A Comparative Evaluation of Dotted Raster-Stereography and Feature-Based Techniques for Automated Face Recognition

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Abstract-Automated face recognition systems are fast becoming a need for security-related applications. Development of a fool-proof and efficient face recognition system is a challenging domain for researchers. This paper presents comparative evaluation of two candidate techniques for automated face recognition application, viz. dotted Rasterstereography and feature-based system. The relevant performance parameters - accuracy, precision, sensitivity and specificity - measured for the two techniques using IPRL Database of images are reported. The results suggest that dotted Raster-stereography based face recognition system has better accuracy, precision, sensitivity and specificity, and hence is a preferred choice as compared with feature-based system for such sensitive applications where high face recognition accuracy is required. On the other hand, feature-based technique is faster in terms of the training and testing times required. Hence such applications where volume of face recognition work is large and high speed is required with some compromise in accuracy being acceptable then feature-based technique may also be the technique of choice.

Keywords—Raster-stereography; dotted raster-stereography; feature based; face recognition; IPRL

I. INTRODUCTION

In today's world where computer- and IT-based systems are being used everywhere for different applications, user authentication is a key requirement to ensure security of these systems and applications. Implementing system protection with user ID and password is a common practice in e-mail, online banking and ATM systems. However, if password is hacked or stolen, then these apparently secure systems become vulnerable to unauthorized access. Long and hard passwords are not easy to remember; similarly the probability to guess short and simple passwords is high. Hence for these reasons, password protected systems are not very secure.



Fig. 1. Different biometric systems (a) Finger scan (b) Iris scan (c) Facial recognition (d) Retina scan (e) Hand scan (f) Full body scan (g) Voice scan (h) Project hostile intent (i) Signature scan (j) Keystroke scan and (k) Gait analysis.

In recent times, biometric-based identification or recognition is being incorporated in security technologies. A biometric feature is a distinctive and computable attribute of a human being that can be used to authenticate an individual. A biometric system is capable to compute both physiological and behavioral patterns of a person for the purpose of recognition [1]. The physiological domain is based on measurement or scan of a part of the human body, e.g. face [2], finger [3], hand [4], iris and retina [5-6]. On the other hand, the behavioral domain is based on measurement from some specific action of a person, e.g., gait characteristics, keystroke scan, signature scan, voice scan [1] and hostile intent [7]. Each of these biometric techniques has its own privacy concern and health risk [8], as shown in Fig. 1. Face recognition system [9] is a recommended technique for person identification as compared with the other biometric systems.

II. FACE RECOGNITION SYSTEMS

A. Background

Face recognition or identification is a process of matching a face from all available face-images in the system database [9]. Facial identification is a stereo-photogrammetric system, which has less health related issues. It is non-contact, nondestructive and radiation free technique [10]. A face can be recognized even with partial facial information, which can be captured with inexpensive cameras. From the last couple of years, automated face recognition, being one of the prominent applications of facial image analysis has become an attractive domain for researchers.

B. Literature Review

The preliminary work related to human facial identification system described the domain of psychology [11] and engineering [12]. Kelly [13] commenced research for automated facial identification; later Kanade [14] continued the significant work in the same domain. Darwin [15] and Galton [16] described facial recognition technique as a biometric system. Eigenfaces [17], [18] as well as Fisher faces [19]-[21] techniques recognized as a reliable mechanism especially for huge datasets. On the other hand a graphmatching method was one of a useful technique related to feature based method [22], [23]. Face recognition and tracking system in videos are now very interesting area for the last few years [24].

Sun *et al.* [25] used a specialized form of machine learning based on high level face features to identify human faces. Researchers have discussed ways to improve the performance of face recognition techniques [26]-[32]. In [33], [34], classification-based methods were used for the purpose of face identification. The performance of this technique was good. A component-based technique for face recognition is discussed in [35]. Xu *et al.* [36] specified about the change in performance of face recognition techniques with change of environment, lighting and expression of faces.

C. Face Recognition Techniques

Facial recognition systems are now one of more attractive and popular area for the researchers. The techniques required to recognize human faces can be categorized in three diverse approaches, mainly known as: i) Holistic; ii) Feature-based; and iii) Hybrid (Fig. 2).



Fig. 2. Categorization of face-recognition techniques.

In this paper, two approaches of machine-based face recognition have been discussed: i) dotted Raster-stereography [37]; ii) feature-based [38]. Dotted Raster-stereography is a holistic approach, in which identification takes place on the basis of global attributes i.e. curvature patterns of human face in term of pixels and their corresponding coordinate values. In featured-based technique, identification is performed on the basis of local features obtained from the human face (nose-eyes-mouth). The research work presented here compares, for these two techniques, the performance measures of accuracy, precision, sensitivity and specificity, using the Image Processing Research Lab (IPRL) database of images.

III. IMAGE PROCESSING RESEARCH LAB (IPRL) DATABASE OF IMAGES

The images of IPRL database were recorded in Image Processing Research Laboratory (IPRL) at Usman Institute of Technology (UIT), Karachi, Pakistan. This database contains a variety of facial images recorded with different illumination, facial orientation and expression of human faces. Each facial image has its corresponding facial curvatures as well in term of dotted patterns (Fig. 3). This database currently holds 800 human face images with five orientations (frontal, left, right, up and down). It also holds the facial key features of these faces in the form of dots. To describe face recognition based on dotted raster-stereography mean (M) and Gaussian (G) are obtained as decision parameters. Table I presents a snapshot of IPRL database. Fig. 3 shows a snap shot of IPRL database images.



Fig. 3. IPRL Database sample (left: original facial images, right: their dotted-curvature-patterns).

TABLE I. SNAPSHOT OF IPRL DATABASE

Attributes	Description				
Total no. of human faces	800 human faces (both male & female)				
Classifications	4000 human faces, 4000 facial curvatures				
Nature of images	Static				
Single or Multiple faces	Single				
Attributes of images	Colored				

Resolution	Various			
Facial Pose	Frontal, left (-15°), right (+15°), down (-15°), up (+15°)			
Facial Expression	N/A			
Illumination	N/A			
Light Condition	Dark Illumination			
Accessories	With and without Beard, with and without glasses			
3D Data	N/A			

IV. DOTTED RASTER-STEREOGRAPHY TECHNIQUE

The proposed face recognition technique using dotted Raster-stereography consists of three basic steps: registration of face, identification of face; and recognition of face as given in the flow chart shown in Fig. 4.

Dotted raster grid, consisting of green color-dots of equal spacing (0.6 mm), was projected on human face. Because of the curved surface of human face, distortions were created and recorded in term of coordinate values. Fundamental curvatures κ_1 and κ_2 were calculated respectively, which are the main source of curvatures mean (M) and Gaussian (G). These dotted curvature patterns in Table II are easily picks using image processing algorithms. Pixels and their corresponding coordinate values of each dot in curved patterns are representing the face curvature patterns of each person.

A. Mathematical Model of Dotted Raster-stereography Technique

Human faces can be mapped as curved surfaces, curvature patterns were generated when dotted grid (raster) projected on facial surface of human using multimedia projector. Using a digital camera these curvature patterns were recorded and use as an input for the computer system. Designed algorithm was used to find the pixel and corresponding coordinate values in term of (x, y). Using the developed mathematical model the horizontal and vertical curvatures ' κ_1 ' and ' κ_2 ' were calculated. These two facial curvatures were used to calculate decision parameters mean (M) and gaussian (G) curvatures. In our work M and G were the main source of face recognition.

B. Fundamental Curvatures ($\kappa 1$, $\kappa 2$)

The fundamental curvatures ' κ_1 ' and ' κ_2 ' represents the horizontal and vertical curvatures simultaneously of human face in the face-recognition system described in this work (Fig. 5).

C. Mean and Gaussian Curvatures (M, G)

Mean and Gaussian facial curvatures can be obtained using equations (1) and (2), while $\kappa \rho = 1$, where ' ρ ' is the radius of curve generated by facial curvatures of human face.

$$Mean = \frac{\kappa_1 + \kappa_2}{2} \dots \dots (1)$$

Gaussian = $\kappa_1 \times \kappa_2 \dots \dots (2)$

There are four basic types of curvatures of a small surface element [39] as shown in Fig. 4 and the fundamental curvatures (κ_1 and κ_2) decision is described.



Fig. 4. Four basic types of curvatures

The following Fig. 5 shows the flow of proposed system technique.



Fig. 5. Flow diagram of dotted Raster-stereography system.

TABLE II. OBSERVATION TABLE: CURVATURE PATTERNS, COORDINATE VALUES AND DECISION PARAMETERS





Fig. 6. Mathematics of Raster-stereography.

D. Mathematics of Curvature Extraction

In our mathematical model, 'd' was the small gap (distance) between two points in the original grid. When this raster grid was projected on the face of human, grid were distorted and provided the facial curvature information of human face. When distorted grid generated linear spacing 'd' is converted into arc length 's' (Fig. 6). The study of this arc length provided the detail of facial curvatures of human face. From the geometry of Fig. 6, it is obtained that angular distance = κs and $\kappa \rho = 1$), the result for curvatures κ , we obtained:

$$\kappa \approx \pm \frac{1}{s} \sqrt{24 \left(1 - \frac{d}{s}\right)}$$
(3)

 κ_1 and κ_2 are the horizontal and the vertical curvatures.

V. FEATURE-BASED TECHNIQUE

Feature-Based technique described in this work is based on core features selection of the human face i.e. mouth, nose and eyes. In this technique, edge density (ED) and sum of square for error (SSE) are the two parameters required to recognize a face. In the first step, ED is calculated. An ED can be described as it is an edge, which belongs to the boundaries among two dissimilar classes of intensity. Mathematically ED is a ratio between perimeter (E) and area (A) as given in Fig. 7. This relation is described in the following equation 4.

$$ED = \frac{E}{A} \quad \dots \quad (4)$$

In second step, the SSE is calculated for the purpose of face recognition [39].



Fig. 7. The feature-based approach is based on edge density.

A. Mathematical Model of Feature Based Technique

Edge density (ED) is a ratio between perimeter (E) and the area (A_e) where perimeter E is the average of perimeters A, B and C; A_e is the area of eye rectangle, whose perimeter is A.

$$ED = \frac{E}{A_{c}}$$
(5)

where
$$E = \frac{(A+B+C)}{3}$$

 $A = \text{perimeter of eye} = 2(L_e + W_e)$
 $B = \text{perimeter of nose} = 2(L_n + W_n)$
 $C = \text{perimeter of mouth} = 2(L_m + W_m)$

 L_{e} , L_{n} and L_{l} are the length of selected rectangular of eyes, nose and mouth.

$$Area = A_e = L_e \times W_e \tag{6}$$

B. Calculation of Sum of Square for Error

Table III shows the calculation of sum of square for error (SSE) for sample face of *IPRL-UIT-2015061-01* from IPRL Database.

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x	у	$\mathbf{x} - \mathbf{M}_{\mathbf{x}}$	$\mathbf{y} - \mathbf{M}_{\mathbf{y}}$	$(\mathbf{x} - \mathbf{M}_{\mathbf{x}})^2$	$(y-M_y)^2 \\$	$(\mathbf{x} - \mathbf{M}_{\mathbf{x}})(\mathbf{y} - \mathbf{M}_{\mathbf{y}})$
67	181	-106.41	-93.08	11323.0881	8663.8864	9904.6428
262	182	88.59	-92.08	7848.1881	8478.7264	-8157.3672
262	231	88.59	-43.08	7848.1881	1855.8864	-3816.4572
68	231	-105.41	-43.08	11111.2681	1855.8864	4541.0628
120	316	-53.41	41.92	2852.6281	1757.2864	-2238.9472
197	231	23.59	-43.08	556.4881	1855.8864	-1016.2572
197	292	23.59	17.92	556.4881	321.1264	422.7328
136	292	-37.41	17.92	1399.5081	321.1264	-670.3872
120	316	-53.41	41.92	2852.6281	1757.2864	-2238.9472
216	315	42.59	40.92	1813.9081	1674.4464	1742.7828
316	351	142.59	76.92	20331.9081	5916.6864	10968.0228
120	351	-53.41	76.92	2852.6281	5916.6864	-4108.2972
2081	3289	0.08	0.04	71346.9172	40374.9168	5332.5836

 TABLE III.
 CALCULATION OF SUM OF SQUARE FOR ERROR

Mean of $x = M_x = 173.41$

Mean of $y = M_v = 274.08$

Variance of x = var(x) = 5945.57

Variance of y = var(y) = 3364.57

Co - variance = cov(x, y) = 484.78

$$\frac{\operatorname{cov}(x,y)}{\operatorname{var}(x)} = 0.0815$$

SSE =
$$(n - 1)[var(y) - \frac{cov(x, y)}{var(x)}] = 370.0937$$

VI. RESULTS

A. Results of Dotted Raster-stereography and Feature-Based Technique

Table IV shows the results of dotted Raster-stereography and feature-based techniques.

B. Accuracy, Precision, Sensitivity and Specificity of Dotted Raster-stereography and Feature-Based Systems

This dotted raster-stereography technique is based on Mean and Gaussian curvatures. Both mean and Gaussian curvatures are based on two fundamental curvatures κ_1 and κ_2 , as shown in Table V.

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			Raster-stereography Technique			Feature-Based Technique	
S. No	Face ID	Sample Faces	Mean (M) cm ⁻¹	Gaussian (G) cm ⁻¹	Sample Faces	Edge Density (ED) cm ⁻¹	Sum of Square Error (SSE)
1	IPRL-UIT- 2015061-01		03.0500	06.0600	A	0.0355	370.0937

2	IPRL-UIT- 2015061-02		8.0250	20.1000	A	0.0427	869.156
3	IPRL-UIT- 2015061-03	000	13.0500	48.1100	A B C	0.0353	866.246
4	IPRL-UIT- 2015061-04		12.0000	33.7500		0.0364	1238.918
5	IPRL-UIT- 2015061-05	(Carlow)	15.6000	55.6700		0.0322	898.414

Mean= M= $(\kappa_1 + \kappa_2)/2$ Gaussian=G= $\kappa_1 \times \kappa_2$

In our test run, 100 faces have been tested in IPRL using dotted Raster-stereography and feature-based techniques. For dotted raster-stereography, 95 faces were correctly recognized. Using feature-based technique, 82 faces were correctly recognized. Table IV shows the facts recorded during test runs for dotted Raster-stereography and feature-based systems.

Table VI shows the results of recognition rate, training and testing time of both the techniques using IPRL database. Runtime of image normalization and alignment excludes the training and testing times.

Parameters	Dotted Raster- stereography	Feature- Based	Parameters	Dotted Raster- stereography (%)	Feature- Based (%)
Number of true positive (TP)	95	82	$Accuracy = \frac{TP + TN}{TP + FP + FN + TN}$	96.00	88.00
Number of true negative (TN)	01	6	$Precision = \frac{TP}{TP + FP}$	96.93	91.11
Number of false positive (FP)	03	8	$Sensitivity = \frac{TP}{TP + FN}$	98.95	95.34

Number of false negative (FN)	01	4	$Specificity = \frac{TN}{FP + TN}$	25.00	42.85
-	-	-	Positive predictive value = $\frac{TP}{TP + FP}$	96.93	91.11
-	-	-	Negative predictive value = $\frac{TN}{FN + TN}$	50.00	60.00

 TABLE VI.
 RECOGNITION RATE AND TRAINING & TESTING TIMES FOR BOTH TECHNIQUES

Technique	Recognition Rate	Training Time (second)	Testing Time (second)
Dotted Raster- stereography	96.00 %	260.5	2.1
Feature-Based	88.00 %	70	1.2

VII. CONCLUSIONS

Each of Dotted Raster-stereography and feature based techniques was tested for 100 faces in Image Processing Research Laboratory, using IPRL database. In case of dotted Raster-stereography technique, following values of performance measures were found: accuracy 96.00 %, precision 96.93%, sensitivity 98.95% and specificity 25.00%. For feature-based technique, the same measured values were: accuracy 88.00%, precision 91.11%, sensitivity 95.34% and specificity 42.85%. Consequently, Dotted Raster-stereography technique is a better approach for face recognition as far as these performance measures are concerned. Feature-based technique is faster in terms of the training and testing times required. Thus overall, such sensitive applications where high face recognition accuracy is required, dotted rasterstereography should be preferred. On the other hand, such applications where volume of face recognition work is large and high speed is required with some compromise in accuracy being acceptable, then feature-based technique may also be the technique of choice.

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