Pose and Age Invariant Face Recognition Algorithms: A survey

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Abstract

Among the various challenges faced by current face recognition algorithms varying pose and aging are two challenges. The difference in face images caused due to rotations are larger than the inter-person differences. This particular challenge has a great potential in applications that involve uncooperative subjects. Facial aging is a relatively new challenge added into the set of challenges faced by current face recognition algorithms. Facial aging is a complex process that affects both the 3D shape of the face and its texture. This challenge has not received as much assistance as the other challenges. In this paper a survey of pose invariant and age invariant face recognition algorithms has been undertaken.

1 INTRODUCTION

Face recognition system has clear advantages over other biometric techniques used for recognition. Face recognition algorithms face some key challenges that it must overcome, such as - variations in illumination, head rotation, facial expression, aging and occlusion. There is no one algorithm that can overcome all these challenges which justifies the extensive research that is done in this field.

A good face recognition system should perform well even in an uncontrolled environment and when uncooperative subjects are involved. Pose variation is one of the key challenges and it attracts a lot of interest from the Computer Vision and Patter Recognition community. A few methods have been proposed in solving the problem of pose variation but none of them are free from limitations and do not solve the problem completely.

Another challenge that has been recently attracted attention is aging. As time passes by the human face undergoes changes due to aging. These changes are not uniform in all cases.These changes include change in Skull size, facial texture, facial hair growth, gain or loss of fat across face, presence of glasses, etc. These changes affect the performance of any face recognition system.

The two challenges Pose variation and Aging have not been completely overcome. Extensive research is carried out to overcome these problems by the computer vision field.

2 POSE INVARIANT ALGORITHMS

Pose invariant face recognition algorithms are particularly useful in an uncontrolled environment and uncooperative subjects. For example, face recognition is important for providing security in public places. It is possible to maintain a database of the people in the public place at any given point of time. Using this it can be determined whether a person of interest is present or not.

The most straightforward approach to this problem would be to maintain a gallery of images of each individual in all possible poses to compensate for the pose variation. However, it is tedious and difficult to gather this gallery of images for each individual. For example, if the database maintains only a single image per person in its database. This leads us to the conclusion that the pose variation problem involves images of a subject that have a different pose as compared to the image stored in the database. If an algorithm is pose invariant, this makes face recognition a non-intrusive technique. This gives it a critical advantage over other biometric techniques.

Pose invariant face recognition algorithms can be classified into two categories: 2D techniques, 3D methods.

2.1 2D techniques

2D techniques can be further classified into three groups - (a) pose-tolerant feature extraction, (b) real view-based matching, (c) 2D pose transformation. The approaches that involve pose-tolerant feature extraction either find face classifiers or perform pre-processing of linear/non-linear mapping in the image space which are robust to variations in pose. Real view-based matching works with multiple images to cover all possible poses for face recogniser. When multiple images of a person are not present in the database real view-based matching performs poorly. In these cases 2D pose transformation can be used to alter the appearance of a known face image to unknown poses to build virtual views to enhance the face recognizer.

2.1.1 Real View-based matching:

In this approach multiple images(real view) of each individual are needed. General face recognition algorithms can tolerate small pose variations (e.g., 15° rotation), this reduces the number of real views needed. Either the raw images or transformations of them are used in the recognition phase to provide tolerance for pose variation. These type of algorithms depend on the recognizer to match the probe views with the views in gallery and provide the closest appearance match.

Beymer [1] proposes an approach to represent faces with templates from multiple model views that cover different poses from the viewing sphere. The recognizer locates eyes and nose features, using these locations it registers the input with model views and uses correlation on model templates to find the best match. This method is simple and gives a good performance but a large number of gallery images per person needs to be collected.

Singh et al. [2] describe a mosaicing scheme that generates a composite face image during enrollment based on the evidence provided by frontal and semi-profile face images of an individual. Face mosaicing eradicates the need to store multiple face images to represent multiple poses of a user's face. Multi-resolution spinning is used to combine the side profiles with the frontal image to generate a composite image of the user. A slightly modified C2 algorithm proposed by Serre et al. is used to compare a probe face image with the gallery face mosaic. In this method a single panoramic view is required but distortions exist in this view.

2.1.2 Pose Transformation in image space:

It is inefficient and redundant to collect multiple images of an individual in different poses for real-view matching. One alternative is to generate virtual views to replace the need for real views. The virtual view generation can be done in 2D space as pose transformation or in 3D space as 3D face reconstruction and projection.

Beymer and Poggio [3] use 2D example views of prototype faces under different rotations. Some techniques are used to rotate the single real view which is available. The set of one real and multiple virtual views are used in a view-based pose-invariant face recognizer. This method is simple, fast and works with a single gallery image. But it has been shown that the pose tolerance provided by this method is small.

Cootes et al. [4] proposed Active shape model (ASM) which is one of the most effective approaches in face recognition. González-Jiménez and Alba-Castro [5] applied the concept of ASM to generate virtual views in different poses using the point distribution model (PDM) they proposed. Both the probe image and the gallery image are labelled with their respective point distribution map. Both the maps are projected onto the PDM and the pose parameter of the gallery image is replaced by that of the probe image. The next step is to recover the synthetic point distribution map which has all image information from the gallery image except pose, which is of the probe image. Thus the pose variation is compensated and EBGM recognizer is used to perform face recognition.

Active appearance models are an extension of ASM. They model the variations of shape represented by point distribution and the textures represented by pixel intensities at the same time. Vetter [6] further extended the concept of AAM by using the optical flow of pixel-wise correspondence between two images in different poses instead of sparse point distributions.

Kahraman et al. [7] enhanced the pose tolerance offered by AAM by increasing the size of the training set with synthetic pose variant face images. During pose normalisation, displacements of the landmarks were recorded while assuming that the landmark's coordinate ratios between rotated view and frontal view are constant.

2.1.3 Pose Transformation in feature space:

Pose tolerance can be done in feature space instead of image space. The feature space transformed data cannot be displayed virtually as face images in the image space. One example of face recognition using feature space transformation is kernel tricks. It maps face images into a higher dimensional non-linear feature space non-linearly. Various kernel based face recognizers like kernel PCAs [8,9] and kernel FDA [10] have been proposed. Liu et al. [11] used Gabor wavelets to pre-process the facial images and extended kernel polynomials to obtain fractional powers in kernel PCA. Kernel tricks uses non-linear transformation encapsulated in dimension reduction. It is simple and fast. However the existing kernel functions are not specific to pose variations and the choice of kernel functions are limited.

Prince et al. [12] proposed a linear statistic model, which can be used to describe pose variations on face images. This model performed very well even under large pose variations. Lee et al. [13] proposed a linear pose transformation method in feature space. The first step was to extract features from input face images at different poses. Next the extracted features were used to transform an input pose image into its corresponding frontal pose image.

2.2 3D methods

Face recognition using 3D models has been one of the most successful approaches recently. They are particularly useful when pose and illumination variations are involved. These approaches are successful because human faces are 3D objects with a particular structure. 3D face models can be reconstructed using either feature or image based techniques. The basic pose recovery method was proposed [14]. It is based on a generic cylindrical shape of the face. Images in arbitrary positions are mapped onto the cylindrical shape and the frontal virtual views are recovered. Given a rotated input probe image, the eyes are first detected then the face boundary and vertical symmetry line. All this is included in the normalisation phase of the implementation. Further, PCA is used as a face recognizer and provided very good results.

2.2.1 Feature-based 3D face reconstructions:

The process of estimating 3D shape information from 2D images is called 3D reconstruction and extensive research is being done in this area. The reconstruction process works on certain properties that can be obtained from a 2D image for example, image intensities, edges, corners, etc. Feature-based 3D face reconstruction uses face shapes from the 2D locations of facial features (eyes,nose,etc).

Jiang et al. [15] extracted facial features for the reconstruction of personalised 3D face models from a single frontal face image and used it for recognition. In this method Bayesian shape localisation is used detect facial features automatically. 100 3D face scans were used as training data. Facial features from input probe image and training data were extracted to find principal components. Personalised 3D face shapes were reconstructed and the facial textures were directly mapped onto the face shape to generate virtual views.

Zhang et al. [16,17] proposed a method in which two orthogonal gallery images per face is used to reconstruct personalized 3D face shape by making use of multi-level quadratic variation minimisation. 3D face shape is reconstructed by minimising a cost function of quadratic variations of 3D surfaces that ensures a second order smoothness.

In these approaches personalised 3D face shapes are reconstructed from a set of facial features specified on facial images. The facial features are sparse and may not always provide the information needed. However a pixel-wise feature set should be used to achieve better reconstruction quality.

2.2.2 Image-based reconstruction:

In this type of reconstruction the relationship between the intensity of pixels and their shape/texture properties are studied. Using reflectance models it is possible to estimate 3D face geometry and fface surface properties.

Blanz and Vetter [18] proposed a face recognition system that makes use of 3D morphable model based on image-based reconstruction and prior knowledge of faces. The prior knowledge is learnt from a set of 3D face scans. Shape and texture information is spanned into different eigen spaces where PCA is performed to form a 3D morphable model. Principal components of shape model and texture model are obtained and they are used to reconstruct personalised 3D models used for face recognition. This method needs only a single image for reconstruction. However the results maybe unstable.

Georghiades et al. [19] proposed illumination cone models that performed face recognition successfully even under pose and illumination variations. This method makes use of photometric stereo. Using a set of frontal face images under different illumination conditions, face shape and surface reflectance property are reconstructed. Virutal views under novel illumination and viewing condition can then be generated. This method gives a very high success rate. One disadvantage of this method is that it requires multiple images under certain restrictions.

3 AGE INVARIANT ALGORITHMS

Aging is a factor that has recently attracted attention with respect to the face recognition research. This factor is both complex and unpredictable as it involves a lot of changes to the properties of the face like skull size, facial texture, facial hair growth, etc. Most algorithms are not designed to overcome this particular challenge. Hence there is an increased interest in overcoming the challenge presented by aging.

Lanitis et al. [20] proposed a model based face recognition that projects a age progressive training set onto a model space. The variation caused due to aging effect is isolated using an aging function which can be operated on the model parameters to produce an image representing the actual age. After estimating the age the probe and training image parameters are obtained at the target age. These parameters are used as feature vectors for recognition.

Wang et al. [21] used an age simulation model (ASM) which transforms image to a target image for recognition. ASm model is used and the shape features are extracted and transformed to texture image. Shape Eigen face and Texture Eigen face are obtained by applying PCA on shape and texture image respectively. Estimation of age is done by using a polynomial aging function along with K-means classification. Feature vector at target age is synthesized by using the estimated age and vector creating function. Shape and Texture vectors are reconstructed and together they produce a facial image which is then used for recognition.

Li et al. [22] proposed a model that creates a Q stack classifier which is basically a framework of stacking classifications with quality measures (in this case age). Multi classifier scheme includes Global PCA patterns and Local Ternary Patterns (LTP) for representing features. Log Likelihood Ratio (LLR) are calculated for PCA and LTP phase and they are combined to form the evidence vector. After normalizing, the vector is given as an input to SVM based kernels for verification.

Li et al. [23] proposed a discriminative model that densely samples location feature description scheme using Scale Invariant Feature Transform (SIFT) and Multi Scale Local Binary Pattern (MLBP) as descriptors and Multi Feature discriminant Analysis (MFDA) as classifier. To extract features the image is normalised and divided into a set of overlapping patches. MFDA is used to reduce the dimensions. PCA is applied to construct 10 random PCA subspace and they are whitened to get rid of intra personal variations. In testing, each test image is divided into slice and classified. Using the min-max score normalization the outputs are normalized.

4 CONCLUSION

Pose variation is a prominent problem for face recognition and it has received a lot of attention in recent times. Many techniques have been proposed to overcome pose variation or at least provide some level of tolerance to pose variation. But complete tolerance for face recognition has not been achieved as of now, which justifies the continuing research and efforts in this area. In this paper 2D and 3D techniques that actively try to overcome pose variations have been reviewed and their disadvantages and advantages have been listed.

Based on this review, some conclusions can be arrived at and they are summarised in this section. Prior knowledge of human faces play a big role in overcoming pose variations in face recognition. 3D face recognition approaches can handle larger pose variations as compared to 2D techniques. Non-linear mapping can find a feature space that is best suitable to represent pose variations but the current research stage is limited to fundamental mapping functions.

Also in this paper a brief summary of various age invariant face recognition algorithms has been provided. This particular challenge has not received as much as attention and interest as the other challenges. But as we move closer and closer to developing a near perfect face recognition system Aging will become more prominent as it would be key in determining how long the system can last.

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