Engineering and Technology Journal
Journal homepage: engtechjournal.org

A New Hybrid Technique for Face Identification Based on Facial Parts Moments Descriptors

Shaymaa M. Hamandi[a*], Abdul Monem S. Rahma[b], Rehab F. Hassan[c].

[a] Department Computer Science, University of Technology, Baghdad, Iraq, 111797@student.uotechnology.edu.iq

[b] Department Computer Science, University of Technology, Baghdad, Iraq, 110003@uotechnology.edu.iq

[c] Department Computer Science, University of Technology, Baghdad, Iraq , 110019@uotechnology.edu.iq

*Corresponding author.

Submitted: 29/10/2020 Accepted: 14/01/2021 Published: 25/03/2021

K E Y W O R D S

Artificial Neural Network, Affine moments, Face recognition, Invariant Moments, Shape descriptor, Zernike moments.

A B S T R A C T

Robust facial feature extraction is an effective and important process for face recognition and identification system. The facial features should be invariant to scaling, translation, illumination and rotation, several feature extraction techniques may be used to increase the recognition accuracy. This paper inspects three-moment invariants techniques and then determines how is influenced by the variation which may happen to the various shapes of the face (globally and locally) Globally means the whole face shapes and locally means face part's shape (right eye, left eye, mouth, and nose). The proposed technique is tested using CARL database images. The proposal method of the new method that collects the robust features of each method is trained by a feed-forward neural network. The result has been improved and achieved an accuracy of 99.29%.

How to cite this article: S. M. Hamandi, A. S. Rahma, and R. F. Hassan, "A New Hybrid Technique for Face Identification Based on Facial Parts Moments Descriptors," Engineering and Technology Journal, Vol. 39, Part B, No. 01, pp. 117-128, 2021.
DOI: https://doi.org/10.30684/etj.v39i1B.1903

1. Introduction

Face recognition techniques are very important, especially in security systems. To identify a face shape, the face should be represented with specific features [1]. The face descriptor should be invariant in illumination, translation, size, rotation, and expression. The descriptor should gain these bases [2]: (1) enormous precision, (2) decreased memory span with store the descriptors, (3) Common applications, (4) A little record on extricating the descriptor, (5) no extreme debasement of execution same time expanding the database.

Recently, the most utilized descriptors are the moment invariants which go about as "The first choice descriptors" [3] which is a standout amongst the critical strategies for making an estimate of the implementation about different descriptor types. Regardless of those distributed studies, a considerable measure of issues even now must be solved [3]-[6].

There are a lot of challenges of face identification because pictures of the individual himself can vary frequently in facial expression, pose, and illumination conditions, these weak points minimize the achievements of the method [7]. The effectiveness of the face identification method usually depends on the extraction of features, in which taking out a feature set from the obtained dataset and matching this feature set with the templates set. The obtained features will be classified into two groups: local features and global features [8].

Those characteristic determinations need been generally used to reduce the information dimensionality. Information diminishment enhances the order performance, those close estimation functions as far as speed, exactness What's more Straightforwardness, Sequential Forward Selection (SFFS) is generally utilized to its effortlessness and speed. Huge number variants also requisition bring is suggested dependent upon those SFS algorithms. [9], Various face recognition and classification techniques have been used to accomplish different results. Artificial neural networks could be described concerning illustration computational models with specific properties, for example, such that the ability will adjust alternately figure out, to sum up, or with bunch alternately sort out information also which operation is in view of parallel methodology. The feedforward neural network was the first and simplest type of artificial neural network devised wherein the connections between the nodes do not form cycles [10].

In this paper, the focus was on global features, the whole face shape moments could be computed, and local features, the shape of face parts like eyes, nose, and mouth moments could be computed. This work proposes a technique to recognize faces using moment shape descriptors applied on the global whole face and different face parts (Right eye, left eye, mouth, and nose), a feature selection process based on SFFS and Feed Forward Neural Network to test this technique on face images of CARL database.

2. RELATED WORK:

Extensive studies have been proposed for face recognition in [11], [12], some of these studies used the moment invariant techniques as a robust statistical shape descriptor [7], [13].

Zhang and Yao Deng [14] in 2016 have proposed a representation technique of face pictures by applying 'dense sampling' around each detected feature point, then extracted 'Local Difference Feature' (LDF) for face representation, 'Principle Component Analysis' (PCA) and 'Linear Discriminant Analysis' (LDA) were utilized to reduce feature dimension and cosine similarity evaluation was used for identification.

Abdol Hossein Fathi and Pendar Ali Reza Zadeh [15] 2016 have introduced a multi-scale and rotation invariant global feature descriptor by applying the Zernike moment on the outputs of Gabor filters.

Paweł Karczmarek and Adam Kiersztyn [16] 2017 have analyzed the attributes and effectiveness of the Choquet integral and fuzzy measurement in the situation of a collection of classifiers with different face parts.

Fatima Akhmedov and Simon Liao [17] 2018 have investigated the applicability of separate orthogonal Hahn and Racah face recognition moments in relation to durability 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 Biometrics (UND) X1 group, the results had shown that recognition rates were between 94% and 94.5% of molten Han moments, and approximately 92% and 94% of the global and local Racah moments combined, on Straight.

Emrah Basaran and Muhittin Gökmen [18] 2018 have proposed a facial identification method employing 'local Zernike Moments' (LZM), which can be used for both recognition and verification. The results showed that the proposed technique had good results compared with using variation features such as illumination, poses, and facial expressions.

Kapil Juneja [19] in 2019 have used multi-features, a multi-algorithm framework for identifying individuals' faces. These faces can be whole faces or partial faces. The distance recognition technique is applied on the whole face, and a ratio-based structural point and curve map is applied on the partial face.

Yaser Khan [20] 2019 has presented a method to automate the search process depended on the mathematical computations on images to specify the features of the face. It concluded that the accuracy of the system is 96.2 %.

Qusay AL-Khalidi and Motlak H.J [21] in 2020 have built a rule to constrain the convolution neural network architecture in the face recognition systems.

3. Face Detection By Viola jones objects detection Technique

The Viola jones objects detection technique recommended by Paul Viola and Michael Jones in 2001. The strategy has the most effective during the 2000s. Viola Jones needs a whole frontal view upstanding countenances [22]. In an elevated stage, the strategy reads an information image using a window searching for facial highlights. At the point when enough highlights are discovered, at that point, this window is announced to be a face. To have distinctive face sizes, this window should be rescaled and the cycle is rehashed. In every window, the scale includes the technique independently from different scales. This technique turns out to be fairly tedious coming about because of the count of the size of the various pictures. To diminish the number of highlights every window needs to be checked and every window has gone through stages. Early stages incorporate fewer highlights to test and can be a lot simpler to pass, however later stages wind up producing many highlights and are all the much requesting. At every stage, the assessment of the highlights for that stage are gathered and if the gathered worth doesn't pass the limit, the stage is fizzling and this window will be not perceived as a face [23].

4. Face shapes moment's calculation

Moments described as scalar quantities that are used for characterizing functions and for computing their different features. Moments are very useful, since calculating them is algorithmically easy and clearly adjusted for any of the picture functions [3]–[6].

Invariant to translation is done by an object moving to a specific place prior to the computing of the moment, then moments have the translation invariance. Gaining "A central-geometric moments"as in μ_{pq} in(1) for a tow dimensions face image f(x , y) and (p+q) order moments [24].

$$\mu_{pq} = \sum_{-\infty}^{\infty}\sum_{-\infty}^{\infty}(x-x_c)^p(y-y_c)^q * f(x.y) \quad (1)$$

Where x_c and y_c consider as dimensions of a face center.

Equation(1) represents a base of the next progress in the moments' descriptor types as illustrated in Figure 1 [13],[25].

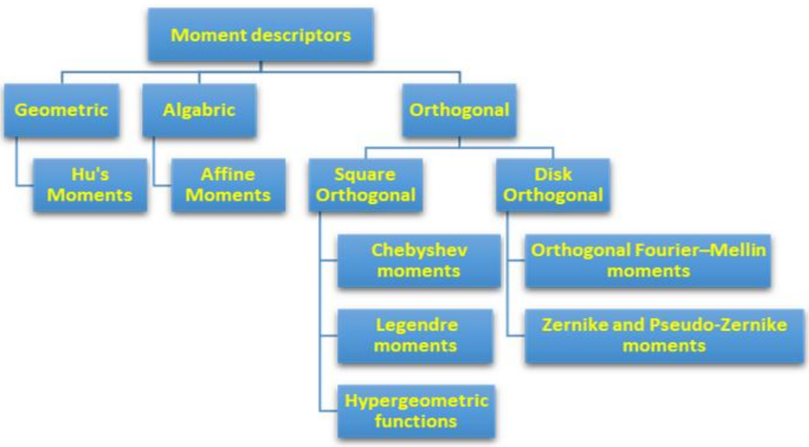

Figure 1: Classifications of moment shapes descriptors

From every kind of the moment descriptors our research picks one subtype of this kind for the experiment, the subtypes are:

I. Geometric Hu Moments Calculation

Hu [3], was investigating the algebraic invariant theories, relying on the central moment equation in Eq. (1) and produce his seven famous invariants to rotate around the root.

First, invariant to scaling is used for normalization as in Eq. (2).

$$\eta u_{pq} = \frac{\mu_{pq}}{\mu_{00}^{\gamma}} \text{ . where } \gamma = \frac{p+q+2}{2}, \text{and } p+q = 2,3,4 \tag{2}$$

After that the seven equations are computed

$$H_1 = \eta\upsilon_{20}+\eta\upsilon_{02}, \tag{3}$$

$$H_2 = (\eta\upsilon_{20}-\eta\upsilon_{02})^2 + 4\eta\upsilon_{11}^2 \tag{4}$$

$$H3 = (\eta\upsilon_{30}-3\eta\upsilon_{12})^2 + (3\eta\upsilon_{21}-\eta\upsilon_{03})^2 \tag{5}$$

$$H4 = (\eta\upsilon_{30}+\eta\upsilon_{12})^2 + (\eta\upsilon 21+\eta\upsilon_{03})^2 \tag{6}$$

$$H5 = (\eta\upsilon_{30}-3\eta\upsilon_{12})\ (\eta\upsilon_{30}+\eta\upsilon_{12})\ ((\eta\upsilon_{30}+\eta\upsilon_{12})^2 - 3(\eta\upsilon_{21}+\eta\upsilon_{03})^2) + (3\eta\upsilon_{21}-\eta\upsilon_{03})\ (\eta\upsilon_{21}+\eta\upsilon_{03})\ (3(\eta\upsilon_{30} + \eta\upsilon_{12})^2 - (\eta\upsilon_{21}+\eta\upsilon_{03})^2) \tag{7}$$

$$H6 = (\eta\upsilon_{20}-\eta\upsilon_{02})\ ((\eta\upsilon_{30}+\eta\upsilon_{12})^2 - (\eta\upsilon_{21}+\eta\upsilon_{03})^2) + 4\eta\upsilon_{11}(\eta\upsilon_{30}+\eta\upsilon_{12})\ (\eta\upsilon_{21}+\eta\upsilon_{03}) \tag{8}$$

$$H7 = (3\eta\upsilon_{21}-\eta\upsilon_{03})\ (\eta\upsilon_{30}+\eta\upsilon_{12})\ ((\eta\upsilon_{30}+\eta\upsilon_{12})^2 - 3(\eta\upsilon_{21}+\eta\upsilon_{03})^2) - (\eta\upsilon_{30}-3\eta\upsilon_{12})\ (\eta\upsilon_{21}+\eta\upsilon_{03})\ (3(\eta\upsilon_{30} + \eta\upsilon_{12})^2 - (\eta\upsilon_{21}+\eta\upsilon_{03})^2) \tag{9}$$

In spite of the Hu seven features were represented to be valuable, they are invariant only to translations, scaling, and rotations [1].

II. Algebraic Affine Moments Calculation

The earliest investigator who studied the invariant to affine transforms are the well-known mathematics expert David Hilbert [4].

David used (1) and compute the affine moments as shown in (10) to (17) [5]:

$$Af_1 = (\mu u_{20}\mu u_{02} - \mu u^2{}_{11})\ /\mu u^4{}_{00} \tag{10}$$

$$Af_2 = (-\ \mu u^2{}_{30}\ \mu u^2{}_{03} + 6\mu u_{30}\mu u_{21}\mu u_{12}\mu u_{03} - 4\mu u_{30}\mu u^3{}_{12} - 4\mu u^3{}_{21}\ \mu u_{03} + 3\mu u^2{}_{21}\ \mu u^2{}_{12})\ /\mu u_{00}{}^{10} \tag{11}$$

$$Af_3 = (\mu u_{20}\mu u_{21}\mu u_{03} - \mu u_{20}\mu u^2{}_{12} - \mu u_{11}\mu u_{30}\mu u_{03} + \mu u_{11}\mu u_{21}\mu u_{12} + \mu u_{02}\mu u_{30}\mu u_{12} - \mu u_{02}\mu u^2{}_{21})\ /\mu u^7{}_0 \tag{12}$$

$$Af_4 = (-\mu u^3{}_{20}\ \mu u^2{}_{03} + 6\mu u^2{}_{20}\mu u_{11}\mu u_{12}\mu u_{03} - 3\mu u^2{}_{20}\mu u_{02}\mu u^2{}_{12} - 6\mu u_{20}\mu u^2{}_{11}\mu u_{21}\mu u_{03} - 6\mu u_{20}\mu u^2{}_{11}\mu u^2{}_{12} + 12\mu u_{20}\mu u_{11}\mu u_{02}\mu u_{21}\mu u_{12} - 3\mu u_{20}\mu u^2{}_{02}\mu u^2{}_{21} + 2\mu u^3{}_{11}\mu u_{30}\mu u_{03} + 6\mu u^3{}_{11}\mu u_{21}\mu u_{12} - 6\mu u^2{}_{11}\mu u_{02}\mu u_{30}\mu u_{12} - 6\mu u^2{}_{11}\mu u_{02}\mu u^2{}_{21} + 6\mu u_{11}\mu u^2{}_{02}\mu u_{30}\mu u_{21} - \mu u^3{}_{02}\mu u^2{}_{30})\ /\mu u^{11}{}_{00} \tag{13}$$

$$Af_5 = (-\mu u^3{}_{20}\ \mu u^2{}_{03} + 6\mu u^2{}_{20}\mu u_{11}\mu u_{12}\mu u_{03} - 3\mu u^2{}_{20}\mu u_{02}\mu u^2{}_{12} - 6\mu u_{20}\mu u^2{}_{11}\mu u_{21}\mu u_{03} - 6\mu u_{20}\mu u^2{}_{11}\mu u^2{}_{12} + 12\mu u_{20}\mu u_{11}\mu u_{02}\mu u_{21}\mu u_{12} - 3\mu u_{20}\mu u^2{}_{02}\mu u^2{}_{21} + 2\mu u^3{}_{11}\mu u_{30}\mu u_{03} + 6\mu u^3{}_{11}\mu u_{21}\mu u_{12} - 6\mu u^2{}_{11}\mu u_{02}\mu u_{30}\mu u_{12} - 6\mu u^2{}_{11}\mu u_{02}\mu u^2{}_{21} + 6\mu u_{11}\mu u^2{}_{02}\mu u_{30}\mu u_{21} - \mu u^3{}_{02}\mu u^2{}_{30})\ /\mu u^{11}{}_{00} \tag{14}$$

$$Af_6 = (\mu u_{40}\mu u_{04} - 4\mu u_{31}\mu u_{13} + 3\mu u^2{}_{22})\ /\mu u^6{}_{00} \tag{15}$$

$$Af_7 = (\mu u_{40}\mu u_{22}\mu u_{04} - \mu u_{40}\mu u^2{}_{13} - \mu u^2{}_{31}\mu u_{04} + 2\mu u_{31}\mu u_{22}\mu u_{13} - \mu u^3{}_{22})\ /\mu u^9{}_{00} \tag{16}$$

$$Af_8 = (\mu u^2{}_{20}\mu u_{04} - 4\mu u_{20}\mu u_{11}\mu u_{13} + 2\mu u_{20}\mu u_{02}\mu u_{22} + 4\mu u^2{}_{11}\mu u_{22} - 4\mu u_{11}\mu u_{02}\mu u_{31} + \mu u^2{}_{02}\mu u_{40})\ /\ \mu u^7{}_{00} \tag{17}$$

III. Orthogonal Moments Calculation

The Zernike moment's calculation has been derived from Teague[6] who has utilized Zernike moments to compute rotation invariant.

The radial polynomial with order=no and repetition=m is computed as below [26]:

$$R_{nl}(r) = \sum_{s=0}^{(n-|l|)/2}(-1)^s \frac{(no-s)!}{s!\left(\frac{n+|l|}{2}-s\right)!\left(\frac{n-|l|}{2-s}\right)} \rho^{no-2s} \tag{18}$$

Where,

no: Positive integer or zeroes

m: Positive and negative integers where n – |m| is even and |m| <= n

ρ: Length from the origin to (x, y) pixel

θ: Angle between ρ and x axis.

The Zernike polynomial is characterized as products as shown in (19),

$$V_{nl}(\rho.\varphi) = R_{nl}(\rho)e^{il\varphi} \tag{19}$$

First, mapping the images to a disk of a unit before computing Zernike moments. Then, the Zernike moments for f (x, y) image with repletion=m and order=no are calculated as in (20):

$$\mathrm{A_{nl}} = \frac{\mathrm{no}+1}{\pi} \sum_{\varphi=0}^{2\pi} \sum_{\mathrm{rr}=0}^{1} \mathrm{V_{nl}^{*}}(\mathrm{rr}.\varphi)\mathrm{f}(\mathrm{rr}.\varphi)\mathrm{rr} \tag{20}$$

5. ROBUST FEATURE SELECTION

The purpose of feature selection is to gain the best subset of features that gives the optimal achievements. Sequential Forward Feature Selection (SFFS) technique is utilized to choose the optimal feature combination which gives the optimal result. This technique is done for the feature which gains the most elevated ranks to minimize the search's time and guaranteeing just optimal feature will be found in the latest feature subset and these processes will minimize the amount of used features[27]. SFFS calculation is a base-up pursuit methodology that starts from an unfilled list and continuously adds highlights chose by some assessment work, that limits the mean square error (MSE). In every emphasis, the component to be remembered for the list of capabilities is chosen among the leftover accessible highlights of the list of capabilities, which have not been added to the list of capabilities. In this way, the new broadened highlights set should create a base order mistake contrasted and the expansion of some other element.

6. FEED FORWARD NEURAL NETWORK TECHNIQUE

Classification is the procedure for discriminating class data from other data sources in the feature space. A feed-forward neural network is an artificial neural network wherein the connections between the nodes do not form a cycle, in this network as shown in figure 2, the data moves in one direction, only beginning with the input nodes, through the hidden nodes ending with the output nodes. There are no cycles in the network [28].

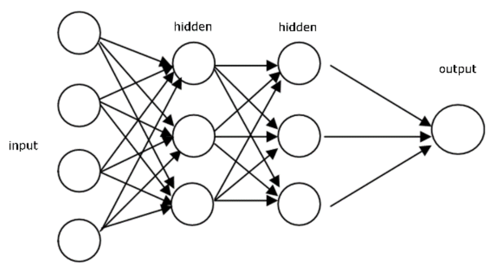

Figure 2: Feed-forward neural network design

7. THE PROPOSED METHOD

Different kinds of features have different intensities of description. For improving that power, various kinds of features have been used rather than only one kind. This research divided into two parts 1) study and compute the various moment kinds on various face shapes, evaluate the results and discover the robust descriptors, 2) propose a technique, selecting various features from each kind (only the best ones) to improve the feature description intensity and benefits from the benefits of each type and solve the drawbacks of them.

To calculate the Hu moments, five steps must be considered as illustrated in the algorithm (1):

Algorithm1: Calculating the Hu moments
Inputs: Tow dimensions face image f (x , y), Threshold1 Outputs: Hu moments (Hu1..Hu7)

Step 1: % Convert grey image into binary image
For every pixel Px in f(x, y)
If Px>= Threshold1, then
Set Px=1
else set Px=0
Step 2: Calculate the core of f(x, y) x_c, y_c
Step 3: For pu =0 to 4
For qu =0 to 4
Calculate µu (pu, qu) ……According to (1)
End for
End for
Step 4: For pu=1 to 4
For qu=1 to 4
Compute ηυ(pu, qu) ……..according to (2)
End for
End for
Step 5: Calculate the seven Hu moment……According to (3) to (9)

To Calculate the Affine moments, these steps have to be considered as in algorithm (2)

Algorithm2: Calculate the eight Affine moments
Input: Tow dimensions face image f(x, y), Threshold1 Output: Seven Affine moments (Af1..Af8)

Step 1: % Convert the grey image into binary image
For each pixel Px in image f(x,y)
If Px>= Threshold1 then
Set Px=1
else set Px=0
Step 2: Compute the core of the image xc, yc
Step 3: For pu = 0 to 4
For qu = 0 to 4
Calculate µu(pu,qu) ……..According to (1)
End for
End for
Step 4: Compute the Affine moments ……..According to (10) to (17)

To calculate Zernike moments, these steps have to be considered as in algorithm (3):

Algorithm3: Computing the Zernike moments
Input: Tow dimensions face image f (x, y), Threshold1, orders n and repetitions m Output: Zernike moments
Step 1: % Convert the grey image into binary image For each pixel Px in image f(x, y) If Px>= Threshold1, then

Set Px=1
else set Px=0
Step 2: calculate the radial polynomial of orders n with repetitions m as in (18)
Step 3: calculate Zernike polynomial as in (19)
Step 4: calculate the Zernike moments of the image f(x, y) according to (20)

By selecting the robust features of every moment descriptor's kind, the moment descriptors will be enhanced by taking advantage of the benefits of every kind and solve the disadvantages. The steps of the proposed method are shown in Figure 3:

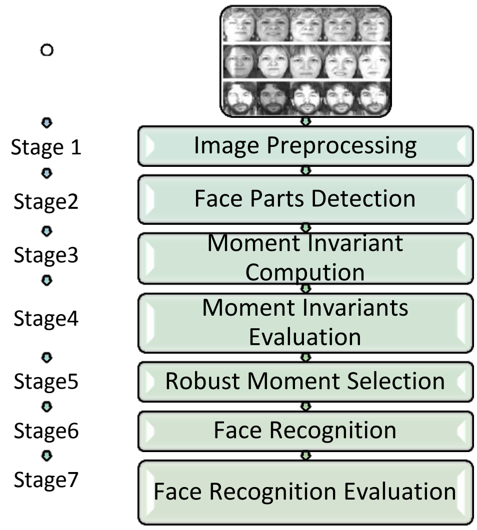

Figure 3: The main stages of the new hybrid moments descriptor.

The new method includes seven steps:

I. Preprocessing Stage:

1) Detect the face area using the Viola-Jones method and then crop the face area.
2) Transferring from color to a grayscale image.
3) Threshold the grayscale image to have (0 or 1) value for every pixel in the image.

II. Face Parts Detection:

1) Detect face parts (global face, left eye, right eye, mouth, and nose) using the Viola-Jones method.

III. Moment Invariants Calculation Stage:

1) Hu moments, Affine moments, and Zernike moments are calculated for every face part using algorithms 1, 2, and 3.

IV. Moment Invariants Estimation Stage:

1) Computing every moment intra-class (inside the class) and inter-class (discrimination between classes).
2) The features will be passed to the next step to select the robust moments.

V. Robust Moments Selection Stage:

1) SFFS technique is utilized for choosing the robust features that give the optimal accuracy.
2) SFFS is utilized to compute the features that give the biggest discrimination ranks to minimize the time of the search.
3) Beginning with a set of zero elements; The feature which results in the best accuracy will be added.

VI. Classification Stage:

1) Feed-forward neural network as in fig. 5 is utilized as a classification technique.

2) Feed-forward neural network is utilized to classify the optimal feature subset into a proper class.
3) Feed-forward neural network is trained with the moments' features to classify the inputted feature vector into the proper faces class.
4) Feed-forward neural network is trained with the proper feature subset that was selected in the robust moment’s selection stage.

VII. Face Recognition Evaluation Stage:

1) The test images are utilized here to test the robustness of the proposed technique.

8. Experimental Results

The accuracy of every moment descriptor of face images is tested using the CARL Database [29], The size of every image is (160 × 120) pixels, CARL dataset involves face images of forty-one individuals (thirty-two males and nine females) under different illumination states as in figure (4). The experimental environment is MATLAB 2019b.

Figure 4: Samples of the CARL database.

I. Moments Invariant Computations

The results of the robust proposed descriptors for every facial part image are illustrated with the results of moment descriptors for global and local faces from the CARL face database as shown in figure 5.

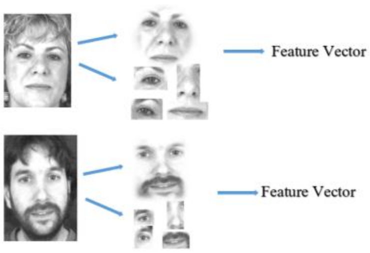

Figure 5: The feature vector for each face and face parts in the database

The datasets were partitioned into 3 portions 70 % of the dataset for the training portion, 15 % of the dataset for the testing portion and, 15 % of the dataset for the validation portion.

Every portion goes through the seven stages of the proposed technique, and by using the equations in section (3) the Hu, Affine, and Zernike moment invariants are calculated for every face image and only the robust features will be chosen.

II. Neural Network Classifier Implementation

A feed-forward neural network classifier is used to make an appropriate structure by updating neural network weights. This network consists of one hidden layer containing 5 neurons, the output layer with ten neurons represents the ten classes of the persons in the dataset as shown in figure 6.

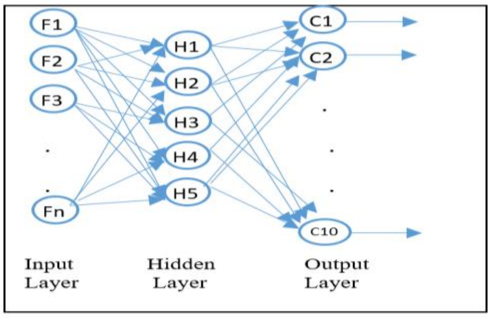

Figure 6: The structure of the Feed-forward neural network classifier.

Figure 7 shows the ROC curves which are represented the plot of the values of the False Positive Rate (FPR) versus the True Positive Rate (TPR) for each face part classifier. The higher the ROC curve (i.e. the closer to the line y = 1) the better the fit. The ROC curve of the global whole face gained the best fit with an accuracy of 95%, followed by the Right eye, left eye, nose, and at the last the mouth ROC curve with the lowest fit.

These results are enhanced by combining the features of the whole face and the features of each face part. The feed-forward neural network classifier is then implemented as shown in figure 7 the ROC curve with a black line.

These results are more enhanced when applying the proposed technique taking only the robust features to make the accuracy of the classifier reach 99%.

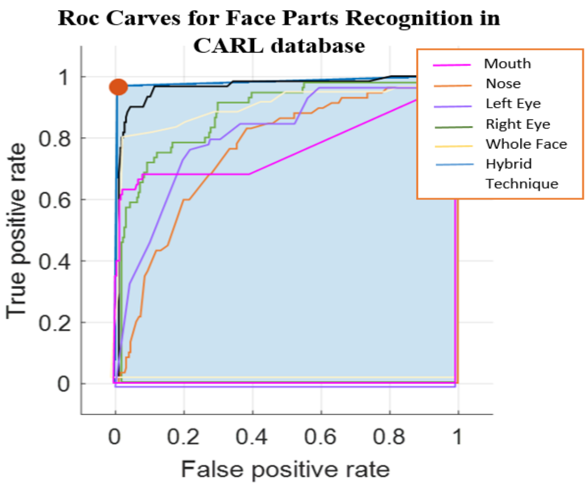

Figure 7: Roc carves for different face parts recognition and the whole face

TABLE I: Accuracy of each moment technique.

Face Part	Moment technique	No. of Features	Accuracy	Best features (SFFS method)
Global Face	Hu	7	74%	Hu3, Hu4
	Affine	7	60%	Aff1
	Zernike	9	81%	Z4, Z6, Z8
	All	23	95%	
Right Eye	Hu	7	68.2%	Hu3, Hu4, Hu5
	Affine	7	68%	Aff5, Aff7
	Zernike	9	80.5%	Z2, Z3, Z8, Z9
	All	23	82%	
Left Eye	Hu	7	53%	Hu1, Hu3, Hu4
	Affine	7	61%	Aff5, Aff7
	Zernike	9	81%	Z2, Z3, Z4, Z6
	All	23	85.5%	
Mouth	Hu	7	50.1%	Hu3, Hu5, Hu7
	Affine	7	40.2%	Aff1, Aff5, Aff7
	Zernike	9	65.2%	Z7, Z8, Z9

	All	23	70.2%	
Nose	Hu	7	56.7%	Hu4, Hu7
	Affine	7	60.4%	Aff5
	Zernike	9	73.9%	Z4, Z6, Z7, Z8, Z9
	All	23	76%	
All Features		115	98.65%	
Robust Hybrid Features		40	99.29%	Above robust features

The whole results are illustrated in Table I which shows the accuracy of applying each moment technique on each face part and choosing the robust moment features. The best features are chosen using the SFFS selection method and the accuracy of each technique is computed when applying Feedforward Neural Network.

And Figure 8 Shows a bar chart of the accuracy of each moment technique when applied to different face parts and the proposed hybrid technique.

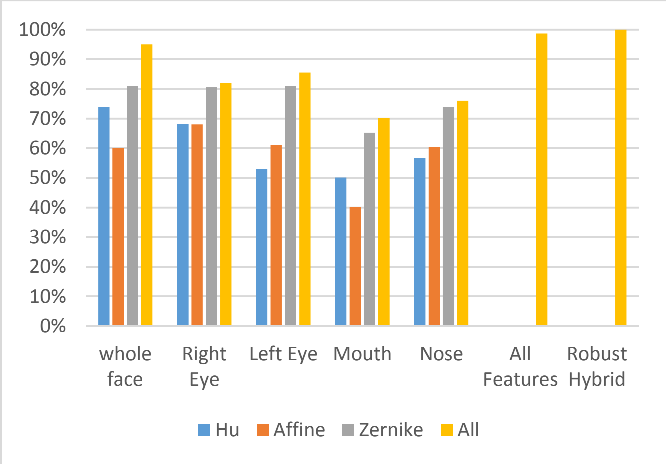

Figure 8: Flow chart shows the accuracy of each moment technique when applied to different face parts and the proposed hybrid technique.

Table II shows the comparison of the proposed method system results with various recent methods that worked on using the CARL dataset. The results show that our proposed method achieves higher accuracy than other methods as shown in Figure 9.

TABLE II: A Comparison Between Previous works on CARL Dataset and The Proposed Hybrid Technique.

Research works	Year	Methodology	Accuracy
M. S. Sarfraz[30]	2017	Deep Perceptual Mapping	84%
Z. M. Abood [31]	2017	Gabor wavelet transform feature	91.4%
S. Athira [32]	2018	KNN	97%
K. Lai [33]	2019	CNN pre-trained	95.35%
Proposed Hybrid Technique	2020	Moment invariants of face parts	99.92%

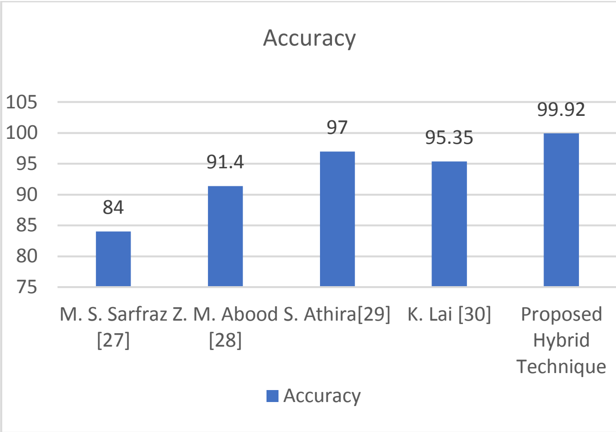

Figure 9: A bar chart shows a comparison between Previous works on CARL Dataset and The Proposed Hybrid Technique.

9. Conclusion and future work

In this paper, a new face recognition technique is proposed. New hybrid face descriptors are presented to enhance the performance of identifying face pictures. Several kinds of moments shape descriptors are calculated and tested (Geometric Hu moments, Algebraic Affine moments, and Orthogonal Zernike moments) for the whole face images and each face part (right eye, left eye, mouth, and nose). The recognition accuracy is not quite enough if using the features of the whole face only or features on any part of the face, but when from each part of the face the robust descriptors were picked to present the hybrid descriptor, the results are enhanced to reach 99.92% in the proposed system which produces a very robust descriptor.

In future work, the features of multi-spectral visions will be used together to produce a robust descriptor to exploit the advantages of each technique.

References

[1] M. Sonka Hlavac, V., & Boyle, R., *Image processing, analysis, and machine vision*. Cengage Learning. ‘ 2014.

[2] H.-K. Kim and J.-D. Kim, “Region-based shape descriptor invariant to rotation, scale and translation,” *Signal Process. Image Commun.*, vol. 16, no. 1–2, pp. 87–93, 2000.

[3] J. Flusser, B. Zitova, and T. Suk, *Moments and moment invariants in pattern recognition*. John Wiley & Sons, 2009.

[4] M. E. Celebi and Y. A. Aslandogan, “A comparative study of three moment-based shape descriptors,” in *International Conference on Information Technology: Coding and Computing (ITCC’05)-Volume II*, 2005, vol. 1, pp. 788–793.

[5] F. Arnia, K. Saddami, and K. Munadi, “Moment invariant-based features for Jawi character recognition,” *Int. J. Electr. Comput. Eng.*, vol. 9, no. 3, p. 1711, 2019.

[6] R. Mukundan, S. H. Ong, and P. A. Lee, “Image analysis by Tchebichef moments,” *IEEE Trans. image Process.*, vol. 10, no. 9, pp. 1357–1364, 2001.

[7] G. A. Papakostas, “Over 50 years of image moments and moment invariants,” *Moments Moment Invariants-Theory Appl.*, pp. 3–32, 2014.

[8] B. Ammour, T. Bouden, L. Boubchir, and S. Biad, “Face identification using local and global features,” in *2017 40th International Conference on Telecommunications and Signal Processing (TSP)*, 2017, pp. 784–788.

[9] C.-L. Lorenz, M. Packianather, C. Bleil De Souza, A. B. Spaeth, and T. I. Lorenz, “Input feature selection and optimization for ANN models predicting daylight in buildings,” 2019.

[10] R. CAPOR-HROSIK, M. T. M. VUKOVIC, and M. PIKULA, “Face Detection by Neural Networks Based on Invariant Moments.”

[11] Y. Kortli, M. Jridi, A. Al Falou, and M. Atri, “Face Recognition Systems: A Survey,” *Sensors*, vol. 20, no. 2, p. 342, 2020.

[12] L. Yaya and C. Guo, "Method of Sparse Representation Face Recognition Fusing Global and Local Features," *J. Gansu Sci.*, no. 4, p. 4, 2017.

[13] S. M. Hamandi, A. M. S. Rahma, and R. F. Hassan, "Comparative Study of Moments Shape Descriptors and propose a new hybrid Descriptor technique," in *2019 Ninth International Conference on Intelligent Computing and Information Systems (ICICIS)*, 2019, pp. 194–201.

[14] J. Zhang, Y. Deng, Z. Guo, and Y. Chen, "Face recognition using part-based dense sampling local features," *Neurocomputing*, vol. 184, pp. 176–187, 2016.

[15] A. Fathi, P. Alirezazadeh, and F. Abdali-Mohammadi, "A new Global-Gabor-Zernike feature descriptor and its application to face recognition," *J. Vis. Commun. Image Represent.*, vol. 38, pp. 65–72, 2016.

[16] P. Karczmarek, A. Kiersztyn, and W. Pedrycz, "An evaluation of fuzzy measure for face recognition," in *International Conference on Artificial Intelligence and Soft Computing*, 2017, pp. 668–676.

[17] F. Akhmedova and S. Liao, "Face Recognition with Discrete Orthogonal Moments," in *Recent Advances in Computer Vision*, Springer, 2019, pp. 189–209.

[18] E. Basaran, M. Gökmen, and M. E. Kamasak, "An efficient multiscale scheme using local zernike moments for face recognition," *Appl. Sci.*, vol. 8, no. 5, p. 827, 2018.

[19] K. Juneja, "Multiple feature descriptors based model for individual identification in group photos," *J. King Saud Univ. Inf. Sci.*, vol. 31, no. 2, pp. 185–207, 2019.

[20] Y. D. Khan, "An Improved Facial Recognition Technique Using Scale and Rotation Invariant Statistical Moments," in *2019 XIth International Scientific and Practical Conference on Electronics and Information Technologies (ELIT)*, 2019, pp. 142–149.

[21] A.-K. Qusay, H. J. Motlak, and H. Al-Libawy, "A new Rule to Constrain Convolution Neural Network Architecture in Face Recognition System," in *Journal of Physics: Conference Series*, 2020, vol. 1530, no. 1, p. 12125.

[22] C. Zhang and Z. Zhang, "A survey of recent advances in face detection," 2010.

[23] D. Hefenbrock, J. Oberg, N. T. N. Thanh, R. Kastner, and S. B. Baden, "Accelerating Viola-Jones face detection to FPGA-level using GPUs," in *2010 18th IEEE Annual International Symposium on Field-Programmable Custom Computing Machines*, 2010, pp. 11–18.

[24] J. Flusser, T. Suk, and B. Zitová, *2D and 3D image analysis by moments*. John Wiley & Sons, 2016.

[25] S. M. Hamandi, A. M. S. Rahma, and R. F. Hassan, "A New Hybrid Shape Moment Invariant Techniques for Face Identification in Thermal and Visible Visions," in *2020 21st International Arab Conference on Information Technology (ACIT)*, 2020, pp. 1–9.

[26] M.-K. Hu, "Visual pattern recognition by moment invariants," *IRE Trans. Inf. theory*, vol. 8, no. 2, pp. 179–187, 1962.

[27] A. Marcano-Cedeño, J. Quintanilla-Domínguez, M. G. Cortina-Januchs, and D. Andina, "Feature selection using sequential forward selection and classification applying artificial metaplasticity neural network," in *IECON 2010-36th annual conference on IEEE industrial electronics society*, 2010, pp. 2845–2850.

[28] J. Schmidhuber, "Deep learning in neural networks: An overview," *Neural networks*, vol. 61, pp. 85–117, 2015.

[29] V. Espinosa-Duró, M. Faundez-Zanuy, and J. Mekyska, "A new face database simultaneously acquired in visible, near-infrared and thermal spectrums," *Cognit. Comput.*, vol. 5, no. 1, pp. 119–135, 2013.

[30] M. S. Sarfraz and R. Stiefelhagen, "Deep perceptual mapping for cross-modal face recognition," *Int. J. Comput. Vis.*, vol. 122, no. 3, pp. 426–438, 2017.

[31] Z. M. Abood, G. S. Karam, and R. E. Haleot, "Face Recognition Using Fusion of Multispectral Imaging," in *2017 Second Al-Sadiq International Conference on Multidisciplinary in IT and Communication Science and Applications (AIC-MITCSA)*, 2017, pp. 107–112.

[32] S. Athira and O. V. R. Murthy, "Face Authentication Using Thermal Imaging," in *Computational Vision and Bio Inspired Computing*, Springer, 2018, pp. 1006–1014.

[33] K. Lai and S. N. Yanushkevich, "Multi-Metric Evaluation of Thermal-to-Visual Face Recognition," in *2019 Eighth International Conference on Emerging Security Technologies (EST)*, 2019, pp. 1–6.