International Journal of Computing and Digital Systems
ISSN (2210-142X)
Int. J. Com. Dig. Sys.13, No.1 (Mar-23)

http://dx.doi.org/10.12785/ijcds/130132

Face Identification Approach Using Legendre Moment and Singular Value Decomposition

Mohammed Hasan Abdulameer[1] and Raaed Adnan Kareem[2]

[1]*University of Kufa/ Faculty of education for women, Department of computer science, Najaf, Iraq*
[2]*University of Kufa/ Faculty of computer science and mathematics, Najaf, Iraq*

Received 29 Jun. 2021, Revised 22 Jun. 2022, Accepted 5 Mar. 2023, Published 16 Mar. 2023

Abstract: Face recognition refers to the identification of a person based on facial features. A facial feature can be used in a variety of computer vision techniques, including face detection, expression detection, and a variety of video surveillance This paper presents a facial identification approach for dealing with face images from video cameras such as CCTV cameras. The proposed method is divided into three stages: preprocessing, feature extraction, and identification. First, the preprocessing stage relied on face detection, cropping, and unifying the image dimensions. Second, feature extraction is accomplished through the use of Legendre moment and singular value decomposition (SVD). Finally, the Manhattan classifier is used to complete the face identification. In the experiments, two face datasets are used: SCface dataset from surveillance cameras and ORL face dataset taken under diverse circumstances. The best performance for the ORL database was (98.75%) percent, whereas the best result for the SCface database was (99%) percent.

Keywords: Biometric, Face Identification, Legendre moment , SVD , Manhattan Classifier

1. Introduction and Overview

Today, protection and surveillance structures are critical in high-risk areas such as airport, organizations, military, groups, and so on. Face popularity is an important step in a surveillance device for greater and more accurate surveillance. Its complexity includes a large measurement subspace, a variety of expressions, lighting conditions, and so on [1], [2]. Motivates the development of a new and higher set of rules that genuinely enhance the safety of such systems. Face popularity grew as a result of the need for private identification in the fields of personal and comfortable structures, making it one of the most important fields of various biometric technologies [3]. This face recognition technology is an effective tool that has a wide variety of applications in the areas of information retrieval, self - service banking services, security authentication, etc [4]. Face recognition is either identification or verification. identification, if we need to recognize the person from many people (one-to-many), either verification, it's recognized the person if he or not (one-to-one) [5]. One of the most important and useful factorizations in linear algebra is singular value decomposition (SVD). We describe how SVD is used to solve face feature extraction difficulties [6]. Besides, Legendre moments are orthogonal moments that have been used in a variety of applications of pattern recognition [7]. In this paper we propose effective method to identify the face image from many images by using Legendre moment and singular value decomposition (SVD). The remaining sections of the paper are organized as follows: theoretical background about the topic is presented in section 2, proposed methodology is explained in section 3, experimental results are shown in section 4, and the conclusion is presented in section 5.

Face recognition has come a long way during the last years. The success of face recognition depends on the feature extraction and recognition, which have been discussed in almost all previously proposed techniques [8]. In [9], The principal component analysis (PCA) and neural networks are merged. In the database, the most prominent features of a variety of human faces were extracted, and the corresponding values were determined. As a result, if a new image was inserted into the system for recognition, the key features were extracted and the contrast between the source images and the stored images was calculated. As a result, some distinguishing characteristics of the most recent facial image will be lost.

The framework used in [10] is a hybrid of Gabor wavelets and General Discriminant Analysis (GDA), and it is referred to as appearance-based since features are

E-mail address: mohammed.almayali@uokufa.edu.iq, Raaed.79ak@gmail.com

extracted from the original face image. The feature vectors were subspace modeled. The development of Gabor filters for facial feature extraction is also discussed. For both identification and verification works, the technique has been thoroughly tested. Gabor waves greatly improve machine performance.

In [11], A face recognition procedure created on LBP and LNMF is proposed. According to recent neighborhood distance classification, the parameter matrix can be obtained from a test sample database containing a projection of a non-negative subspace, and better pattern recognition results were eventually achieved. The results of the experiment showed that the proposed method would dramatically improve image recognition rates.

In [12], SVD was used to represent each face image whereas Individual values are able to represent face images, and individual values of the face images at different resolutions have a nearly linear connection. The appropriate high resolution (HR) face image pairings for each input low resolution (LR) face can then be selected from the face gallery. The mapping functions to interpolate the two matrices in the SVD representation can be learned based on the selected (low resolution and high resolution) pairs to more accurately recreate HR face images. As a result, the final assessment of high-frequency detail in high-resolution facial photographs is more accurate and dependable.

Furthermore, in [13] a new method for producing virtual images from original images using single value analysis (SVD) is proposed in order to obtain richer face representations. The virtual images acquired increase the size of the training sample set while also representing reasonably stable low-frequency facial information, resulting in improved durability and classification accuracy. They integrated the virtual samples with the genuine samples, allowing them to identify the items with additional information. In this paper, the legendary moment approach with SVD is proposed as face identification solution for security purposes.

To overcome the consistency problem, Jingjing Liu et al.[14], developed a new K-SVD-based dictionary learning technique in this study. The suggested method, in particular, incorporates several constraints into a typical k-SVD-based dictionary learning framework and enforces an optimization procedure to meet the structure preservation criterion. This new method was able to continuously include the manifold constraints during the optimization process, resulting in a superior resolution that is resistant to input sample variance. Extensive testing on a variety of typical face databases revealed a consistent performance gain when compared to several similar current methods. The MK-JSRC method employed information from the dictionary learned using the updated KSVD algorithm. To tackle the problem that is not provided for the manifold restrictions, the proposed learning method is combined with the organizing technique. Furthermore, the suggested MK-JSRC problem may be readily separated into three sub-problems based on recent advances in the alternating direction multiplexing method (ADMM): image recognition with multiple restrictions, kernel limits, and feature limitations. Experiments on five datasets revealed that the performance of the proposed MK-JSRC for face recognition can be improved from set to set when the necessary parameters are selected correctly.

M. Ayyad et al. [15] developed a new discrete wavelet transform (DWT) domain fusion of two projection-based face recognition methods. These two algorithms use left and right singular vectors to perform linear fit weighted discriminant analysis (RW-LDA) and singular value decomposition (SVD). The use of Min-Max and Z-Score normalization strategies, followed by the fusion approach, improves identification rate and training time on two well-known databases, according to this study. The performance of the strategy given in this paper is improved by using wavelet as a feature extraction method. As a result, the computational complexity of RW-LDA was greatly lowered. RW-LDA/QR is also a good dimensionality reduction technique and has a great discrimination ability. To improve performance, the left and right singular vectors of SVD were employed instead of singular values.

Diaa et al. [16], introduced a comprehensive face recognition (FR) system using transfer learning in fog computing and cloud computing in their paper. Because of the major representation, the developed system used Deep Convolutional Neural Networks (DCNN); nonetheless, there are various circumstances that can affect the performance of deep FR, such as blockages, expressions, lighting, and posture. To extract relevant facial features, DCNN is utilized. These characteristics enable us to compare faces quickly. The system is taught to recognize a group of individuals and to learn by incorporating new persons into its treatment and improving its forecasts for those it currently has. Three distinct standard machine learning methods (Decision Tree, K-Nearest Neighbor, and Supporting Vector Machine) were used to test the suggested recognition approach. The suggested system was tested on three facial image datasets (SDUMLAHMT, 113, and CASIA). The proposed algorithm results in a higher accuracy (99.06%).

A comparison of the results of the most recent literature mentioned above can be summarized in table I.

2. Theoretical Background

A. Legendre moments

Teague [7] in 1980, introduced the Legendre moments, which are moments with Legendre polynomials as kernel functions. Legendre moments are orthogonal moments that have been used in a variety of applications of pattern recognition. They can be used to achieve a near-zero continuity measure in a series of moment functions, allowing the moments to correspond to the image's independent characteristics. The projection of the image intensity function into Legendre polynomials is used to define Legendre moments. With image intensity function f(x,y), the two-dimensional

TABLE I. COMPARISON OF THE RESULTS OF SOME RECENT LITERATURE

Author	year	Method	Dataset	Acc. (%)
Menglu Wu. et al. [11]	2016	LBP+LN	Yale	96.67
		MF	ORL	94.17
Muwei Jian, et al. [12]	2015	SHI	LFW	92
G. Zhang, et al. [13]	2018	SVD	ORL	94.48
Jingjing Liu, et al. [14]	2018	K-SVD	AR	99
			Yale-B	98.4
			LFW	55.7
			Georgia	76.2
			CMU-PIE	93.2
M. Ayyad, et al. [15]	2019	SVD+RW-LDA	ORL	97.75
			GT	89.24
Diaa et al. [16]	2020	DCNN	SDUMLA-HMT	99.6

Legendre moments of order (a+b) are described as follows in Equation 1 [17], [18]:

$$LP_{ab} = \frac{(2a+1)\times(2b+1)}{4}\int_{-1}^{1}\int_{-1}^{1} P_a(x)P_b(y)f(x,y)\,dxdy \tag{1}$$

x and y belong to the interval [-1,1]

Legendre polynomial, $LP_a(x)$, of order a is described in Equation 2:

$$LP_a(x) = \sum_{k=0}^{a}\{(-1)^{\frac{a-k}{2}}\frac{1}{i}\frac{(a+k)!x^k}{(\frac{i-k}{2})!(\frac{i+k}{2})!k!}\}_{a-k=even} \tag{2}$$

Legendre polynomials' recurrence relation, $LPa(x)$ become as follows Equation 3:

$$LPa(x) = \frac{(2a-1)xLP_{a-1}(x)-(a-1)LP_{a-2}(x)}{a} \tag{3}$$

whereas $LP_0(x) = 1$, $LP_1(x) = x$ and $i > 1$. Whereas, the space defined for the Legendre polynomial is within an interval [1, 1], an equal dimensions image $(N\times N)$ pixel with $f(i, j)$ intensity function, $0 \le i,\ j \le (N-1)$ is scaled in the space of $-1 < x$, $y < 1$. In the result of this, (1) can be expressed in discrete form Equation 4:

$$LP_{ab} = \lambda_{ab}\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} P_a(x_i)P_b(y_i)f(i,j) \tag{4}$$

whereas the normalizing constant,

$$\lambda_{ab} = \frac{(2a+1)(2b+1)}{N^2} \tag{5}$$

The normalized pixel coordinates in the interval [-1, 1] are represented by xi and yj, that are given in Equations 6 and 7:

$$x_i = \frac{2i}{N-1} - 1 \tag{6}$$

$$y_i = \frac{2i}{N-1} - 1 \tag{7}$$

B. *Singular Value Decomposition (SVD)*

Singular Value Analysis (SVD) is the foundation for a variety of other techniques, such as classification techniques, dynamic mode decomposition (DMD), and proper orthogonal decomposition (POD). When it comes to manipulating data from complex structures, high dimensions are a common problem. Large size data sets, such as audio, image, or video data, can be included in these systems. Images are components of a high-dimensional vector space since they usually involve a large number of measurements (pixels). Many images, on the other hand, are compressible, which means that related information can be expressed in a much smaller subspace. In terms of dominant patterns, SVD provides a systematic method for determining a low-dimensional approximation of high-dimensional results. Data-driven technology that detects patterns solely through data, without the use of professional experience or intuition. The SVD algorithm is numerically stable and provides a hierarchical representation of data in terms of a new coordinate system described by the data's dominant correlations. In addition, unlike the eigen-decomposition setup, the SVD is guaranteed to have some matrix. To analyze a large set of data such as $Z \in \mathbb{C}^{nm}$:

$$Z = \begin{bmatrix} | & | & \dots & | \\ Z_1 & Z_2 & \dots & Z_m \\ | & | & \dots & | \end{bmatrix} \tag{8}$$

Images transformed into column vectors with a number of elements such as pixels in the image are represented $Z \in \mathbb{C}^n$ columns. The k-index is a mark that denotes the set of k-characteristic measures. Z consists of a time-series of facts, and $z_k = z(k\Delta t)$. The n-state dimension is often very large, in the order of millions or more of degrees of freedom. Snapshots are also referred to as columns, and m represents the number of snapshots in Z. For several systems $n \gg m$, it results in a tall matrix, in contrast to a short matrix at $n \ll m$. Any matrix with a complex value $Z \in \mathbb{C}^{nm}$ has a unique matrix analysis called SVD:

$$Z = \mathrm{U\Sigma V}^{*} \tag{9}$$

$U \in \mathbb{C}^{nn}$ is unitary matrix, with orthonormal columns, also $V \in \mathbb{C}^{mm}$, but $\Sigma \in \mathbb{R}^{nm}$ is a matrix with real, positive or zeros entries on the diagonal and zeros off the diagonal. The simple (*) means the transpose of a complex conjugate. U and V must be unitary to be used widely. When $n \geq m$, On the diagonal, the matrix S has at most m positive or negative components, and it could be written as: $\Sigma = \begin{bmatrix} \hat{\Sigma} \\ 0 \end{bmatrix}$

The economy SVD can be used to precisely describe Z [19]:

$$Z = \mathrm{U\Sigma V}^{*} = [\hat{U}\ \hat{U}^{\perp}] \begin{bmatrix} \hat{\Sigma} \\ 0 \end{bmatrix} V^{*} = \hat{U}\hat{\Sigma}V^{*} \tag{10}$$

The full SVD and economy SVD are shown in Fig.1 and Fig.2.

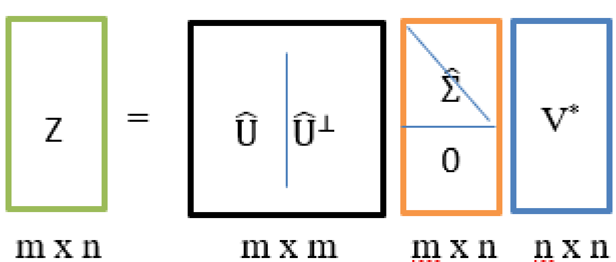


Figure 1. Full SVD

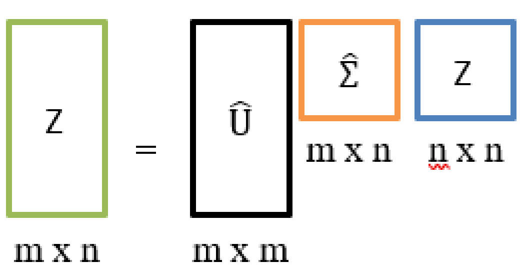


Figure 2. Economy SVD

All columns of $\hat{U}^{\perp}$ cover vectors that are matching and orthogonal with that spanned by $\hat{U}$. The left singular vectors of Z are the columns of U, and the right singular vectors are the columns of V. Singular values are the diagonal elements of $\hat{\Sigma} \in \mathbb{C}^{mm}$, and they are sorted from largest to smallest. The number of non-zero singular values determine Z's rank. The numerical implementation of SVD is both essential and mathematically advantageous, as it is the backbone of computing science and engineering [19], [20]

C. *Manhattan Classifier*

The Manhattan distance [21], which is used to calculate the distance between two points or vectors, is often used in the classification and identification of faces in image processing and computer vision. The Manhattan distance is the number of two points or vectors' differences. The Manhattan distance between point $a = (a_1, a_2, a_3, \ldots, a_n)$ and point $b = (b_1, b_2, b_3, \ldots, b_n)$ shown in Equation 11:

$$Manhtn(A, B) = \sum_{i=1}^{n} |a_i - b_i| \tag{11}$$

3. THE PROPOSED METHODOLOGY

In this study, we propose a new face recognition system based on a combination of face features from two approaches by combining Legendre moments with the SVD algorithm and the Manhattan Distance Classifier is for face identification. The identification process begins with the Pre-processing stage, where the image needs to face detection and then face cropping. Fig.3 depicts the whole proposed method:

The first step is to find Legendre polynomial which is utilized to find the Legendre moments. Obtaining a Legendre polynomial is quite different from finding a Legendre moment that has nothing to do with the picture. At the beginning, we take the image rows and columns' dimensions, the lowest of which is the Legendre polynomial length. The number of rows in this Legendre polynomial is determined by the Maximum order, denoted by m, and the number of columns in the Legendre polynomial. the Legendre polynomial represents the shortest distance between rows or columns. it is based on three steps as follow:

1) The first row in polynomial will be ones only as formula 12:
$$P(1, i + 1) = 1 \tag{12}$$
2) The second row in polynomial is calculated according to Equation 6
3) The number of remaining rows depends on the previous rows that were calculated on Equations 12 and 6, which in turn depend on maximum order.

After completing the Legendre Polynomial calculation, the Legendre moments calculation begins, where two rows

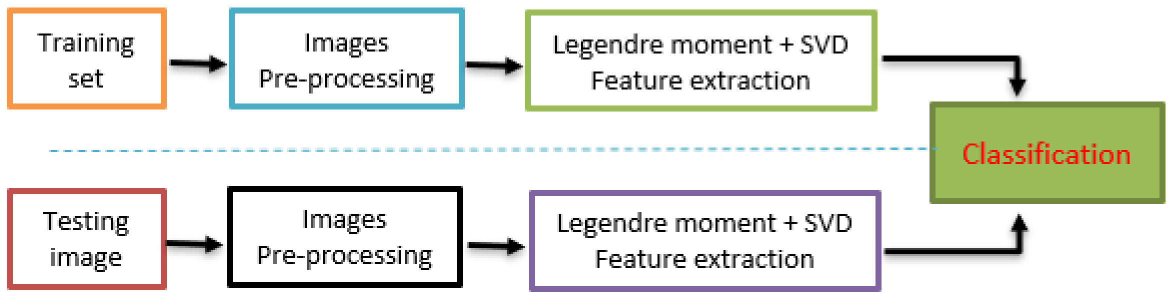


Figure 3. The Proposed Methodology

are taken from the Legendre polynomial matrix and multiplied together as in Equation 4. The result is dotted with the image data, then we find the sum for this matrix and then we multiply the result in Equation 5 to get the value of the Legendre moment. Programmatically, by applying the Legendre moment function with a value of maximum order = 5 to the image, we get an array of features with a size of 37×37, converting this array into a features vector RX.

For the SVD algorithm: a set of steps is applied to the image to obtain two parameters: Eigen value and Eigen vector, where we calculate the SVD for each 5×5 sub-array of the image to extract the Eigen value and Eigen vector and then put these values into a uniform vector at the end. We can summarize the entire process of adopting SVD by going through the following Equations: Compute the square matrix $C1$ by Equation 13, since, Z is a 5×5 sub-array:

$$C1 = Z^T \times Z \tag{13}$$

Find the eigen values λ_i from the Equation 14, Since, I mean a determent matrix and S represent a matrix of eigen values.

$$|C1 - \lambda_i \times I| = 0 \tag{14}$$

Since,

$$S = \begin{bmatrix} \lambda_{1,1} & \dots & \lambda_{1,5} \\ \vdots & \ddots & \vdots \\ \lambda_{5,1} & \dots & \lambda_{5,5} \end{bmatrix} \tag{15}$$

After that, we need to extract U matrix based on Equation 16, to get the eigen vectors

$$C2 = Z \times Z^T \tag{16}$$

Then we compute the eigen values λ_i of $C2$ matrix based on Equation 17:

$$|C2 - \lambda_i \times I| = 0 \tag{17}$$

And we find the corresponding eigen vectors (r_i)based on Equations 18, 19 and 20:

$$(C2 - \lambda_i \times I) \times r_i = 0 \tag{18}$$

r_i must be orthonormal.

$$u_i = \frac{r_i}{||r_i||} \tag{19}$$

Since, u_i represent values of the eigen vectors whereas U represent a matrix of eigen vectors.

$$U = \begin{bmatrix} u_{1,1} & \dots & u_{1,5} \\ \vdots & \ddots & \vdots \\ u_{5,1} & \dots & u_{5,5} \end{bmatrix} \tag{20}$$

The SVD implements on 5×5 sub-array, this sub-array passes over all of the pixels of the image and extracts four features from it to put in the vector D; these four features are the value of the position (1,1) of the U array and the values of the positions (1,1), (2,2), and (3,3) from the matrix S, as shown in Equation 21:

$$D = [U(1,1)\ S(1,1)\ S(2,2)\ S(3,3)] \tag{21}$$

Then, in the matrix XT, the features of vector D are combined with the features of vector RX, as shown in Equation 22:

$$XT = [RX\ D] \tag{22}$$

In general, the SVD produces the greatest number of features for that image because there are three matrices that are close to the original image, so the number of features produced by the SVD is greater than the number of image vectors. Each row of the matrix XT represents a single feature vector of the training images obtained from D and RX. Similarly, the image of the testing process is managed in the same way that the image of the training process is managed. The image is then classified using the Manhattan Classifier using Equation 11 to determine the identity of the intended person, whether he is present or not by find the minimum distance between the test vector (YT) and the training vector (XT) based on following Equation 23:

$$Distance = \sum_{k=1}^{n} |XT(k,n) - YT(1,n)| \tag{23}$$

4. EXPERIMENTAL RESULTS

A. Experimental Results of ORL Dataset

This database contains images of 40 participants [22], each participant has ten different images, each with a different facial expression and angle. Fig.4 show samples from this dataset. We run the proposed algorithm (Legendre + SVD) five times with five different cases:90% training vs 10% testing, 80% training vs 20% testing, 70% training vs 30% testing, 60% training vs 40% testing, and 50% training vs 50% testing. We discovered that the highest accuracy rate was 98.75 when the training rate was 80% and the test rate was 20%, while the lowest accuracy was 94 when both the training and testing rates were 50%. Table II and Fig.5 analysis of the results obtained of the cases we utilized.

TABLE II. RECOGNITION RATES OF THE PROPOSED LEGENDRE and SVD FOR ORL DATASET

K-Fold	No. of Training Images	No. of Testing Images	Recognition Accuracy
1	360	40	95%
2	320	80	98.75%
3	280	120	97.50%
4	240	160	96.88%
5	200	200	94%

Furthermore, we compared the proposed Legendre + SVD method to Legendre and SVD separately to demonstrate the method's stability. all the methods are tested on ORL dataset, with a training rate of 80% training and 20% testing that yielded the best results previously. The obtained results showed that the proposed Legendre + SVD had higher accuracy than Legendre and SVD, as shown in 6. When comparing the suggested technique to existing SVD-based methods in the literature, we discovered that our proposed method produced better results, as shown in the table III.

TABLE III. COMPARATIVE STUDY BETWEEN OTHER TECHNIQUES AND PROPOSED TECHNIQUE ON ORL DATASET

Author	Technique	Best Acc.
G. Zhang, et al.	SVD	94.48%
M. Ayyad, et al.	SVD+RW-LDA	97.75%
Proposed method	Legendre moments + SVD	98.75%

B. Experimental Results of Scface Dataset

In this database [23], 130 people were photographed using five different resolution video surveillance cameras (cam1, cam2, cam3, cam4, and cam5). Cam1 and Cam5 were used for night monitoring where the images taken from cam1 at night assigned as cam6, and images taken by cam5 at night identified as cam7. The following procedures are followed by all database participants: Each person stands in front of the surveillance cameras in both the light and the dark. the distances were (4.20 meters, 2.60 meters, and 1 meter), each person had 21 photos taken in various lighting conditions and at various distances, directions, and angles.

1) The Results of Distance-1

Seven cases were tested at the first distance (4.20 meters), with images taken from Cam2-Cam7 for training and Cam1 for testing. The sample images from the chosen distance are depicted in Fig.7 The accuracy of face recognition was low at the chosen distance due to a lack of image resolution, long shooting distance, different lighting conditions and shooting angles for each camera. The test images taken from cam2 and cam4 achieved the best recognition of 90% in this distance, while the test images taken from cam6 with the lowest resolution achieved the lowest recognition of 25%. Before the initial processing, the dimensions of the original images in this distance were 100×75 pixels, which were unified to 90×70 pixels and the face is detected and cropped for every image. Table IV and Fig.8 shows the details of the results for distance 1 with 7-fold cross validation.

TABLE IV. RECOGNITION RATES FOR DISTANCE-1, (4.20 METERS) BASED ON LEGENDRE MOMENTS AND SVD

K-fold	Training images	Testing images	Recognition accuracy
1	480 (Cam2,3,4,5,6,7)	80-Cam1	87.5
2	480 (Cam1,3,4,5,6,7)	80-Cam2	90
3	480 (Cam1,2,4,5,6,7)	80-Cam3	78.75
4	480 (Cam1,2,3,5,6,7)	80-Cam4	90
5	480 (Cam1,2,3,4,6,7)	80-Cam5	81.25
6	480 (Cam1,2,3,4,5,7)	80-Cam6	25
7	480 (Cam1,2,3,4,5,6)	80-Cam7	32.5

2) The Results of Distance-2

In order to efficiently examine the proposed method, seven cameras are used in this test, but at different distances of 2.60 meters. The images in this dimension had original dimensions of 144×108, but after preprocessing, the dimensions became 100×85. We utilized 560 images, including 480 training images and 80 testing images. Fig.9 depicts different samples of images from seven cameras and the proposed method is implemented using k-fold cross validation. The best recognition accuracy was 98.75 percent for test images taken from cam2 and cam3, while the worst recognition accuracy was for cam6 test images, as shown in Table V and Fig.10.

3) The Results of Distance-3

The imaging distance was closer in the third distance than in the previous distances, with a distance of (1.00 meter) that only providing high resolution images. The original images had dimensions of 224 x 168, which were reduced

Figure 4. ORL Samples

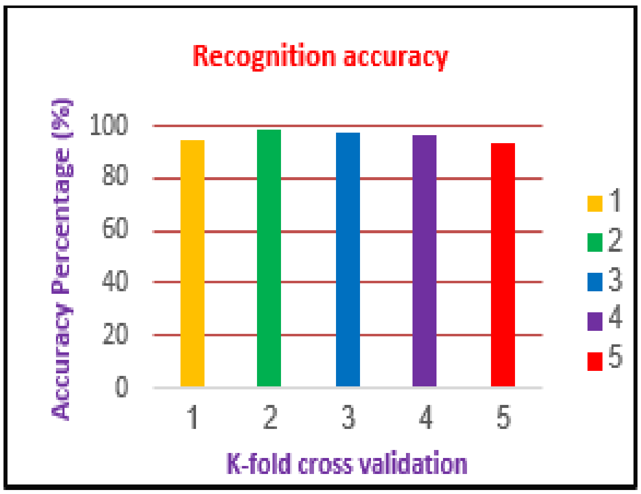


Figure 5. Recognition Rates of the Legendre and SVD for ORL Dataset

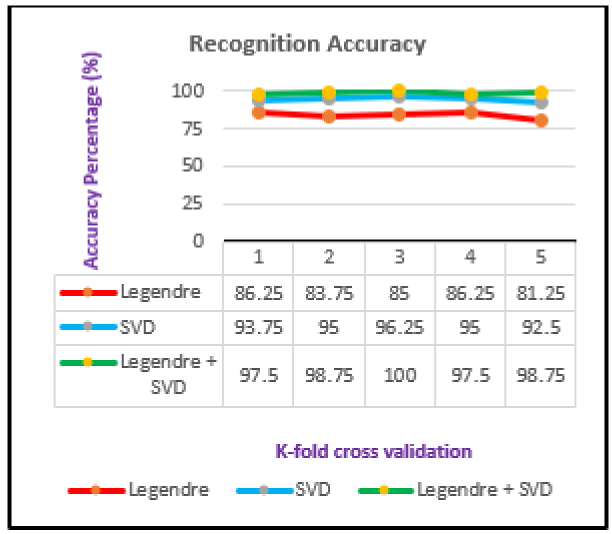


Figure 6. Comparative study of recognition rate of Legendre, SVD and legendary + SVD on ORL dataset

TABLE V. RECOGNITION RATES FOR DISTANCE-2 (2.60 METERS) BASED ON LEGENDRE MOMENTS AND SVD

K-fold	Training images	Testing images	Recognition accuracy
1	480 (Cam2,3,4,5,6,7)	80-Cam1	96.25
2	480 (Cam1,3,4,5,6,7)	80-Cam2	98.75
3	480 (Cam1,2,4,5,6,7)	80-Cam3	98.75
4	480 (Cam1,2,3,5,6,7)	80-Cam4	96.25
5	480 (Cam1,2,3,4,6,7)	80-Cam5	55
6	480 (Cam1,2,3,4,5,7)	80-Cam6	40
7	480 (Cam1,2,3,4,5,6)	80-Cam7	43.75

to 126 x 100 after pre-processing and face cropping. The 7-fold cross validation is used, with 480 images used in the training process and 80 images used in the testing process. Fig.11 depicts various samples from seven cameras. When the test images were taken from cam2, the best accuracy was 98.75 percent, as shown in table VI and Fig.12.

4) The Results of Combining All Three Distances

In this case, 500 images were used at random from the cameras for the three dimensions, whereas 10 images were collected from the three dimensions for each person, as seen in Fig.13. The 5-fold cross validation was used in the test. The best result of the proposed method was (99%) as shown in the table VII and Fig.14.

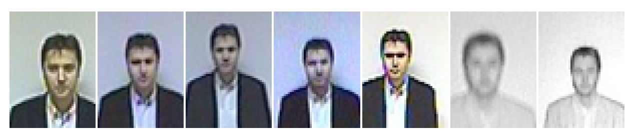


Figure 7. Samples of 7 Cameras from Distance-1

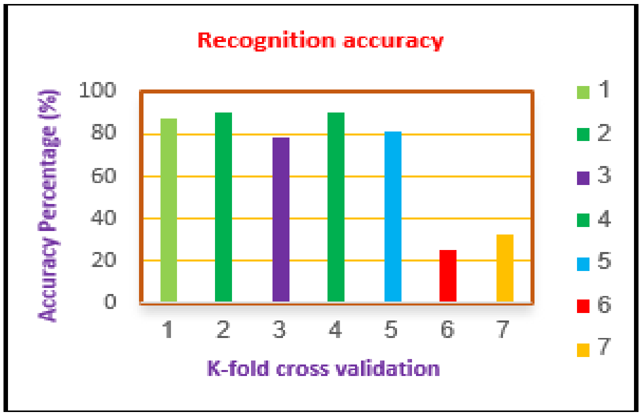


Figure 8. Recognition Rates for distance-1

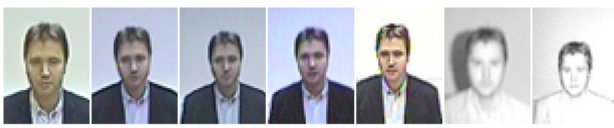


Figure 9. Samples of 7 Cameras from Distance-2

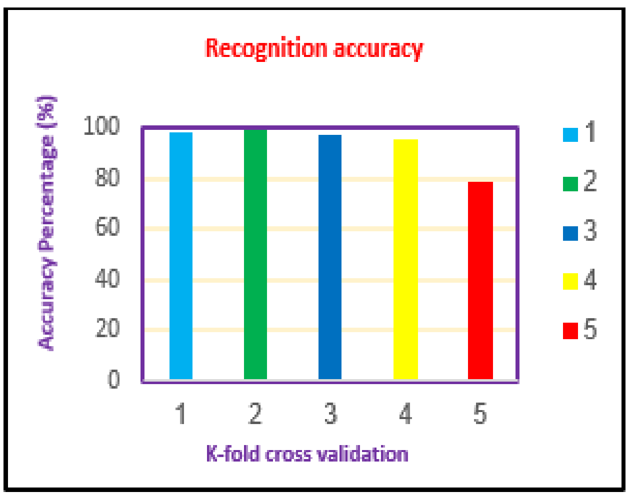


Figure 14. Recognition Rates for combining all three distances

TABLE VI. RECOGNITION RATES FOR DISTANCE-3 (1.00 METER) BASED ON LEGENDRE MOMENTS AND SVD

K-fold	Training images	Testing images	Recognition accuracy
1	480 (Cam2,3,4,5,6,7)	80-Cam1	96.25
2	480 (Cam1,3,4,5,6,7)	80-Cam2	98.75
3	480 (Cam1,2,4,5,6,7)	80-Cam3	93.75
4	480 (Cam1,2,3,5,6,7)	80-Cam4	90
5	480 (Cam1,2,3,4,6,7)	80-Cam5	67.5
6	480 (Cam1,2,3,4,5,7)	80-Cam6	47.5
7	480 (Cam1,2,3,4,5,6)	80-Cam7	52.5

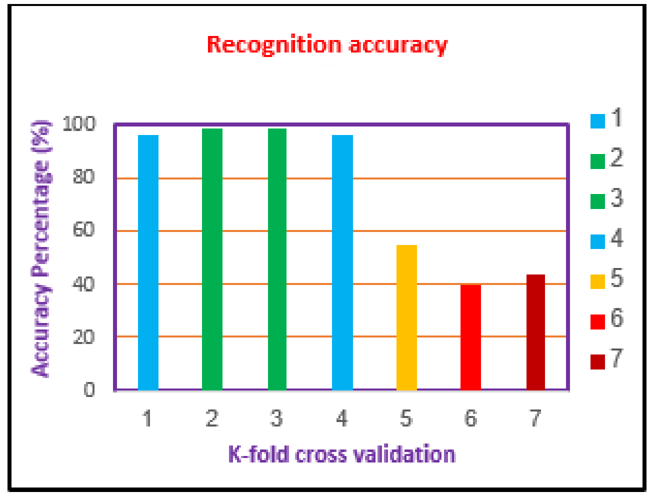


Figure 10. Recognition Rates for distance-2

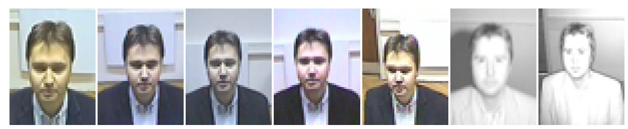


Figure 11. Samples of 7 Cameras from Distance-3

In table VIII and Fig.15. we made a comparison of the proposed algorithm (Legendre + SVD) with both Legendre and SVD algorithm, where we used 240 images from each distance in SCface database, (240 (80%) for training and 40 (20%) for testing for each of the three algorithms. The best recognition accuracy in our proposed algorithm was 97.5% in third distance, while the best recognition accuracy in Legendre was 77.5% in second distance, and in the SVD algorithm, the best recognition accuracy was 92.5% in third distance, and thus it becomes clear that our proposed algorithm is superior to both Legendre and SVD.

TABLE VII. RECOGNITION RATES FOR COMBINING ALL THREE DISTANCES

K-fold	No. of training images (80%)	No. of testing images (20%)	Recognition accuracy
1	400	100	98
2	400	100	99
3	400	100	97.27
4	400	100	95.45
5	400	100	78.18

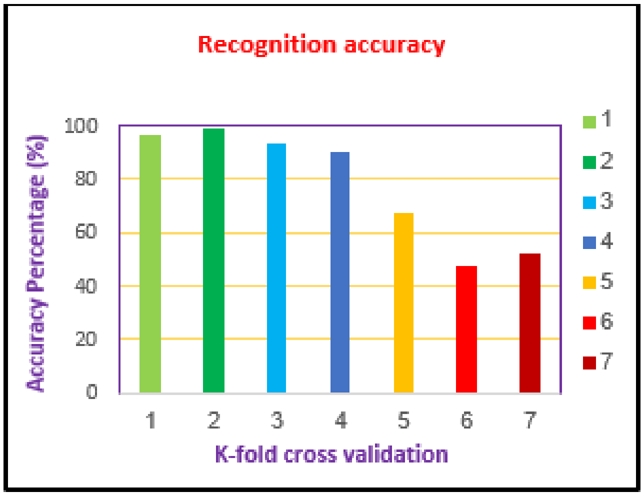


Figure 12. Recognition Rates for distance-3

Figure 13. Samples from Three Distances

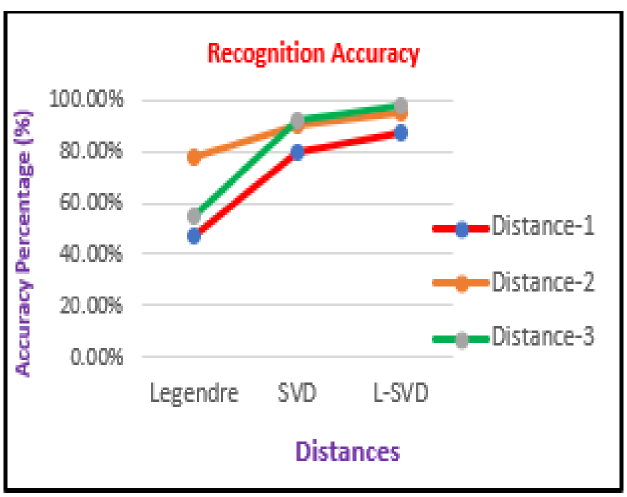


Figure 15. Comparative Study of Recognition Rate of Legendre, SVD and Legendre + SVD on Scface Dataset

5. CONCLUSION

This paper describes a method for recognizing faces that is based on Legendre moments and singular value decomposition (SVD). The Legendre moments and SVD are used for facial feature extraction, while the Manhattan classifier is used for recognition. The ORL dataset and the SCface dataset were both used in the study. We demonstrated in both datasets that Legendre with SVD is sufficient for face recognition tasks in a variety of situations. The power of the proposed method is demonstrated by the fact that it can produce consistent matching results on images from various scenarios. Finally, we believe that using more powerful classifiers would significantly improve the current performance of face recognition. The proposed method can be used in real-world applications such as law enforcement agencies, airports, and building access management, among others. Future research will look into and investigate the use of a variety of classifiers that can be assigned based on the input face's class.

TABLE VIII. COMPARATIVE STUDY OF RECOGNITION RATE OF LEGENDRE, SVD AND LEGENDRE + SVD ON SCFACE DATASET

Distance	Recognition Accuracy		
	Legendre Moments	SVD	Legendre + SVD
D1	47.5	80	87.50%
D2	77.5	90	95%
D3	55	92.5	97.50%

References

[1] S. Almabdy and L. Elrefaei, "Feature extraction and fusion for face recognition systems using pre-trained convolutional neural networks," *International Journal of Computing and Digital Systems*, vol. 9, pp. 1–7, 2021.

[2] F. Khodadin and S. Pudaruth, "An intelligent camera surveillance system with effective notification features," *International Journal of Computing and Digital Systems*, vol. 9, no. 6, pp. 1251–1261, 2020.

[3] F. Alsaqre, "Human face recognition using class-wise two-dimensional principal component analysis," *International Journal of Computing and Digital Systems*, vol. 9, no. 2, pp. 335–343, 2020.

[4] D. N. Parmar and B. B. Mehta, "Face recognition methods & applications," *arXiv preprint arXiv:1403.0485*, 2014.

[5] H. Moon, "Biometrics person authentication using projection-based face recognition system in verification scenario," in *International Conference on Biometric Authentication*. Springer, 2004, pp. 207–213.

[6] N. Muller, L. Magaia, and B. M. Herbst, "Singular value decomposition, eigenfaces, and 3d reconstructions," *SIAM review*, vol. 46, no. 3, pp. 518–545, 2004.

[7] M. R. Teague, "Image analysis via the general theory of moments," *Josa*, vol. 70, no. 8, pp. 920–930, 1980.

[8] M. H. Abdulameer, S. N. H. Sheikh Abdullah, and Z. A. Othman, "Support vector machine based on adaptive acceleration particle swarm optimization," *The Scientific World Journal*, vol. 2014, 2014.

[9] A. S. Navaz, T. Dhevisri, and P. Mazumder, "Face recognition using

principal component analysis and neural networks," *March-2013, International Journal of Computer Networking, Wireless and Mobile Communications. Vol*, no. 3, pp. 245–256, 2013.

[10] L. Shen, L. Bai, and M. Fairhurst, "Gabor wavelets and general discriminant analysis for face identification and verification," *Image and Vision Computing*, vol. 25, no. 5, pp. 553–563, 2007.

[11] M. Wu and T. Lu, "Face recognition based on lbp and lnmf algorithm," in *2016 15th International Symposium on Parallel and Distributed Computing (ISPDC)*. IEEE, 2016, pp. 368–371.

[12] M. Jian and K.-M. Lam, "Simultaneous hallucination and recognition of low-resolution faces based on singular value decomposition," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 25, no. 11, pp. 1761–1772, 2015.

[13] G. Zhang, W. Zou, X. Zhang, and Y. Zhao, "Singular value decomposition based virtual representation for face recognition," *Multimedia Tools and Applications*, vol. 77, no. 6, pp. 7171–7186, 2018.

[14] J. Liu, W. Liu, S. Ma, C. Lu, X. Xiu, N. Pathirage, L. Li, G. Chen, and W. Zeng, "Face recognition based on manifold constrained joint sparse sensing with k-svd," *Multimedia Tools and Applications*, vol. 77, no. 21, pp. 28 863–28 883, 2018.

[15] M. Ayyad and C. Khalid, "New fusion of svd and relevance weighted lda for face recognition," *Procedia computer science*, vol. 148, pp. 380–388, 2019.

[16] D. Salama AbdELminaam, A. M. Almansori, M. Taha, and E. Badr, "A deep facial recognition system using computational intelligent algorithms," *Plos one*, vol. 15, no. 12, p. e0242269, 2020.

[17] S. Annadurai and A. Saradha, "Face recognition using legendre moments." in *ICVGIP*. Citeseer, 2004, pp. 461–466.

[18] C.-W. Chong, P. Raveendran, and R. Mukundan, "Translation and scale invariants of legendre moments," *Pattern recognition*, vol. 37, no. 1, pp. 119–129, 2004.

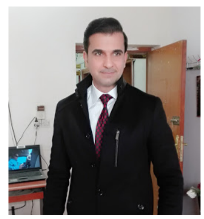
[19] A. A. Aljarrah and A. H. Ali, "Human activity recognition by deep convolution neural networks and principal component analysis," in *Further Advances in Internet of Things in Biomedical and Cyber Physical Systems*. Springer, 2021, pp. 111–133.

[20] N. K. E. Abbadi and E. Saleem, "Automatic image colorization based on svd and lab color space," 2018.

[21] K. Ponnmoli and D. S. Selvamuthukumaran, "Analysis of face recognition using manhattan distance algorithm with image segmentation," *International Journal of Computer Science and Mobile Computing*, vol. 3, no. 7, pp. 18–27, 2014.

[22] "The orl database of faces," 2001.

[23] M. Grgic, K. Delac, and S. Grgic, "Scface–surveillance cameras face database," *Multimedia tools and applications*, vol. 51, no. 3, pp. 863–879, 2011.



Mohammed Hasan Abdulameer Mohammed Hasan Abdulameer received his BSc in computer science from in 2002 from Al mamoun university, MSc in computer science in 2006 from Iraqi commission form computer and informatics and PhD computer science from national university of Malaysia in 2015. He is currently assistant professor in Kufa University, Iraq. His fields of interest are artificial intelligence, Natural language processing, face recognition.

Raaed Adnan Kareem Raaed Adnan Kareem is currently a M.Sc. student in faculty of computer science and mathematics at Kufa University, Najaf, Iraq. His research areas include computer vision and Artificial intelligence.