Illumination-Effects Compensation in Facial Images

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Abstract— **Based on the concepts of the linear object classes and the principal components analysis, an illumination-effects compensation method is presented in this paper to transform an arbitrary-lit face image whose illumination effects are pre-determined, into a front-lit face image.**

I. Introduction

The appearance of a person is highly dependent on the lighting conditions. Often slight changes in illumination produce large changes in the person's appearance. In face recognition, since the face images in the known face database are taken under front-lit illumination conditions, recognition of a face image taken under a different illumination condition becomes difficult. Compensating for image variations caused by illumination changes is therefore crucial and can improve the recognition results. This compensation is performed in two modules: illumination-effects determination and illumination-effects compensation. In the illumination-effects determination module, illumination effects are determined in the input image. In the illumination-effects compensation module, the face image is compensated for the determined illumination effects by synthesising a face image under front-lit illumination conditions.

Several methods, e.g. neural networks, can be used for illumination-effects determination [5]. This paper deals with the illumination-effects compensation and assumes that the illumination effects in the images are known.

There are a few existing methods for illumination-effects compensation [5]. Among these methods, Brunelli's illumination-compensation method [2] is probably the best method. This method has been implemented and tested by the author of this paper for comparative evaluation purpose. The results indicate that Brunelli's method is not sufficiently robust for compensation of illumination effects. There are several factors that make this method unreliable. These factors are given below.

1. The feature locator is found to be sensitive to changes in illumination.
2. The optical flow algorithm on which it is based, fails to find correspondence between the reference image, taken under front-lit illumination conditions, and the input image with arbitrary illumination effects. Figure 1 shows an example of a reference face image taken under front-lit illumination, an input image containing some illumination effects, the geometry-adjusted image under Brunelli's method, and the correspondence vector of the reference and the adjusted images.
3. Given a perfect correspondence vector for the reference and the input images, the final stage of Brunelli's method still cannot perform a good illumination compensation. The residuals are large and the corrected image is poor.

To obtain a better performance for compensation of illumination effects, a method, called the Illumination-Effects Compensation Method (IECM), is proposed in the following section using the theories of the Linear Object Classes (LOC) [7] and the Principle Components Analysis (PCA) [6].

This paper is organised as follows. In Section II, the proposed illumination-effects compensation method is presented. In Section III, experimental results are given. These results are then discussed in Section IV. Finally, concluding remarks are given in Section V.

II. Proposed Illumination-Effects Compensation Method

Given a 3D object, there are a variety of different ways to perform visible-surface determination, illumination, and shading in computer graphics [4]. The process of creating 2D images from 3D models is called *rendering*. Different rendering methods such as z-buffer, list-priority algorithm, radiosity, ray-tracing, etc. can be found in [4]. To use these techniques and generate a face image under front-lit illumination from a face image with arbitrary illumination effects, 3D models should be generated from 2D images, which is a difficult task for face images containing illumination effects.

Vetter and Poggio [7] proposed a simpler tech-

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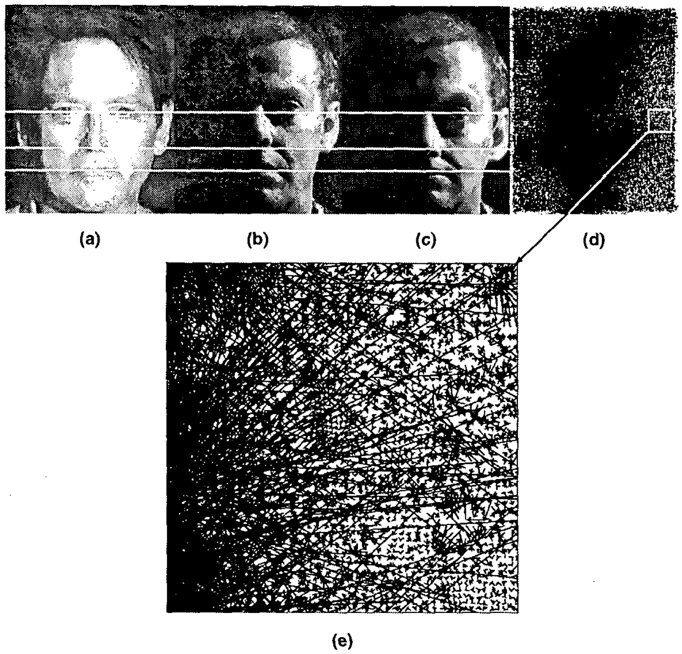

Fig. 1. Brunelli's correspondence extraction method. (a) Reference face image. (b) Input image. (c) Geometry adjusted image. (d) Correspondence vector of the reference and the adjusted images. (e) Enlarged part of the correspondence vector.

nique, called *linear object classes*, that can be used under restricted conditions. This technique is based on 2D models and does not need any depth information. This technique can provide additional artificial example images of an object when only a single image is given, and is originally proposed for generating a novel pose of an object from a different pose of the object. The image transformations that are specific to the relevant object class are learnt from example poses of other prototypical objects of the same class.

There are 3D objects whose 3D shapes can be represented as a linear combination of a sufficiently small number of prototypical objects. Linear object classes have the property that new poses of any object of the class under uniform affine 3D transformations can be generated exactly if the corresponding transformed poses are known for the set of prototypes.

Vetter-Poggio's method involves computation of the correspondence between the images of the objects, linear decomposition of the correspondence field of the new images into the correspondence fields of the examples, similar decomposition of new texture into the example textures, and synthesis of the new image. This method has only been used for synthesising face images of novel pose. It has not been applied to the synthesis of face images of novel illumination.

The main limitation of this method, however, is the existence of linear object classes and the completeness of the available examples. This is equivalent to whether object classes can be modelled through linear object classes. Presently there is no final answer to this question, apart from simple objects where the dimensionality is given through their mathematical definitions. The application of the method to a small example set of human faces, provides preliminary promising results at least for some faces. Based on their experiments, Vetter and Poggio have concluded in [7] that the linear object class method may be a satisfactory approximation even for complex objects such as faces. Given a linear space such as the face space, one can choose among different sets of basis vectors that will span the same space. The basis set used by Vetter and Poggio is the original set of images themselves. However, other potential basis set can be used as well.

One popular method for choosing the basis set is applying the PCA to the example set. Since the basis set found by the PCA is orthogonal (and can be easily normalised to be made orthonormal), reconstruction of new images can be performed if sufficient number of example face images are used. This orthogonality produces a more stable set of linear coefficients [1]. This may produce a better approximation of a different face image.

The IECM synthesises a front-lit face image from an arbitrary-lit input face image. The method utilises the theories of the LOC and the PCA. The proposed method is described as follows.

Algorithm 1: (**Illumination-Effects Compensation**)

The illumination-effects compensation process is performed in two stages as described in the following.

Training: In the training stage the following operations are performed.

1. One training set for each class of illumination effects is constructed using as many example images as possible.
2. An image is manually selected from each training set and is named the reference image of the set. Although this selection is an arbitrary choice, the employed principle is that the face should be located in the centre of the image.
3. All images of each training set are aligned based on the associated reference image.
4. The PCA is applied to each training set, and the basis images are generated.

Synthesis: Given the illumination effects, the following operations are performed in the synthesis stage.

1. A set of weights $\boldsymbol{w}$ is calculated based on the input image I_{in} and the basis images. This is done by projecting the input image onto each basis image of the training set representing similar illumination effects as that of the input image.
2. A face image I_{out} is synthesised under front-lit illumination using the calculated weights and the basis images of the training set representing front-lit illumination.
3. A set of weights $\bar{\boldsymbol{w}}$ is calculated based on the synthesised image I_{out} and the basis images. This is done by projecting the image onto each basis image of the training set representing front-lit illumination.
4. A face image $\bar{I_{in}}$ is synthesised under the illumination effects similar to the input image using the calculated weights $\bar{\boldsymbol{w}}$ and the basis images of the training set representing the similar illumination effects as that of the input image.
5. The sum of squared difference error between I_{in} and $\bar{I}_{in}$ is obtained using

$$\begin{aligned} E(\boldsymbol{w}) &= \frac{1}{2}\sum_{x,y}(I_{in}(x,y) - \bar{I}_{in}(x,y))^2 \\ &= \frac{1}{2}\sum_{x,y}(I_{in}(x,y) - (\boldsymbol{\mu}_k + \frac{1}{N}\sum_{i=1}^{N} w_i \boldsymbol{b}_i))^2 (1) \end{aligned}$$

where $\boldsymbol{\mu}_k$ is the mean image of the training set with the similar illumination effects as that of the input image, N is the number of example images in that training set, and $\boldsymbol{b}_i$ represents the basis images obtained by performing the PCA on that training set.
6. The error E is minimised by modifying $\boldsymbol{w}$ using the conjugate-gradient algorithm [8].
7. A jump is performed to Step 2 unless the error stops decreasing or a fixed number of iterations are reached.

To develop a practical system using the process described above, example face images that contain different lighting conditions are required. Using a 3D head database of 63 people, face images with 66 illumination-effects per person are generated and grouped into 66 illumination-effects classes. This classification is done based on the lighting conditions of each face image. In each image, specific direction and distance of a single light source are implemented. The longitudinal and latitudinal of the light source directions are within $15° - 75°$ degrees of the camera axis. Alignment is performed to adjust scale, orientation, and position of faces within images.

In order to minimise the error function, any standard minimisation algorithm could be used. There are several different methods for optimisation. They can be divided into two main groups: gradient and non-gradient methods. The gradient methods are characterised by the fact that they use derivatives of the object function, either explicitly or numerically obtained, to find the optimal solution. The non-gradient methods, however, have other ways of finding a search path to the optimal solution.

The conjugate-gradient method [3] is a minimisation technique to find the lowest energy. The method is similar to a steepest-descent minimisation. The procedure for the steepest-descent minimisation is as follows: (i) the gradient is calculated in all directions, (ii) the path of steepest descent is chosen - this is in the form of a straight line but makes measurements of the energy at small increments, (iii) when the energy stops decreasing the process is repeated. The conjugate-gradient minimisation adopts the same procedure, but also uses information from the previous iteration steps to select the optimal route.

III. Experimental Results

Four experiments are carried out to evaluate the performance of the IECM. Both the IECM and Brunelli's method [2] are implemented and their performances are compared. The test set used in these experiments is built as follows.

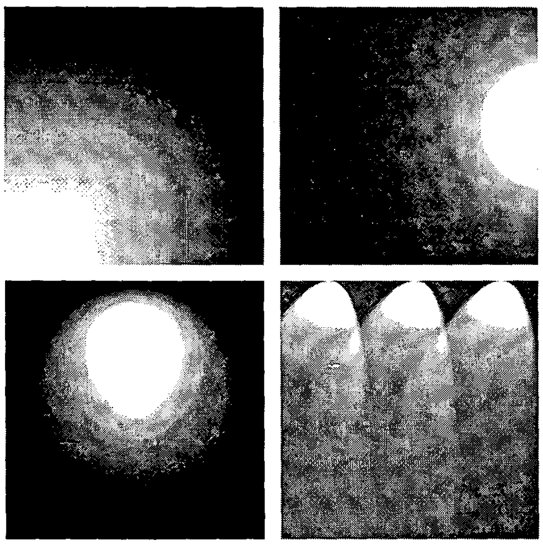

Fig. 2. Four illumination masks used in creation of the test set.

Test Set: A set of front-view face images of 80 subjects taken under front-lit illumination conditions are collected by the author. The face images are 128×128 gray-level, each containing only the face area of a subject. The images are all aligned. Four 128×128 gray-level images are generated by computer as illumination masks. In each mask, a specific illumination effect is implemented. These illumination masks are shown in Figure 2. Using the 80 face images and the four illumination masks, a test set of 400 face images are created. This test set consists of five subsets. Subset 1 contains 80 original front-lit face images. Each of Subsets 2-5 contains 80 face images generated by superimposing each illumination mask on each face image of Subset 1. Before superimposing an illumination mask on a face image, the illumination mask is weighted using one of the five pre-selected weights - 1.0, 0.93, 0.89, 0.84, and 0.8, randomly. The pre-selection has been conducted in such a way as to degrade the synthesised images' brightnesses by up to 20%. The weighting operation is performed in order to include more variations in illumination condition by producing different illumination effects from each mask, randomly. Example images of Subset 4 are demonstrated in Figure 3.

Four experiments are performed on this test set. In each experiment, the face images of Subset 1 and one of Subsets 2-5 are used. In the following, the procedure for Experiment 1 is described. The procedure for Experiments 2-4 are the same except that one of Subsets 3-5 is used instead of Subset 2.

The percentage errors obtained from Experiments 1-4 are summarised in Table I for Brunelli's method and for the IECM. A discussion of the obtained results is given in the next subsection.

IV. Discussions

According to Table I, the proposed IECM outperforms Brunelli's method in all experiments. While the percentage error for Brunelli's method rises significantly to 83% when three light sources are used, the percentage error for the IECM increases only slightly to 23% for the same experiment. The IECM achieves significantly lower percentage errors in all experiments for the synthesised images than those of Brunelli's method. In other words, the corrected images generated by the IECM have higher similarities with their original images than those generated by Brunelli's method.

The IECM is confronted with a problem which is the completeness of the available example face images. The results discussed above are based on the experiments performed on a small test set. The test set did not contain all the possible illumination effects. A simple solution to the completeness problem would be the inclusion of more face images containing all possible illumination effects in the ensembles of face images.

V. Conclusions

An illumination-effects compensation method (IECM) is proposed in this paper for dealing with face image variations that are due to illumination changes. In the IECM, the determined illumination effects in the face image are compensated for by synthesising a face image under front-lit illumination conditions. The IECM utilises the theories of the linear object classes and the principal components analysis.

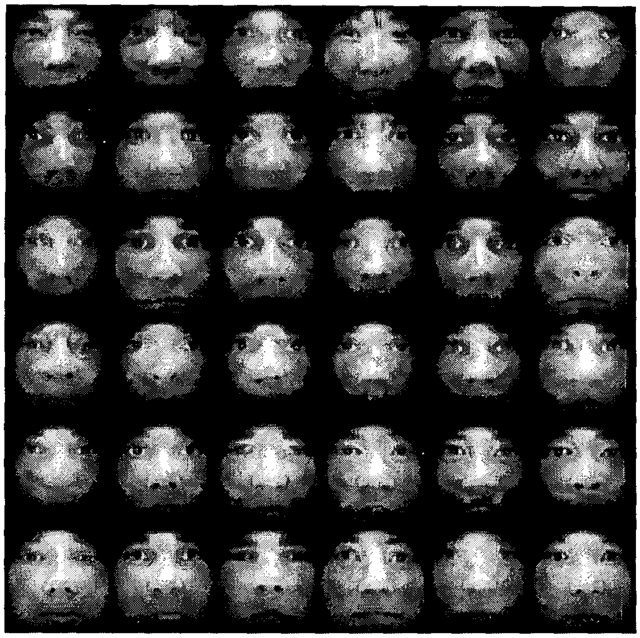

Fig. 3. Example images from Subset 4.

TABLE I
PERCENTAGE ERRORS OBTAINED FROM EXPERIMENTS 1-4.

Method	Experiment	Subsets	Percentage Error
Brunelli	1	1 and 2	62
	2	1 and 3	65
	3	1 and 4	71
	4	1 and 5	83
IECM	1	1 and 2	14
	2	1 and 3	17
	3	1 and 4	17
	4	1 and 5	23

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