x) is also an illumination insensitive measure.

In practical application, the ratio of y-gradient of image to x-gradient of image might be infinitude derived by zero value of x-gradient of image. Thus, it cannot be directly used as the illumination insensitive measure. These considerations lead us to defining Gradientfaces as follows.

Definition 1: I be an image under variable lighting conditions, then Gradientfaces G of image can be defined as

$$G = \arctan(\text{Iy-gradient}/\text{Ix-gradient}), \qquad G \in [0,2\pi]$$

where Ix-gradient and Iy-gradient are the gradient of image I in the x, y direction, respectively.

C. The Implementation:

In order to extract Gradientfaces, firstly, we need to calculate the gradient of face image in the x, y direction, then

Gradientfaces can be computed by the definition (8). There are many methods for calculating the gradient of image. However, the numerical calculation of derivative(gradient) is typically ill-posed. To compute the gradient stably, we smoothen the image first with Gaussian kernel function. With a convolution- type smoothing, the numerical calculation of gradient is much more stable in calculation. Furthermore, it should be pointed out that the main advantage for using Gaussian kernel is twofold: (a) Gradientfaces is more robust to image noise and, (b) it can reduce the effect of shadows. The implementation of Gradientfaces can be summarized as

Input: Image I

Output: The Gradientfaces of I

1. Smoothen input image by convolving with Gaussian Kernal Function

   $I' = I * G(x,y,\sigma)$ (8)

   Where * is the convolution operator a

   $G(x,y,\sigma)=\frac{1}{2\pi\sigma^2}\exp(-x^2 + y^2)$ (9)

   is the Gaussian kernel function with standard deviation σ. π
2. Compute the gradient of image I by feeding the smoothed image though a convolution operation with the derivation of Gaussian kernel function in the x,y directions

   $Ix=I'*Gx(x ,y, \sigma)$and$I=I'*Gy (x , y ,\sigma)$ (10)

Where $Gx (x ,y, \sigma)$ and $Gy (x , y ,\sigma)$are the derivation of Gaussian kernel function in the x,y directions, respectively.

3. Compute the illumination insensitive measure by

$G= \arctan (Ix/Iy) € [0,2\pi]$ (11)

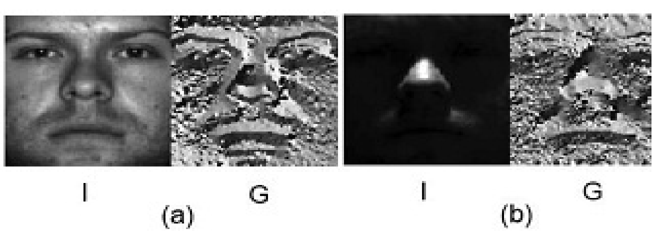

Figure 2 Original image and corresponding gradient faces (a)ideal face image and its gradient faces (b) face image with severe illumination and its gradient faces

Fig.2 shows the original images and the corresponding Gradientfaces. As can be seen, Gradientfaces can extract the important features of face, such as facial shapes and facial objects (e.g., eyes, noses, mouths, and eyebrows) even under extremely lighting, which are key

features for face recognition. Therefore, Gradientfaces is an illumination insensitive measure. Furthermore, compared with original images, the relative position of key features represented by Gradientfaces is not changed. Therefore, Gradientfaces is insensitive to object artifacts

D. Recognition Protocol

Instead of generating a feature vector in the pixel domain, Gradientfaces is extracted from the gradient domain, whose components are the argument of gradient. Therefore, in order to calculate the similarity between Gradientfaces, we define the distance (L1 distance) between

two Gradientfaces vectors G1 and G2 as follows:

$d(G1,G2)=\sum\min(|g1i-g2i|,2\pi-(|g1i-2i|)$ (12)

where $G1=(g11,g12\ldots\ldots g1n)$ and $G2=(g21,g22\ldots\ldots g2n)$ are the Gradientfaces vectors, is the dimensionality of the vector. It is worth noting that the smaller d(G1,G2) means the higher similarity. In this correspondence, we evaluate the performance of face recognition by template matching method, and apply the minimum-distance classifier for its simplicity, n metric defined is used as our distance measure. For the other competing method, the distance mea sure n metric is defined under the conventional sense. It should be pointed out that template matching method rather than other learning methods, such as PCA and LDA, is used to evaluate the performance of different methods, this is because the learning methods (PCA, LDA, etc.) have some capability for handling illumination while template matching method does not have. Therefore, the results achieved by template matching method can directly show the capability for handling illumination of different methods.

IV. TESTING AND RESULTS

The Yale face database is taken from the Yale Center for Computational Vision and Control. It contains 165 grayscale images of 15 individuals. Original image size is 320* 243 pixels. All images are manually cropped to include internal structures (such as the brow, eyes, nose, and mouth), and resized to 64 pixels.During face recognition using gradient method a image from the testdata base of Yale B is submitted . Based on the gradient face algorithm corresponding image is processed from trained set of data.

A. Results:

As a first step we are submitting a image from test database which consists of 40 images as shown in Fig.3 Then the written program in MATLAB calculates the gradient face of submitted image using gradient face algorithm.

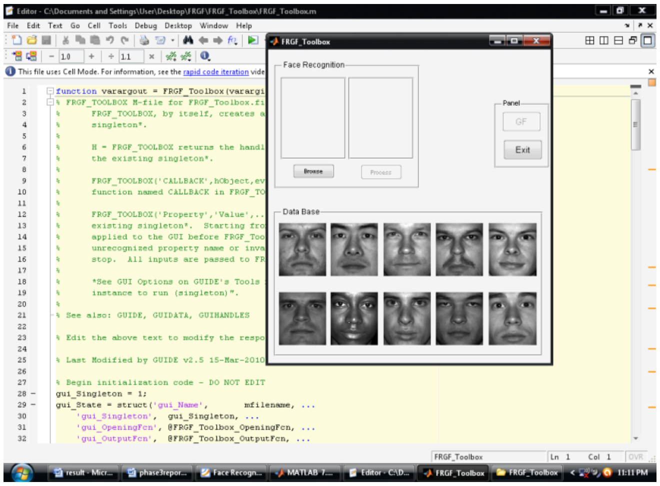

Figure 3 Giving input to the system

During the submission of the test image we will select anyone of the image as shown in Fig. 4 from test data base which consists of thirty different images of different illuminations which are choosen from yale B database.

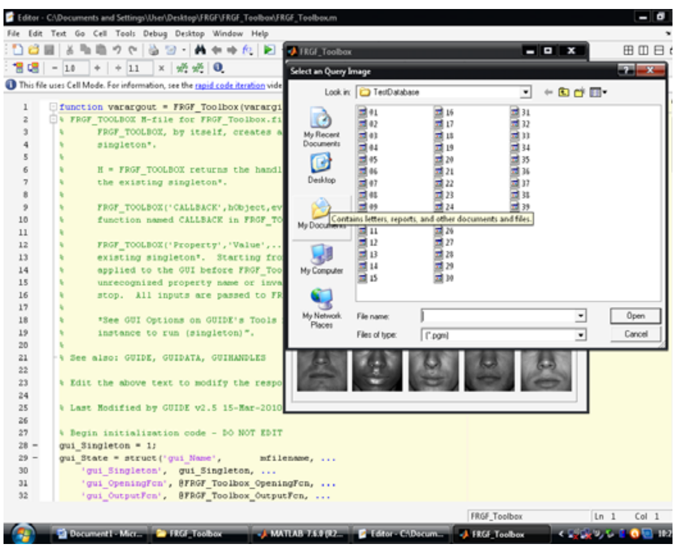

Figure 4 Test database

As a next process the given testdata image is compared with the images in trained data set and the compared using distance vector the perfect match is found and gives as output shown in Fig.5

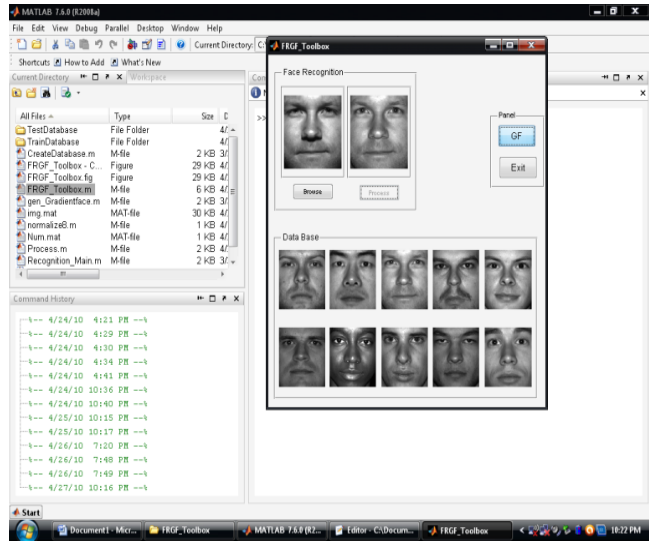

Figure 5 Matching of images

In the next step calculated gradient face of the corresponding image is displayed as shown in Fig.6. The process is continued as many times needed by submitting different images. Finally select exit to exit the process.

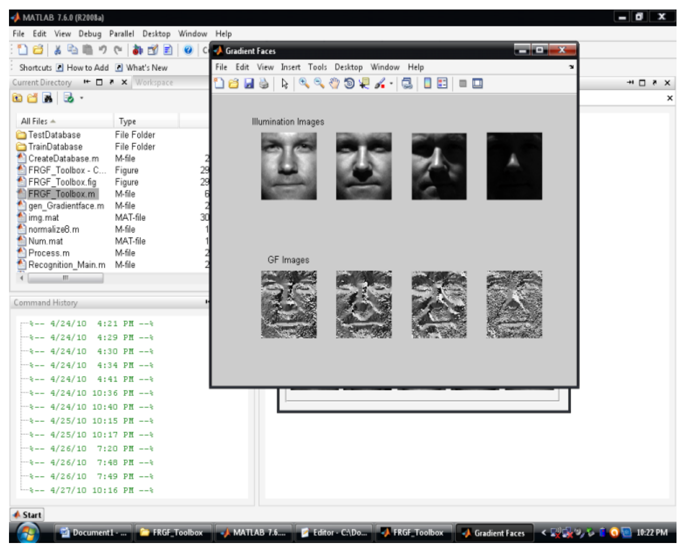

Figure 6 Gradientfaces of corresponding image.

The computational time of Gradientface is less than the others. Therefore, Gradientface is a computationally efficient method.

The experiment was designed to use one image per subject choose from subset 1 as reference image sets, the other images from subset 1 to 5 as query image sets, in turn. Table I shows that the recognition results of different methods on different query sets. As can be seen, Gradientfaces outperforms MSR, SQI, and LTV methods on all subsets. The recognition accuracy of MSR and SQI drops significantly when query image come from subsets (subsets –5) with the extremely lighting conditions. Gradientfaces and LTV methods achieve very high recognition rates on all subsets. Fig.7 shows the graphical representation of recognition rate of all the methods

TABLE.I PERFORMANCE COMPARISON OF YALE B DATABASE

Method	**MSR**	**SQI**	**LTV**	**Gradient faces**
Subset 1	97.1	96.3	100.0	100.0
Subset 2	90.95	88.09	100.0	100.0
Subset 3	78.81	85.00	99.17	99.76
Subset 4	62.86	69.08	95.17	96.23
Subset 5	70.3	76.62	97.22	99.7
Average	76.77	80.61	97.93	98.96

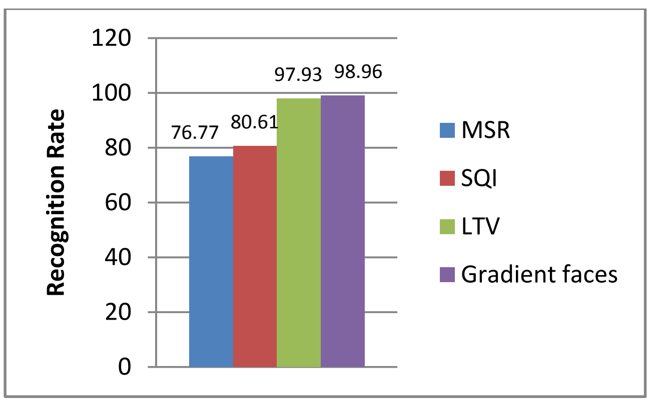

Figure 7. Graphical representation of comparison on Yale B Database

Efficiency

The efficiency of the proposed Gradientface on PIE database by measuring the CPU time, and compare it with the other competing algorithms. Therefore, Gradientface is a computationally efficient method. Various experiments have been systematically performed. Fig.8 shows the graphical representation the comparison of CPU time in Seconds/Image

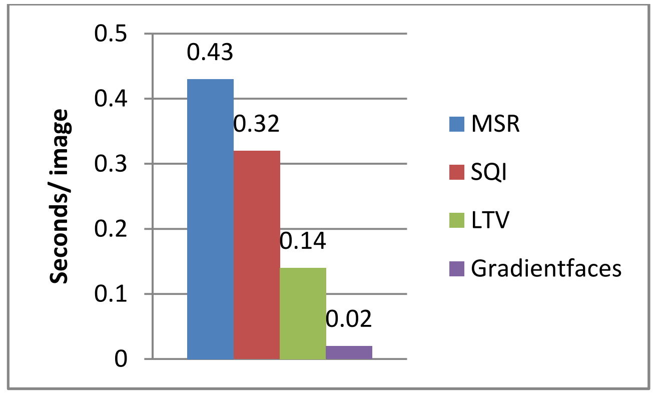

Figure 8 Bar chart representing comparison of CPU time in Seconds/Image

.Gradientfaces can effectively reduce the effect of shadows and noise. Gradient faces is able to apply directly to any single face image neither does it require any prior information on 3-D face shape and many training samples. In addition,Gradientfaces has low computational cost such that it can be applied to practical applications.

V. CONCLUSION AND FUTURE ENHANCEMENT

A. *Conclusion*

In this correspondence, we propose a Gradientfaces method as an image preprocessing technique for face recognition under varying lighting. This method transforms image into the gradient domain first, then an illumination insensitive measure (Graidnetfaces) is extracted for recognizing. The work relies on the widely accepted assumption might be approximately smooth. The high recognition rates achieved Gradientfaces on all databases have justified this assumption , and show that Gradientfaces is effective method for illumination Problem in face recognition, and robust to different lighting and noise.

B. *Future enhancements*

The project presented is able to perform accurately. Since the system is implemented in MATLAB, which is an interpreted language, speed benefits could be made by implementing computationally intensive parts in C or C++.

All the algorithms can be implemented using Fourier transformation technique. It is always possible to get more infective algorithm than we are having now a days so for this implemented algorithms also it can be implemented soon.

Gradientfaces is an effective method for face recognition under varying illumination so it is more benefited it made use of varying illumination.

VI. REFERENCES

[1] H. Shim, J. Luo, and T. Chen, *"A subspace model-based approach to face relighting under unknown lighting and poses,"* IEEE Trans. Image Process., vol. 17, pp. 1331–131, 2008.

[2] T. Zhang, B. Fang, Y. Y. Tang, G. He, and J. Wen, *"Topology preserving non-negative matrix factorization for face recognition,"* IEEE Trans. Image Process., vol. 17, pp. 57–58, 2008.

[3] J. Zou, Q. Ji, and G. Nagy, *"A comparative study of local matching approach for face recognition*," IEEE Trans. Image Process., vol. 16, no. 10, pp. 2617–2628, Oct. 2007.
[4] Z. Liu and C. Liu, *"A hybrid color and frequency features method for face recognition,"* IEEE Trans. Image Process., vol. 17, pp. 1975–1980, 2008.
[5] S. M. Pizer and E. P. Amburn, "*Adaptive histogram equalization and its variations*," Comput. Vis. Graph., Image Process., vol. 39, no. 3, pp. 355–368, 1987.
[6] S. Shan,W. Gao, B. Cao, and D. Zhao, *"Illumination normalization for robust face recognition against varying lighting conditions," in Proc.* IEEE Workshop on AMFG, 2003,
[7] M. Savvides and V. Kumar, "*Illumination normalization using logarithm transforms for face authentication*," in Proc. IAPR AVBPA, 2003, pp. 59–556.
[8] D. W. Jacobs, P. N. Belhumeur, and R. Basri, *"Comparing images under variable illumination," in Proc.* IEEE Conf. Computer Vision and Pattern Recognition, 1998, pp. 610–617.
[9] J. Tumblin and G. Turk, "LCIS: *A boundary hierarchy for detail-pre- serving contrast reduction,"* in ACM SIGGraph, 1999, pp. 83–90.
[10] A. S. Georghiades, P. N. Belhumeur, and D. J. Kriegman, *"From few to many: Generative models for recognition under variable pose and illumination," in Proc.* th IEEE Int. Conf. Automatic Face and Gesture Recognition, 2000, pp. 277–28.