Technique for recognizing faces using a hybrid of moments and a local binary pattern histogram

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ABSTRACT

The face recognition process is widely studied, and the researchers made great achievements, but there are still many challenges facing the applications of face detection and recognition systems. This research contributes to overcoming some of those challenges and reducing the gap in the previous systems for identifying and recognizing faces of individuals in images. The research deals with increasing the precision of recognition using a hybrid method of moments and local binary patterns (LBP). The moment technique computed several critical parameters. Those parameters were used as descriptors and classifiers to recognize faces in images. The LBP technique has three phases: representation of a face, feature extraction, and classification. The face in the image was subdivided into variable-size blocks to compute their histograms and discover their features. Fidelity criteria were used to estimate and evaluate the findings. The proposed technique used the standard Olivetti Research Laboratory dataset in the proposed system training and recognition phases. The research experiments showed that adopting a hybrid technique (moments and LBP) recognized the faces in images and provide a suitable representation for identifying those faces. The proposed technique increases accuracy, robustness, and efficiency. The results show enhancement in recognition precision by 3% to reach 98.78%.

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1. INTRODUCTION

Applications for detecting and recognizing faces in images are one of the most important fields, and they are widely used in many institutions for various purposes. Those applications include monitoring, banking, validation, forensic investigation, police investigations, robotic intelligence, and health sciences. Every applied system of face analysis requires different and multiple requirements. Therefore, the techniques, algorithms, and approaches to face analysis depend on the application, standardization, and generalization that are usually difficult to perform and inaccurate. That is because many of the major problems have not yet been resolved. The face analysis research community is still confronting the challenges of face detection and recognition [1]. Although simulating the human visual system is the best solution, it is considered a complex heuristic approach because must account for multiple details such as colors, textures, movement, and audio information. Nevertheless, because of the rapid development in information technology that makes this possible, the recent trend has focused on multimedia analysis, which combines multiple approaches to obtain more accurate and satisfactory results [2]. Research and analysis in the applications to detect and recognize faces are useful contributions to enable institutions that conduct face analysis research to build more robust systems by combining different methods.

This paper aims to contribute to this effort by taking advantage of the strengths of two techniques that have been used to detect and recognize faces: moments and local binary pattern histograms (LBPHs). This approach uses the strongest elements in each method separately and hybridizes them to obtain an algorithm that can detect and recognize faces more robustly and accurately. The proposed technique aims to fill the large gap that exists in previous techniques to identify and recognize the faces of people in images by providing greater accuracy and higher quality by hybridizing the two previous algorithms. The analysis in this paper first evaluates the simpler classification methods for each technique separately (moments and LBPH). Then it tries to improve the rate of detection and recognition of faces using the hybridization of those two techniques to reduce the redundancy of the feature vectors. Finally, it compares the results to determine the accuracy, robustness, and performance of the suggested hybridization process.

2. REVIEW OF EXISTING METHODS

Extensive studies have been proposed for face recognition, including some that used the moment invariant techniques as a robust statistical shape descriptor [3], [4]. Following are brief descriptions of them. In 2020, Riri *et al.* [5] presented algorithms that were evaluated on a data set consisting of 98 images. The results showed that their proposed method performed with an accuracy of 84% compared to learning algorithms that used linear discriminant analysis (LDA) as the classifier. In 2016, Zhang *et al.* [6] proposed a technique of representing face images by applying “dense sampling” to every detected feature points. Then they extracted the local difference feature (LDF) for face representation. Principal component analysis (PCA) and LDA were used to reduce the feature dimensions, and cosine similarity assessment was used for identification. Slimani *et al.* [7] aimed to bridge the gap by conducting a large-scale evaluation of 46 variables using LBPs to identify facial expressions. Those authors conducted their experiments on various datasets (candidate key (CK), the Japanese female facial expression (JAFFE), and multimedia understanding group (MUG) facial expression database) to get results of 100%, 95%, and 96% respectively.

Basaran *et al.* [8] in 2019 investigated the applicability of separate orthogonal Hahn and Racah face recognition moments concerning robustness against lighting, facial expressions, and altered facial details. The proposed method was tested using the Olivetti Research Laboratory (ORL) database from the University of Notre Dame (UND) Biometrics X 1 group. The results showed recognition rates between 94% and 94.5% for molten Hahn moment, and approximately 94% and 92% of local and global Racah moments combined, on straight. The authors claim to have created a software system to demonstrate their research findings. Juneja [9] in 2018 proposed a facial identification study employing local Zernike moments (LZM) for both recognition and verification. The results showed that the proposed technique performed well with features such as illumination, pose, and facial expressions. In 2019, Khan [10] used multi-features, a multi-algorithm framework, to identify individuals’ faces, including whole faces and partial faces. The distance recognition technique was applied on whole faces, and a ratio-based structural point and curve map was applied on the partial faces. In 2019, Fachrurrozi *et al.* [11] presented a method to automate the search process that depended on mathematical calculations on images to specify the features of the face. The accuracy of that system was 96.2%. Raheem *et al.* [12] proposed many stages that used several methods such as agglomerative hierarchical clustering and LBP. In an image that contained multiple faces, they used content based image retrieval (CBIR), which is characterized by the same image property. The authors reached an accuracy ratio of 64.61%. In 2019, Moshayedi *et al.* [13] studied the knowledge and identification of the moon's shapes, the design of the converted Raspberry Pi base system was considered. They designed a system with the ability to capture images, perform image preprocessing with the help of a converted graphical user interface (GUI) written in Python.

Dakua *et al.* [14] present an approach to reconstruct liver surfaces in a low-contrast computed methodology. They used both qualitative and quantitative assessments performed on liver data show promising segmentation accuracy when compared with baseline truth data that reflect the potential of the proposed method. Their contributions were: a discrete cosine transform methodology based on random resonance has been developed to enhance the contrast of the pathological liver images, they proposed a new formula to prevent the limits of the organism caused by the cellular automated methods and proposed a level method to generate intermediate segmentation lines from two segmented segments. Authors have tested the algorithm on real datasets obtained from two sources. Xiberta *et al.* [15] proposed two segmentations techniques semi-automatic and dynamic programming-based approaches, authors found that both approaches are useful to reduce the time needed to segment the internal organs of pig from hours (manual process) to minutes or seconds (dynamically). Heikkilä *et al.* [16] studied the high noise level and low contrast properties of medical images that remain major bottlenecks in segmentation despite increasing imaging modalities. The researchers proposed a new formula to prevent traditional cellular automata from seeping into surrounding areas at a similar density. The author used a set of levels to automatically split the rest of the slides. The author evaluated the method thoroughly on the databases of the York, MICCAI Grand Challenge workshop. While a false positive ratio, a false negative ratio, and a specificity of 0.019, 7.62×10-3 and 0.75 were found, respectively.

Almost all the results from these previous efforts lack accuracy, robustness, and quality. This paper uses two of those techniques to create a hybrid that bridges the gap to obtain more accurate, robust, and high-quality results. The two techniques are the algorithms of moments and LBPH. The features of the faces will be extracted from each image depending on the features of that image. The descriptors will be calculated, and classifiers will be determined and stored as records in binary files that represent a temporal database. As a result, each face has a record in the database. The database is then used to identify and recognize an object by comparing it with a face's image in a standard tested database (ORL).

3. PROPOSED WORK (METHOD)

In the proposed technique, features are extracted from input images, descriptors are created based on these computed features, the values of these descriptors are considered as classifiers to recognize faces, the descriptors of face images are saved in binary (.cwf) files in a database. The database is used in face identification. The algorithms of moments and LBPH are used to implement the proposed technique. The standard oto-rhino-laryngologique (ORL) dataset is based and used as training. Using the hybrid technique, we can improve face recognition. Each face image in the dataset contains the ID number of the individual. The proposed framework includes the main steps shown in Figure 1. They are: i) face detection phase, ii) training of faces detected phase, iii) descriptors are created and classifiers are computed and stored in binary files as a dataset of records, and iv) recognition of faces detected phase.

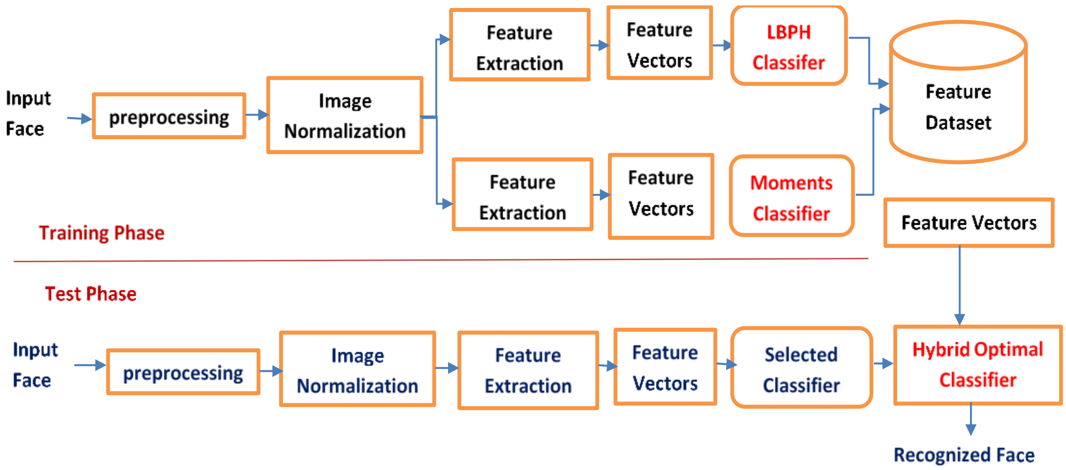

Figure 1. Main block diagram of proposed hybrid technique

3.1. Local binary pattern histogram (LBPH)

This section is divided into several subsections to study and explains the mechanism of using the LPB algorithm as follows: in the LBP, the image is divided into 3×3 blocks of pixels as a matrix, a comparison between the value center pixel in each block with its surrounding pixels values are made, which turns into binary numbers, the comparison process assumes that, if the value of the surrounding pixel is greater than the value of the center pixel, then the value is set to 1, otherwise, the value is set to 0. After having eight binary numbers for surrounding pixels of each center pixel, the binary values replace with decimal values. Once the values of all surrounding pixels of the center pixel are obtained, a histogram is created to represent the texture images, and the operator function LBP is defined as in (1) and (2).

This paper indicates that the use of LBP produces rather long histograms which slows down the recognition speed especially on large-scale face databases. To solve this problem, symmetric center LBP (CS-LBP) [17] has been used, CS-LBP is a region of interest descriptor. Instead of comparing the value of each pixel with the value of the central pixel, the central symmetrical pixel pairs are compared. Therefore, the number of comparisons is reduced by half for the same number of neighboring pixels, and this idea has accelerated the face recognition process using LBP [18], [19].

3.1.1. Face detection phase

Facial detection methods can be classified into many categories [20], [21] which are interrelated and can be combined to improve the face detection rate. To compare different methods, different parameters can be used in the face detection stage and considering as descriptors. The performance of the algorithm is approximated using the positive detection ratio and false detection ratio according to their descriptor or classifier. As the general errors in the detection scheme, the false-negative represents the low detection ratio, and the positive detection ratio represents the high face detection ratio. The proposed technique analyzes the face detection method based on LBP, which is an appearance-based method. Usually, this type of method provides good results [22].

3.1.2. Face recognition phase

The task of face recognition uses LBP as a still image to identify individuals in a set of images. The images are tested through a pre-trained system provided with a set of images that have been classified to identify each face image [23]. Face recognition in LBP is divided into the following tasks: identity verification, verification, watch list, and implemented sequentially.

3.1.3. Feature extraction based LBPH

LBPH has a powerful feature to classify textures. To extracts image features, LBP has been combined with histograms of oriented gradient (HOG) descriptors to produces classifiers. This enhances the efficiency of face detection when used with the standard ORL database and some database sets. This process uses the following steps [24]:

– Parameters: required parameters are calculated. The LBPH has four parameters used as classifiers to recognize the face: radius, neighbors, grid X, and grid Y.
– Training the algorithm: this uses the standard ORL database that contains facial images of people that must be recognized.
– Application of the LBP process: the algorithm uses the idea of the sliding window depending on two parameters: the radius and the neighbor pixels that surround the central pixel, as shown in Figure 2. This yields decimal values to define the label the eight pixels be neighbors. It is expressed as (1):

$$\mathrm{LBP}(x_c,y_c)=\sum_{n=0}^{7} S(G_n-G_c)2^n \tag{1}$$

where, G_n is the grey value of the central pixel, G_c is the gray value of the surrounding eight pixels, and $S(k)$ is a function defined as (2):

$$S(k)=\begin{cases}1 & \text{if } k\geq 0\\ 0 & \text{if } k<0\end{cases} \tag{2}$$

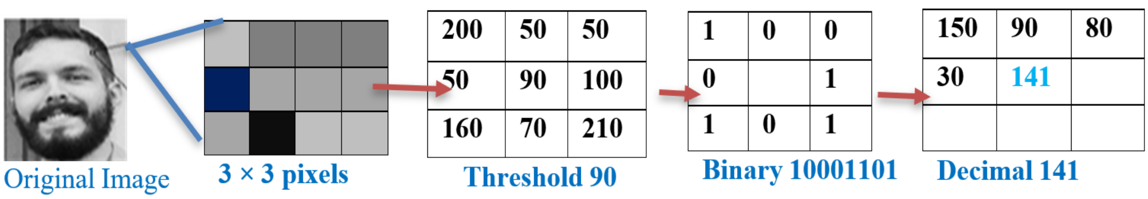

Figure 2. LBP procedure [25]

– Extracting the histograms: using the image generated in step 3, Grid X and Grid Y parameters are used to divide the image into multiple images, as shown in Figure 2. The image in Figure 2 is grayscale, and each histogram contains 256 positions with values from 0 to 255. This final histogram represents the features of the original image, and it is used later as a classifier, as shown in Figure 3.
– Performing face recognition: the algorithm was trained using the ORL database. Each histogram is constructed and used to represent every image in the trained database set. The comparison uses several approaches like Chi-Square, Euclidean distance, and absolute value. Euclidean distance is used depending on (3):

$$D=\sqrt{\sum_{i=1}^{n}(\mathrm{hist}\ 1_i-\mathrm{hist}\ 2_i)^2} \tag{3}$$

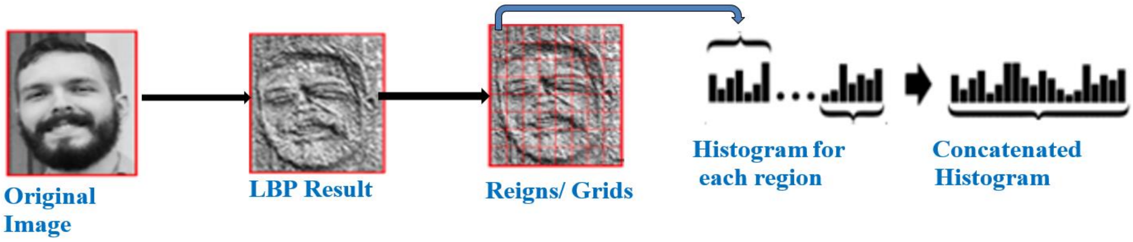

Figure 3. Extracting the histograms [25]

3.2. Using moments to analyze objects

An image consists of objects, which are sequences of numbers. To recognize and analyze foreground region R in the image, some numbers are calculated for the foreground region R. These numbers are called the moments [26], [27]. Moments indicate distinct features such as area, shape, centroid, object orientation, and inertia. Several moments can be used to analyze and distinguish objects in the image, such as the lowest order moments, natural central moments, central moments, and central angles. Digital image moments provide a very elegant way to describe the binary image area with a small number of intuitive and highly descriptive values. The equation (4) describes the public equation of any order moment [28]:

$$\mu_{pq} = \sum_{(m,n)\in R} (m-\bar{m})^p (n-\bar{n})^q f(m,n) \quad (4)$$

The sum of p+q gives the order of the moments, and p and q can take any values. If the value of parameters is (p=0, q=1) or (p=1, q=0) that means it is a first-order moment. Calculating moment values produces a series of numbers that can be used to distinguish objects in the image. These are the foreground region's pixel values; the background region is neglected. In region R, the values of the pixel at row R_i and column C_j in the foreground are computed as the sum of the products of Row value x raised to power k and Column value y raised to the power of j in Rx and y. The moment order=powers sum=(k+j) as shown in (5) [29].

$$m_{kj} \triangleq \sum_{\text{Row, Column} \in R} \text{Row}^{k}\, \text{Column}^{j} \\ \&= \sum_{x.y\in R} x^k y^j; k\geq 0; j\geq 0 \quad (5)$$

3.2.1. Lower order moments

The moments of the lowest ranking can be described assuming that M_{kj} are the normal moments of foreground region R of the image I(k, j). Supposing that area A appears in region R at position (X_c, Y_c). Then the area and region centroid point is calculated as in (6).

$$\& \; A = \text{Area} = m_{00} \\ x_c = \frac{m_{10}}{m_{00}}, y_c = \frac{m_{01}}{m_{00}} \text{ or } \bar{x} = \frac{M_{10}}{M_{00}} \bar{y} = \frac{M_{01}}{M_{00}} \\ (x_c, y_c) = \text{Centroid} = \left\{\frac{m_{10}}{m_{00}}, \frac{m_{01}}{m_{00}}\right\} \quad (6)$$

3.2.2. Foreground region R centroid moments, μ_{kj}

Central moments are computed according to their geometric and physical meanings. Supposing that (Xc, Yc) is the region R centroid and assuming that (X, Y) represents the rows and columns of any pixel P in region R. The central moment M_{kj} of R is given by (7) [30].

$$\mu_{kj} = \sum_{(x,y)\in R} (x-x_c)^k (y-y_c)^j; (k,j)\geq 0 \quad (7)$$

3.2.3 Normalized central moments, v_{kj}

Central moments have been normalized to produce other moments that are fixed on the scale of changes occurring in foreground region R and are the translation constant. If M_{kj} is the central moment of the foreground region R. Then V_{kj} represents the normalized central moments of region R, given in (8).

$$v_{kj} = \frac{\mu_{kj}}{\mu_{00}^{(k+j+2)/2}}; (k,j)\geq 0 \quad (8)$$

3.2.4. Orientation of the region, ϕ

Calculating the parameters, normalized central moments V_{kj}, first-order moments M_{kj}, and central moments U_{kj} leads to characterizing R, and it leads to invariance to translation and scaling of R. However, they are variant in the rotation of the foreground region R. The principal angle ϕ is used to measure the foreground orientation of region R in digital images. The (9) shows object-orientation [30].

$$\begin{aligned} \phi &= \frac{1}{2} a\tan 2(2\mu_{11}, \mu_{20} - \mu_{02}) \\ &= \frac{1}{2}\tan^{-1}\left(\frac{2\mu_{11}}{\mu_{20}-\mu_{02}}\right) \end{aligned} \quad (9)$$

4. EXPERIMENTAL RESULTS

The research implementation stages have been divided into the following parts: moments technique, local binary pattern histogram technique, and hybridization between those two techniques. The following subsections describe the training of the two techniques through the standard database ORL in two phases. The first is training and recognition, and then how more efficient and accurate face recognition results are obtained.

4.1. Exacting features and determining classifiers

All the features extracted using the LBPH technique in subsection 3.1.3 have been calculated according to (1)-(3). They are stored in the binary file as a database of records, and each record represents a set of classifiers that are used later in the face recognition phase. Also, all the features extracted using the moment's technique treated in section 3.2 have been calculated according to (4)-(10). They are stored in the same binary file as a database of records, and each record represents a set of descriptors or classifiers which are used later in the face recognition phase. The structure of the binary file database is similar to what is shown in Table 1.

Table 1. Structure of binary file database

Technique	Descriptors/classifiers				
LBPH	Radius	Orientation	Grid X	Grid Y	Distance
Moments	Moment value μ_{pq}	Region centroid/Area around (x_c, y_c)	Normalized central moments v_{kj}	Orientation ϕ	Invariant moments

4.2. Tested dataset

To test the efficiency of the experimental results of the proposed hybrid algorithm, experiments were conducted on the standard ORL database. It includes images of 40 subjects. There are 10 images of every subject in a variety of orientations, which makes up a total of 400 images. Those images are in grayscale, and their pixel values range between 0 and 255. The normalization of the image is conducted as shown in Table 2.

Table 2. Experimental dataset (ORL)

Total images	Subjects per image	Trained images	Trained time/s
400	10	400	8

4.3. Moments summarize raw moment

The moments summarized in (1) have been derived from geometric moments named Hu moments. These are non-negative integers, which have been calculated according to (1). Raw moments are invariant to rotation, translation, and resizing, and there is a group of seven moments which are a non-linear combination of normalized moments up to the third order. The first raw moment, R1 is analogous to the inertia moment around the centroid of the image. The last raw moment, R7 is skew invariance. Table 3 shows 10 feature vectors for 10 orientations of subject 1 sample 1 in the ORL dataset. The values in Table 3 indicate that all the values of the first moment (R1) are equal for all orientations of subject 1, and the variation in the order of the moments is low. The higher the order of moments, the higher are the variations. It should be noted that there are specific negative values, and there is a very large variation in those values. This affects the efficiency of a classifier, and the classification results are weak.

Table 3. Feature vectors of the sample image using raw moment of subject 1

Image	R_1	R_2	R_3	R_4	R_5	R_6	R_7
1-1	0.0131	1.1244	1.7621	2.7103	1.0496	2.363	-2.9358
1-2	0.0131	0.9921	1.6166	1.7361	-0.6815	1.918	0.1163
1-3	0.0131	0.9866	2.460	3.2627	-2.0830	2.458	-0.4947
1-4	0.0131	1.0865	1.7305	1.4922	-1.1104	0.296	0.4948
1-5	0.0131	0.8735	0.2410	1.3661	-0.2284	-4.333	-0.0551
1-6	0.0131	0.9896	2.0361	1.8513	-2.2277	-1.655	1.6146
1-7	0.0131	1.1781	3.7678	4.4662	5.4195	13.224	1.0495
1-8	0.0131	1.0104	2.2461	2.5555	0.851	5.732	0.0790
1-9	0.0131	1.5520	2.3714	2.0693	-3.0364	-3.051	2.1537
1-10	0.0131	0.9214	2.5188	2.6451	-2.7781	1.931	0.2545

4.4. Orientation of the region, φ

The (9) is used to calculate the raw moments up to the third order, which results in a feature vector up to the seventh order. Table 4 shows 10 features for 10 face orientations, and the results are a feature vector that has undergone linear recognition analysis and transformation. The number of subjects used is increased from 10 to 50 in the form of sequential steps, and the jump step is 3, as shown in Table 4. It has been observed that 63% is the percentage of face recognition that occurs for face orientation when using moments.

Table 4. Feature vector of sample image using raw moments subject 2

Image no.	Raw moments of order 3: Orientation of the region, φ						
	φ_1	φ_2	φ_3	φ_4	φ_5	φ_6	φ_7
2-1	0.232106	0.000587	0.542788	0.18173	0.106117	-0.11132	0.114703
2-2	0.229017	0.000288	4.330554	0.18175	0.342781	0.130464	0.152275
2-3	0.244291	0.000739	2.77237	0.16516	-0.18985	-0.12731	0.121532
2-4	0.234298	0.000181	1.838581	0.177474	0.130075	0.110133	0.130399
2-5	0.239196	0.000472	1.268621	0.179565	-0.13353	0.110306	-0.12304
2-6	0.23881	0.000177	1.85772	0.286794	0.458927	0.11128	-0.31689
2-7	0.243201	0.001284	8.302906	0.261877	0.563293	-0.00959	0.416858
2-8	0.249257	0.000856	1.429241	0.120337	-0.12148	-0.1102	-0.11072
2-9	0.241097	0.000227	5.176105	0.541497	1.345381	-0.11252	0.162834
2-10	0.245026	0.000264	1.306464	0.32130	0.240603	-0.11145	-0.11463

4.5. Using orthogonal moments

Orthogonal moments are capable of representing the features of the image with a Min. of coefficients and accuracy rate, through the experimental results, orthogonal moments have been observed much suitable for feature representation of complex face images which are almost similar compared to variations in size, pose, and orientation within smaller regions, we worked with orthogonal moments and used it for recognition of faces, it has been used to identify different images of faces. In the experiment that used the orthogonal moment features (O), different orders of the moments (2 to 6) were selected and calculated as shown in Table 5.

Table 5. The feature vector of sample image using orthogonal moments of order 3, subject 2

Image No.	O_{20}	O_{02}	O_{11}	O_{21}	O_{12}	O_{30}	O_{03}	O_{40}
2-1	0.630146	0.576177	1.016352	-1.02772	-0.97946	-1.52283	-1.50392	2.745453
2-2	0.591155	0.689645	0.997223	-0.88384	-0.94851	-1.4879	-1.62490	2.712697
2-3	0.655017	0.661265	1.055558	-1.04319	-1.03285	-1.54638	-1.59680	2.757582
2-4	0.592927	0.6204	0.957181	-0.87709	-0.88653	-1.47573	-1.53728	2.684474
2-5	0.575116	0.676499	1.019936	-0.90916	-1.00164	-1.49895	-1.62664	2.741392
2-6	0.567606	0.70133	0.955957	-0.79248	-0.90876	-1.46515	-1.62683	2.705298
2-7	0.753609	0.669043	1.116487	-1.18364	-1.10983	-1.65188	-1.61243	2.889758
2-8	0.686332	0.607345	1.028329	-1.05051	-0.97669	-1.57214	-1.53227	2.798169
2-9	0.652628	0.749567	1.026864	-0.92732	-0.98328	-1.52831	-1.68223	2.769508
2-10	0.713316	0.681758	1.101063	-1.11991	-1.10409	-1.63034	-1.63367	2.893186

4.6. Using fidelity criteria

Some additional fidelity criteria are used to estimate the quality and error rates as shown in Table 6 of matching images. Different thresholds are used, and the experiment was performed on 400 images of the ORL dataset, using 10 subjects as samples in different orientations. Table 7 shows the average values of three fidelity criteria mean squared error (MSE), Chi-Squared, and peak signal-to-noise ratio (PSNR).

Table 6. Recognition rate using the proposed hybrid technique

	Evaluation criteria				
Control parameters (permissible error (ε0))	Total attempts	Subjects/image	False attempts	FAR	RR
0.01	400	10	13	7.7%	92.3%
0.02	400	10	18	12.3%	87.7%
0.03	400	10	25	16.6%	83.4%
0.04	400	10	33	21.3%	78.7%
0.05	400	10	32	22.5%	77.5%

Table 7. Fidelity criteria

Average MSE	Average Chi-squared x^2	Average PSNR
26.521	3.962	35.834

5. RESULTS AND DISCUSSION

In the subsequent subsections, the results will be analyzed, evaluated, and discussed. The efficiency, performance comparisons, and accuracy of the proposed technique are confirmed. The results were presented in tables, not for statistical reasons, but for ease of use by researchers in the future.

5.1. Performance comparison

After preprocessing to separate the background and foreground of the face in the image by using the LBPH technique and equalizing the histogram to determine the location of the face in the image, then repetitive information like the face background and hair is removed, and the translation errors of the images are decreased. Figure 4 shows the rate of classification error using the hybrid of raw moments and LBPH techniques starting from the highest seventh order down to the lowest order. Figure 4 illustrates the practical description of (9).

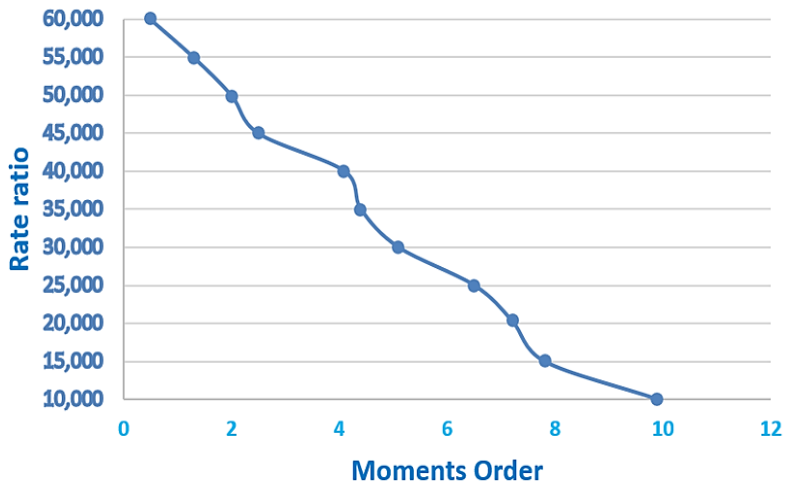

Figure 4. Classification error rate using different order moments classifier

In the classifier step, the invariant moment was used with the LBPH algorithm, and 5 images were selected from each subject randomly in the training process. The rest of the images were used for testing. The testing process showed that there was no overlap with the training process. The simulation of the result performed on the ORL database showed that the error rate for face recognition in the face localization step was less than the same process used without the face localizing step. In contrast, localizing the face in the hybrid algorithm using an invariant moment yields a better classifier performance than traditional methods. Those results are summarized in Tables 8 and 9.

Multiple experiments have been conducted to extract the features and recognize the faces using the three techniques (moments, LBP, and the proposed hybrid method) to compare their performance. For images in the ORL database, experiments were conducted with various sizes and orientations from the database set. The number of subjects that were viewed was increased from 5 to 40 by increments of 5, and each subject contained 10 images. The classification accuracy that was obtained using moments, LBP, and the proposed method is shown in Table 10.

Table 8. Experimental results for various orders of raw moments

Features vectors		Testing phase	
Categories	Number of feature elements	Classification error rate	
		Suggested method	Ref [2]
n=1, 2, …, 7	28	7.9%	8.50%
n=6, 7, 8	27	7.4%	4.50%
n=6, 7, 8	22	3.8%	3.40%
n=7, 10	22	2.2%	2.30%

Table 9. Experimental results for the best order of raw moments

Face recognition	Errors		Classification error rate
	Tilt Error	Translation Error	
False face localization	++	++	5.2%
True localization	17.5	26.7	1.3%
True localization (proposed hybrid method)	4.2	5.4	1%

Table 10. Performance analysis

Number of subjects	Percent recognition		
	LBP	Moments	Proposed hybrid
5	95%	99.9%	100%
10	71%	97.9%	98%
15	62.26%	96.9%	97%
20	54%	97.8%	96%
30	52%	94.46%	96%
40	51.21%	92.82%	94.06%
50	45.5%	91.95%	97.02%

5.2. Analysis of results

Findings shows the identification ratio using LBP, moments, and the proposed hybrid method. In the case of using the moments, there is no stability in the face recognition as the number of images increases. Whereas the proposed hybrid method retains good face recognition when the number of images increases and the percentage increases when the number of the images increases.

5.3. Evaluation of results

The suggested hybrid system points to a new method that is been based on the fusion of the moments method with the local binary patterns histogram (LBPH). The performance with an invariant moment alone is 86.06-99.5% and 88-98.9% with LBPH, while the recognition with hybrid alone is 96.94-99.6%. The optimal results have been obtained with the use of both approaches, and it has been shown that there is a higher rate of recognition with a lower error rate utilizing a hybrid technique.

6. CONTRIBUTION

The proposed technique helps to overcome the large gap that exists in the previous technique. Identifying and recognizing the faces of individuals in images with better accuracy, robustness, performance, and efficiency. Using a process that is a hybrid of two previous algorithms.

7. CONCLUSION

The paper presents a review of two localization methods for face recognition in a binary image. After the preprocessing step, the localization of the face was determined by using the moments and LBPH methods, where both methods depend on determining the center of the object as the basis for identifying the surrounding shapes. Then the face is separated from the shapes of the surrounding based on its features in the standard dataset image, which has been used for training and testing. The values of invariant moments, central moments, and LPBH are used as defining features of the face and to separate it from surrounding shapes. Those features are considered to be classifiers. The results were based on the standard database ORL, and they indicate that the procedure will contribute to and influence future research directions, providing opportunities to develop more accurate and efficient applications in the field of face recognition.

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