Human Face Identification using Moments and Transformations

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Abstract. Face recognition one of the most promising techniques such that the importance of biometric user identification is increasing every day, several methods have been suggested to perform it such as classification, deep learning, statistical, moments, etc., this work describes different approaches to develop biometric technique, based on the moments and transformation. The proposed method for face recognition is based on Legendre moments and singular value decomposition for feature extraction. Local approaches by dividing images into several blocks (overlapped blocks and non-overlapped) have been adopted to gain the best recognition rate, as well as normalization using the Z-score method, which has been used. The outcomes experimental showed that the suggested system is effective, it has been tested using ORL face image databases with 10 cases and achieved a recognition rate from 85.27-100%, also, applied on FEI Brazil face database with 10 cases and achieved a recognition rate from to 79.77-100%.

Keywords. Face Recognition, Legendre Moments, Singular value decomposition.

1. Introduction
Face recognition is considered as an aspect of biomedical technology that is serviceable for a lot of applications in banking, human-computer interaction, implementation security and retrieval of the database, personal identification passports, driver licenses, law enforcement, surveillance system, etc. One of the key biometric technologies has become more important because of rapid developments in technology such as digital cameras, the Internet and mobile devices, and growing security demands. Face recognition has many advantages over other biometric technology, it is automatic, non-intrusive, and user friendly. But face recognition is one of the difficult issues in science, so far no suitable solution has been identified for all face recognition applications. Because of point of view, posture, illumination, and voice, the large range of variations in the human face deteriorate the recognition efficiency of the Face recognition systems. But everybody agrees that the method of face recognition is good if it has less computational complexity, the good output of recognition, and fewer memory occupies[1].

Dimensionality reduction and feature extraction are very important aspects of any Face Recognition system. Face images while small in size have high dimensionality which leads to very high computational time, complexity, and occupation of memory. Any classifier's success depends primarily on the highly biased features of the face images[2], [3].

2. Related Works
Khalid M. Hosny[4] proposed a new approach. The refined translation scale of the Legendre moment invariants was obtained by the exact calculation of the original Legendre moments, which eliminated the approximation. The fast and direct calculation of the central moments of Legendre significantly reduced the calculation time. Due to the significant reduction in computational complexity, the refined set of Legendre invariants was suitable for large images. The performance of the descriptors was assessed using a standard image set.

R. Akbari and ETL. [5] proposed a new approach, a vector recognition algorithm based on Legendre's characteristic moment, was presented as an attempt to solve the problem of a single image. In our experiments, a subset of 200 images from the FERET database and 100 images from the AR database were used. The results showed for AR and FERET achieved an accuracy of 91% and 89.5%, respectively[6].

D. Sridhar and Dr. Krishna[7] proposed a new approach to hybrid facial recognition that relies on LDA and PNN LMs. LMs are scaled orthogonally and invariably so that they are ideal for the expression of properties of facial images. The suggested facial recognition approach has three phases: the first is feature extraction using LMs, the second is the reduction of complexity through linear discriminant analysis (LDA) and the third is a probabilistic neural network (PNN) for classification. The linear discriminant analysis looks in addition to minimizing complexity, in the direction of maximum class discrimination. When certain image samples are usable, a combination of Legendre moments and linear discriminant analysis was used to boost the ability of linear discriminant analytics. The probabilistic neural network provides a quick and simple grading of facial images. The system proposed provides a speedier and best recognition rate compared to other methods.

R. Kapoor and P. Mathur [8] suggested a new approach to moments-based facial recognition. Four possible methods of extraction were used: moments in Zernike, moments in Hu, accumulators, and moments in Legendre. The moments Legendre and Zernike have a set of polynomial bases and can be used to view an image with a minimum redundancy of information. These are based on the polynomial principle and can be used to get a picture of current operands. Hu moments provide a sequence of seven moments deriving from traditional geometric moments. These moments are permanent for rotation, translation, and scaling. The cumulative is delicate to the picture details and was therefore useful to describe the picture's properties. Moments of different orders were calculated for the extraction of entities, which form the vectors of entities. The acquired feature vectors were saved to the database, and three different classifiers were matched. They calculated the range of the images for the accumulators and glued them with wavelets.

G. Singh and I. Chhabra [9] proposed a new method based on known statistical moments: Zernike Moments (ZM) and pseudo-Zernike moments (PZM), and two-dimensional descriptors of the polar harmonic transformation (PHT). Experimental results also show that PHTs work better than ZM and PZM in terms of scale invariance, rotation invariance, and noise invariance and achieve an accuracy of 97.25%, 98.7%, and 94% and have a very low computational effort since they were used to calculate the Radial cores required time was significantly less.

O.M. Parkhi and ETL. [10] proposed a new method of face recognition, either from a single photograph or from a series of faces captured on a recording. Advances in developments in this field are due to two factors: I end-to-end learning with a coevolutionary neural network (CNN) and (ii) the availability of large-scale training records for the task. They made two contributions: First, they demonstrated how to bring together a very large collection of data (2.6 million images, more than 2,600 people) in a loop using a mixture of automation and humans. and they discuss the compromise between data purity and time; Second, they examined the complexity of deep network training and face recognition to present methods and procedures that could be used to achieve comparable and cutting-edge results compared to LFW and YTF benchmarks.

A. Chiang and S. Liao [11] proposed a numerical integration approach for improving the precision of the estimation of the Legendre moment. Reconstructions of higher-order images of Legendre moments up to 240 have been carried out to explain the enhanced calculation scheme. Legendre has analyzed the distributions of image information in a collection of finite moments with the moments produced with
greater precision. He concluded that each finite set of Legendre moments individually describes the image's unique properties, while the Legendre moments pairs reflect most of the image's properties.

G. Zhang and ETL. [12] proposed a new approach for accumulating two sets of singular decomposition values (SVD) of virtual samples of single right vectors and single left vectors for each training sample grade. The created virtual images not only enhance the training patterns but also gain knowledge that was more inclusive of the faces, resulting in greater accuracy in facial recognition. It also provides a simple and effective approach for the automated assessment of adaptive weight for three measurement groups, including the original samples and two default sample sets, without manual interference. The weighted score fusion strategy will provide more additional details from multiple sources, as well as a better result in facial recognition. Experiments with three reference data sets showed that their proposed method was robust and enables better facial recognition precision compared to the previous methods.

P. Chrikos and ETL. [13] suggested developing a face detection method that would prevent the prevention of privacy threats, which could include automatic video analysis. Face detection in frames or videos is the first step that occurs in human-centered video analysis, e.g. by automated face recognition. They also make automatic facial recognition impossible, by making facial recognition more difficult. They are looking at the use of two approaches for that reason. Second, they consider a naive approach, that is to say, they use additive or impulsive noise for the input picture until the face is no longer immediately recognizable. Second, they investigated how the SVD-DID approach is applied to facial recognition. Their experimental findings revealed that both approaches achieve high facial recognition failure rates.

As we have seen, face recognition gained a high significance with different applications, as a result of their resistance to several variance and challenges such as noise, illumination, rotation, etc.

3. Methodology of the Proposing Approach

There are several methods suggested to features extraction for face recognition, which we will proposed Legendre moments and SVD.

3.1. Legendre Moments

Teague [14] launched Legendre moments. Legendre moments as kernel function were obtained from Legendre polynomials. Teague initially suggested Legendre polynomials. These are orthogonal moments that can reflect an image with minimal redundancy of the information. So the moments reflect the independent features of a picture.

Legendre moments of order \((p+q)\), the two-dimensional, are defined as in equation (1):

\[
L_{pq} = \frac{(2p + 1)(2q + 1)}{4} \int_{-1}^{1} \int_{-1}^{1} P_p(x) x^p P_q(y) f(x,y) \, dx \, dy; \quad x, y \in [-1,1]
\]

(1)

Where Legendre polynomial, \(P_p(x)\), of order \(p\) is given by

\[
P_p(x) = \sum_{k=0}^{p} \frac{(-1)^{p-k}}{2^p (p-k)! (p+k)!} x^{p-k} y^k
\]

(2)

The recurrence relation of Legendre polynomials, \(P_p(x)\), is given as follow:

\[
P_p(x) = \frac{(2p-1)P_{p-1}(x)(1-x^2)}{p} \]

(3)

Where \(P_0(x) = 1\), \(P_1(x) = x\) and \(p > 1\). Because the Legendre polynomials description region is the interior of \([-1,1]\), a square image with intensity function of \(N \times N\) pixels \(f(i,j), 0 \leq i, j \leq (N-1)\), is scaled in the region of \(-1 < x, y < 1\). In the result of this, Eq. (1) can now be expressed in discrete form as[14],[15]:

\[
L_{pq} = \lambda_{pq} \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} P_p(x_i) P_q(y_j) f(i,j)
\]

(4)

Where the normalizing constant,
\[
\lambda_{pq} = \frac{(2p+1)(2q+1)}{N^2}
\]

\(x_i\) and \(y_i\) define the coordinates of normalized pixels within the range of \([-1,1]\), which are given by:

\[
x_i = \frac{2i}{N-1} - 1 \quad \text{and} \quad y_i = \frac{2j}{N-1} - 1
\]

3.2. Singular value decomposition

Singular Value Decomposition (SVD) is a method of numerical analysis that is used in matrix diagonalization. SVD has many strong mathematical characteristics and has been widely applied to various activities. SVD can extract unique properties from a matrix for example. Singular image values have very high stability and represent the algebraic image’s inherent properties. From the sense of image processing, we can interpret an image to be a matrix containing non-negative scalar entries. The SVD on \(A\) for a size image \(A\) is defined as follows \(NxM\):

\[
A = U S V^T
\]

Where

\(A\) = An matrix with \((m \times n)\) dimensional

\(U = m \times m\)

\(V = n \times n\)

\(U\) and \(V\) are considered orthogonal matrices and \(S\) is an \(m \times n\) and considers a diagonal matrix. That is \(U\) is computed as the eigenvector of \((AA^T)\) and \(V\) is computed as the eigenvector of \((A^T A)\) that denoted as\([16]\):

\[
AA^T = USV^T (USV^T)^T = USV^T V SU = US^2 U^T
\]

\[
A^T A = (USV^T)^T USV^T = VSU^T USV^T = VS^2 V^T
\]

3.3. The Proposed System of Hybrid System

The proposed system merge more than one methods to improve the performance of the recognition system in parallel, the main steps showed in figure(1):

**Figure 1.** the Main Steps of The Proposed System.

3.3.1. The Environment of The Proposed System
For face-recognition researchers, there are various face databases available. These databases are different in terms of scale, scope, and purpose. For researchers to be able to compare the final rate of results directly, it is advisable to use a standard test face recognition database. Small research teams obtain the images in a lot of these databases for researching face recognition. We evaluate the proposed method using FEI (Brazilin) and ORL (AT&T) database and achieved better performance.

### 3.3.2. Preprocessing
Several steps have been adopted, main of them:
1. Image resize: in this step, the dimensions of all images are resized to a specified scale (100*100).
2. Converting images to double mode, neglect this step may because several problems such as all parts of the image will appear in white when it displays.
3. Converting color image (RGB) to the grayscale image.

### 3.3.3. Features Extraction
In this step, features are extracted from the image using two parallel ways first using Legendre Moments and others using singular value decomposition.

### 3.3.4. Normalize vectors
Before fusion two features vectors must normalize each one in this proposed system Z-score normalization has been used as follow:

\[
Z - \text{score} = \frac{(\text{Feature vector}) - \text{Mean(Feature vector)}}{\text{Standard deviation(Feature vector)}}
\]

(10)

### 3.3.5. Fusion vectors
The Fusion method of features vectors produce a highlight improvement of the performances by reducing the accepted results, Fusion has been used effectively for many years in large scale automatic recognition systems with three types (fusion at the feature extraction step, fusion at the matching scores, and the decision).

### 3.3.6. Matching
Has been done using a Euclidean distance measure for matching. The recognition rate and error rate of the proposed system are calculated by the following equation and report in our experiments:

\[
\text{Recognition rate} = \frac{\text{number of recognized samples}}{\text{total number of samples}} \times 100\% \tag{11}
\]

\[
\text{Recognition error rate} = \frac{\text{number of non recognized samples}}{\text{total number of samples}} \times 100\% \tag{12}
\]

### 4. Results and Discussion
The proposed system pointed to a new approach based on the fusion of moments methodology (Legendre) as well as the transformation approach (SVD), the performance with LMs alone is 83.05-100\% with AT&T and from 78-100\% with FEI while the recognition with SVD alone is 76.94-100\% with AT&T, also, 66-92.5\% with FEI but the best results are obtained using Fusion both methods and we noted that the higher recognition rate with lower error ratio using a hybrid system that achieved 85.27-100\% with AT&T, also, 79.77-100\% with FEI. Generally, the overall results for several cases are shown in Table 1, 2, and 3 and Figure(2).

| No. | Cases(training-testing) | Poses for training | No. of training | Poses for testing | No. of testing | Recognition error(%) | Recognition rate(%) |
|-----|-------------------------|-------------------|----------------|------------------|---------------|---------------------|-------------------|
| 1   | Case(9-1)               | 1-9               | 360            | 10               | 40            | 0.00                | 100.00            |
| 2   | Case(8-2)               | 1-8               | 320            | 9-10             | 80            | 1.25                | 98.75             |
| 3   | Case(7-3)               | 1-7               | 280            | 8-10             | 120           | 1.67                | 98.33             |
| 4   | Case(6-4)               | 1-6               | 240            | 7-10             | 160           | 1.88                | 98.12             |
### Table 2. The Result Of All Cases Applied on FEI Database.

| No. | Cases(training-testing) | Poses for training | No. of training | Poses for testing | No. of testing | Recognition error(%) | Recognition rate(%) |
|-----|-------------------------|--------------------|-----------------|-------------------|----------------|---------------------|--------------------|
| 1   | Case(9-1)               | 1-9                | 450             | 10                | 50             | 0.00                | 100.00             |
| 2   | Case(8-2)               | 1-8                | 400             | 9-10              | 100            | 2.50                | 97.50              |
| 3   | Case(7-3)               | 1-7                | 350             | 8-10              | 150            | 5.50                | 94.50              |
| 4   | Case(6-4)               | 1-6                | 300             | 7-10              | 200            | 6.67                | 93.33              |
| 5   | Case(5-5)               | 1-5                | 250             | 6-10              | 250            | 6.88                | 93.12              |
| 6   | Case(5-5)swap           | 6-10               | 250             | 1-5               | 250            | 7.09                | 92.91              |
| 7   | Case(4-6)               | 7-10               | 200             | 1-6               | 300            | 9.00                | 91.00              |
| 8   | Case(3-7)               | 8-10               | 150             | 1-7               | 350            | 12.50               | 87.50              |
| 9   | Case(2-8)               | 9-10               | 100             | 1-8               | 400            | 19.00               | 81.00              |
| 10  | Case(1-9)               | 10                 | 50              | 1-9               | 450            | 20.23               | 79.77              |

### Table 3. The Result of All Cases Applied on FEI And AT&T Face Database.

| Database | Cases(training-testing) | LMs error rate (%) | LMs recognition rate (%) | SVD error rate (%) | SVD recognition rate (%) | Recognition error(%) | Recognition rate(%) |
|----------|-------------------------|--------------------|--------------------------|-------------------|--------------------------|---------------------|--------------------|
| AT&T     | Case(9-1)               | 0.00               | 100.00                   | 0.00              | 100.00                   | 0.00                | 100.00             |
|          | Case(8-2)               | 1.25               | 98.75                    | 0.00              | 100.00                   | 1.25                | 98.75              |
|          | Case(7-3)               | 2.50               | 97.50                    | 2.50              | 97.50                    | 1.67                | 98.33              |
|          | Case(6-4)               | 3.75               | 96.25                    | 2.50              | 97.50                    | 1.88                | 98.12              |
|          | Case(5-5)               | 3.50               | 96.50                    | 4.50              | 95.50                    | 2.50                | 97.50              |
|          | Case(5-5)swap           | 5.50               | 94.50                    | 3.00              | 97.00                    | 1.00                | 99.00              |
|          | Case(4-6)               | 6.25               | 93.75                    | 7.50              | 92.50                    | 3.75                | 96.25              |
|          | Case(3-7)               | 7.50               | 92.50                    | 8.93              | 91.07                    | 5.72                | 94.28              |
|          | Case(2-8)               | 8.44               | 91.56                    | 13.75             | 86.25                    | 6.88                | 93.12              |
|          | Case(1-9)               | 16.95              | 83.05                    | 23.06             | 76.94                    | 14.73               | 85.27              |
| FEI      | Case(9-1)               | 0.00               | 100.00                   | 7.50              | 92.50                    | 0.00                | 100.00             |
|          | Case(8-2)               | 3.75               | 96.25                    | 5.00              | 95.00                    | 2.50                | 97.50              |
|          | Case(7-3)               | 6.67               | 93.33                    | 9.50              | 90.50                    | 5.50                | 94.50              |
|          | Case(6-4)               | 6.67               | 93.33                    | 10.00             | 90.00                    | 6.67                | 93.33              |
|          | Case(5-5)               | 8.00               | 92.00                    | 15.00             | 85.00                    | 6.88                | 93.12              |
|          | Case(5-5)swap           | 7.60               | 92.40                    | 15.84             | 84.16                    | 7.09                | 92.91              |
|          | Case(4-6)               | 9.34               | 90.66                    | 20.00             | 80.00                    | 9.00                | 91.00              |
|          | Case(3-7)               | 14.86              | 85.14                    | 27.50             | 72.50                    | 12.50               | 87.50              |
|          | Case(2-8)               | 20.00              | 80.00                    | 33.00             | 67.00                    | 19.00               | 81.00              |
|          | Case(1-9)               | 22.00              | 78.00                    | 34.00             | 66.00                    | 20.23               | 79.77              |
Figure 2. a) Diagram show the error rate of the whole AT&T database; b) Diagram show recognition rate of whole AT&T database; c) Diagram show error rate of whole FEI database and d) Diagram show recognition rate of whole FEI database.

5. Conclusions and Future Research Directions
It is concluded that:
1. Extraction S array of the SVD method gives the best recognition rate comparing with other matrices (U & V).
2. The best value of the order for Legendre moments is 4, every value less than 4, give the worst recognition rate, and greater than 4, doesn't affect on recognition rate with consuming time and space.
3. The proposed system approved that using a hybrid technique increased recognition rate compared when using LMs or SVD alone.
4. The same number of training and testing (eg. 5, 5), but with different poses gave variation in a recognition rate.
5. Complexity in the image has high effects on the recognition rate, for example, the Brazilian database has so many complexities compared with the AT&T database.

References
[1] K. Ismael, S. Irina, “Face recognition using Viola-Jones depending on Python”, Indonesian Journal of Electrical Engineering and Computer Science, 2020, ISSN: 2502-4752, DOI: 10.11591/ijeecs.v20.i3.pp1513-1521.
[2] M. Alam, T. Chowdhury, S. Ali, “A smart login system using face detection and recognition by ORB algorithm”, Indonesian Journal of Electrical Engineering and Computer Science, 2020, ISSN: 2502-4752, DOI: 10.11591/ijeecs.v20.i2.pp1078-1087.
[3] Arulananth T S, Baskar M, Sateesh R, “Human face detection and recognition using contour
"generation and matching algorithm", Indonesian Journal of Electrical Engineering and Computer Science, 2019, ISSN: 2502-4752, DOI: 10.11591/ijeecs.v16.i2.pp709-714.

[4] Khalid M. Hosny, “Refined translation and scale Legendre moment invariants”, journal homepage: www.elsevier.com/locate/patrec, Pattern Recognition Letters 31 (2010) 533–538.

[5] R. Akbari, M.K. Bahaghighat and J. Mohammadi, “Legendre Moments for Face Identification Based on Single Image per Person”, 2010 2nd International Conference on Signal Processing Systems (ICSPS).

[6] Carlos M., Marcos del, Jesus B., "Chapter 4 Facial Identification Based on Transform Domains for Images and Videos", IntechOpen, 2011.

[7] D. Sridhar1, Dr. I.V. Murali Krishna2, “Combined Classifier for Face Recognition using Legendre Moments”, Computer Engineering and Applications Vol. 1, No. 1, June 2012.

[8] R.Kapoor, P.Mathur, “Face Recognition Using Moments and Wavelets”, Journal of Engineering Research and Applications (IJERA), ISSN: 2248-9622, Vol. 3, Issue 4, Jul-Aug 2013, pp. 82-95.

[9] G.Singh and I.Chhabra, “Human face recognition through moment descriptors”, Proceedings of 2014 RAECs UIET Panjab University Chandigarh, 06 – 08 March 2014.

[10] O.M. Parkhi, A.Vedaldi and A. Zisserman, “Deep Face Recognition”, 2015

[11] A.Chiang and S.Liao, “IMAGE ANALYSIS WITH LEGENDRE MOMENT DESCRIPTORS”, Journal of Computer Science 11 (1): 127-136, 2015, ISSN: 1549-3636, 2015.

[12] G.Zhang, W.Zou, X.Zhang, X.Hu, and Y.Zhaod, “Singular value decomposition-based sample diversity and adaptive weighted fusion for face recognition”, JID:YDSPR AID:2045/FLA, [m5G; v1.191; Prn:28/11/2016; 8:48] P.1 (1-7), 2016.

[13] P.Chriskos, J. Munroy, V. Mygdalisy, and I.Pitasy, “FACE DETECTION HINDERING”, 2017.

[14] Thawar Arif, Zyad Shaaban, Lala Krekor, Sami Baba, Object Classification Via Geometrical, Zernike, and Legendre Moments, Journal of Theoretical and Applied Information Technology, 2005 – 2009, JATIT.

[15] Chee-Way Chong, P. Raveendran, R. Mukundan. "Translation and scale invariants of Legendre moments", Pattern Recognition, 2004

[16] A.N.Hashim and N.K.Shalan, “Face recognition using Hybrid techniques”, Journal of Engineering and Applied Sciences 14(12): 4158-4163,2019, ISSN: 1816-949X, 2019.