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Traditional Approaches for Image Recognition by ANF Methods

K. Shirisha,
CSE Department,
Mahatma Gandhi Institute Of Technology Hyderabad, India
kshirisha662@yahoo.in

***Abstract* - In this paper, we propose an integrated face recognition system that is robust against facial expressions by combining information from the computed intra person optical flow and the synthesized face image in a probabilistic framework. Making recognition more reliable under uncontrolled lighting conditions is one of the most important challenges for practical face recognition systems. We tackle this by combining the strengths of robust illumination normalization. Our experimental results show that the proposed system improves the accuracy of face recognition from expressional face images and lighting variations. we propose to develop this paper by using ANF(appearance, normalization, feature) methods.**

***Keywords* – Face recognition, constrained optical flow, mask image, synthesized image, masked synthesized image.**

I. INTRODUCTION

FACE recognition has been studied for several decades. Comprehensive reviews of the related works can be found in [14], [21]. Even though the 2-D face recognition methods have been actively studied in the past, there are still some inherent problems to be resolved for practical applications. It was shown that the recognition rate can drop dramatically when the head pose and illumination variations are too large, or when the face images involve expression variations. Pose, illumination, and expression variations are three essential issues to be dealt with in the research of face recognition.

To improve the face recognition accuracy, researchers have applied different dimension reduction techniques, including principle component analysis (PCA) [3], linear discriminate analysis (LDA) [13], independent component analysis (ICA) [1], discriminate common vector (DCV) [2], kernel-PCA, kernel-LDA [5], kernel-DCV [10], etc. In addition, several learning techniques have been used to train the classifiers for face recognition, such as SVM.

This paper focuses mainly on the issue of robustness to expression and lighting variations. For example, a face verification system for a portable device should be able to verify a client at any time (day or night) and in any place (indoors or outdoors). Traditional approaches for dealing with this issue can be broadly classified into three categories: appearance-based, normalization based, and feature-based methods. In direct appearance based approaches, training examples are collected under different lighting conditions and directly (*i.e.* without undergoing any lighting preprocessing) used to learn a global model of the possible illumination variations.

In this paper, we focus on the problem of face recognition from a single 2-D face image with facial expression. Note that this paper is not about facial expression recognition. For many practical face recognition problem settings, like using a passport photo for face identification at custom security or identifying a person from a photo on the ID card, it is infeasible to gather multiple training images for each subject, especially with different expressions. Therefore, our goal is to solve the expressive face recognition problem under the condition that the training database contains only neutral face images with one neutral face image per subject. A constrained optical flow algorithm was proposed, which can deal with position movements and intensity changes at the same time when handling the corresponding feature points. With our proposed constrained optical flow algorithm, we can calculate the expressional motions from each neutral faces in the database to the input test image, and estimate the likelihood of such a facial expression movement. Using the optical flow

information, neutral images in the database can be further warped to faces with the exact expression of input image.

II. EXISTING SYSTEM

CONSTRAINED OPTICAL FLOW COMPUTATION:

The computational algorithms of traditional optical flow cannot guarantee that the computed optical flow corresponds to the exact pixels in different images, since the intensity variations due to expression may mislead the computation of optical flow. The brightness constancy constraint, however, is not valid in many circumstances. Therefore, with the generalized dynamic image model (GDIM) proposed by Negahdaripour and Yu [16], generalized the optical flow constraint to

$$I_x(r)u(r) + I_y(r)v(r) + I_t(r) + m(r)I(r) + c(r) = 0 \quad (1)$$

Where m(r) and c(r) denote the multiplier and offset factors of the scene brightness variation field, I is the image intensity function, the subscripts x, y and t denote the spatiotemporal partial derivatives, r is a point in the spatiotemporal domain, and [u(r),v(r)]T is the motion vector at the point r .

A. Overall Face Recognition Processing Flow

Face recognition is a visual pattern recognition problem. A face is a three dimensional object subject to varying illumination, pose, expression is to be identified based on its two-dimensional image (or three- dimensional images obtained by laser scan). A face recognition system generally consists of 4 modules - detection, alignment, feature extraction, and matching. Localization and normalization (face detection and alignment) are following processing steps before face recognition (facial feature extraction and matching) is performed.

The overall architecture of the face recognition processing flow system is shown in the Fig. 1.

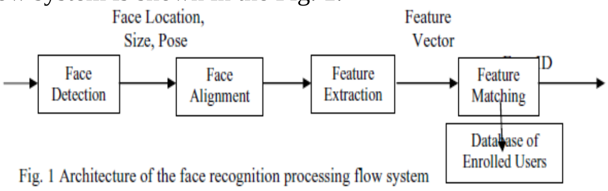

Fig. 1 Architecture of the face recognition processing flow system

The steps for above face recognition processing flow,

- Face detection segments the face areas from the background.
- Face alignment is aimed at achieving more accurate localization and at normalizing faces, whereas face detection provides coarse estimates of the location and scale of each face. Facial components and facial outline are located; based on the location points,
- The input face image is normalized in respect to geometrical properties, such as size and pose, using geometrical transforms or morphing,.After a face is normalized, feature extraction is performed to provide effective information that is useful for distinguishing between faces of different persons and stable with respect to the geometrical and photometrical variations.
- For face matching, the extracted feature vector of the input face is matched against those of enrolled faces in the database; it outputs the identity of the face when a match is found with sufficient confidence or indicates an unknown face otherwise.

III. PROPOSED FACE RECOGNITION SYSTEM

A. *Basic Concept*

We treat the expression-invariant face recognition system as a probabilistic maximum a posteriori (MAP) classification problem. To do this, we formulate the problem as follows

$$\arg\max_{N_i,E} P(N_i,E|I), \quad i=1,2,\ldots,N \qquad (2)$$

Where *I* is the input image, Ni is the neutral face image for the *i*th subject in training data set, and *E* denotes the expression motion field between *I* and *Ni*. The optical flow field *E* is not specifically defined yet, which will be discussed later. The direction of *E* could be either from *I* to *Ni* or the opposite way. Based on the Bayes theorem and the assumption of independence Between *Ni* and *E* , (2) can be rewritten as

$$\arg\max_{N_i,E} P(N_i)P(E)P(I|N_i,E), \quad i=1,2,\ldots,N \qquad (3)$$

B. *Expression Images*

The intra person expression motion fields of the subjects in the training dataset, which are exclusive from the testing data, are collected in the training procedure. There are two advantages of the above optical flow normalization scheme: (1) all expressive face images of all subjects have the same dimension of motion fields, and (2) all optical flows are computed and represented with the same geometry.

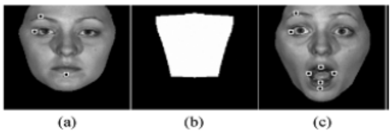

Fig. 2. Illustration of mask definition and warping: (a) reference image and feature points, (b) initial mask, (c) input expression image.

Fig. 2 shows the mask definition used for specifying the valid pixels in the face images. We first defined the standard mask image [Fig. 2(b)] from the global neutral face image [Fig. 2(a)].When there is an input image with expressions [Fig. 2(c)], the mask is then warped according to the three feature points shown in Fig. 2(a).

C. *Lighting Variations*

In lighting image, Normalization based approaches seek to reduce the image to a more “canonical” form in which the illumination variations are suppressed. For example, even though LBP features are completely invariant to monotonic global gray-level transformations, their performance degrades significantly under changes of lighting direction and shadowing – see Fig. 3.

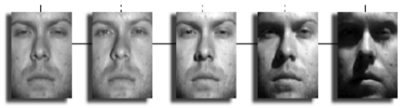

Fig 3 Lighting Images

D. *Overall System Architecture*

The overall architecture of the proposed face recognition system is shown in the Figure 4.

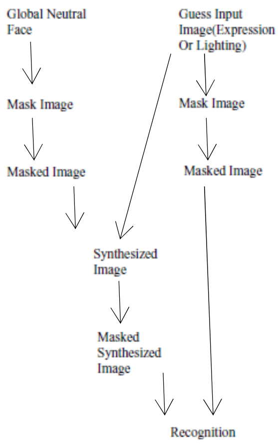

Fig. 4 Block diagram of the proposed Face Recognition System

IV. EXPERIMENTAL RESULTS & CONCLUSION

Fig. 5 shows the 25 normalized face images of one subject after the normalization procedure.

Fig 5 Sample images for expression. The left-top most is the neutral face. The others are the face images with angry, disgust, fear, happy, sad, and surprise expressions in columns from left to right with increasing levels in rows from top to bottom.

A. Preprocessing

We manually labeled 21 feature points, including three points for each eyebrow and four points for each eye, one at the nose tip and the other six around the mouth region. With the labelled points, the distance between the outer corners of both eyes is used as the reference to normalize face images.

B. Mask Image

Using a mask image to eliminate the undesired area of an image is an important technique in remote sensing analysis. The principle behinds the mask technique is to multiply the source image by the mask image that contains two values—1 for preserved areas and 0 for undesired areas.

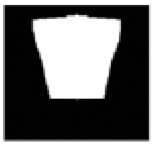

Fig.6. Mask Image

C. Masked Image

Masking an image enables a developer to create images with irregular shapes dynamically. Masking is often used to create a user interface that is more compelling and less boring. The application of a mask to an input image produces an output image of the same size as the input.

Fig.7. Masked Images

D. Synthesized Image

Synthesis Image refers to synthesis of still images as well as synthesis of facial animations. For example, the technique of synthesizing facial expression images can be directly used for generating facial animations, and most of the facial animation systems involve the synthesis of still images. Digital Personnel is a computer-based facial expression synthesizer. It synthesizes animated, life-like, facial expressions of an individual in synchrony with that individual's speech. The system is speech driven, that is, as an individual speaks the appropriate facial expressions are generated simultaneously.

Fig 8 synthesized Images

E. Masked Synthesized Image

Masking is often used to create a user interface that is more compelling and less boring. The application of a mask to an input synthesized image produces an output image of the same size as the input.

Fig 9 Masked Synthesized Images

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