High-Resolution Face Verification using Pore-Scale Facial Features

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Abstract- *Pose-invariant face-verification method, which is robust to alignment errors, using the HR information based on pore-scale facial features. A new key point descriptor, namely, pore-Principal Component Analysis (PCA)- Scale Invariant Feature Transform (PPCASIFT)—adapted from PCA-SIFT—is devised for the extraction of a compact set of distinctive pore-scale facial features. Having matched the pore scale features of two-face regions, an effective robust-fitting scheme is proposed for the face-verification task. Experiments show that, with one frontal-view gallery only per subject, our proposed method outperforms a number of standard verification Methods and can achieve excellent accuracy even the faces are under large variations in expression and pose.*

Keywords- Face image representation, face verification, Aggregation algorithm, face matching, pore matching.

I. INTRODUCTION

Face verification is a one-to-one matching problem, which validates (or not) the claimed identity of a person. The claim is either accepted or rejected based on a certain threshold. Face verification has been widely used in security systems and electronic commercial systems due to the easy access to face acquisition.

Many of the face recognition algorithms are based on holistic facial features, which project the lexicographic ordering of raw pixels onto a certain subspace. Examples include Eigen faces, Fisher faces, locality preserving projection (LPP), etc.

The local features are extracted from local regions or parts of the images only, based on some transformations or descriptors. Commonly used local features include Gabor wavelets, local binary pattern (LBP), etc. The Gabor representation of faces is similar to that of the human visual system, which is robust against illumination and expression changes. LBP was originally designed for texture classification, and was introduced to face recognition. The representation is invariant to illumination changes and rotation. Recently, the Local Phase Quantization (LPQ) operator was proposed for the recognition of blurred faces based on quantizing the Fourier transform phase in local neighborhoods.

Another HR face-recognition method was proposed based on facial-marker detection. This method uses LoG blob detection for marker extraction after applying the active appearance model (AAM) to detect and remove facial features such as the eyes, nose, mouth, etc. However, only a very limited quantity of marker-scale features can be extracted from human faces, so the features only complement the traditional methods.

II. REVIEW OF THE PARALLEL-BLOCK AGGREGATION ALGORITHM

The new robust fitting scheme, namely parallel-block aggregation, is proposed to refine the candidate constrained matching results. As the keypoint/block matching may result in one-to-many or many-to-many matches, matching from gallery faces may differ from that from testing faces. In our experiments, we only consider the block matching from a testing face image to a gallery face image.

In order to achieve a robust and accurate face verification performance, we propose a new, robust fitting scheme, namely parallel-block aggregation.

The proposed method is robust to alignment errors and poses variations, while the gallery set requires only a single image per subject. The PSIFT and PPCASIFT features are highly distinctive, and PPCASIFT can efficiently reduce the computational time of the matching process to about 9% of that of PSIFT, while asimilar performance level can be maintained.

PPCASIFT descriptor:

A new descriptor is proposed, namely Pore-Principal Component Analysis (PCA)-Scale Invariant Feature Transform (SIFT) (PPCASIFT), which can achieve a similar performance to the Pore-SIFT (PSIFT) descriptor but which requires only 9% of the PSIFT descriptor’s computation time in the matching stage. Most pore-scale facial features are similar to each other when they are observed individually, because most of them are blob-shaped, and the surrounding region of each keypoint has almost the same color. However, the spatial distribution of pores on the skin is distinctive. To improve the method's efficiency, we propose a more compact key point descriptor in this paper, namely Pore-PCA-SIFT (PPCASIFT), which is adapted from PCA-SIFT and which uses PCA to reduce the dimensionality of the descriptor.

III. IMAGE PROCESSING

Image processing is a physical process used to convert an image signal into a physical image. The image signal can be either digital or analog. The actual output itself can be an actual physical image or the characteristics of an image. The most common type of image processing is photography. In this process, an image is captured or scans using a camera to create a digital or analog image. In order to produce a physical picture, the image is processed using the appropriate technology based on the input source type. In digital photography, the image is stored as a computer file. This file is translated using photographic software to generate an actual image.

In imaging science, **image processing** is processing of images using mathematical operations by using any form of signal processing for which the input is an image, a series of images, or a video, such as a photograph or video frame the output of image processing may be either an image or a set of characteristics or parameters related to the image. Most image-processing techniques involve treating the image as a two-dimensional signal and applying standard signal-processing techniques to it. Images are also processed as three-dimensional signals where the third-dimension being time or the z-axis.

Image processing usually refers to digital image processing, but optical and analog image processing also are possible. This article is about general techniques that apply to all of them. The acquisition of images (producing the input image in the first place) is referred to as imaging.

Closely related to image processing are computer graphics and computer vision. In computer graphics, images are manually made from physical models of objects, environments, and lighting, instead of being acquired (via imaging devices such as cameras) from natural scenes, as in most animated movies. Computer vision, on the other hand, is often considered high-level image processing out of which a machine/computer/software intends to decipher the physical contents of an image or a sequence of images (e.g., videos or 3D full-body magnetic resonance scans).

In modern sciences and technologies, images also gain much broader scopes due to the ever growing importance of scientific visualization (of often large-scale complex scientific/experimental data). Examples include microarray data in genetic research, or real-time multi-asset portfolio trading in finance.

The colours, shading, and nuances are all captured at the time the photograph is taken the software translates this information into an image. When creating images using analog photography, the image is burned into a film using a chemical reaction triggered by controlled exposure to light. The image is processed in a darkroom, using special chemicals to create the actual image.

This process is decreasing in popularity due to the opening of digital photography, which requires less effort and special training to product images. The field of digital imaging has created a whole range of new applications and tools that were previously impossible. Face recognition software, medical image processing and remote sensing are all possible due to the development of digital image processing. Specialized computer programs are used to enhance and correct images.

Signal processing is a discipline in electrical engineering and in mathematics that deals with analysis and processing of analog and digital signals , and deals with storing , filtering , and other operations on signals. These signals include transmission signals , sound or voice signals , image signals , and other signals e.t.c.

Out of all these signals , the field that deals with the type of signals for which the input is an image and the output is also an image is done in image processing. As it name suggests, it deals with the processing on images. It can be further divided into analog image processing and digital image processing.

Analog image processing

Analog image processing is done on analog signals. It includes processing on two dimensional analog signals. In this type of processing, the images are manipulated by electrical means by varying the electrical signal. The common example include is the television image.

Digital image processing has dominated over analog image processing with the passage of time due its wider range of applications.

Digital image processing

The digital image processing deals with developing a digital system that performs operations on an digital image. Digital image processing is the use of computer algorithms to perform image processing on digital images. As a subcategory or field of digital signal processing, digital image processing has many advantages over analog image processing.

It allows a much wider range of algorithms to be applied to the input data and can avoid problems such as the build-up of noise and signal distortion during processing. Since images are defined over two dimensions (perhaps more) digital image processing may be model in the form of multidimensional systems.

IV. APPLICATIONS OF DIGITAL IMAGE PROCESSING

MEDICINE

1) Inspection and interpretation of image obtained from X –rays, MRI scans.
2) Analysis of cell images, of chromosome karyo types.

AGRICULTURE

1) To detect diseased leaf, stem, fruit
2) To quantify affected area by disease.
3) To find shape of affected area.
4) To determine color of affected area
5) To determine size & shape of fruits.

INDUSTRY

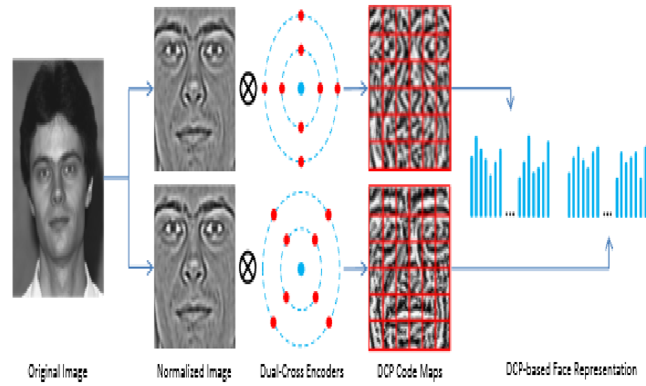
1) Automatic inspection of items on a production line.
2) Inspection of paper samples.

LAW OF ENFORCEMENT

1) Finger print analysis.
2) Sharpening of speed camera image.

V. DUAL-CROSS PATTERNS

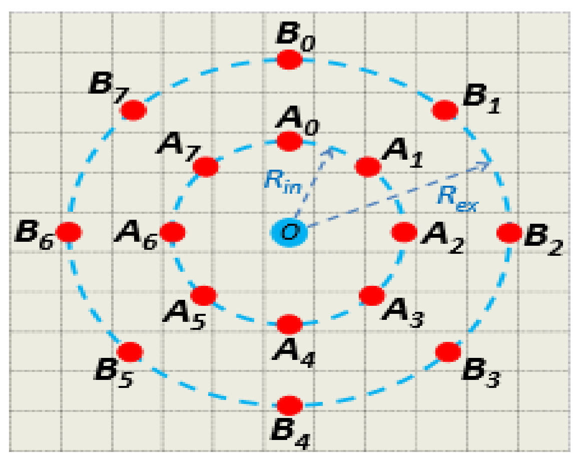
The design of a face image descriptor consists of three main parts: image filtering, local sampling, and pattern encoding.



The implementation of image filtering is flexible: possible methods include Gabor wavelets [7], Difference of Gaussian (DoG), or the recently proposed discriminative image filter [18]. In this paper, we focus on local sampling and pattern encoding, which are the core components of a face image descriptor.

Local Sampling

The essence of DCP is to perform local sampling and pattern encoding in the most informative directions contained within face images. For face recognition, useful face image information consists of two parts: the configuration of facial components and the shape of each facial component. The



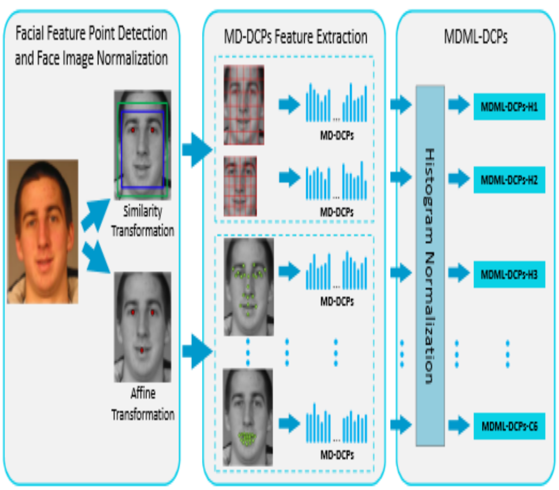
shape of facial components is, in fact, rather regular. After geometric normalization of the face image, the central parts of several facial components, i.e., the eyebrows, eyes, nose, and mouth, extend either horizontally or vertically, while their ends converge in approximately diagonal directions (π/4 and 3π/4). In addition, wrinkles in the forehead lie flat, while those in the cheeks are either raised or inclined. Based on the above observations, local sampling of DCP is conducted as shown in Fig. 1. For each pixel O in the image, we symmetrically sample in the local neighborhood in the 0, π/4, π/2, 3π/4, π, 5π/4, 3π/2, and 7π/4 directions, which are sufficient to summarize the extension directions of major facial textures. Two pixels are sampled in each direction. The resulting sampled points are denoted as {A0,B0;A1,B1;··· ;A7,B7}. As illustrated in Fig. 1, A0,A1,··· ,A7 are uniformly spaced on an inner circle of radius Rin, while B0,B1··· ,B7 are evenly distributed on the exterior circle with radius Rex.

VI. MULTI-DIRECTIONAL MULTI-LEVEL DUALCROSS PATTERNS

A face representation scheme based on DCP named Multi-Directional Multi-Level Dual-Cross Patterns (MDML-DCPs) to explicitly handle the challenges encountered in unconstrained face recognition.

The MDML-DCPs Scheme

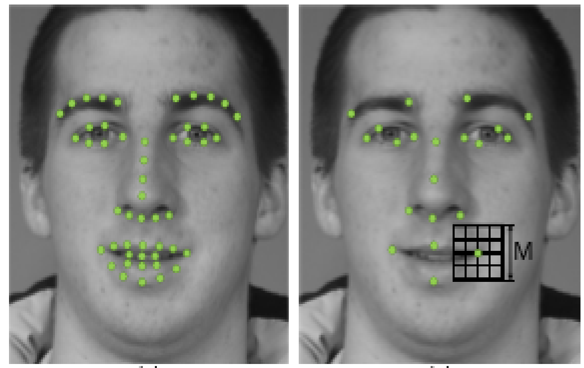
A major difficulty in unconstrained face recognition is that many factors produce significant intra-personal differences in the appearance of face images.



variations in illumination, image blur, occlusion, and pose and expression changes. We mitigate the influence of these factors using multi-directional gradient filtering and multi-level face representation.

MDML-DCPs combines both holistic-level and component-level features, which are computed on the normalized images by the two transformations. Holisticlevel features capture comprehensive information on both facial components and facial contour. However, it is also sensitive to changes in appearance of each component caused by occlusion, pose, and variations in expression.

In contrast, component-level features focus on the description of a single facial component, and thus are independent of changes in appearance of the other components. In this way the information generated by these two feature levels is complementary and appropriate fusion of the two promotes robustness to interference



(a) (b)

VII. EXPERIMENTAL RESULTS

Image Database A face image database was created for the purpose of benchmarking the face recognition system. The image database is divided into two subsets, for separate training and testing purposes. During SOM training, 25 images were used, containing five subjects and each subject having 5 images with different facial expressions. Fig. 7 shows the training and testing image database constructed.

Face Recognition has three view

1. Multi view

It requires different poses

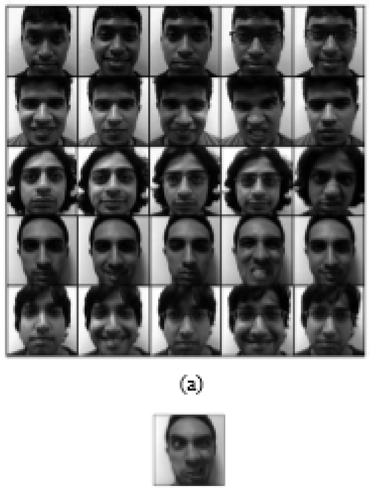
2. Cross view

It requires specific views, alignment is needed to estabilish correspondence between two face in different poses.

3. Matching based face recognition

Alignment free, proposed method adopt this advantages, so the accurate alignment of faces is unnecessary.

Multimedia hardware such as(HDTV) and digital camera ,it has become easy to access high resolution(HR)images. This analyze more sophisticated feature.



(a)

(b)

Fig. 7. Training and testing image database. (a) Image database for training. (b) Untrained image for testing

Traditional facial features like face shape, eyes, nose and mouth.HR face recognition is a relatively recent topic, it extract subtle information such as(moles, scars)mark scale features,(pores, hair)pore scale features.

The face recognition system presented in this paper was developed, trained, and tested using MATLAB.

VIII. VARIATION IN FACIAL EXPRESSION, EYE WEAR,AND PORE

Variation in Facial Expression, Eye Wear, and Lighting Using a second database constructed at the Yale Center for Computational Vision and Control, we designed tests to determine how the methods compared under a different range of conditions. For sixteen subjects, ten images were acquired during one session in front of a simple background. Subjects included females and males (some with facial hair), and some wore glasses. The first image was taken under ambient lighting in a neutral facial expression and the person wore glasses. In the second image, the glasses were removed. If the person normally wore glasses, those were used; if not, a random pair was borrowed. Images 3-5 were acquired by illuminating the face in a neutral expression with a Luxolamp in three positions.

The last five images were acquired under ambient lighting with different expressions (happy, sad, winking, sleepy, and surprised). For the Eigenface and correlation tests, the images were normalized to have zero mean and unit variance, as this improved the performance of these methods. The images were manually centered and cropped to two different scales: The larger images included the full face and part of the background while the closely cropped ones included internal structures such as the brow, eyes, nose, mouth, and chin, but did not extend to the occluding contour.

To classify an image of a person, that image was removed from the data set and the dimensionality reduction matrix W was computed. All images in the database, excluding the test image, were then projected down into the reduced space to be used for classification. Recognition was performed using a nearest neighbor classifier. Note that for this test, each person in the learning set is represented by the projection of ten images, except for the test person who is represented by only nine

IX. CONCLUSION

In this project, we have addressed the problem of HR face verification based on pore-scale facial features. The proposed method is robust to alignment errors and poses variations, while the gallery set requires only a single image per subject. The PSIFT and PPCASIFT features are highly distinctive, and PPCASIFT can efficiently reduce the computational time of the matching process to about 9% of that of PSIFT, while a similar performance level can be maintained. Furthermore, the proposed parallel-block-aggregation and matching-density schemes can be applied to other image analysis tasks such as object recognition, image annotation, since they provide an approach to transforming point matching into similarity measurement.

X. FUTURE ENHANCEMENT

In our future work, we will investigate the fusion of pore-scale facial features from HR images with larger-scale facial features from LR images. We will also study how to further improve the efficiency of the proposed method, and apply it to other important areas like face recognition and 3D face reconstruction.

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