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# 2D Face Recognition Under Expression And Illumination Variations Using Optical Flow And Synthesized Face Image

ESTHER.M[1] MEENAKSHI.S[2] SIVA SUBRAMANIAN.M[3]

[1] M.Phil Research Scholar, Department of Computer Science, J.P College of Arts and Science Ayikudy-Tenkasi

[2]Assistant Professor, Department of Computer Science, J.P College of Arts and Science Ayikudy-Tenkasi

[3]Assistant Professor, Department of Computer Science, J.P College of Arts and Science Ayikudy- Tenkasi

## Abstract

**Face recognition is something that people can do easily. But in the case of computer vision it has remained a difficult problem. Face recognition is one of the most successful applications of image analysis and understanding. Some of the face recognition techniques are for identifying faces with expressions variations. An optical flow algorithm has developed to identify faces robustly under expression and illumination variations by using a single training sample per subject. Synthesized face images in a probabilistic framework is also used with optical flow algorithm to improve accuracy and recognition rate. In this paper, the problem of face recognition under expression, and illumination variations is handled. The problem of face recognition from a single 2D face image with facial expression is based on integrating the optical flow information and image synthesis.**

**Keywords – Optical Flow, Image Synthesis, Face Recognition, Expression Variation.**

## I. INTRODUCTION

Face recognition is the identification of individuals from images of faces. Face recognition has been a vast area of research for several years. A detailed description of the related works is given in the paper [7]. There is much interest in identifying faces using ID's, passports, credit cards, private licenses. There are so many face recognition algorithms for identifying the face in

normal circumstances. The changes in pose, illumination and expression may drop the face recognition rate. There are number of algorithms to handle pose and illumination variations. The face recognition algorithms for handling expression variations are still under research.

There are various dimension reduction techniques applied by many researchers. PCA [9], LDA [6], ICA [1], DCV [2], Kernel PCA, Kernel LDA [10], Kernel DCV [4] are based on this technique. Linearity is the main disadvantage of PCA, LDA, and fisher faces. The recognition rate can be improved by selecting a suitable dimension reduction technique. But it requires more number of images for each subject. It is difficult to provide multiple training images for each subject

Eigen faces can be considered as one of the first approaches in this sense Kirby and Sirovich [8] adopted the PCA. This was the beginning of the appearance based methods for face recognition. After Eigenfaces, different statistical approaches have appeared that improve the results of Eigenfaces under certain constraints.
Many holistic methods are based on Eigen face decomposition. Here face images are represented as vectors by concatening the pixels of the image line-by-line. Then the average vector is computed that represents a mean face. Also, a difference vector is computed for each user to qualify the differences to the mean face.

The LDA has been proposed as a better alternative to the PCA. It expressly provides discrimination among the classes, while the PCA deals with the input data in their entirety, without paying any attention for the underlined structure. Indeed the LDA provides better classification performances only when a wide training set is available. In some approaches, such as the fisher faces the PCA and LDA are combined together. PCA is considered as a preliminary step in order to reduce the dimensionality of the input space, and then the LDA is applied to the resulting space, in order to perform the real classification.

The algorithms handling for expression variations can be broadly classified into morphable model based and optical flow based. In morphable model based technique the input image is warped into a neutral face kept in the training database. The main disadvantage of this technique is that all images can't be warped into neutral face if some texture is missing. The optical flow method has been used in face recognition under expression variations [3], [8], [7], and [5]. In [3] and [5] optical flow has been used in the task of expression recognition. Martinez [8] handled face recognition with expression variations by using weighted optical flow method. The loss of some texture problem can be minimized by giving less weight to more changed features and more weight to less changed features. The motion estimation procedure [7] for face recognition under expression variation did not handle intensity variations. From the input image and source image the motion vector is calculated. It is nothing but the pixel correspondence between the images. By using the motion vector the source image is synthesized into some image. Then the similarity between the synthesized image and the input image is calculated. The image with maximum similarity will be identified as the matched image. The main advantage of this paper is that the database requires single image per subject.

In this paper discussed as 1. The optical flow computational technique is explained in section 2. The proposed face recognition system under expression and illumination is described in section 3. The experimental results obtained by the proposed technique are presented in section 4. The conclusion is given in the last section.

## II. OPTICAL FLOW COMPUTATOIN

The optical flow algorithms alone cannot be applied for face recognition under expression variations because the intensity variations due to expressions may cause false recognition. So illumination variation is also handled by using normalization.

The expression-invariant face recognition system is treated as a probabilistic maximum a posteriori (MAP) classification problem. To do this, the problem is formulated as follows:

$$\underset{N_i,E}{argmax}\ P(Ni, EI), i = 1,2, \ldots, N \qquad (1)$$

where I is the input image, $N_i$ is the neutral face image for the $i^{th}$ subject in training data set, and E denotes the expression motion field between I and $N_i$. The optical flow field E is not specifically defined yet. 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 $N_i$ and E, equation (1) can be rewritten as

$$\underset{Ni,E}{\arg max} P(Ni)P(E)P(I/Ni, E) \qquad (2)$$

Furthermore, the prior probability for each candidate is assumed equally probable, i.e., P ($_{Ni}$) is constant for all. The formulation can be simplified as

$$\underset{Ni,E}{\arg max} P(E)P(I/Ni, E) \qquad (3)$$

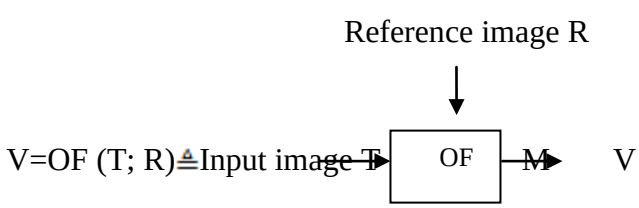


Fig. 1 Symbolizations of OF() operators.

### A. Prior probability of the expression motion

The proposed constrained optical flow estimation algorithm is used to calculate the deformation between the input image and the subject $N_i$, which is defined as a directional OF( ) operator and depicted in Fig. 1. Note that OF(T;R) operator is to apply the proposed constrained optical flow estimation algorithm to estimate the pixel motion vectors from one image T to a reference image R.

A training procedure is necessary to further calculate the probability of the expression movement P (E). It is necessary that all the optical flow fields used in both training and testing procedures are in the same coordinate. The traditional expressive optical flow is computed from a neutral face image $N_i$ of person i to an expression image $EX_{i,k}$ with expression k of the same subject. However, the computed optical flows are generally not in the same coordinate, since the geometry of neutral faces is different from each other. Some research considers only the motion vectors at certain feature points to overcome this problem, but only limited information about facial movement is used in this case.

A different solution for optical flow normalization is proposed, as shown in Fig. 2. Instead of computing the intraperson optical flow $OF_{intra,i\_k}$ directly from the neutral face to an expressive face image for each person, it is started from a global neutral face $N_0$ to obtain the interperson optical flow and the overall optical flow $OF_{all,i\_k}$=OF($N_o$;$EX_{i\_k}$). The intraperson optical flow can then be computed by pixel-wise subtraction as shown in the next page:

$$OFintra, i - k \triangleq OF(No; EXi - k) - OF(No; Ni)$$
$$= OFall, i - k - OFinter, i$$

(4)

The intraperson 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 of $N_0$.

To further define P (E) with preservation of identical geometry and dimensionality for each Ni, the same strategy is used in the testing procedure, i.e., the intraperson optical flow. The motion information E in P (E) is defined as

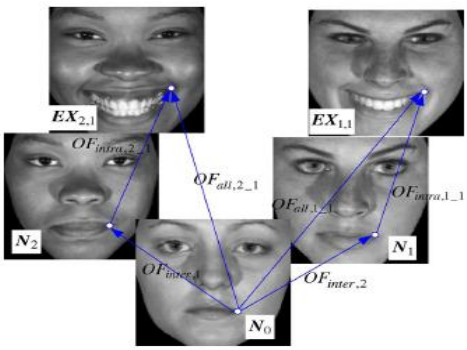


Fig .2 Illustration of decomposing input optical flows $(OF_{\text{all}})$ to interperson $(OF_{\text{inter}})$ and intraperson $(OF_{\text{intra}})$ parts.

$$E \triangleq u(x,y)@No = OF(No;I) - OF(No;Ni) \quad (5)$$

where $OF(No;I)$ is the overall optical flow from global neutral face to input image I, $OF(No;Ni)$ is the interperson optical flow from N0 to the guessed neutral face Ni, and $u(x,y)$ is the intraperson optical flow from Ni to I. Moreover, the symbol "$@No$" in the subscript denotes the optical flow represented with the geometry of N0, even though the intraperson optical flow is defined as the pixel-wise motion from Ni to I.

### B. Conditional Probability of the Expression Motion

With the facial motion computed from the proposed constrained optical flow algorithm, a face image can be synthesized. The function denotes the synthesis operator that warps the source image to a new one through the motion vector, as depicted in Fig. 3(a). Note that the motion vector should be in the same coordinate of source image. Although the motion vectors and intensity variation coefficients are obtained in our optical flow estimation, this operator only involves geometric warping determined by the optical flow and the brightness variations is not used in the face synthesis. The operation Syn(S: OF(S: T)) can be defined as an OF-Syn operator, and symbolize it as depicted in Fig. 3(b).

Under such procedure, the source image can be transferred to the expression and geometry of any target image, and the variation between images due to expression can be reduced. The conditional probability is assumed to be proportional to the similarity between input image (used as the target image) and the synthesized image, from neutral face and the computed optical flow field. Since the optical flow used for synthesizing neutral face to a certain expression must be represented with the same geometry of, the intraperson optical flow in the previous section is not appropriate in this circumstance.

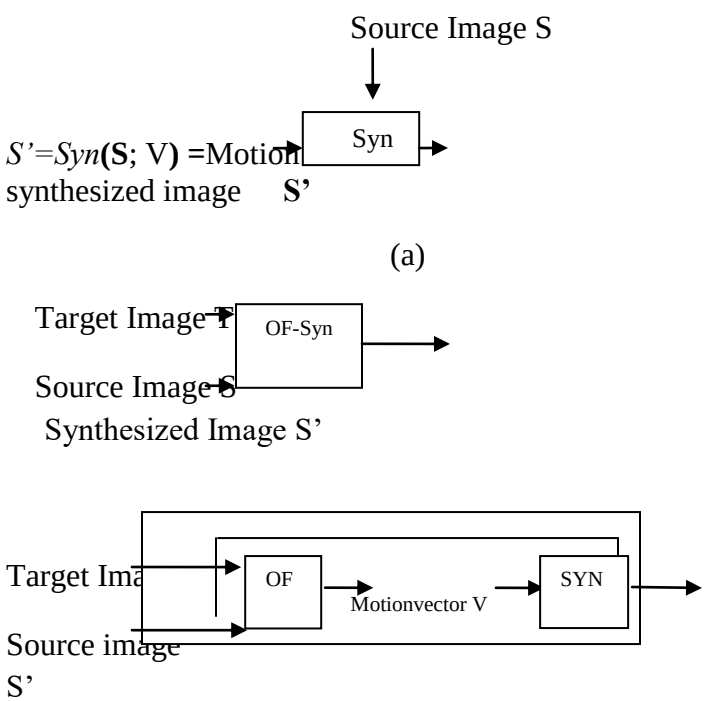


Fig. 3 Symbolization of (a) Syn and (b) OF- Syn operators.

An estimated intraperson optical flow under the geometry of is needed, i.e.,

$$u(x,y)@Ni = OF(Ni;I) \quad (6)$$

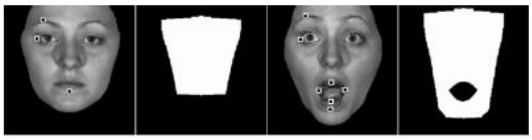


Fig. 4 Illustration of mask definition and warping: (a) reference image and feature points, (b) initial mask, (c) input image, and (d) warped and sheared mask for the input image.

Fig. 4 shows the mask definition used for specifying the valid pixels in the face images. The standard mask image [Fig. 4(b)] from the global neutral face image [Fig. 4(a)]. When there is an input image with expressions [Fig. 4(c)], the mask is then warped according to the three feature points shown in Fig. 4(a). Moreover, the region within the mouth is excluded in the region of interest [as shown in Fig. 4(d)], since it cannot be synthesized due to the lack of texture in the corresponding region of the neutral image.

### C. Face Recognition Algorithm

Create masked images for all the neutral faces in the training database. For the test image, create the corresponding masked image. Run an optical flow algorithm and image synthesis on the image pair, using the enhancements. Find the probability of matching between test image and synthesized images. The image with the maximum similarity will be identified as the matched image.

### D. Illumination Handling

The illumination problem is quite difficult. The changes induced by illumination are often larger than the difference between individuals then there is a chance of false identification. The proposed system handled illumination problem by normalization.

## III. EXPERIMENTAL RESULTS

The proposed system is implemented using an IDL program where it is evaluated for recognizing the image. The performance of the algorithm is evaluated on several real images. It also works for color images. These pictures are the most widely used standard test images used for face recognition algorithms. The image contains a nice mixture of detail, flat regions, shading and texture that do a good job of testing various image processing algorithms.

Fig. 5 Training images

Fig. 6 Masked Images of the Training Images

Fig. 7 Images for testing process

Fig. 8 Test image

Fig. 9 Masked image of the test image

Fig. 10 Matched image

Fig. 11 Test image

Fig. 12 Masked image of the test image

Fig. 13 Matched image

### A. Recognition Rate

To evaluate the performance of the face recognition techniques several performance metrics are available. The recognition rate is used to analyses the performance.

$$RR = \left(\frac{NumberOfCorrectlyIdentifiedFaces}{TotalNumberOfFaces}\right) * 100$$

The RR values for the various face recognition methods are given below.

Table. 1. Performance analysis of RR value

| Method | Recognition Rate |
|---|---|
| Wavelet | 87.25% |
| Gabor | 90.34% |
| Novel Approach | 98.63% |

### B. Performance Analysis Of Various Face Recognition Techniques

As the aim of this paper is to identify face under expression and illumination variations with single neutral face per subject, the neutral database contains neutral faces for all the images. For the test database the expressive face images are used for each neutral face. The proposed face recognition algorithm is done for all the expressive face images with illumination application if required. It is shown that the face recognition rate is 98.63% which is better than other methods previously used.

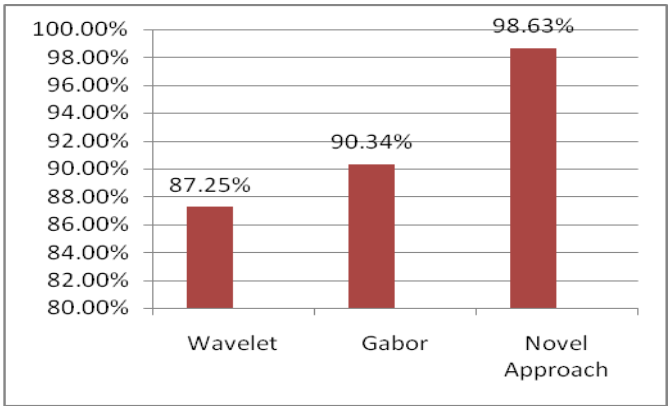


Fig.14. Performance analysis of various face recognition techniques

## IV. CONCLUSION

This proposed method is to identify images with expression and illumination variations using optical flow method and image synthesis. From the experimental results it is significant that the proposed face identification algorithm has improved face recognition rate as compared to the previous methods. This paper also handles the illumination variations well. In future, the multimodal biometric system can be included. For example, face and fingerprint, face and palm print, face and iris, face and speech, and face, fingerprint,

and hand geometry. Face videos can also be considered.

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