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A New Trend for Face Recognition Features

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***Abstract*— This paper introduces a new trend for face recognition features. It is based on dividing the face into four horizontal & five vertical regions [16]. Each region is divided into an optimum number of eight vertical and seven horizontal partitions. One approach using average per partition features and another using histogram per region features are considered. Algorithms to find the minimum of Euclidean distance (ED) between a test image and a matching DB registered image are discussed. Both algorithms achieved 100% recognition rate (RR) with ORL & Yale databases. A new definition for RR that is termed inclusive recognition rate (RR_i) is suggested. RR_i supports testing images belonging to DB subject's images or not.**

Keywords*— *Face features, Face partitions, Face recognition, Face regions, Image identification

I. Introduction

For two decades or more, the subject of face recognition (FR) has attracted the interests of many researchers [1-13]. This is due to the variety of applications used, such as identity authentication, access control and in security arrangements. The problem of automatic FR involves mainly three key steps, face detection, feature extraction and face identification. Usually face identification is performed by obtaining a best match between an unknown subject's image and a sequence of DB images captured normally by cameras.

FR approaches can be categorized as holistic, feature-based and hybrid ones [13]. Feature-based approaches depend on extracting local features of the face that are used as input data for structural classifiers. Pure geometry, dynamic link architecture and hidden Markov models [11] belong to this category. Pure geometry approaches use distances and angles between eye corners, mouth extremes, nostrils and chin top [9]. Correlation-based recognition uses normalized correlation between a normalized input and DB images [5]. Image histogram features were used for recognition based on minimum distance between a probe image and a gallery of DB images [4, 5]. However a multitude of different recognition approaches may be found in the literature [13]. More recently used approaches use Gabor wavelet [5, 6], for FR as in dynamic link architecture by Lades et al[14] and its extentions by Wiskott et al [15]. A Radon transform and a wavelet and Radon transform-based approaches were applied in [10].

In fact all pervious approaches show gradual enhancements in the recognition rate. The best claimed values were around 99% with a different image database (AR one) [1, 2]. This makes it necessary to propose new trends that may produce essential enhancements in the recognition rates with the ORL & Yale databases.

In view of the above, the paper is arranged as follows: In sec II the proposed new trend for FR features is introduced. Section III presents a technique for feature reduction. A proposed definition for an inclusive recognition rate RR_i is introduced in sec IV. This recognition rate supports images that belong to DB subject images as well as those not belonging. Sec V presents threshold values that separate between recognition and rejection of test images. Rejection and acceptance rules are suggested in sec VI.

II. The proposed new trend

Undoubtly human faces have different features related to their different face regions. For example, the region containing the eyes has features different from those regions containing the nose or mouth. Specifying features of the whole face fuses those of the different regions together and this may affect the process of face recognition.

Dividing the face into different regions or strips that incorporate one or more sensing organs may result in more accurately - defined face characteristics. Performing comparisons based on such division principle may lessen the effect of fusion when dealing with features of the whole face and may also enhance face recognition rates.

In a previous publication by the authors [16] the face was divided into four horizontal regions or strips containing the forehead, eyes, nose and mouth with chin. Also the face was divided into five vertical regions as shown in fig (1).

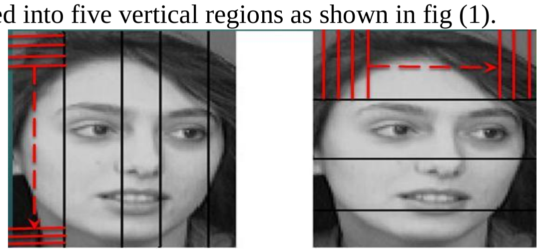

Figure 1. Proposed Face Regions.

Based on the just-mentioned division principle, the proposed new trend is introduced. Two simple recognition techniques using Average Per Region Columns (APRC) or rows(APRR) features and histogram Per Region (HPR) features are applied and tested with the ORL image database. The metric for recognition is the minimum ED between the test image and a DB image.

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A. *Algorithms for RR*

The ORL DB images are divided into two halves, one containing 100 registered images and the other containing 100 test images. Both halves belong to 20 registered subjects. Each image is normalized to 112*92 pixels. Each image is divided into 4-horizontal regions and 5 vertical ones.The average per horizontal region columns (APRC), or the average per vertical region rows (APRR) are the proposed features. An algorithm for histogram features per region (HPR), is also considered.

B. *Algorithm 1: (APRC)*

1. Set TR=0, FR=0.
2. For i=1 to 100 do
3. For r=1 to 100 do
4. For j=1 to 4 do
5. Estimate APCi & APCr
6. Form matrix

$$ED[j_x r] = \sqrt{\sum_{nc=1}^{92}\left(\frac{APC_i}{APFi} - \frac{APC_r}{APFr}\right)^2}$$

7. Next j
8. Next r
9. Compute the average of each column of ED.
10. If a true match occurs increment TR otherwise increment FR.
11. Next i.
12. Compute $RR = TR/(TR + FR)$.

N.B. nc = no. of columns for a horizontal region.
The APRR algorithm would be similar to the above one except nr= no. of rows for a vertical region, changes from 1 to112 and j changes from1 to 5.

C. *Algorithm 2: (HPR)*

HPR refers to histogram features per region.This algorithm will also be similar to the above one except ***ED[j$_x$r]*** would be 9x100 with its elements computed as follows

$$ED[j_x r] = \sqrt{\sum_{nf=1}^{29}(F_i - F_r)^2} \Big/ 256$$

Where j = index of regions i.e. changes from 1 to 9.
Fi = a histogram feature of an input image.
Fr = a histogram feature of a registered image.
nf = feature index.

The results in table 1 were obtained as compared with some recently-published approaches.

TABLE I. COMPARISON OF RR WITH SOME PREVIOUS RESULTS.

Authers	Used Approach	RR %
Proposed Method	APRC	100
Proposed Method	HPR	100
H. Gulati et al [3]	Hybrid Hist & Eigen value	96.75
S. Singh et al [4]	Hist	95

It should be noted that the no. of features involved in the computation of RR with the above methods would be as in Table II.

TABLE II,NO. OF FEATURES FOR THE PROPOSED TECHNIQUES.

Approach	No. of feature
APRC (column level)	4 x 92 = 368
APRR (row level)	5 x 112 = 560
HPR	9 x 29 = 261

N.B. A histogram has 29 features (MATLAB 2012).
The no. of features in table II is relatively high. The following section discusses feature reduction in APRC and APRR techniques.

III. APRC feature reduction

In order to improve recognition time the number features in APRC and APRR approaches ought to be reduced. This may be achieved by dividing each region into a number of partitions (segments) each incorporating a number of columns or rows. The no. of columns (or rows) per partition is varied from 2 up to 20 columns (or rows). For each no. tests are conducted and the RR computed and so on until a maximum no. of columns (or rows) are reached while maintaining the maximum value of RR i.e. 100%. Obviously, such maximum value of columns (or rows) corresponds to a minimum number of partitions. The average per partition was considered in the tests. The algorithm followed in the above tests is as follows.

A. *Algorithm 3:Average Per Region Partitions*

- Divide an input image into four equal horizontal regions *imgi.*
- Divide each registered image (DB image) as above *imgr.*
- *nc* = no. of columns per partition.

Perform the following steps

1. for nc =2 to 20 do
2. for an input imgi starting with i=1, do
3. Compute no. of partitions / region,
$np = 92/nc$ ***(for both input & registered images)***
4. Compute average per partition APPi for each region of imgi.
5. Compute average per partition APPr for each region of imgr (Registered image).
6. Compute ED between imgi & imgr

$$ED(imgi, imgr) = \sqrt{\sum_{j=1}^{4*np}\left(\frac{APPi}{APFi} - \frac{AP\,Pr}{APFr}\right)^2} \quad \textbf{(1),}$$

j= partition index. APF is the average per face.
7. Repeat steps 4, 5, 6 for the 100 registered images.
8. Select imgr having minimum ED$_{min}$ with imgi (best match).
9. Increment i & go to step 2 until i reaches 100 (test images).
10. Compute recognition rate RR where,

$$RR = TR/(TR + FR) \quad \textbf{(2)}$$

11. Repeat steps from 1 to 10 for next nc.

TR = no. of true recognitions.
FR = no. of false recognitions.

As before the ORL DB images are divided randomly into two halves, one includes 100 registered images and the other contains 100 test images. Both halves belong to 20 registered subjects. Each image is pixel normalized to 112x92.as before.

This algorithm was repeated for the vertical regions as well where nr = no. of rows per partition and $np = 112/nr$.

N.B. Values of APPi & APPr are normalized by dividing each by its corresponding full face average i.e. APFi & APFr. Implementing this algorithm on ORL database produced the results shown in table III, table IV, figure (2) and figure (3).

TABLE III AVERAGE OF nc COLUMNS AND RECOGNITION PERFORMANCE.

nc	1	2	3	10	13	14	15	16	19	20
RR%	100	100	100	100	100	99	99	99	98	97
Ftre..Red. %	100	50	33.93	10.71	8.03	7.14	7.14	6.25	5.4	5.4

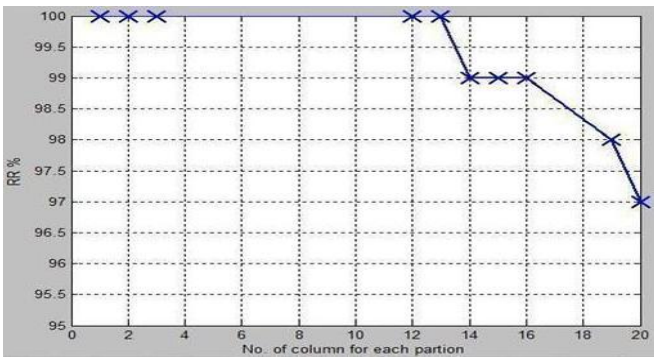

Figure 2. Recognition rate (RR) with nc per horizontal region.

TABLE IV average of nr rows and recognition performance.

nr	1	2	3	10	13	14	15	16	19	20
RR%	100	100	100	100	100	100	99	99	98	97
Ftre. Red.%	100	50	33.93	8.93	8.03	7.14	7.14	6.25	5.4	5.4

Where Ftre. Red. is Feature Reduction.

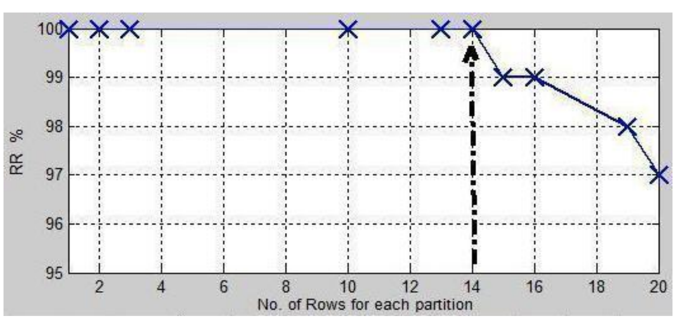

Figure 3. Recognition rate (RR) with nr per vertical region..

Where the optimum number of columns in horizontal partitions is 13 meaning that the minimum (optimum) number of horizontal partitions is seven per region. But the optimum number of vertical partitions is eight as the optimum number of rows is fourteen. The number of features is reduced to only 8% for horizontal regions and to only about 7% for vertical regions. This means that the no.of horizontal region features reduces to only 28 and that for vertical regions features to only 40 .

IV. A proposed definition for RR

As is well-known the recognition rate as estimated in the literature is based on the fact that all test images belong to subjects of a DB and RR is as expressed in eq (2). The RR is estimated from the no. of images that are correctly(Truly) recognized divided by the no. of test images. The just introduced definition of RR does not take into account the case of test images that do not belong to DB subjects. Such images should be rejected by the recognition scheme. Therefore two new concepts may be introduced.

TJ, (True Rejection) means the no. of images that are truly rejected.

FA, (Falsely Accepted) means not rejected i.e. no of images that are falsely not rejected which means that they are falsely recognized or accepted.

In view of this a new concept contributing to the definition of RR can be introduced as follows:

$$JR = TJ/(TJ + FA) \qquad (3)$$

Where:

JR is the rejection rate i.e. the number of images that are truly rejected to the total no. of test images from outside the DB.

Also the RR as defined in (2) should be modified to include no. of images belonging to DB subjects that may be falsely rejected FJ. Accordingly RR of eqn.(2) would be as follows:

$$RR = TR/(TR + FR + FJ) \qquad (4)$$

Combining definitions in eqs. (3) & (4) a new definition of RR that may be termed inclusive RR or RR_i may then be introduced as follows.

$$RR_i = (TR + TJ)/(TR + FR + TJ + FA + FJ) \qquad (5)$$

A nearly similar concept for rejection and acceptance was introduced in two recently published papers [2, 3]. They define a false acceptance rate (FAR) and a false rejection rate (FRR).

V. Threshold Values

To test the ability of a proposed algorithm to indicate whether the test image belongs to subjects of a DB or not, a threshold level (value),is chosen. If the distance between the test image and one or more DB images falls within that level, the image is declared accepted i.e. belongs to a DB subject. As before extensive tests were performed on 100 faces (images) of 20 subjects of ORL database and 48 for another 20 subjects of Yale DB.

Needless to say that if the test image distance to all DB images is not within the threshold, the image is declared rejected i.e. not belonging to the DB subjects..

It is clear that the value of threshold affects the number of accepted images as well as the no of rejected ones. The higher the threshold value, the higher the number of accepted images. This in turn means increase of false acceptance rate (FAR). On the contrary, the lower the value of the threshold, the higher the number of images rejected i.e. higher false rejection rate (FJR). This principle applies to techniques that use ED as a metric for matching. Tests were conducted on images from DB's, ORL & Yale where each of FAR and FJR are estimated for different values of threshold. This was carried out for both APP technique & HPR one. Results are plotted in figures (4) & (5). The optimum values of thresholds are 0.22 for APP algorithm and 0.31 for HPR algorithm.

A selection of a value for the threshold based on the next minimum value of ED was first adopted. But it was agreed to use the idea of optimum threshold proposed in [1] as presented above.

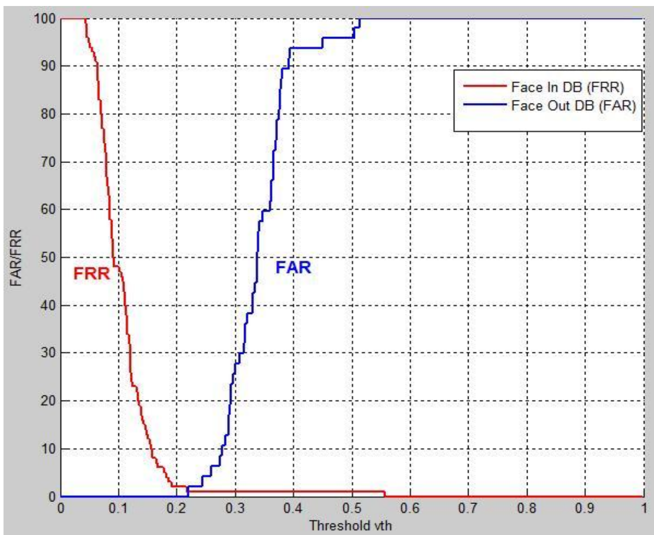

Figure 4 Optimum value of threshold in APP Algorithm.

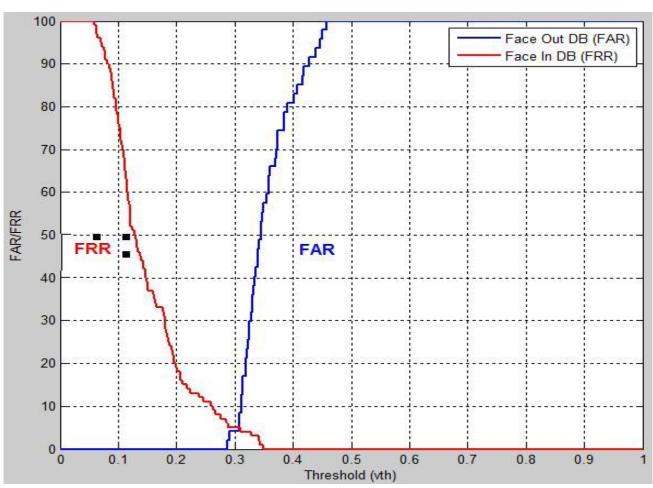

Figure 5 Optimum value of threshold in HPR Algorithm.

With these values of threshold, extensive tests were conducted on 100 images of 20 subjects of ORL DB and 48 images for another 20 subjects of Yale DB as before. This was carried out for the two techniques APP (average per partition) and HPR (histogram per region). RR_i for the two techniques were 98.64% and 95.92% respectively.

However sample results for the two recognition schemes were tested with five input images, three belonging to the ORL DB subjects and two from outside the database subject images. Results are shown fig (6) for APP and fig (7) for HPR. It is shown that the 3 images belonging to ORL DB are truly recognized but the other two outside ones are truly rejected.

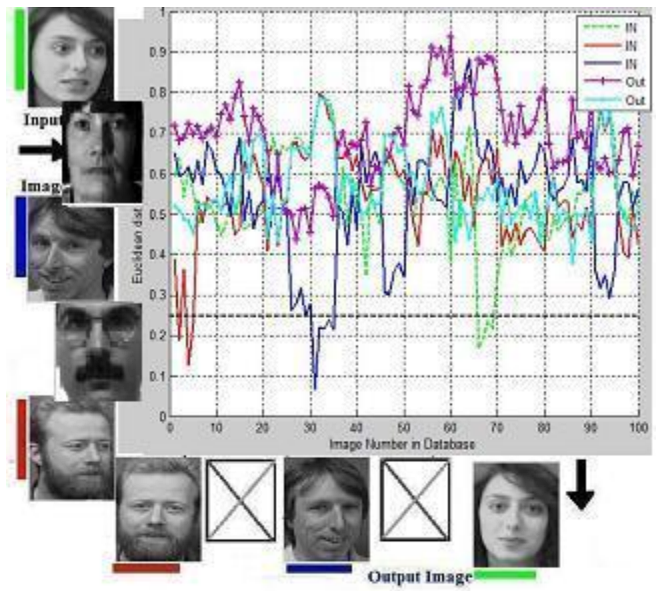

Figure 4. Results of a sample test of five faces (three from the DB and two from outside DB) in APPAlgorithm.

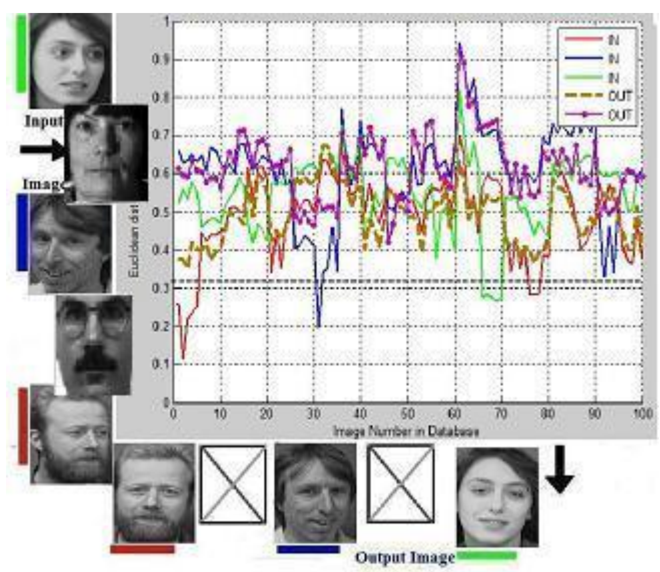

Figure 5. Results of a sample test of five faces (three from the DB and two from outside DB) in HPR Algorithm.

VI. Acceptance and Rejection Rules

It was observed that the techniques using the minimum distance ED_{min} as a metric for matching between images have such distance out stepping the threshold value of each. It was also observed that at least two of the other four registered subject's images outstep the threshold as well. This may imply that to have correct (true) recognition, a test image must match more than one of the subject's DB images and not only one. The same principle can be applied to false acceptance (for images from outside the DB) only one (false) matching is not sufficient to justify its acceptance. Therefore to have true or correct acceptance one may suggest that a test image should have matching values with at least half of a subject's registered images based on a threshold value. However a general rule may be drawn from this principle as follows.

Acceptance (Recognition) Rule: "A test image may be credited as accepted (or recognized) only if it matches at least half of subject's DB registered images."

Similarly a rejection rule can be drawn (regarding outside test images) as follows.

Rejection Rule: "A test image may be credited as rejected if and only if half of the subjects available test images are rejected by the system."

If only one test image is available, as may happen in practical applications, rejection or acceptance may be credited if the test image was also rejected or accepted by another recognition technique.

It was observed in all the tests conducted with APP & HPR that false recognition, false acceptance or false rejection each was based on only one match or mismatch with one registered image only. Therefore according to the rules of acceptance and rejection introduced above, such acceptance or rejection cannot be credited as they did not satisfy the half number suggested i.e. they may be ignored.

In view of this for the APP & HPR techniques FA, FJ and FR may be ignored and RR_i for each technique would be 100% instead of the values considered in sec.V above.

VII. Conclusion

A new trend for face recognition features has been introduced and discussed in this paper. The trend is based on dividing each face region into a number of partitions that has been shown to be optimum of seven horizontal or eight vertical per region. Extracting features from such partitions produced 100% RR's for either APP or HPR recognition techniques. An inclusive recognition rate RR_i, optimum values of thresholds, acceptance and rejection rules have also been introduced and discussed.

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