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Illumination and Pose Invariant Face Recognition: A Technical Review

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Abstract

Face recognition being the most important biometric trait it still faces many challenges, like pose variation, illumination variation etc. When such variations are present in both pose and illumination, all the algorithms are greatly affected by these variations and their performance gets degraded. In this paper we are presenting a detail survey on 2D face recognition under such uncontrolled conditions. Here we have explored different techniques proposed for illumination and pose problem in addition with the classifiers that have been successfully used for face recognition in general. The objective of this review paper is to summarize and compare some of the well-known methods for better understanding of reader.

1. Introduction

Face recognition (FR) in a very simple term, is a process of recognizing the face of a person by a system. However, identifying faces through a digital eye is not an easy nut to crack. Whenever face recognition is used across the surveillance system it is often very difficult to acquire the faces in controlled environment. So there has to be a system which is capable of recognizing the faces captured even in poor lightning conditions and variations in poses as against the faces taken in controlled environment. Although many approaches have been proposed during last decade; however, real-world scenarios remain a challenge. Moreover, all the techniques are greatly affected by variations and their performance get degraded when variations in both pose and illumination are present. The illumination problem arise when the same face appears differently due to the change in lighting and pose variation comes from the fact when there exists head rotation.

During the last decade, the predominant approaches towards the face recognition system that have been proposed can be classified into four main categories [1,2,3] : 1.Holistics method, which uses whole face region; 2. Model based methods which employ shape and texture of the face, along with 3D depth information; 3. Template based face recognition, where face templates are extracted and used for recognition; and 4. Techniques using Neural Networks. If all the approaches of four categories listed above are taken into considered, many problems have been solved; but still so many of them remain in this field of research. In this paper, we provide an overview of all the leading illumination and pose approaches which are widely used throughout the world for illumination and pose problem. We explored the methods of implementation of each approach and on the basis of this exploration, we are presenting a survey paper that comprises as much literature study for the reader to understand that what exactly the variations are that can be caused by variation in illumination and pose, what approaches had been taken up till now to make continuous improvements in existing systems and their drawbacks etc. We also provide a comprehensive review on classifiers that have been successfully used in face recognition system.

The paper is organized as follows: in Sect. 2, overview of face recognition system, the basic steps involved in a face recognition system, Sect. 3, discuss about the challenges in face recognition system followed by the latest efforts taken in the line of research as illumination and pose problem. Classifiers that have been used successfully in field of face recognition are reviewed in Sect. 4. Finally, a summary and conclusions are given.

2. Face Recognition system

There are enormous applications where a person's identity is important. For the same, there are many different identification technologies available, many of which have been in commercial use for years. The most common person verification and identification methods today are PIN systems (Personal Identification Number) [4, 5]. However, the problem with such techniques is that it is possible for somebody to forget this PIN, or it can be stolen for misuse. These problems can be overcome using "biometrics" identification systems, which use pattern recognition techniques to identify people using their characteristics [4, 5]. Some of those methods are fingerprints, retina recognition, and iris recognition and face recognition etc., [4].

Face recognition is an important sub-domain of object recognition for which research community has shown their growing interest since last so many decades [1, 2, 3]. Since then, with the rapid evolution of the technology and the commercialisation of technological achievements, face recognition became more and more popular. Face recognition finds many applications in crucial areas such as security, user login by face recognition, human-computer interaction, face finding system, AFRS, album etc. Face Finding System is a system that can automatically find images that match the specified faces from the database. AFRS track the movement and behaviors of the person who entered the capturing region. It identifies the face of the person by a rectangle region and keeps tracking the position of the face even when the face is moving. Album helps the home users manage their photos by some advanced features such as face location, automatic recognition, and name labeling. Recent studies show that keneya government is planning to use face recognition at ATMs to replace persons credentials.

The advantages of face recognition system are that it is used for manual inspection. It is least intrusive from sampling point of view. It helps in accomplishing the screening of unwanted individuals in a crowd. It only needs small-scale verification for surveillance purpose.

However , if other side of the coin is seen face needs to be well lighted by controlled source and must be well aligned for accuracy. Most existing face recognition systems, however, work only for frontal or nearly frontal images of faces under controlled environment as it contains much of information.

2.1. Basic steps in face recognition system

General steps in any face recognition system as depicted in figure 1 are discussed below:

First an image of the face is acquired. This acquisition can be accomplished by digitally scanning an existing photograph or by using an electro-optical camera to acquire a live picture of a subject.

Second, software is employed to detect the location of any faces in the acquired image. This task is difficult, and often generalized patterns of what a face "looks like" (two eyes and a mouth set in an oval shape) are employed to pick out the faces.

Feature extraction being the third step is important towards classification task. Different vendors use different methods to extract the identifying features of a face.

The fourth step is to compare the features generated in step three with those in a database of known faces. Instead of capturing the image and then detecting face in that image, other steps can be performed on an image in the given database. Just as the human perception system uses both local features and the whole face region to recognize a face, a machine recognition system should use both.

3. Challenges in Face Recognition System

Though face recognition have been a grown up research area, however, there still remain many problems that must be overcome to develop a robust face recognition system that works well under various circumstances such as illumination, pose, expressions,illumination and expressions, illumination and pose, and lastly llumination and expression and pose variations, as shown in figure 2 [1]. The results reveal that all the recognition techniques were successful on large face databases recorded in well-controlled environments. But under uncontrolled environments their performance gets deteriorated mainly due to variations in illumination and head rotations. Such variations have proven to be one of the biggest problems of face recognition systems.

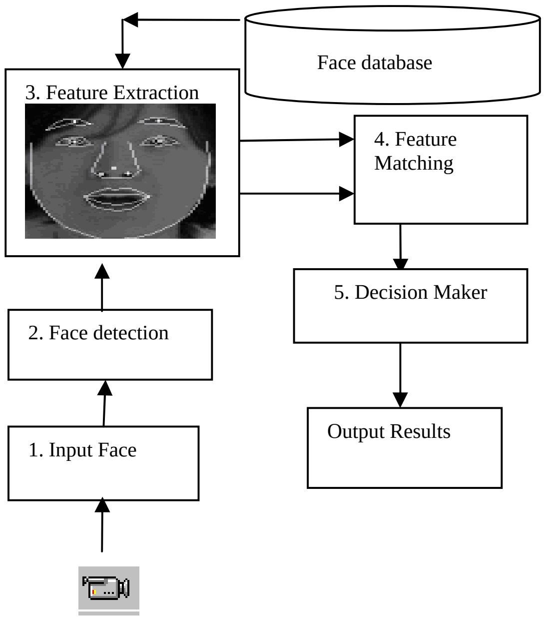

Figure 1. Basic face recognition system

Figure 2. Challenges in Face recognition system

Since we are presenting a review paper on illumination-pose invariant face recognition systems so it is very essential to head in the direction of knowing what basic approaches had been adopted to deal with illumination-pose invariant face recognition system. First we will deal with approaches that specifically dealt with illumination problem followed by approches towards pose problem.

3.1. Approaches to illumination variations

Illumination problem arises due to uneven lightning on faces as illustrated in figure 3. This uneven lightning brings variations in illumination which affects the classification greatly since the facial features that are being used for classification gets effected due to this variation.

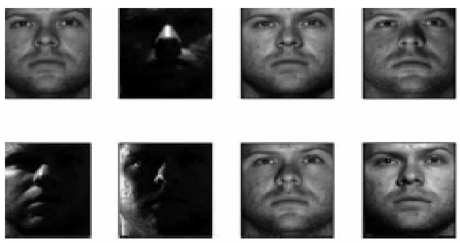

Figure 3. The Illumination Problem

In the past few years, many approaches to cope up with illumination variations have been proposed. All the approaches towards illumination problem can be broadly categorized as: transformation of images with variable illumination to a canonical representation, extracting illumination invariant features, modeling of illumination variation and utilization of some 3-d face models whose facial shapes and albedos are obtained in advance [6]. Now, here onwards we will move into the respective algorithms that are used for each approach along with the comparison between the results obtained by each algorithm on the basis of their complexity and accuracy.

Among the earliest one is *transformation of images with variable illumination to a canonical representation*. It was Adini, Moses, and Ullman [7] who first observed it. However, a theoretical proof of it has been given in [8] on the basis of eigenface system projection. Eigenfaces have been widely used for the detection of unknown faces in an image and for person identification. Belhumeur et al. [9] and Bartlett et al. [10] adopted the PCA by discarding the first few principal components and achieved better performance for images under different lighting conditions. Their assumption is that first principal components only capture variations due to lighting. Consequently, some important discarded components can influence the recognition under normal lighting conditions. Further, Belhumeur et al. [11] proposed Virtual eigenspace which could be constructed from a single image, whereas the real eigenspace cannot be constructed directly from a single image. Arandjelovic et al. [12] proposed simple image filtering techniques for rapid recognition under varying illumination and pose. This technique has demonstrated a reduction of 50–75% in recognition error rates, with a recognition rate of 98% of the individuals.

In addition, few researchers concentrated throughly on *features that are invariant to variation in light*. This has been achieved by extracting only those features that are not affected by variations in lighting conditions. To name a few of such representation of image are gradient faces [13], 2D Gabor Filter [14,15], DCT coefficients [16,17], LBP Feature [26].

One such method of extracting illumination insensitive features for face recognition under varying illumination is Gradient faces. It is derived from the image gradient domain such that it can discover underlying inherent structure of face images since the gradient domain explicitly considers the relationships between neighboring pixel points. The efficiency of the gradient face algorithm as reviewed on the PIE database is maximum in terms of CPU time i.e 0.09 seconds/image. Gradient faces is able to apply directly to any single face image neither does it require any prior information nor many training images. On the contrary, Gradient faces have low computational cost such that it can be applied to practical applications as in [18].

Gabor filter has been used in most cases to extract features of the facial images. It has been applied as in [14] to specific areas of the face region, corresponding to nodes of a rigid grid, where for each node the Gabor coefficients are extracted. Gabor filters as feature extraction proved to be an efficient approach; however they dramatically increase the computational cost.

In [16], the Discrete Cosine Transform was employed by Chen et al. to compensate for illumination variations in the logarithm domain. Shim et al [18] used subspace model to relighting the face under unknown lighting and poses. Jacobs et al. [19] presented a method based on the fact that, for point light sources and objects with Lambertian reflectance, the ratio of two images for the same object is simpler than the ratio of images for different objects. Liu et al. [20] used a ratio image to solve the illumination variation. Similar method has been proposed by Wang, et al. [21], which aimed to acquire an illumination-invariant face feature image for a group of images of the same subject. In [22], a hybrid approach based on the use of PCA and correlation filters was proposed. In Du et al. [23] a wavelet based normalization method was presented. It was Gao and leung [24] presented a new approach namely line edge map. This was an extension of simple edge map technique.

The Local Binary Pattern (LBP) [25] is an invariant feature extraction type algorithm. It was first proposed for the use of texture description by Ojala and it has been used in the last years to compensate and normalize illumination in face detection and recognition contexts. In the original formulation of LBP the center pixel cannot be compared with itself. So in some cases LBP cannot capture the local structure of the image area under analysis correctly. For overcoming this drawback, the modified LBP (mLBP) [26] is given by Froba and Ernst. Local ternary pattern (LTP) [27] was proposed by Tan and Triggs, which was also an extension of LBP. In [28] it has been presented novel solution for achieving illumination invariant face recognition for indoor, cooperative- user applications, using active near infrared imaging techniques, and for building accurate and fast face recognition systems.

However, the drawback is that it is not yet suitable for uncooperative user applications such as face recognition in video surveillance. Nor it is suitable for outdoor use due to strong NIR component in the sunlight.

Third and recently used one is *modelling of illumination variation*. This approach is, in spirit, an appearance-based method. However, it differs substantially from previous methods in that a small number of training images are used to synthesize novel images under changes in lighting and viewpoint. However, because the space of lighting conditions is infinite dimensional, sampling this space is no small task. This can be simplified by a convex cone termed as illumination cone is formed from the set of images of an object in fixed pose but under all possible illumination conditions [29]. This illumination cone can be well approximated by a low-dimensional linear subspace .Under variable lighting, the set of images is characterized by a family of illumination cones parameterized by the pose. The illumination cones for non-frontal poses can be constructed by applying an image warp on the extreme rays defining the frontal cone. To construct the illumination cone, the shape and albedo of each face is reconstructed. Even few number of imges seen in a fixed pose, but illuminated by point light sources at varying, unknown positions is used to estimate its surface geometry and albedo map up to a generalized bas-relief (GBR) transformation [30]. Using the estimated surface geometry and albedo map, synthetic images of the face could then be rendered for arbitrary lighting directions and viewpoint. Further, the cone has been simplified in two ways as proposed in [31,32]: using a subset of the extreme rays and approximating it as a low-dimensional linear subspace. The method thus proposed argued to claimed that they are different from [33, 34, 35] as this method are generative and also it requires only a few images to predict large image changes. It is, in spirit, most closely related to the synthesis approaches suggested in [36] and stands in stark contrast to the illumination insensitivity techniques argued for in [37, 38]. Each pose-specific illumination cone is generated by warping the frontal illumination cone images corresponding to its extremal rays. After this a recognition algorithm can be applied for finding out the matches. All the approaches thus are in contrast to [39] where all faces are modelled by a single collection of low-dimensional subspaces, with each subspace modeling the appearance of all faces in one particular view.

The fourth method of compensating the illumination problem is *utilization of some 3-d face models* whose facial shapes and albedo are obtained in advance. A 3D morphable model is used to generate 3D face models from three input images from each person in the training database. Thus the 3D models are rendered under varying pose and illumination conditions to build a large set of synthetic images. An example is given by Blanz and Vetter in [40] that proposed a method to create 3D face models from a single image. Zhang and Cohen morphed 3D generic model from multi-view images by way of using a cubic polynomial [41]. An example of the triplet of training images used is shown in the top row of figure 4. The bottom row shows two synthetic images created by rendering the newly generated 3D face model.

Figure 4. Generation of 3D model

In all the recent approaches, a 3-D model of a face is utilized to transform the input image into the same pose as the stored prototypical faces, and then direct template matching is used to recognize faces [42, 43, 44]. In another approach, an Active Appearance Model of a generic face is deformed to fit to the input image, and the control parameters are used as a feature vector for classification [45].

Literature puts forward that although approaches based on 3D face models are robust to uncontrolled conditions, they still suffers from drawback viz; the computational cost which is very high as compared to 2D approaches and the accuracy is much more dependent on number and quality of the selected features. In addition it is still doubtable that whether 3D facial reconstruction from a single view image or multi-view images can be considered good enough.

3.2 Approaches to pose variations

The pose problem illustrated in figure 5 where the same face appears differently due to changes in viewing condition. Post-invariance recognition capability is crucial to a face recognition system because in general it is difficult, if not possible, to control the imaging direction when acquiring images of human faces.

Figure 5. Sample images from Indian database

Till now many different methods have been proposed by various researchers to handle the rotation problem. Basically they can be divided into three classes: multiple images based approaches where multiple images per person are available; hybrid approaches in which multiple training images are available during training but only one database image per person is available during recognition and single image/shape approaches which require no training. Up to now, the second type of approach is the most popular one. The third approach does not seem to have received much attention.

In *multi_image based approaches*, the template based correlation matching scheme [38] was earliest one. In this approach, pose estimation and face recognition are coupled in an iterative loop which makes the computational cost high. Li et al. [46] has proposed view-specific eigenfaces as to build one eigen face set for each view for pose invariant face recognition. In extension to Choi et al. [47] has proposed a new approach to handling illumination and pose variations which is motivated by the two-dimensional view-based face recognition methods having multiple eigenspaces. The geometrical relations between the facial feature points were used to assign facial images to the proper pose class, achieving a rate of 99.5%. The proposed method has several advantages. Since the method is based on 2D images and does not need to estimate the 3-D shape, it is computationally much more efficient than the other methods based on 3D models.

The second and the most popular one is *hybrid approach*. Moreover, as it utilizes prior class information, it is probably the practical method up to now. We have reviewed three representative methods here, the first one is the linear class based method [48], the second one is the graph matching based method [49] and the third is the viewbased-eigenface approach [50]. The image synthesis method is based on the assumption of linear 2D object classes and the extension of linearity to images which are 2D projections of the 2D objects. Here a correspondence between images of the input object and a reference object is established. And then the correspondence field for the input image is linearly decomposed into the correspondence fields for the examples. Compared to the parallel deformation scheme this method reduces the need to compute the correspondence between images of different poses.

The graph matching based method with Elastic Bunch Graphic Matching (EBGM) proposed in [50], basically assumes a planar surface patch in each key feature point (landmark), and learns the transformation of landmark under face rotation. It demonstrated substantial improvements in face recognition under rotation, however; the drawback of this method is the requirement of accurate landmark localization which is not an easy task especially when illumination variations are present.

In order to achieve pose invariant recognition view-based eigenfaces method are an extension to most popular eigenface approach [9]. These methods explicitly code the pose information by constructing an individual eigenface for each pose. Despite their popularity, these methods have some common drawbacks that be listed out: they need many example images to cover all possible views, and the illumination problem is separated from the pose problem.

Probabilistic approach to face recognition that takes into account the pose difference between probe and gallery images has been proposed in [51]. This model made the face recognition system more robust to changes of pose in the probe image. The experimental results show that this approach achieves a better recognition rate than conventional face recognition methods over a much larger range of poses. For example, when the gallery contains only images of a frontal face and the probe image varies its pose orientation, the recognition rate shows less than a 10%; difference until the probe pose begins to differ by more than 45°, whereas the recognition rate of a PCA-based method begins to drop at differences as small as 10°.

On the contrary, the third class of approaches includes *low-level feature based methods*, invariant feature based methods, and the 2D model based method. There are many papers on invariant features in the computer vision literature. To our knowledge, serious application of this technology to face recognition has not yet been explored. However, it is worthwhile to point out that some recent work on invariant methods based on images may shed some light in this direction. However due to its complexity and computational cost, any serious attempt to apply this technology to face recognition has not yet been made except few in [52]. It has presented a face re-rotating approach based on linear shape prediction and image warp based on the strategy of generating virtual views from one single face image, that is, synthesize novel views of the given ace. Fuang et al. [53] proposed a recognition system which is insensitive to viewing directions and it requires only one sample view per person. Proposed approach utilizes the similarities of a face image against a set of faces from a training set at the same view to establish pose-invariant representations of a person in different poses. Experimental results indicate that the proposed approach achieves high recognition rates even for large pose variations. Arashloo et al. [54] addresses the problem of face recognition under arbitrary pose where no images have been used in training. Here in a hierarchical MRF-based image matching method for finding pixel-wise correspondences between facial images viewed from different angles is proposed and used to densely register a pair of facial images. The method needs no training on non-frontal images and circumvents the need for geometrical normalization of facial images. It is also robust to moderate scale changes between images. The proposed approach is evaluated on the CMU PIE database and promising results are obtained.

4. Classifiers

Face recognition is actually a pattern matching classification task i.e. the given facial image is transformed into features, after which a classifier trained on example faces decides whether that particular facial image is present in the database or not. This section briefly tries to cover some of the classifiers that have been used successfully in face recognition domain. Classifiers till now that have been successfully used are Euclidian distance [31], nearest neighbour classifier [55], neural network [56,57,58,59.60,61], Bayesian classifier [58], HMM [67], Svm [71], rough neural network [74], Radial Basis Function (RBF) [75,76,77] and Adaboost [78,79,80]. Here onwards word “image” refers to facial image.

Euclidian distance has been very often used in object recognition. It is a technique where the distance between the keypoints on the test image and the keypoints on the training image is calculated. Based on the differences decision is taken whether an image belongs to a particular class or not. However, this would require computing the distance of the test image to all training images of all subject over all viewpoints, and would be computationally expensive.

One of the widely used classifier is nearest neighbour classifier (NNC). It is one of the supervised statistical pattern recognition algorithms. This has achieved consistently high performance, without *a priori* assumptions about the distributions from which the training images are drawn. It is accomplished in the way that it involves a training set of both positive and negative cases. A new image is classified by calculating the distance to the nearest training image; the sign of that point then determines the classification of the image under consideration. In the standard eigenfaces approach [55], the nearest center (NC) criterion is used to recognize a new face. This seems to be quite simple, but computationally very intensive.

Neural networks (NN) are well known classifiers which have been used widely in face detection [56, 57, 58, 59.60, 61] when detection rate is in focus. Rowley et al. [56] presented a neural network-based upright frontal face detection system. When neural network scans the entire image for finding possible faces without any prior knowledge [56, 60], it needs high computation. Despite of this, some neural network classifier when used in the face detection problem have auto ability in extraction of the characteristics of the complicated face templates [56]. To sum up, the limitations of NN include high computations between the layers of the neural networks and also problems in adjusting the topology of the network.

As per Bayesian classifier in [63] is considered, Bayes alone has reported 92.2% of classification rate. In [64] it is combined with Gabor to improve the performance. In [65], a probabilistic visual learning (PVL) method is developed for face recognition. Another way of Bayesian classification of faces is proposed in [66], called probabilistic reasoning models (PRM), based on some assumptions of the class distributions.

Hidden Markov Model (HMM) proposed by Samaria [67] was a new approach to face recognition. A discrete-time Hidden Markov Model can be viewed as a Markov model whose states cannot be explicitly observed [68]. HMM along with DCT coefficients [16] was capable of reducing the error to 0.5% which was much more, about 13 % in Top-down HMM + gray tone features approach [69]. In addition to this M.Biecego et al. [70] have used wavelet coding along with HMM. Its results showed that this approach outperformed the former with error rate of 0%.

More recently, the support vector machine (SVM) [71] is popular for visual object recognition. SVMs belong to the class of maximum margin classifiers. They perform pattern recognition between two classes by finding a decision surface that has maximum distance to the closest points in the training set which are termed support vectors. In [72] author has successfully used SVM as face recognizer. Multi-Pose Face Recognition in color images, which addresses the problems of illumination and pose variation has put forth in [73] where SVM has been used on Gabor features for face recognition. The face recognition accuracy based on SVM is relatively high. However, in SVM, both the training and testing process is a little time consuming if the face database is very large.

Rough neural network proposed by K.singh et al. [74] as classifier which uses a rough neurocomputing approach for classification of images in the context of rough sets. The rough neural network is two layer architecture with approximation neurons as input layer, and an output layer with a single decider neuron. The success rate of the proposed algorithm reported to be 96.5% on an average. However, the limitation includes the small number of training and testing images have been used.

Radial Basis Function (RBF) networks are used for tracking and recognition purposes [75,76, 77]. Since no warping is done, the RBF network has to learn the individual variations as well as possible transformations. The performance appears to vary widely, depending on the size of the training data.

One of the very important classifier is AdaBoost [78], which is a binary classifier that does classification between two classes. All the given features are compared with boosting along feature dimensions. But in case of a multi-class scenario, as in [79, 80] researchers have used a majority voting strategy to combine all pair-wise classification results. AdaBoost has the potential of fast training and testing for real-time face recognition.

5. Summary

As we have gone through the literature and reviewed most of the recent developments in face recognition none of the techniques is able to provide best performances under all uncontrolled circumstances. Although, face recognition has been claimed to be an almost solved problem, however recognition under uncontrolled conditions remained a field of research. This review paper mainly focuses on the research efforts for illumination and pose problems.

Most of the strategies that have been analyzed claim satisfactory recognition rates only when tested on standard databases or some part of them. As per database is concerned, CMU-PIE has been widely used for pose and illumination problem.

Another important issue is the classifiers that are used for face recognition. Some of the widely used classifiers have been discussed in classifier section. The recognition rate claimed by each of them depends on the database used and the number of subjects on which classification task has been performed.

Face recognition from video and multimodal recognition is going to have an important role in next generation smart environments. We have tried our best to provide researchers a comprehensive review in the field of illumination and pose invariant face recognition along with the recognizers/classifiers that have been used.

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