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Translation based Face Recognition using Fusion of LL and SV Coefficients

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Abstract

The face is a physiological trait used to identify a person effectively for various biometric applications. In this paper we propose Translation based Face Recognition using Fusion of LL and SV coefficients. The novel concept of translating many sample images of a single person into one sample per person is introduced. The face database images are preprocessed using Gaussian filter and DWT to generate LL coefficients. The support vectors (SV) are obtained from support vector machine (SVM) for LL coefficients. The LL and SVs are fused using arithmetic addition to generate final features. The face database and test face image features are compared using Euclidean Distance (ED) to compute the performance parameters.

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Keywords: Biometrics; Discrete Wavelet Transform (DWT); Face Recognition (FR); Fusion; Support Vector Machine (SVM).

1. Introduction

The personnel identification and personal data must be protected from hackers as the technology is advancing day by day. The traditional methods of identifying using ID badges, Passwords and Pins etc., are not reliable, since these devices can be lost or stolen. An alternative method to identify a person is Biometrics, which is more reliable as this technique is related to human body parts and behavior of a person. The biometrics are broadly classified into two groups viz., physiological biometrics and behavioral biometrics. The physiological biometric traits such as Face, Iris, Palm print, Fingerprint, DNA etc., have constant characteristics. The behavioral biometric traits such as Signature, Gait, Voice, Keystroke etc., have variable characteristics based on the behavior of a person. The biometric provide high level of security by denying access to unauthorized persons. In recent years biometrics is being used in every field of technology such as home security, industries, educational institutes, access to electronic devices to defense areas, preparation of country database, cloud computing, Big data analysis etc. Face recognition is one of the better physiological biometric traits to recognize a person for several activities. The face recognition has an advantage compared to other biometric trait recognition, since it does not require any physical interaction or cooperation of a person while acquiring face images. The face recognition system has three sections viz., enrolment section, test section

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and matching section. Face database images are acquired using sensors and features are extracted using spatial or transform domain technique in enrolment and test sections. The features of test and database images are compared using distance formulae or classifier in matching section.

Contribution: In this paper many image samples of a person are translated into one image sample using average technique. The fusion of DWT and SVS are used to generate features.

Organization: The paper is organized as follows. In section 2, the literature surveys of published papers on biometrics are discussed. The proposed model to identify a person effectively is explained in section 3. The performance analysis of proposed method and comparison between the proposed and existing methods are conducted in section 4. The conclusion is given in section 5.

2. Literature Survey

In this section, the existing various techniques of biometrics are discussed. Thai Hoang Le and Len Bui¹ proposed a model on Face Recognition Based on Support Vector Machine (SVM) and 2-Dimensional Principle Component Analysis (2DPCA). In this model feature vectors are obtained using 2DPCA technique and then different classifiers like Multi Layer Perception (MLP), K-Nearest Neighbour (K-NN) and SVM are used for recognition. The experiment result shows that the combination of 2DPCA and SVM yields a greater accuracy. Harin Sellahewa and Sabah A. Jassim² proposed Image-Quality-Based Adaptive Face Recognition. This model presents an approach to overcome one of the main constraints like varying lighting conditions. Image quality (Q) is measured in terms of illumination distortion in comparison to known reference image. Reference image is obtained by averaging images of 38 individual faces. Later Global luminance distortion in Q (GLQ) is calculated for each image. If GLQ is less than a predefined threshold, normalization is performed. Later wavelet transform like Pyramid Scheme is applied for feature extraction. At a resolution level of k, the pyramid scheme decomposes an image I into 3k + 1. The highest identification accuracy is achieved by fusing the similarity scores of LH and HL sub-bands. Kai Dong-Hyuk Shin et al.³ proposed A Block-Based Noise Estimation using Adaptive Gaussian Filtering. The standard deviation that used for the filter is found out from the input noisy image. For calculating the noise, level, image is divided into blocks and select the smooth block which carrying lowest standard deviation. Applying Gaussian filter which smoothen image and calculating the noise level from the filtered image and difference block images of the noisy input image. Zhao-Rong Lai et al.4 proposed the Discriminative and Compact Coding for Robust Face Recognition. Here they say about Discriminative & Compact Coding (DCC) and introduced multiple errors measurements into regression models. There are 2 types of proposed models here, 1) Multi-scale error measurements. 2) Inspire within-class collaborative representation.DCC is robust parameter to produced the stable regression residual which is more important for classification. Xiaobing Pei et al.⁵ proposed Manifold Adaptive Label Propagation (MALP) for Face Clustering. Proposed model deals with the semi-supervised clustering problems. MALP tries to find graph weight matrix along with the graph edges of the given data set. MALP integrates sparse representation constraint into regular framework of Label Propagation (LP), which can enhance the performance of LP in face clustering problem. Proposed algorithm is tested on datasets like ORL, YALE, Extended YALEB and PIE, better results are obtained compared to existing LP methods. Ran He et al.⁶ proposed Two Stage Nonnegative Space Representation for Large Scale Face Recognition. This paper relatively know about the nonnegative space representation approaches, which is called Two Stage Space Representation (TSR) which is used in large scale database for face recognition. In this experiment TSR decomposes into outlier detection stage and recognition stage. And here they first proposed general multi-subspace framework and next, base on the learn matrix, collaboration representation. Randa Atta and M. Ghanbar⁷ Proposed An Efficient Face Recognition System Based on Embedded DCT Pyramid. Each face image is decomposed into non-overlapping blocks of approximation sub bands and a set of reversed L-shape blocks with high frequency coefficients in the detailed sub bands. Inter dependency among the sub bands are finds out by composite spatial orientation tree of the blocks and efficient coefficients of the DCT pyramid is selected by use Set Partitioning in Hierarchal Trees (SPIHT). These coefficients are used as the features for the face recognition. Nearest Neighbour (NN) and Euclidean distance methods are used to classify the similar images of the database and test images.

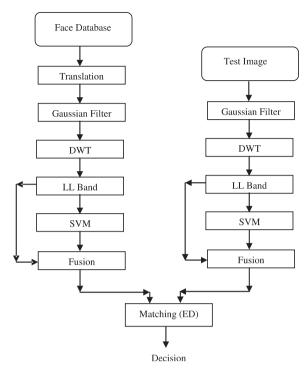


Fig. 1. Proposed Model.

3. Proposed Model

The face recognition based on novel concept of converting many images of single person into one image and features extracted using DWT and SVM is introduced in this section. The block diagram of the model is shown in Fig. 1.

3.1 Face databases

The various databases such as ORL, JAFFE, Indian Female, Indian Male and L-Speck are used to test the model for performance analysis.

3.1.1 Olivetti Research Laboratory $(ORL)^8$

The database has forty persons with ten images per person i.e., it has four hundred images in total. The face images are captured with different lighting conditions, facial expressions, timings and angles with each image of size 92 * 112.

3.1.2 Japanese Female Facial Expressions (JAFFE)⁹

The database consists of ten persons with twenty images per person i.e., it has two hundred images in the database. The images are captured based on expressions such as emotional, happy, disgust, angry, natural movement, surprise etc. with each image of size 256 * 256 with grey scale format.

3.1.3 Indian female 10

The database has eleven persons with twenty two images per person i.e., it has two hundred forty images in total. The images are captured based on facial orientations with different emotional expressions with each image of size 640*480.

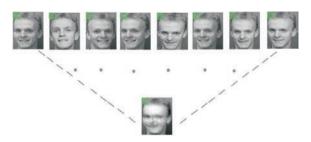


Fig. 2. Translation of Image Samples.

[10 12 16 98]	[17	16	15	85]	Γ1	2	19	0	100]	1	22	9	11
55 69 33 87	56	29	83 3	107	6	66	21	93	207	36	2	32	79
25 24 35 67	25	64	95	7	6	52	84	3.	50	32	98	5	100
45 21 98 78	45	21	98	78 l	9	5	41	38	3 18	90	48	98	108

Fig. 3. Fair 4 * 4 Matrix for Translation.

3.1.4 Indian male 10

The face database of two hundred and twenty images of eleven persons. The face images are captured on different orientation angles with various expressions with each image of size 640 * 480.

3.1.5 L-SPACEK face database

The database has one hundred and twenty persons with nineteen images per person i.e., it has two thousand two hundred and eighty images. The database has image size of 320*280 with BMP format. The images are captured with different expressions of a person.

3.2 Translation of images

The number of image samples per person is converted into single image per person to save execution time and memory. The average intensity values of all images are used to derive single image per person. Eight images of single person are converted into single image as shown in Fig. 2.

3.2.1 Illustration of translation using 4 * 4 matrices

The four 4 * 4 matrices are considered as shown in Fig. 3 to demonstrate the translation.

Each 4*4 matrices are converted into column vectors as shown in Fig. 4. The four column vectors are converted into single column vector by computing element by element average values as shown in Fig. 5(a). The column vector is converted into matrix as shown in Fig. 5(b). The translation of many images of a person into single image is always an advantage of less execution time of an algorithm in real time and the memory required to one image is less compared to many images per person. The mathematical model to convert many images into one image is given in Eqn. 1.

Consider an image size of $\mathbf{m} * \mathbf{n}$ and convert into single column vector of size ((m * n), 1). The total numbers of column vectors are equivalent to total number of images per person. The average element values of all column vectors are computed using Eqn. 1.

$$X_{avg} = [X_{avg(i)}] = \frac{\sum_{j=1}^{N} x(i,j)}{N}, \quad 1 \le i \le (m*n)$$
 (1)

For i = 1.

$$X_{avg1} = \frac{\sum_{j=1}^{N} x(1,j)}{N} = \frac{x(1,1) + x(1,2) + \dots + x(1,8)}{8}$$

۲10 ر	Γ 17 ₁	[12]	[01 <u>]</u>
55	56	66	36
25	25	62	32
45	45	95	90
12	16	19	22
69	29	21	02
24	64	84	98
21	21	41	48
16	15	00	09
33	83	93	32
35	95	35	05
98	98	38	98
98	85	100	11
87	107	207	79
67	07	00	100
L ₇₈ J	L ₇₈ J	L ₁₈ J	L ₁₀₈ J

Fig. 4. Column Vector of 4 * 4 Matrices.

Fig. 5. Single Column Vector and Corresponding Matrix.

For i = 2,

$$X_{avg2} = \frac{\sum_{j=1}^{N} x(2, j)}{N} = \frac{x(2, 1) + x(2, 2) + \dots + x(2, 8)}{8}$$

For i = m * n,

$$X_{avg(m*n)} = \frac{\sum_{j=1}^{N} x(m*n, j)}{N} = \frac{x(m*n, 1) + x(m*n, 2) + \dots + x(m*n, 8)}{8}$$
(2)

where: N = Number of images per person

m =Number of rows in a matrix

n = Number of columns in a matrix

The column vector of X_{avg} is converted back to m*n image to translate many images to one image.

3.3 Gaussian filter

The Gaussian smoothing operator is a 2-D convolution operator i.e., used to blur images and remove detail noise. The Gaussian filter function is given by Eqn. 3 with mean distribution of zero.

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2 + y^2}{2\sigma^2}}$$
 (3)

where, σ is the standard deviation of the distribution.

Gaussian filters are linear low pass filters which masks perfectly simulate optical blur and remove the details of the image. The degree of the smoothing is controlled by the σ , larger the σ smoothing will be more. In the spatial domain the image is multiplied by appropriate kernel but in the frequency domain an image and a filter function are multiplied pixel by pixel to obtain the filtered output.

3.4 Discrete Wavelet Transform (DWT)¹¹

The transformation is used to obtain frequency resolution and temporal resolution for low and high frequencies respectively. The DWT divides an image into approximation and detailed sub bands. The approximation sub band has significant information of an image. The detailed sub band has information on horizontal, vertical and diagonal details. The low pass filters and high pass filters are used to generate approximation and detailed sub bands respectively. The four sub bands such as LL band formed by low pass filter and low pass filter, LH band formed by low pass and high pass filter, HL band is formed by high pass filter and low pass filter, HH band is formed by high pass filter and high pass filters.

3.5 Support Vector Machine (SVM)¹²

It is used to find the position of the feature vectors, image compression and to classify the data. The support vectors are the data points located near to the hyper-plane.

The classifier divides into two groups using hyper-plane as class 1 and class 2 i.e., plus plane is X: W.X+b=1 and minus plane is X: $W \cdot X + b = -1$. Where the W is the weight vector and it is perpendicular to the hyper-plane, X is the feature vector and b is the position of the feature vector. The proposed method uses SVM for data compression. The support vectors of LL band coefficients are considered and fused with LL band coefficients to derive final features.

3.6 Euclidean-distance

The final features of test images are compared with final features of images in the data base using Euclidian Distance (ED) to identify a person using Eqn. 4.

$$ED = \sqrt{\sum_{i=1}^{M} (Pi - qi)^2} \tag{4}$$

where.

M = No of coefficients in a vector.

Pi = Coefficients values of vectors in database.

qi =Coefficient values of vectors in test image

4. Performance Analysis

In this section, the definition of performance parameters and results analysis based on TSR, FRR, FAR and EER are discussed.

4.1 Definitions of performance parameters

i. False Rejection Ration (FRR): The ratio of number of genuine persons rejected to the total number of persons inside the database as given in the Eqn. 5.

$$FRR = \frac{\text{Number of genuine persons in the database rejection}}{\text{Total number of persons inside the database}}$$
 (5)

Table 1. Variations of Performance Parameters with PID and POD for ORL Database.

PID	POD	Opt TSR (%)	Max TSR (%)	EER (%)
10	30	90	100	10
16	24	81.25	93.7	18.75
20	20	80	100	20

Table 2. Variations of Performance Parameters with PID and POD for JAFFE Database.

PID	POD	Opt TSR (%)	Max TSR (%)	EER (%)
6	4	83.33	100	16.66
5	5	80	100	20

ii. False Acceptance Ratio (FAR): The ratio of number of imposter persons accepted as genuine to the total number of persons outside the database as given in Eqn. 6.

$$FAR = \frac{Number of imposter persons accepted as genuine}{Total number of persons outside the database}$$
(6)

iii. Total Success Rate (TSR): The ratio of number of genuine persons recognized correctly to the total number of persons inside the database as given in Eqn. 7.

$$TSR = \frac{\text{Number of the genuine persons recognized correctly}}{\text{Total number of the persons inside the database}}$$
 (7)

- iv. Equal Error Rate (EER): The optimum error between the FAR and FRR. The value of EER is intersection of FRR and FAR. The lower EER gives the better efficiency of an algorithm.
- 4.2 Performance evaluation using various face databases

4.2.1 ORL face database

The database is created by considering ten persons inside the database (PID) and thirty persons outside the database (POD) to observe the variation of FRR, FAR, TSR and EER for different threshold values of the proposed model. The performance values of FAR and TSR increases with threshold, where as the percentage FRR values decreases with threshold. It is observe that the percentage TSR value is 90% corresponding to 10% EER and maximum TSR is 100%. The variations of percentage EER, optimum TSR and maximum TSR for different combinations of the PID & POD for ORL face database is given in Table 1.

It is observed that, the values of the optimum TSR decreases and EER increases as PID increases. The optimum TSR values are directly proportional to POD, where as the values of EER are inversely proportional to POD.

4.2.2 JAFFE face database

The database is created by considering ten persons inside the database (PID) and thirty persons outside the database (POD) to observe the variations of FRR, FAR, TSR and EER for different threshold values of the proposed model. The performance values of FAR and TSR increases with Threshold, where as the percentage FRR values decreases with threshold. It is observe that the percentage TSR value is 83.33% corresponding to 16.66% EER and maximum TSR is 100%. The variations of percentage EER, optimum TSR and maximum TSR for different combinations of the PID & POD for JAFFE face database is given in Table 2.

It is observed that, the values of the optimum TSR decreases and EER increases as PID increases. The optimum TSR values are directly proportional to POD, where as the values of EER are inversely proportional to POD.

Table 3. Variations of Performance Parameters with PID and POD for Indian Male Database.

PID	POD	Opt TSR (%)	Max TSR (%)	EER (%)
5	5	20	100	80
6	14	33.33	100	60
8	12	50	100	50
12	8	58.33	91.667	44

Table 4. Variations of Performance Parameters with PID and POD for Indian Female Databases.

PID	POD	Opt TSR (%)	Max TSR (%)	EER (%)
6	16	83.33	100	10
8	14	87.5	100	12.5
12	10	83.33	100	16.66

4.2.3 Indian male database

The database is created by considering ten persons inside the database (PID) and thirty persons outside the database (POD) to observe the variation of FRR, FAR, TSR and EER for threshold value variations of the proposed model. The performance values of FAR and TSR increases with Threshold, where as the percentage FRR values decreases with threshold. It is observe that the percentage TSR value is 58.33% corresponding to 44% EER and maximum TSR is 91.667%. The variations of percentage EER, optimum TSR and maximum TSR for different combinations of the PID & POD for Indian Male face database is given in Table 3.

It is observed that, the values of the optimum TSR decreases and EER increases as PID increases. The optimum TSR values are directly proportional to POD, where as the values of EER are inversely proportional to POD.

4.2.4 Indian female database

The database is created by considering ten persons inside the database (PID) and thirty persons outside the database (POD) to observe the variations of FRR, FAR, TSR and EER for different threshold values of the proposed model. The performance values of FAR and TSR increases with Threshold, where as the percentage FRR values decreases with threshold. It is observe that the percentage TSR value is 87.5% corresponding to 12.5% EER and maximum TSR is 100%. The variations of percentage EER, optimum TSR and maximum TSR for different combinations of the PID & POD for Indian Female face database is given in Table 4.

It is observed that, the values of the optimum TSR decreases and EER increases as PID increases. The optimum TSR values are directly proportional to POD, where as the values of EER are inversely proportional to POD.

4.2.5 L-SPACEK database

The database is created by considering ten persons inside the database (PID) and thirty persons outside the database (POD) to observe the variations of FRR, FAR, TSR and EER for different threshold values of the proposed model. The performance values of FAR and TSR increases with Threshold, where as the percentage FRR values decreases with threshold. It is observe that the percentage TSR value is 100% corresponding to 0% EER and maximum TSR is 100%. The variations of percentage EER, optimum TSR and maximum TSR for different combinations of the PID & POD for L-SPACEK face database is given in Table 5.

It is observed that, the values of the optimum TSR decreases and EER increases as PID increases. The optimum TSR values are directly proportional to POD, where as the values of EER are inversely proportional to POD.

Table 5. Variations of Performance Parameters with PID and POD.

PID	POD	Opt TSR (%)	Max TSR (%)	EER (%)
10	30	100	100	0
20	20	90	95	0.05
10	40	100	100	0
20	30	90	95	0.066
30	20	90	93.33	0.08

Table 6. Comparison of Performance Parameters.

Sl. No.	Authors	Techniques Used	Opt TSR(%)	Max TSR (%)
1	D. Murugan et al. 13	Gabor filter + DWT	84.8	92
2	Pallavi D. Wadkar et al. 14	DWT	82.85	90
3	B. M. Sujatha et al. 15	DWT+FFT+CLBP	80	93.33
4	Proposed Model	DWT+SVM	90	100

4.3 Comparison of proposed algorithm with existing algorithms for ORL face database

The performance parameters viz., optimum TSR and maximum TSR of the proposed method is compared with existing methods presented by D. Murugan *et al.*¹³ Pallavi D. Wadkar *et al.*¹⁴ and B. M. Sujatha *et al.*¹⁵ is shown in Table 6. It is observed that the values of the optimum TSR and maximum TSR are high in the case of proposed algorithm compared to existing algorithms.

The proposed algorithm is superior compared to existing algorithms for the following reasons.

- i. The novel concept of converting many images per person into single image using averaging technique.
- ii. The SVM is applied on LL band of DWT and the support vectors (SV's) are considered for features.
- iii. The LL band coefficients are fused with SV's to generate final feature set.
- iv. The proposed algorithm is very efficient as the images are compressed based on Image averaging technique, DWT and SVM.

5. Conclusion

The face recognition used to identify the person for various applications. In this paper many image samples of a person with variations in illumination and angles are translated into one image sample per person. The features are generated using the fusion of LL band coefficients with SV coefficients. The ED is used to compare features of test images with face database features to compute TSR, FAR, FRR and EER. In future the algorithm can be tested with hardware to compute execution time and memory requirement. The algorithm can also be implemented using combination of texture features and SVs.

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