Illumination Invariant Novel Approaches for Face Recognition

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***Abstract*—Most of current identification and verification systems like access control and surveillance require reliable person identification technique. The primary goal of such systems is that resources are accessed only by legitimate users. Inefficient person identification systems may become vulnerable thereby allowing impostors. Under these circumstances biometric systems such as automated face recognition finds its immense application. In this paper, we investigate the use of five novel approaches for learning low-dimensional representation of a face image using the concept of transmutation and its variants. Experiments were conducted on two standard datasets namely ORL and Grimace and comparisons among the proposed algorithms have been carried out. The results revealed that transmutation method outperforms its variants.**

***Index Terms*—face recognition, transmutation method, feature extraction, preeminent transmutation method, mean transmutation, weighted preeminent transmutation method, preeminent mean transmutation method**

I. Introduction

Person identification has become one of the most important concerns in the current scenario of globalization. Amongst various forms of Person identification including passwords, keys, etc, biometric is considered to be one of the distinct, measurable and robust physiological traits of an individual. Thus, various forms of biometrics are being employed to verify the claimed identity of an individual. Every individual carries one's own personal identification in the form of one's face, which is extremely hard to be falsified. Face biometric is gaining popularity over others techniques such as fingerprint, iris, voice, gait, etc due to its very nature of being non-intrusive. Face recognition is a process of matching a given face image against set of face images stored in the image database. However, this process is not a simple task as stated in its definition. This is because of internal and external factors that influence the appearance of an individual [1]. Research communities are devising new approaches for solving these challenges like variations caused due to illumination, pose, occlusion, aging, race difference and is continuing to progress at a faster pace. This paper proposes five different approaches for recognizing a face under different illuminations with small variations in expressions and pose. It is based on the underlying assumption that between two samples of same subject even if changes do occur, it is relative at least in some dominant positions. This factor is used for encoding images which are then used in decision making.

Face Recognition – An Insight

Face Recognition usually comprises of two phases namely training phase and recognition phase as depicted in Fig. 1. The training phase starts with preprocessing of training images (database images) to extract face from a complex background. This is followed by applying an algorithm on the preprocessed images to generate feature vectors. At the end of this step the feature vectors are stored in a proper format for comparison with test images during recognition phase.

Recognition phase usually involves three steps. First step is the detection of the face in a complex background and localization of its exact position. Next step is the extraction of facial features followed by normalization to align the face with the stored face images in training phase. Finally, classification or matching happens on the basis of the criteria that the comparison of the database images and the test image crosses a threshold.

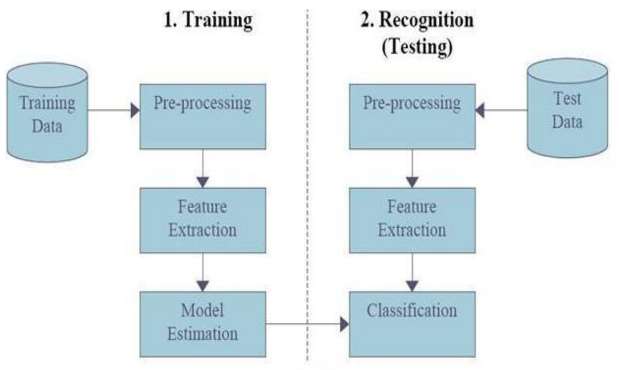

Figure 1. Training and recognition phases.

The following flowchart in Fig. 2, illustrates whole process of face Recognition carried out in the proposed system.

Typically, face images are represented in face space and their reconstruction will be similar to the original face image resulting in very low reconstruction errors. On other hand, non-face or unknown face images will results in reconstruction error which is larger than the acceptable level i.e. threshold. With respect to a known face image, the distance measure is used to determine its nearness.

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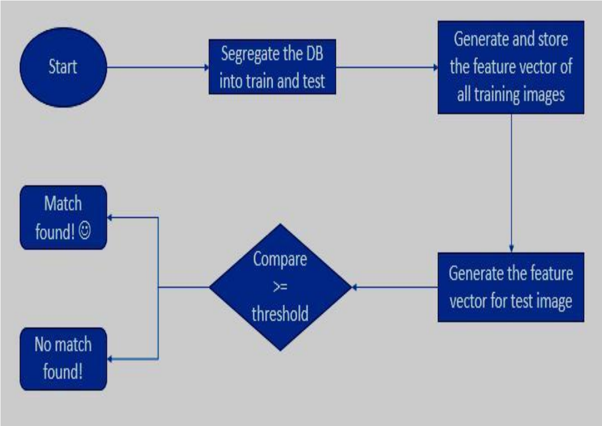

Figure 2. Flowchart for proposed system.

II. Related Work

Illumination problem is caused by conditions such as weather, time of day, shadow and uneven lighting conditions. This problem has a trivial impact on correct recognition of face images. These variations cause change in facial features and automated face recognition system will misclassify such face images as un-known image.

Erald VUÇINI [2] proposed a novel pipeline to develop a Face Recognition System robust to illumination variation. They considered the case when only one single image per person is available during the training phase. In order to utilize the superiority of Linear Discriminant Analysis (LDA) over Principal Component Analysis (PCA) in regard to variable illumination, a number of new images illuminated from different directions have been synthesized from a single image by means of the Quotient Image. An iterative algorithm has been used for the restoration of frontal illumination of a face illuminated from any arbitrary angle carried on a set of 450 images.

Weilong Chen *et al* [3] suggested that, one ideal way of solving the illumination variation problem was to normalize a face image to a standard form under uniform lighting conditions. In fact, the human visual system usually cares about the main features of a face, such as the shapes and relative positions of the main facial features, and ignores illumination changes on the face while recognizing a person. Accordingly they proposed a novel illumination normalization approach to remove illumination variations while keeping the main facial features unimpaired. In their proposed approach, a discrete cosine transform (DCT) was employed to compensate for illumination variations in the logarithm domain. Since illumination variations mainly lie in the low-frequency band, an appropriate number of DCT coefficients were truncated to minimize variations under different lighting conditions.

Xiaohua Xie *et al* [4] considered the fact that the effect of illumination is mainly on the large-scale features (low-frequency components) of a face image. In solving the illumination problem for face recognition, most (if not all) existing methods either only used extracted small-scale features while discard large-scale features, or perform normalization on the whole image. In the latter case, small-scale features may be distorted when the large-scale features are modified. They argued that large-scale features of face image are important and contain useful information for face recognition as well as visual quality of normalized image. Moreover, they suggested that illumination normalization should mainly perform on large-scale features of face image rather than the whole face image. Along this line, a novel framework for face illumination normalization has been proposed. A single face image has been first decomposed into large- and small- scale feature images using logarithmic total variation (LTV) model. After that, illumination normalization has been performed on large-scale feature image while small-scale feature image was smoothed. Finally, a normalized face image was generated by combination of the normalized large-scale feature image and smoothed small-scale feature image.

Faisal R. Al-Osaimi *et al* [5] considered that since the performance of appearance based face recognition algorithms are adversely affected by illumination variations. Illumination normalization can greatly improve their performance. They presented a novel algorithm for illumination normalization of color face images. Face Albedo was estimated from a single color face image and its co-registered 3D image (pointcloud). The intensities of the light sources and the parameters of the lighting model were estimated by fitting Phong's model onto the skin data of the face. Their fully automatic illumination normalization algorithm for color facial images, unlike other techniques it takes into account the cast shadows, multiple directional light sources (including extended light sources), the effect of illumination on colors and both Lambertian and specular light reflections. In addition, it does not assume any prior knowledge about the facial pose or expressions.

Bongjin Jun *et al* [6] in their paper proposed a novel illumination-robust face recognition technique that combined the statistical global illumination transformation and the non-statistical local face representation methods. When a new face image with arbitrary illumination was given, face image preprocessing step, transformed each input face images into sixteen replicate images exhibiting different illumination conditions using a statistical bilinear model-based indirect illumination transformation. Each illumination transformed image was then represented by a histogram sequence that concatenates the histograms of the non-statistical multi-resolution uniform local Gabor binary patterns (MULGBP) for all the local regions. This was facilitated by dividing the input image into several regular local regions, converting each local region using several Gabor filters, and converting each Gabor filtered region image into multi-resolution local binary patterns (MULBP). However, their method requires significantly greater computation time.

Heydi Méndez Vázquez *et al* [7] considered the fact that Local Binary Patterns (LBP) is one of the most used methods in face recognition. They presented a different way of obtaining the regions that are used to construct the LBP histograms, in order to improve its performance in front of illumination problems. Their proposed method took into account the shape of the face to build a triangular mesh in which a better description of the face image through LBP was achieved. Experimental results conducted on Yale B database showed that under varying lighting conditions, the proposal improved the performance of the uniform LBP method. Finally, it is necessary that their method requires a previous geometric normalization of the face images, but this is also the case of the original LBP method.

Sarala Ramkumar *et al* [8] proposed a hybrid approach combining the holistic and feature based approaches. The proposed method of the Hybrid algorithm classified images of individual persons into separate classes. The performance of their Hybrid algorithm was implemented with the YALE & ORL face databases taken at different postures, by varying the lighting and facial expressions. It attained 96% recognition rate under varying postures and illumination conditions and it naturally outperformed the standard Holistic algorithms.

Dongsoo Shin *et al* [9] proposed illumination robust face recognition by separating an identity factor and an illumination factor using symmetric bilinear models. The translation procedure in the bilinear model required a repetitive computation of matrix inverse operations to reach the identity and illumination factors. Their computation mayresult in a non-convergent case when the observation has noisy information or the model is over-fitted. To alleviate this situation, they suggested a ridge regressive bilinear model that combined the ridge regression into the bilinear model. Their Experimental results showed that the ridge regressive bilinear model significantly outperformed other existing methods such as the Eigen-face, quotient image, and the bilinear model in terms of the recognition rate under a variety of illuminations.

Terrence Chen *et al* [10] presented the Logarithmic Total Variation (LTV) model for face recognition under varying illumination, including natural lighting condition, where we can hardly know the strength, the directions, and the number of light sources. The proposed LTV model has the capability to factorize a single face image and obtain the illumination invariant facial structure, which was then used for face recognition. The merit of this model was that neither does it require any lighting assumption nor does it need any training process. One assumption of their work was that small scale facial structures may be the key for frontal face recognition. Since their model reached very high recognition rate using PCA recognition, this assumption can be true.

Sanun Srisuk *et al* [11] introduced a novel concept of illumination normalization for robust face recognition under different illumination conditions. The concept was extended from the Self Quotient Image (SQI) by which the 2D Gabor filter was applied instead of weighted Gaussian filter in order to increase more efficiency of the face recognition. Their experimental result, which was conducted on Yale face database B, has shown that their proposed method required only single image, no need of prior alignment and less computational time and reached a very high recognition rate of 96%, even in the case of extreme varying illumination.

III. Proposed Methods

Every image can be represented in the form of a matrix. Like if a matrix has dimensions, 200x200, it means it is a 2-dimensional matrix having 200 rows and 200 columns, and a total of 40000 pixels. With these pixel values, we perform computation, find uniqueness and generate feature vectors for face images. These feature vectors are then used to classify face as recognized or unrecognized. For all our methods, we convert the image to a grayscale image, so that all images are single channel and 2 dimensional. Single channel means that image matrix has pixel values representing intensity in 1 channel. The intensities are represented in a value indicating the intensity of black-white combination. We use 8 bits to represent the pixel values. So the intensities can vary from 0 to 2^8 – 1, i.e. 0 to 255. 0 means absolute black and 255 means absolute white. For some of our approaches, these intensity values are the basis of computation. Preprocessing is carried out to resize the image into a square sized one. For instance, the original sizes of grimace images are 200x180 and were resized to 180x180 images.

A. Transmutation Method

Here, we convert the image matrix into a matrix containing only λ and δ values as in Fig. 3. We find out the highest intensity value in each column, record it's position, now keeping that position's value as λ, we put all δ's in that particular row and column. So, in each row and each column, we have a single position having a value of λ, all other entries are . Suitable values for λ and δ have to be chosen for effective coding of images.

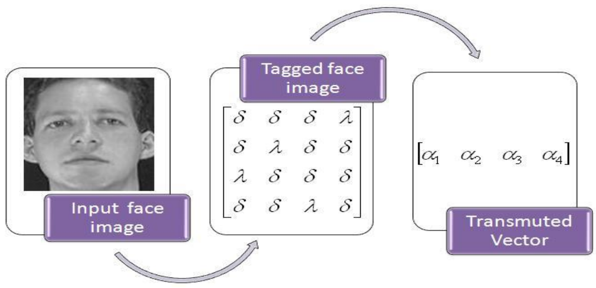

Figure 3. Image tagging using transmutation method.

Then we generate the feature vector. The feature vector of all images has the size, same as the number of columns in the image. λ marked positions are captured as sequence vector which become the feature vectors and are of size n, where is the number of columns. Like this, we generate the feature vectors for all images and store them. Whenever, a query image is given, its feature vector is generated and compared against all the feature vectors of the image database.

Algorithm 1:

Resize all images to an nxn dimension

for all columns:

for all rows:
find the position of row having highest intensity value
put λ at that position
put δ at all other positions in that column and row
end
make an entry for this column in feature vector
end
generate feature vector and store it.

B. Mean Transmutation Method

This method requires multiple samples of the same subject image captured under different external factors. Thus obtained mean sample is considered in computing the transmuted vector.

Algorithm 2:

for all images of a subject in training set:
for each row:
for each column:
mean[row][col] = k -> samples
end
end
generate transmutation vector
end

C. Preeminent Transmutation Method

This method doesn't require square matrix, so we can take the image in its original form for further computation. However, images need to be gray. In this method, we find the ω preeminent intensities for every subject image. These ω values are coded in the feature vector

Algorithm 3:

for each element in the image matrix:
find ω1, ω2, ω3, ……
end
compute transmutation vector

D. Preeminent Mean Transmutation Method

This is an extension of Preeminent Transmutation Method. Here too, we find ω preeminent intensities for every subject image for the sample image.

Algorithm 4:

for all face images per subject: obtain mean sample:
find ω1, ω2, ω3, …… of each image
end
make an entry of ω's positions in feature vector

E. Weighted Preeminent Transmutation Method

This method requires gray-scale images as a part of pre-processing. In this method, we find the 3 highest intensities in each column. For each column, we find the position of those 3 rows which have the highest intensity. Then we assign weights to the top 3 positions in increasing order of their intensity. The feature vector contains the weighted sum of these 3 positions. The position with the highest intensity is given weight 1, the position with second highest intensity is given weight, 0.67 and the position with third-highest intensity is given weight 0.33. For feature vector, we multiply the weights to the respective positions and sum the 3 of them to get a value for that particular column in the feature vector.

Algorithm 5:

for all columns: for all rows:
find pos1, pos2, pos3 //they hold the position where top 3 intensities are found
val = (pos1 + 0.67*pos2 + 0.33*pos3)
end
make an entry for this column in feature vector
end

IV. Results and Discussions

A. Datasets

Two standard face datasets namely ORL [12] and Grimace [13] have been used for experimentations. The ORL dataset consists of 40 subjects each having 10 different face images taken at different times with variations in illumination, expression and upright, frontal positions. Out of 400 images, 175 images were used for training set and 200 images for testing which includes both known and unknown faces. The grimace dataset consists of 18 subjects each having 20 face images. Here too, the images variations in illumination, expression and pose. A subset of this dataset with 120 images in train set and 240 images in test set have been used for experimentation. Sample images from both the datasets are depicted in Fig. 4(a) and Fig. 4 (b) respectively.

(a) ORL

(b) Grimace

Figure 4. Sample face images from ORL & grimace dataset.

B. Recognition Accuracy

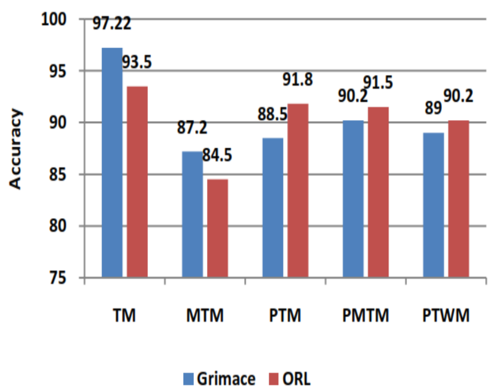

Figure 5. Comparison of accuracy.

The accuracy of the proposed techniques is plotted in Fig. 5. The results indicate that transmutation method technique yields higher recognition rate when compared to all other methods. We can also notice variations in every method's accuracy i.e. some methods work well on some database, the reason being the robustness of a method to withstand certain variations. For instance, transmutation and mean transmutation methods yields higher accuracy on Grimace which has slight variations in pose than on ORL. On other preeminent transmutation, preeminent mean transmutation and weighted preeminent transmutation gave higher accuracy on ORL dataset.

C. *Hypotheses Class*

A hypotheses class is a layout that allows visualization of the performance of an algorithm. Each column represents the instances in a predicted class, while each row represents the instances in an actual class. The name stems from the fact that it makes it easy to see if the system is confusing two classes. A sample hypotheses class for Transmutation method on grimace database is given in Fig. 6.

	P' (Predicted)	N' (Predicted)
P (Actual)	179 (TP)	1 (FN)
N (Actual)	0 (FP)	20 (TN)

Figure 6. Hypotheses class for transmutation on grimace.

where:

- True Positive (TP): Given an image in the database, our algorithm correctly recognizes it.
- False Negative (FN): Given an image in the database, our algorithm fails to recognize it.
- False Positive (FP): Given an unknown image, our algorithm incorrectly recognizes it as someone else from the database.
- True Negative (FN): Given an unknown image, our algorithm doesn't recognize it.

An algorithm is said to be best, if it has less FN and FP. It is evident from figure 6 that our transmutation method is best when compared to other variants of it as it is yielded in 0 FP and 1 FN (which is acceptable).

D. *Statistical Parameters*

Some of the common statistical parameters used in face recognition include sensitivity, specificity, accuracy and precision.

- Sensitivity measures the proportion of actual positives which are correctly identified.

$$Sensitivity=TP/(TP+FN)=TP/P$$

- Specificity measures the proportion of negatives which are correctly identified.

$$Specificity=TN/(TN+FP)=TN/N$$

- Accuracy measures the proportion of total correctly identified results to the total results.

$$Accuracy=(TP+TN)/(P+N)$$

- Precision is defined as the proportion of the true positives against all the positive results.

$$Precision=TP/(TP+FP)$$

For instance, the values for each of the aforesaid parameters for transmutation method are stated in the Table I.

TABLE I. STATISTICAL PARAMETERS FOR TRANSMUTATION METHOD.

Statistical Parameter	Value
Sensitivity	0.994
Specificity	1.0
Accuracy	0.995
Precision	1.0

The values obtained for different databases are well above 0.99 and in some parameters it has reached 1 as desirable. This indicates the effectiveness of the transmutation technique.

V. CONCLUSIONS AND FUTURE ENHANCEMENT

This paper proposed a newer approach of tagging images. The advantage with such a transmutated image is that it is sparse and hence encoding is easier. One of the key features of the transmuted vector is that it is quite robust to perturbations in the internal and external factors. Yet another advantage is that generation and transmission of transmuted vectors is much faster than the other methods. Several variations have been experimented in transmutation approach and results have shown that recognition performance is fairly satisfactory. The time complexity for generation is (n) unlike others which have much higher complexities. Future work can be directed towards differential weights to the leading pixels instead of two code rule.

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