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Face recognition under pose variation with local Gabor features enhanced by Active Shape and Statistical Models

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ABSTRACT

Face recognition is one of the most active areas of research in computer vision. Gabor features have been used widely in face identification because of their good results and robustness. However, the results of face identification strongly depend on how different are the test and gallery images, as is the case in varying face pose. In this paper, a new Gabor-based method is proposed which modifies the grid from which the Gabor features are extracted using a mesh to model face deformations produced by varying pose. Also, a statistical model of the scores computed by using the Gabor features is used to improve recognition performance across pose. Our method incorporates blocks for illumination compensation by a Local Normalization method, and entropy weighted Gabor features to emphasize those features that improve proper identification. The method was tested on the FERET and CMU-PIE databases. Our literature review focused on articles with face identification with wide pose variation. Our results, compared to those of the literature review, achieved the highest classification accuracy on the FERET database with 2D face recognition methods. The performance obtained in the CMU-PIE database is among those obtained by the best methods published.

1. Introduction

Face recognition has a wide range of possible applications from person identification and surveillance to electronic marketing and advertising for selected customers. Face recognition in real time is a topic of active research, and several methods have been proposed to perform this task [1–4].

Most studies focus on frontal face recognition, reaching high accuracy on internationally available face databases. An important number of studies have focused directly on face recognition under the assumption that the face has already been localized [5,6].

Among the most widely cited methods for face recognition based on feature extraction are Eigenfaces [7], based on Principal Component Analysis (PCA), Fisherfaces [8], based on Linear Discriminant Analysis (LDA), and methods based on Independent Component Analysis (ICA) [9,10]. In [11], the Local Binary Pattern (LBP) method was proposed, in which the face image is divided into square windows where a binary code is generated whenever a pixel exceeds the value of the average within the window. Also some papers report addressing the problem of face recognition in low resolution images [12]. This method uses a multidimensional scaling approach where low resolution images are embedded in a Euclidean space which is used to perform the matching between gallery and test images. Gabor wavelets [13–16] have been used to extract local features achieving outstanding results in face recognition.

Among the methods based on Gabor Wavelets are the Elastic Bunch Graph Matching (EBGM) method [17], the Gabor Fisher Classifier (GFC) [18], the Local Gabor Binary Pattern Histogram Sequence (LGBPHS) [19], the Histogram of Gabor Phase Patterns (HGPP) [20], Local Gabor Textons (LGT) [21], Learned Local Gabor Pattern (LLGP) [22], Local Gabor Binary Pattern Whitening PCA (LGBPWP) [23], and the Local Matching Gabor method (LMG) [24–27]. In [28], the face was divided into patches without overlap, and then the best patches were selected and weighted with an LDA strategy in a greedy search. Finally, the local scores of the patches were combined with a global score obtained from the low frequency components of the FFT applied to the whole face, including its external boundary. Magnitude and phase Gabor features were combined in [29]. The LBP operator was used on the Gabor magnitude features and the LXP operator (Local Xor Pattern) on the Gabor phase features. Then, the face was divided into regions, and histograms of each region were computed on

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LGBP and LGXP features. Every region dimensionality was reduced using LDA, and finally the regions were compared with cosine distance. In [30], Gabor features in face images at higher and lower resolutions were used.

Face recognition under varying pose continues to be an area of active research. There are various approaches to solving this problem using 2D as well as 3D methods. Some methods use a single face as input and build a 3D model called the 3D Morphable Model [31–33]. The 3D Morphable Model is based on a vector space representation of faces built using vectors of shape and texture. The parameters of the models are computed using a set of Eigen vectors obtained previously by training with images from 3D scans. A fully automatic face frontalization method using a 3D model was introduced in [34]. It works for poses varying up to $\pm 45^\circ$ on the yaw axis and $\pm 30^\circ$ on the tilt axis. In [35], an automatic method was developed to find correspondences between 2D facial feature points and a 3D face model. The 3D face model built was then rotated to generate the frontal view.

In our literature review, we focused on 2D methods because they are widely used and are applicable in real time. Nevertheless, the goal of this work is to develop a more accurate recognition method for rotated faces, not to create the fastest possible implementation. There are several methods that use 2D techniques to perform face recognition across pose. A method that performs frontalization by dividing the face into different components is presented in [36]. Several methods use Active Appearance Models (AAM) to frontalize the face [37–39] and perform the match with a frontal face from a gallery set. In [40] the image is divided into non-overlapping patches and then a statistically aligned model is built for each patch to perform a warping in the region. Using the same idea of patches, the image is divided into non-overlapping patches and a statistical model is constructed on each one at the score level [41]. This method models how the matching score varies when the input face pose is at a certain angle. A face recognition Gabor-based method using a regressor with a coupled bias-variance tradeoff is proposed in [42]. In this method, a statistical model is built at the score level, as in [41]. Some methods use face representations in a latent space to perform the recognition [43,44]. In [45] a dictionary learning method designed for face recognition is presented.

Several recent papers have shown that the Local Matching Gabor (LMG) method [24] and its variants [25,26] reach the best results for frontal face recognition. In the LMG method, a total of 4172 Gabor jets are employed to extract features at five different spatial resolutions and eight different orientations. A Borda count method is used to compare the inner products between the Gabor jets from the input face image and the Gabor jets from faces in the gallery [46]. In our previous work based on Gabor-feature face classification [26], faces are normalized using the eye position for coronal axis rotations (on the same face plane). Also, our previously proposed method included weights for the Gabor jets using an entropy measure and a preprocessing step with Local Normalization (LN) yielding results that are among the best face classification results reported on the FERET and AR databases [25,26,47]. Our method performed competitively with other published methods on face occlusions and in the presence of noise. Nevertheless, for face poses with increasing angles out of the face plane, the face normalization step loses the correction effect and, as in most 2D face recognition methods, performance declines significantly. For example, methods reaching near 100% for frontal face recognition may drop by up to 40% with pose variations $\pm 60^\circ$ [40].

In this paper, a new method for face recognition under pose variation is proposed. This method uses Active Shape Models (ASM) [48] to reposition Gabor jets on the face according to face pose. Because of local changes in the 2D face image with varying pose, we also use a local statistical model [41] to compensate for face pose. These new extensions to our previous LMGEW method that uses entropy-weighted features and fusion among LMG and LBP features [26] yield significant improvements in face recognition under varying pose. We tested our method and its variants using the FERET and CMU-PIE databases, which are among the most used databases to evaluate methods of face recognition across pose. The FERET database has pose variation between $\pm 60^\circ$, and has been used in many recent publications of face recognition across pose [33–35,41–43,49]. According to our literature review, our method reached the highest classification performance published in the FERET database with 2D face recognition methods. The CMU-PIE database has pose variations near $\pm 90^\circ$ and also has been used in most recent publications of face recognition across pose [33–35,42,43,49–51]. The performance of our method on the CMU-PIE database is among those that reached the highest classification performance.

2. Methodology

Our proposed model for face recognition based on local matching Gabor consists of three main modules [24]: image alignment using ASM, feature extraction through Gabor jets

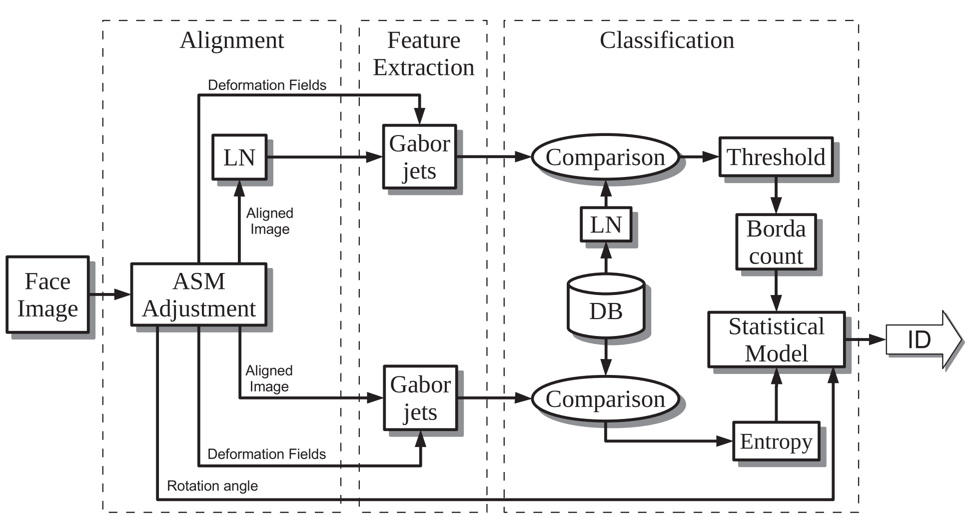

Fig. 1. The proposed method consists of three main modules: image alignment based on ASM, feature extraction through Gabor jets computation, and classification using entropy weights and statistical model matching.