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REVIEW ARTICLE

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POSE INVARIANT FACE RECOGNITION: A SURVEY

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ABSTRACT

Face recognition now becomes one of the most active researches in computer vision and pattern recognition. All the current face recognition methods fail when pose variations are considered. To overcome this problem pose invariant face recognition methods are used. For invariant poses face recognition can be done by using Markov Random Fields. In the proposed approach, the input face image is divided in to a grid of overlapping patches, and globally optimal set of local warps is estimated to synthesize the patches at the frontal view. A set of possible warps for each patch is obtained by aligning it with images from a training database of frontal faces. The alignments are performed efficiently in the Fourier domain using an extension of the Lucas-Kanade algorithm that can handle illumination variations. The problem of finding the optimal warps is then formulated as a discrete labeling problem using an MRF. The reconstructed frontal face image can then be used with any face recognition technique. Local Gabor Binary Pattern was selected as the face recognizer due to its effectiveness. The virtual frontal views are reconstructed from non frontal face images by using Markov Random Fields. This literature survey gives in detail about the various pose invariant face recognition methods.

Key words: Eigen faces, Fisher faces, Morphable Model, Active Appearance Model, Light fields.

INTRODUCTION

Face recognition is one of the most important biometric techniques and has the advantages of being passive and natural as compared other biometric techniques like finger print recognition and iris recognition. But pose variations are most prominent unsolved problem in face recognition. A few promising methods are proposed to solve the problem of recognizing faces in arbitrary poses such as 3D morphable model [1],Active Appearance Model[2],Eigen faces and Fisherfaces[7],Eigen Light Fields[10] etc. But this methods are not free from limitations and is not able to fully solve the problems of pose in face recognition. Face recognition across pose refers to the recognition of face image in different poses by computers. Pose variations becomes serious challenges in current face recognition system due to the complex 3D structures and surface reflectivity of human faces. The most serious challenging task in pose invariant face recognition algorithms is to obtain the natural characteristics of the faces which are free from pose variations. Pose invariant face recognition can be carried out in 2D and 3D models. Many algorithms are implemented in 2D and 3D models to obtain better results.

The performance of face recognition algorithms degrades when there are variations in the face with pose, illumination and expressions. Face recognition algorithms like Eigen faces and Fisher faces can be applied to 2D faces [7].This algorithms are used in pose variations but produces low recognition rates. Face recognition differ for 2D and 3D techniques. Face recognition across pose and illumination can be handled by the algorithm which simulates the process of image information in 3D space using computer graphics and it estimates the 3D faces and texture of faces from single images. The main drawback of this algorithm is that it requires many manually selected landmarks for initialization. Furthermore; the optimization process is computationally expensive and often converges to local minima due to a large number of parameters that need to be determined. Another recently proposed method [3] estimates the facial albedo and poses at the same time using a stochastic filtering framework and performs recognition on the reconstructed frontal faces. The disadvantages of this approach lies in the use of an iterative algorithm for updating the albedo and pose estimates leading to accumulation of errors from step to step.

Given a nonfrontal face image, the 3D pose normalization algorithm [4] uses the pose dependent correspondences between 2D landmarks points and 3D model vertices inorder to synthesize the frontal view. The main drawback of this method is the dependence on the fitting of landmarks using the Active Appearance Model (AAM) [2].On the other hand, 2D techniques do not require the 3D prior information for performing pose-invariant face recognition. The AAM algorithm propose by Coots et al [2] fits a statistical appearance model to the input image by learning the relationship between perturbations in the model parameters and the induced image errors. The main disadvantages of this approach are that each training image requires a large number of manually annotated landmarks. Gross et al. [10] proposed the Eigen light-field(ELF) method that unifies all possible appearances of faces in different poses within a 4D space (two viewing directions and two pixel positions). However, this method discards shape variations due to different identity as it requires a restrict alignment of the image to the light field space. Recently, Prince et al. [5] use and affine mapping and pose information to generate observation space from the identity space. Patch-based approaches for face recognition under varying poses have received significant attention from the research community. These methods were motivated by the fact that 3D face is composed of many planar local surfaces and thus, an out-of-plane rotation, although nonlinear under 2D imaging projection, can be approximated by linear transformations of 2D image patches. As a result, modeling a face as a collection of sub regions patches is more robust to pose variations than the holistic appearance.

LITERTURE REVIEW

Eigen faces and Fisher faces: On seeing that correlation methods are computationally expensive and require enormous amount of storage, it is normal to go behind dimensionality reduction schemes. A technique that is commonly used for dimensionality reduction in computer vision mostly in face recognition is principal components analysis (PCA) [16]. This technique selects in linear projection and maximizes the scatter of all projected samples by dimensionality reducing it. If the image is linearily projected with Eigen vectors of same dimension as in the original images, then it is known as Eigen faces. Here the classification is performed by means of a nearest neighbor classifier in the reduced feature space and then the Eigen face method is equivalent to the correlation method. A drawback of this method is that there is unwanted information in the scatter which is maximized not only to the between class scatter that is helpful for classification, but also for the within-class scatter for classification purposes. Thusif PCA is applied to face image under varying illumination, the projection matrix will contain Eigen face which maintains the projected features space. The points that are present in the projected space will not clustered and not as good the classes that are grimed together. The Eigen face method has the advantages that, the variations within classes lies in a linear subspace of the image space.Consequently,the classes are convex and linearly sepearable.Dimensionality reduction can be done using linear projection and can conserve linear sepearability.But Dimensionality reduction is stilla problem in recognizing a face as it is insensitive to lighting conditions.So,class specific linear methods can be used for dimensionality reduction and simple classifiers to reduce the feature space,as a result better recognition rates can be obtained than the Eigen face method. Fisher's Linear Discriminant (FLD) [7] is used as a class specific method, it can shape the scatter inorder to make it additional consistent for classification. This method has low error rate and less computation time. The disadvantage of Fisher faces method is that it produces low recognition rates.

Active Appearance Model: Analysis applied to the image frame and is generated by applying scaling and offset to the intensities.Then, correlations are made between shape and texture and a combined appearance model is generated. The reconstruction can be obtained by producing the texture ina meanshaped patch then warping it consequently to facilitate the model points lay on the image points. The parameters of appearance model and shape transformation gives the shape of the image patch which are defined by the position of the model points in the image frame so as to represent the model. This method makes use of correlation between errors in model parameters and the remaining texture errors. The disadvantage of this method is that it cannot be used for tree like structures with varying number of branches.

Morphable Model: Morphable model of 3D faces captures the class specific properties of the faces.These properties are learned automatically from a dataset of 3D scans.The face recognition systemcombines deformable 3D models with a computer graphics simulation of projection and illumination.This makes intrinsic shape and texture fully independent of extrinsic parameters.Given a single image of a person, the algorithm automatically estimates 3D shape, texture, and all relevant 3D scene parameters. In this framework, rotations in depth or change of illumination are very simple operations, and all poses and illumination are covered by a single model. Illumination is not restricted to Lambertian reflection, but takes into account specular reflections and cast shadows, which have considerable influence on the appearance of human skin. This approach is based on a morphable model of 3D faces that captures the class-specific properties of faces. These properties are learned automatically from a dataset of 3D scans. The morphable model represents shapes and textures of faces as vectors in a high-dimensional face space, and involves a probability density function of natural faces within face space. This method estimates all 3D scene parameters automatically, including head position and orientation, focal length of the camera and illumination direction. This is achieved by a new initialization procedure that also increases robustness and reliability of the system considerably. The new initialization uses image coordinates of between six and eight feature points. The morphable face model [1] is based on a vector space representation of faces that is constructed such that any bowed combination of shape and texture vectors. Continuous changes in the model parameters generate a smooth transition such that each point of the initial surface moves toward a point on the final surface. Dense point-to-point correspondence is crucial for defining shape and texture vectors. 3D morphable model is prevailing and adaptable representation of human faces. 3D morphable model prevailing andadaptable representation for human faces. The disadvantage of this method is it requires many manually selected land marks for initialization.

Eigen light field method: In many face recognition application scenarios the pose of the probe and gallery images are different. The gallery image might be a frontal "mug-shot" and the probe might be a ¾ view captured from a surveillance camera in the corner of the room. The number of gallery and probe images may also vary. The gallery may consist of a pair of images of each subjects, perhaps a frontal mug-shot and full profile view, like the images typically captured by police departments. The probe may be a similar pair of images, a single ¾ view, or even a collection of views from random pose. Until recently face recognition across pose (i.e. when the gallery and probe have different has received very little attention in the literature. Algorithms have been proposed which can recognize faces or more general objects at a variety of pose. Most of these algorithms require gallery images at every pose, however. Algorithms have been proposed which do generalized across pose but this algorithm computes 3D head models using a gallery containing a large number of images per subject captured with controlled illumination variation. It cannot be used with arbitrary galleries and probes. Note, however, that concurrent with this work there has been a growing interest in face recognitionacross pose. This method can use any number of gallery images captured at arbitrary poses, and any number of probe images also captured with arbitrary poses. A minimum of 1 gallery and 1 probe image are needed, but if more images are available the performance of our algorithm generally gets better. This algorithm operates by estimating (a representation of) the light-field of the subject's head. First, generic training data is used to compute an Eigen-space of head light-fields, similar to the construction of Eigen-faces [7]. Light-field is simple used rather than images. Given a collection of gallery or probe images, the projection into the Eigen-space is performed by setting up a least squares problem and solving for the projection coefficients similarly to approaches used to deal with occlusions in the eigenspace approach [7]. This simple linear algorithm can be applied to any number of images, captured from poses. Finally, matching is performed my comparing the probe and gallery light-fields using a nearest neighbor algorithm. The light-field specifies radiance of lightalong all rays in the scene hence; the light-field is the set of all possible features that could be used by an appearance-based algorithm. Any number of images can be used, from one upwards, in both gallery and probe sets. The light-field correctly rerenders images across pose. This algorithm can use any number of gallery images captured at arbitrary pose and number of probe images also captured with arbitrary poses.

Tied Factor Analysis: Face recognition algorithms perform very unreliably when the pose of the probe face is different from the gallery face: typical feature vectors vary more with pose than with identity.A generative model that creates a one to many mapping from an idealized identity space to the observed data space is proposed [5].In identity space the representationfor each individual does not vary with pose.The measured feature vector generated by a pose contingent linear transformationbut the of the identity variable is modeled in the presence of Gaussian noise.This model is termed as tied factor analysis.The choice of the linear transformation depends on the pose but the loadings are constant for a given individual. Expectation-Maximization (EM) algorithm is used to estimate the linear transformations and the noise parameters in the training data. A probabilistic distance metric that allows a full posterior over possible matches is proposed. A novel feature extraction process is introduced and investigates recognition performance by using the FERET,XM2VTS and PIE databases.This method is probabilistic and provides a posterior probability for the matching to a gallery or for whether the two faces match or belong to different people. The algorithm is based on a generative model that describes how an underlying poses invariant representation created the pose varying observed data.The advantages of this method are that the system is fast and recognition rate is high.The main disadvantages are complexity is high and accuracy is less.

PROPOSED METHOD

A patch based method for synthesizing the virtual frontal view from a given non frontal face image using MRFs and an efficient variant of the BP algorithm is proposed.By aligning each patch in the input image with the images from a training database of frontal faces,a set of possible warps is obtained for the patch.The alignments are then carried out efficiently using an illumination invariant extension of the Lucas-Kanade (LK)algorithm in the frequency domain.The objective of the algorithms is to find the globally optimal set of local warps that can be used to predict the image patches at the frontal view.This goal is achieved by considering the problem as a discrete labeling problem using an MRF.

The reconstruction of virtual frontal view from a given non frontal face image using Markov Random Field is proposed.Frontal and non frontal features are generated by SIFT algorithm.This features are input to SVM classifier.It will classifies frontal and non frontal images.If the image was non frontal, it was transformed to frontal view using Markov Random Field.The proposed method is a patch based method. The input face image is divided into a grid of overlapping patches. A set of local warps is estimated each patch by aligning it with the corresponding patches of the training images using Lucas Kanade algorithm in frequency domain. The objective of the Lucas Kanade algorithm is to generatea set of local warps that can be used to predict the image patches at the frontal view. In order to synthesize the virtual frontal view, each patch is transformed using the warp and all the transformed patches are combined together to create a frontal face image. The advantages of this approach are that it does not require manually selected facial land mass or head pose estimation. The recognition rate is also high for this method. The goal of the algorithm is to find a globally optimal set of warps for all the patches in the input image such that we can predict the input face at the frontal pose by transforming these patches using the obtained warps. This problem can be turned into a discrete labeling the problem with a well defined objective functions using a discrete MRF. In this approach, the training data base need not contain the frontal images of the person in the input image I. Local Gabor Binary Pattern(LGBP) [18] was selected as the face recognizer due to its effectiveness. In this method, a feature vector is formed by concatenating of the histograms of all the local Gabor magnitude pattern maps over an input image. The histogram intersection is used as the similarity measurement in order to compare two feature vectors.

CONCLUSION

Reconstruction of the virtual frontal view from non frontal images using Markov Random Field is developed. By dividing the input image into overlapping patches, a globally optimal set of local warp can be estimated to transform the patches to frontal view. Each patch is aligned with images from a training database of frontal faces in order to obtain a set of possible warp for that node. By using an extension of the L K algorithm that accounts for substantial illumination variations, the alignment parameters are calculated efficiently in the Fourier domain. The set of optimal warp is obtained. The set of optimal warps is obtained by formulating the optimization problem as a discrete labeling algorithm using a discrete MRF and an efficient variant of the BP algorithm. The energy function of the MRF is also designed to handle illumination variations between different image patches. The advantage of the proposed method is that it does not require manually selected facial landmarks or head pose estimation for initialization.

FUTURE TRENDS

In the future, the possibility of synthesizing the probe image not only to the frontal pose, but also to other viewingangles may be developed. This will help the algorithm become more robust to large poses in the input images. A pyramidal implementation of the LK alignment algorithm can also be incorporated in to the proposed approach in order to reduce the effect of patch size on the results.

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