ILLUMINATION INVARIANT HUMAN FACE RECOGNITION ALGORITHMS: A SURVEY

ABSTRACT

An effective face recognition algorithm faces numerous challenges that degrade its performance. Among these challenges 'Illumination variation' is one of the key problems that arise under an uncontrolled environment. In this paper an extensive and up-to-date survey of the existing techniques to address this problem is presented. This survey covers all the approaches that try to solve the varying illumination problem.

1. INTRODUCTION

The interest in face recognition started in 1960s. Since then face recognition has been one of the most relevant applications of image analysis. The challenge lies in building an automated system for recognizing faces that can be considered to be as good as the human ability to recognize faces. Face recognition remains an unsolved problem i.e. there does not exist one algorithm that can perform perfectly under uncontrolled situations. Every face recognition algorithm faces some key challenges that it must overcome, such as – variations in illumination, head rotation, facial expression, aging and occlusion.

Face recognition research is not only motivated by the fundamental challenge it poses, but also due to the potential application it offers to the society ranging from human computer interaction to authentication and surveillance. A good face recognition algorithm can perform well in situations involving one or more key challenges.

Among the key challenges varying illumination is considered the main problem because the differences caused due to the variation is more significant than the differences between individuals. The variation in illumination causes variation in direction and energy distribution of the ambient illumination, and leads to major differences in the shading. The variations of both global face appearance and local facial features also cause problems for automatic face detection/localization, which is the prerequisite for the subsequent face recognition stage. Moreover, in an application, the illumination variation is always coupled with other problems such as pose variation and expression variation, which increase the complexity of the automatic face recognition problem. There are two main approaches to Illumination processing: Active approach, Passive approach.

2. ACTIVE APPROACHES

In active approaches the image is captured in a consistent illumination condition using various techniques, so as to decrease the effect of variation of illumination during the recognition phase. The use of additional devices (optical filters) is required in this approach to acquire different modalities of face images that are not affected by illumination. Few of the active approaches are:

- **3D information**:

  This method extracts 3D information from face while capturing the image by using active sensing devices like 3D laser scanners or stereo vision systems. This extracted 3D information can be represented in different ways such as range image, profile, Extended Gaussian Image (EGI), etc. Better performance can be achieved by fusing 2D face image with 3D face information.

  Kittler et al. [1] reviewed the full spectrum of 3D face processing, from sensing to recognition. It consists of the various 3D face recognition models and the ways in which they can be used.

- **Infrared**:

  The infrared spectrum ranges from 0.7μm to 10mm. It can be divided into 5 bands, namely Near-Infrared, the Short-Wave Infrared, the Mid-Wave Infrared, the Long-Wave Infrared and Far-Infrared. Near-IR and SWIR belong to reflected infrared, while MWER and LWIR belong to thermal infrared. The information about the reflected energy from the object surface is contained in the reflected infrared. This is related to the illumination power and the reflectance property of the surface. Thermal Infrared directly relates to the thermal radiation from object which depends on the temperature of the object and emissivity of the material. PCA can be applied to infrared images where its performance is comparable to visible images.

1) Thermal Infrared

With minor illumination changes and for subjects with no eyeglasses, the thermal image for face recognition does not result in significant difference compared to visible images. In situations where the illumination change is huge the performance achieved by radiometrically calibrated thermal face images than that based on visible image. Some disadvantages of Thermal images are the temperature of the environment, physical conditions and psychological conditions will affect the heat pattern of the face. Infrared is also opaque to eyeglasses. These issues motivate the combination of thermal infrared image with visible images for face recognition. The image produced by employing fusion method provides the combined information of both the visible and thermal images and thus provides more reliable information for construction more efficient face recognition system. Thermal IR imagery is independent of ambient lighting conditions as the thermal sensors only capture the heat pattern emitted by the object.

2) Active Near-IR Illumination

Near-IR band falls into the reflective portion of the infrared spectrum, and it lies between the visible light band and the thermal infrared band. It has advantages over the visible light band and the thermal infrared band. It can be reflected by objects, it can serve as an illumination source. Also it is invisible making active Near-IR illumination unobtrusive. Near-IR can easily penetrate glass. It attracts more and more attention because of its preferable attribute and low cost. Zhao and Grigat [4] performed face recognition in Near-IR images based on Discrete Cosine Transform (DCT) and SVM classifier.

Infrared image may be independent of visible illumination but it is not independent of the environmental illumination. This is because environmental illumination contains energy even in the infrared spectrum. The variation of this component in the environmental illumination will cause variation in the captured image. For indoor environment the infrared energy in environmental illumination is low and does not affect the image gravely, while in outdoor environment the energy can be very strong.

Li et al. [5] present a Near-IR image based face recognition system. First a design of NIR image capture device that minimizes influence of environmental lighting on face images is described. Using AdaBoost learning face and facial localization and face recognition are performed. The evaluation conducted shows that the system achieves excellent accuracy, speed and usability.

3) Active Differential Imaging

This technique can be used to solve the illumination variation problem even for outdoor application. In this type of imaging, an image is obtained by pixel-to-pixel differentiation between two successive frames: one with an active illuminant on and the other with the illuminant off. In the first image the scene is illuminated by the combination of both the ambient illumination and the active illumination, while in the second image the face is illuminated by ambient lighting. The difference of these two images will contain the scene under the active illuminant and will be independent of environmental illumination under the assumptions that it is a still scene, a linear response of the camera to the scene radiation and no saturation. Near-IR illumination is used as the active illumination for active differential imaging system because of its invisibility.

Specific sensors that can perform differential imaging have been proposed in [6][7][8]. Possible violations of the assumptions made can cause problems for active differential imaging, for example, the subject may move during the capture.

Face recognition experiments carried out on faces captures by active Near-IR differential imaging system produced very low error rates even in scenarios with dramatic ambient illumination changes [10][11].

3. PASSIVE APPROACHES

These approaches attempt to overcome illumination variation in face images due to environment illumination change. These approaches can be classified into 4 categories, namely, Illumination invariant modeling, Illumination invariant feature extraction, Pre-processing and normalization, and 3D Morphable Model.

3.1. ILLUMINATION INVARIANT MODELING

This approach models the process of image formation by either using a statistical model or a physical model. Statistical model does not require assumptions regarding the surface properties and analysis techniques like PCA, LDA, ICA etc are applied on a training set containing images of varying illumination, so as to define a subspace which covers all the illumination variations. On the other hand, the Physical model requires assumptions regarding the surface reflectance properties. The different techniques that can be used as illumination models are:

1) Linear Subspaces:

A photometric alignment approach was proposed by Shashua using which the algebraic connection can be drawn between all images of an object taken under varying illumination conditions. A k Linear Reflectance Model is defined for each surface point which is given by the scalar product of a vector in the k-dimensional Euclidean space of invariant surface properties and a arbitrary vector. A surface is said to be Lambertian, when it obeys Lambert's Cosine law and it has Lambertian Reflectance. Lambertian Reflectance occurs when an object viewed from various angles, still has the same radiance or isotropic luminance. In the case of Lambertian surface where images are in a 3D linear subspace a set of 3 images, each from a linearly independent source is sufficient. Using this information the surface normal and the albedo can be recovered. This is known as Photometric Stereo.

Belhumeur et al. presented a 3D linear subspace method which is a variation of the photometric alignment model. In this method, three or more images of the same human face under varying lighting conditions to construct 3D basis for the linear subspace. After this the distance between the test image and linear subspaces of the faces belonging to each identity are compared to achieve a better recognition performance.

To make the 3D linear subspace model robust to shadows Batur and Hayes proposed a segmented linear subspace model where in each image in the training set are segmented into regions that have similar surface normals, then linear subspace is estimated for each region and thus reducing the influence of shadow.

2) Illumination Cone:

Images of a convex object with Lambertian surface taken from a fixed pose but illuminated by a number of distant point sources forms a convex Illumination Cone. This was proved by Belhumeur and Kriegman. Dimension of this cone is given by the number of distinct surface normals. Using this model Georghiades et al. [12] presented a generative appearance based-method for recognizing human faces under variations in lighting and viewpoint. The computation of the exact illumination cone is sometimes difficult as there are a large number of extreme rays that make up their cones, but several recent studies have theoretically established that computation of full cone would be unnecessary.

Let x € IR^3 denote an image with n pixels of a convex object with a Lambertian reflectance function illuminated by a single point source at infinity, represented by a vector s € $IR3$ such that its magnitude $|s|$ represents the intensity of the source and the unit normal $s/|s|$ represents the direction. Let B € IR^{n*3} be a matrix where each row b in B is the product of the albedo with unit normal for a point on the surface projecting to a particular pixel in the image. Under the Lambertian assumption, x is given by:

$$X = max\ (B_s, 0)$$

Where max $(B_s, 0)$ sets to zero all negative components of the vector B_s. If the object is illuminated by k light sources at infinity, then the image is given by the superposition of the images that would have been produced by the individual light sources. Due to this superposition the possible images of a convex Lambertian surface, taken under varying strength and direction of point sources at infinity is a convex cone. Any image in the illumination cone can be computed by using the extreme rays for the sub-normals using the formula:

$$X_{ij} = max\ (B_{si}, 0)$$

Where $s_{ij} = b_i * b_j$ are rows of B with $i \neq j$. It is clear that there are at most $m(m-1)$ extreme rays for $m \leq n$ distinct surface normals [7].The use of an accurate illumination cone consisting of images in varying illumination conditions can be effectively used improve the face recognition across various illumination.

3) **Spherical Harmonics**:

This method is proposed by Basri and Jacobs [14]. They show that ignoring cast shadow the intensity of an object surface can be approximated by a 9-dimensional linear subspace on a spherical harmonic representation. The 9-dimensional linear subspace is also called as harmonic plane. It helps in providing an accurate approximation for the illumination cone of an object with convex Lambertian surface. All the harmonics have a negative value, except for the first harmonic (which has a constant value). Hence the harmonic images are not real images but are “abstractions” as pointed out in [14]. Thus, the nine images are not taken in real lighting instead they are taken under synthetic harmonic lighting and are synthesized using standard techniques such as ray-tracing, etc. Hence, information about an object’s surface, albedos and normals must be known prior to the computation of the harmonic subspace. Thus, Spherical harmonics can be used to represent lighting and the effects of Lambertian materials. Using these results algorithms that use convex optimization to enforce non-negative lighting functions can be constructed.

Rammamoorthi and Hanrahan [15], also developed a method that uses spherical harmonics for the computation of a lower dimensional linear approximations (i.e., lesser than 9 dimensional) to illumination cone.

4) **Nine point lights**:

Lee et al. showed that there is a configuration of nine point source directions such that a subspace resulting from nine images of an individual under nine different lighting sources can be used effectively for recognition under varied illumination conditions.

Depending on the lighting angle with respect to the camera axis, the images in a training set are grouped into subsets. The first subset covers angles 0°-25°; the second subset covers angles 25°-50° and so on. Using the image of each person under these 9 different lighting conditions, as the basis vectors, a linear subspace for each person can be constructed. The nine images could be real images taken under real lighting conditions or could be simulated images, that have been rendered using geometric and albedo models. The error rate of the former is zero, while that of the later is 2.8 percent, which is similar to the error rate of 9D harmonic planes (2.7 percent), as given in [16]. Hence, the 9D harmonic planes and the nine point lighting method using rendered images are said to be closely associated with each other.

The main advantage of this method is that offline preprocessing on training data or 3D reconstruction as in the case of spherical harmonics is not needed as there is no training involved. Also, large set of images for each individual is not required in the training set.

5) **Generalized Photometric Stereo**:

Generalized Photometric Stereo process is used to recover class-specific albedo/shape matrix which consists of albedo and the surface normal vectors of each basis object, using multiple images taken from the same viewpoint but with varying lighting conditions. Most 2D methods are confounded by images taken under varied illumination, but 3D methods are unaffected by this challenge. Hence, 3D methods allow for illumination correction. Photometric stereo is one such method where, multiple images of a face from same viewpoint are taken in different lighting conditions. The changes in pixel intensities at each point of image, are used to deduce the surface orientation, which are represented by surface normals. Surface normals are vectors that are perpendicular to a given object's surface at that point. Gökberk et al. [17] performed recognition experiments using numerous 3D representations and they concluded that "...surface normals are better descriptors than the 3D coordinates of the facial points". This method directly calculates the surface normals of face and hence it is a good approach for face recognition. Paper [18] gives more information on using photometric stereo for the purpose of face recognition.

3.2. ILLUMINATION INVARIANT FEATURES

The purpose of these approaches is to extract facial features that are robust against illumination variations. There are several illumination invariant representations of faces, some of them are edge map, image intensity derivatives, and image convolved with a 2D Gabor-like filter. These representations can also be used with a log function to generate variations in the representations. However these representations by themselves are not sufficient to overcome images with varying illumination.

1) **Features Derived from Image Derivatives**:

Line edge map can be used for face recognition. The edge pixels are grouped into line segments, and the similarity between two line segments can be measured by using a revised Hausdorff Distance method. The direction of image gradient is found to be insensitive to change in illumination. Chen et al. [20] showed that the probability distribution of the image gradient is a function of the surface geometry and reflectance, which are the intrinsic properties of the face. The performance obtained by using gradient direction for recognition is close to illumination cone approach.

Zhao and Chellappa presented a method based on Symmetric Shape from Shading for illumination insensitive face recognition. By utilizing symmetry of every face and the similarities in shape among all faces, a prototype image with normalized illumination can be obtained from one training image with unknown illumination. This prototype can be used to enhance face recognition.

2) Quotient Image (QI):

Shashua et al. [19] proposed quotient image (QI), which is the ratio of albedo between a face image and a basis image for each pixel. The quotient image depends only on the relative surface texture information and is free of illumination. However, the performance of QI depends on the bootstrap database. QI based methods are simple and efficient solution to illumination variances. However QI assumes that the face image includes only diffuse reflection, which is the reflection of light from a surface such that an incident ray is reflected at many angles rather than at just one angle.

In 2004, Wang et al [22] proposed Self Quotient image (SQI) by using single image. The SQI is defined as the ratio of an image and its smooth versions and it is given by the equation:

$$Q = \frac{\mathrm{I}}{\mathrm{F} * \mathrm{I}}$$

Where F is the smoothing kernel, and (F*I) is the smoothed version of I. Q is called the self- quotient image as it is derived by a single image. The differences between QI and SQI are: (1) SQI is calculated from a single image while QI uses multiple images; (2) there is no need of assumptions about face images in SQI. The main advantages of SQI method are: (1) single image with no alignment is needed and (2) It works in show regions too.

In 2005, Chen et al [21] proposed total variation based quotient image (TVQI). The advantages of this method are that no training images are required and no assumption of the light source is made. Although TVQI outperforms the existing methods in recognition, it is complex to compute.

In 2007, Zhang et al [23] proposed Morphological Quotient Image (MQI) based on morphological theory. All the above methods are variations of QI and aim at achieving better results at face recognition due to varying illumination.

3) **Retinex approach**:

Retinex method is based on Reflectance-Illumination model rather than on Lambertian model and it is used for image decomposition. Face image can be decomposed as Reflectance (R) and Illumination (L). Thus the intensity of a face image is given by the product of R and L:

$$I(x, y) = R(x, y) * L(x, y)$$

Where $I(x, y)$ the intensity of image is, $R(x, y)$ is the reflectance ratio of objects to incident light at position (x, y) and $L(x, y)$ is the amount of light incident at position(x, y).

To get an illumination normalized image it is essential to eliminate the illumination variations from the image intensity. For this purpose, the logrithamic operation is used:

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

The luminance is estimated by the smoothed image, which is obtained by passing the image through a Gaussian filter. Smoothing of an image can be done in two ways: single scale retinex approach and multi-scale retinex approach. In the former a single Gaussian function is applied and in the latter a sum of several Gaussian functions with different scales is applied. Finally the illumination normalized output is $R(x, y)$.

4) **Transformation domain features**:

Methods based on the frequency domain representation have achieved impressive results. One such method is the Eigenphase method that transforms face image to the frequency domain and applies PCA to the phase information to extract the features for recognition purposes.. Oppenheim et al [26] have shown that the phase information of an image retains the most of the intelligibility of an image. Their research also shows that an image can be reconstructed using just the phase information. Thus, phase information becomes important to represent 2D images in Fourier domain.

Different approaches can be used to extract the phase information and they are listed out in [27]. A few of them to extract the phase information directly from Fourier transformations of facial images and they are: (1) MagUn approach where in the magnitude spectrum is set to unity, (2) MagAv approach, where in the magnitude spectrum is set to the average magnitude spectrum. CovUn approach indirectly extracts phase information by using the covariance matrix of the the fourier transformations of a face image. Finally, application of PCA to the phase information obtained by using any of the above methods is called eigenphase method.

This method provides stable face recognition even under varying conditions like illumination, pose, expression etc. Hence, they provide better results than the eigenface method.

5) **Local Binary Pattern (LBP)**:

The fact that faces are composed of micro-patterns, gave rise to the idea of using texture descriptors. LBP is on such texture descriptor, which is primarily famous for its computational efficiency and invariance to monotonic gray level changes. It assigns a label to every pixel of an image by thresholding the neighborhood of each pixel and considering the result as a binary number. In [24] two extensions of LBP operator are provided. One defines LBP's for neighborhood of different sizes whilst the other defines uniform patterns: which are circular patterns that contain bitwise transitions from 0 to 1 or vice versa.

The labels generated can then be used for computation a histogram, which is used as a texture descriptor. Usually the uniform patterns are used to assign separate bin for every uniform pattern and all non-uniform patterns are assigned to a single bin to reduce the number of bins. The basic histogram can then be extended into a spatially enhanced histogram, which stores both the appearance and spatial relations of facial regions. The face image is divided into local regions and texture descriptors are extracted from each region independently and finally are combined to form a global descriptor, which describes the whole face.

3.3. PREPROCESSING AND PHOTOMETRIC NORMALIZATION:

Often images are not in the correct form to be plugged straight into a recognition algorithm. The image may contain more information than one single face, and the lighting conditions in the test image may not be the same as in the sample data for training the algorithm. This can greatly affect the effectiveness or the recognition rate of the algorithm. Therefore, to obtain the best possible results, it is necessary to pre-process an image to normalize lighting and remove noise before inserting it into a recognition algorithm. A few of the techniques are:

1. **Histogram Equalization (HE)**:

This technique is used to adjust the contrast of an image during image processing. It increases the global contrast of the images by distributing the intensities on the histogram and this is achieved by increasing the contrast in areas where the local contrast is low. This method is useful in processing images that's have both bright or dark backgrounds and foregrounds. The only disadvantage of this technique is that it is indiscriminate i.e. it may increase the contrast of noise while decreasing the usable signal. The two variations of HE that can be used in face recognition are: Adaptive Histogram Equalization (AHE) and Block-based Histogram Equalization (BHE).

AHE also enhances the contrast of a face image but it does so by computing several histograms, each corresponding to a distinct region of the image and uses them to redistribute the intensity values of the image. Therefore it provides local contrast enhancement but sometimes it leads to amplification of noise in "flat" and "ring" regions. This amplification is minimized in a variant of AHE called the Contrast Limited Adaptive Histogram Equalization (CLAHE).

BHE enhances the face image by dividing it into blocks and applying HE over those blocks. The blocks are overlapped to provide a smooth variation in contrast. Different types of HE that can be used for image enhancement are provided in [25].

2. **LogAbout Method**:

Logarithmic transformations enhance low gray levels and compress the high ones. They are useful for non-uniform illumination distribution and shadowed images. However, they are not effective for high bright images. Liu et al. [28] proposed LogAbout method which is an improved logarithmic transformation as the following equation:

$$g(x,y) = a + \frac{\ln(f(x,y)+1)}{b \ln c}$$

Where $g(x,y)$ is the output image; $f(x,y)$ is the input image; a, b and c are parameters which control the location and shape of the logarithmic distribution.

3. **Sub-Image Homomorphic Filtering**:

In this method, the original image is split vertically in two halves, generating two sub-images from the original one. The next step is to apply a Homomorphic Filter to each sub-image and the resultant sub-images are combined to form the whole image. The filtering is subject to the illumination reflectance model as follows:

$$I(x,y) = R(x,y) * L(x,y)$$

Where $I(x, y)$ is the intensity of the image; $R(x, y)$ is the reflectance function, which is the intrinsic property of the face; $L(x, y)$ is the luminance function.

By assuming illumination varies slowly across different locations of the image and the local reflectance changes quickly across different locations, a high-pass filtering can be performed on the logarithm of the image $I(x, y)$ to reduce the luminance part, which is the low frequency component of the image, and amplify the reflectance part, which corresponds to the high frequency component.

The original image can also be divided horizontally and the same procedure applied. But the high pass filter can be different. The two resultant images are grouped together in order to obtain the output image. Delac et al. [29] propose a modification to this method and based on some tests it was found that by keeping the whole image split vertically and multiplying the horizontally split image by 0.75 they were able to achieve superior results.

4. **Gamma Intensity Correction:**

Shan et al. [30] proposed Gamma Intensity Correction for illumination normalization. The gamma transform of an image is a pixel transform given by:

$$G(x, y) = I(x, y)^{1/\gamma}$$

Where $G(x, y)$ is the output image; $I(x, y)$ is the input image; γ is the Gamma coefficient. The brightness of the output image depends on the value of γ. This method corrects the overall brightness of a face image to a pre-defined canonical face image. This reduces the effect of varying light.

5. **Discrete Cosine Transform (DCT)**:

It has been proved that the illumination variations in a face image mainly lie in the low-frequency band. Therefore, by removing the low frequency part illumination variation can be reduced. Chen et al. [31] proposed that the low frequency DCT coefficients are set to zero to eliminate illumination variations. This method does not require multiple images to be trained. Many variations of DCT and involving DCT have been proposed. The 2D DCT is defined as follows:

$$A(u, v) = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} a(u)a(v)f(x, y)\cos[\pi(2x + 1)u/2M]\cos[\pi(2y + 1)v/2N]$$

And the inverse transform is defined as

$$f(x, y) = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} a(u)a(v)A(u, v)\cos[\pi(2x + 1)u/2M]\cos[\pi(2y + 1)v/2N]$$

Based on the initial idea, Vishwakarma et al. [32] proposed to rescale low-frequency DCT coefficients to lower values instead of zeroing them. Although some comparisons were presented by them there is no experimental result to prove that the proposed system is better than the original DCT method.

Besides DCT, discrete wavelet transform (DWT) is another well known method. It is very similar to DCT in a lot of ways. For instance they both transform the data into frequency domain. They are independent of training data. This method involves discarding low frequency coefficients of the DWT.

6. **Dynamic Morphological Quotient Image (DMQI) method**: In this method mathematical morphology operation is employed to smooth the original image to obtain a better luminance estimate. A quotient image is generated after morphological filtering. However, in DMQI, there is some pepper noise in dark area. Pan et al. [33] proposed a system that fuses DMQI with LBP-based face recognition system. This proposed DMQI-LBP algorithm improves performance compared to the original LBP-based system.

7. **Different Smoothing filters Quotient Image (DSFQI)**: Different Smoothing filters Quotient Image (DSFQI) give a new demonstration in which it is proved that the same smoothing functions with different scales also contribute to extract the illumination invariant features. It tends to retain the remarkable face features such as edges and verges, and gains the intrinsic representation of an object.

3.4. 3D MORPHABLE MODEL

Blanz and Vetter [34] proposed face recognition based on fitting a 3D morphable model. The model describes shape and texture of face separately based on the PCA analysis of the shape and texture of face separately based on the PCA analysis of the shape and texture obtained from a database of 3D scans. The 3D morphable model is based on a vector space representation of faces. In this vector space, any convex combination of shape and texture vectors of a set of examples describes a human face. The shape and texture parameters can be separated from the illumination information. This proposed model can handle illumination and viewpoint variations, but they rely on manually defined landmark points to fit the 3D model to 2D intensity images.

Weyrauch et al. [35] used a 3D Morphable model to generate a 3D face model from three input images of each person. The models are rendered under varying illumination conditions to build a large set of synthetic images. These images are used to train a component-based face recognition system.

4. COMPARISON

It can be seen in Table 1, that some passive approaches achieved excellent performance. However, it cannot be concluded that the illumination problem is well solved. Although good performance is usually reported for most techniques, each technique has its own drawbacks.

The illumination modeling methods require training samples from controlled illumination. The physical modeling of the image formation generally requires the assumption that the surface of the object is Lambertian, which is violated for real human faces. The statistic modeling methods require training samples from as many as possible different illumination conditions to ensure a better performance. The performance of many photometric normalization methods severely depends on the choice of parameters.

As for active approaches, it should be investigated how much the active sensing process will be influenced by the environmental illumination. For example, a number of 3D acquisition techniques make use of intensity/infrared image pairs for 3D reconstruction. The variation in the environmental illumination might cause a problem for the accuracy of 3D reconstruction in those systems.

Usually it is difficult to compare the performance between passive approaches and active approaches because the datasets to test passive approaches are captured under different illumination conditions with the databases captured by active approaches.

5. CONCLUSION

Illumination variation happens to be one of the key challenges for face recognition even till today. This paper has outlined the various approaches that can be used to eliminate the effect of varying illumination on face recognition. The performances, advantages and drawbacks of passive and active approaches have been summarized.A survey of passive and active approaches that address illumination problem has been presented here in table 1

Category	Method	Yale B				Harvard				PIE
		Subset 2	3	4	5	Subset 2	3	4	5	
Illumination Variation Modeling (statistical)	Eigenface	0	25.8	75.7	-	0	4.4	41.5	-	-
	Fisherface	-	-	-	-	0	0	4.6	-	-
Physical Modeling	3D Linear Subspace	0	0	15.0	-	0	4.4	9.2	-	-
	Spherical Harmonics	0	0	2.8	-	-	-	-	-	1.9
	9 point lights	-	-	-	-	-	-	-	-	0.9
Illumination Insensitive Features	Gabor Phase	0	0	2.8	2.7	-	-	-	-	-
	Quotient Image	1.7	38.1	65.9	76.7	-	-	-	-	-
	Self Quotient Image	2.0	1.0	3.0	-	-	-	-	-	-
	Morphological Quotient Image	0	0	0	0.5	-	-	-	-	-
Photometric Normalization	Histogram Equalization	0	11.0	44.9	55.6	1.1	47.9	70.0	87.6	-
	Gamma Intensity Correction	0	11.9	44.9	55.6	1.1	47.9	70.0	87.6	-
	DCT	0	0	0.18	1.71	-	-	-	-	0.36
	Wavelet Reconstruction	0	0	5.24	9.27	-	-	-	-	-
3D Morphable Model		-	-	-	-	-	-	-	-	0.2

Table 1: Error rates of Passive Illumination Invariant approaches (%)

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