Rationale of Class and Feature size on Face Recognition

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ABSTRACT

Multidimensional problems associated with face recognition needs to be analyzed in debris form. In this paper, an efficient algorithm is proposed using Basic Local Phase Quantization (BLPQ), Scaled Gray Level Co-occurrence Matrix (SGLCM) and Singular Value Decomposition (SVD) with two mask processing techniques. Preprocessing crops faces from input images using a face detection method. One hundred features each of BLPQ histogram; SGLCM and SVD are fused to obtain final significant features. Euclidean Distance (ED) measure is used for computing the results. Performance of the proposed algorithm on CMU-PIE face dataset outperforms for different cases considered.

Keywords

Euclidean distance; Face detection; Local phase quantization; Singular value decomposition.

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1. INTRODUCTION

It is highly complicated to consider a real-time situation of recognizing faces. It is better to address specific issue in detail for controlled environments. Expression of human beings is one such issue discussed repeatedly, even with other dominating factors such as illumination and pose variation. Expression conveys information with textures, which is non-trivial for monitoring patients [1]. Decision making of faces or non faces is a critical role to identify a person in any application. Features classification is achieved using different regression techniques [2] and texture [3] of images supports to classify in various applications such as scene understanding and material classification. The similarity or correlation [4] between test and training images is considered to decide matching success. On the other hand, dissimilarity emphasizes the discriminating power of different forms of images. It is still challenging to recognize with the minimum number of training samples used is one [5], since the available data is less.

The class wise recognition of faces focus narrowly based on topic of interest. The contents of images are split into different category of classes and named through labels for each group. The primary goal of proposing a new method is to analyze face recognition performance based on classes and feature sizes of images.

2. LITERATURE SURVEY

Hiranmoy Roy and Debotosh Bhattacharjee, [6] developed Local Gravity Face (LGF) for heterogeneous and illumination-invariant face recognition. LGF uses angle information and it is the direction of the gravitational force from center pixel towards neighborhood pixels. Analysis shows the illumination-invariant feature by considering only the reflectance part of the neighboring pixels and preserves edge information. Recognition rates on the CMU-PIE and Extended Yale B database are better in the presence of complicated variations in illumination and noise**.** Sivaramprasad Mudunuri and Soma Biswas, [7] proposed an automatic approach for face recognition using low resolution images acquired in uncontrolled environment. The distance between low and high resolution training images is transformed using multidimensional scaling through a common transformation matrix. Similarity of two images is obtained using stereo matching cost from a few reference images. Results are better on multi-PIE dataset, surveillance cameras face database, multiple biometric grand challenge database and choke point database.

Mohamed Dahmane, and Langis Gagnon, [8] addressed the face recognition problem with low-resolution images under blur and varying light. Face is represented using local textures with Fourier transform phase. An effective and discriminative feature set is generated by contextual phase with code filtering responses. Experimental results on CMU-PIE, CAS-PEAL-R1, and extended YALE-B databases are better over local binary pattern, histogram of oriented gradients and local phase quantization.

3. PROPOSED WORK

The details of the proposed BLPQ, SGLCM and SVD based Face Recognition (BSS FR) model shown in Figure 1 is discussed in this section.

3.1 Gallery used

CMU PIE database or gallery [9] consists of 68 persons; with each person has variation in pose, illumination and expressions. The facial images of each person are captured with 52 expression variations, 312 illumination changes, 72 images with lights variation and 180 images with talking. Totally there are 616 images per person for 68 persons; there are 41,888 images in complete database. All images are in JPEG format with 640 * 486 sizes. The bits depth of each pixel is 24 and arranged with 72 dots per inch.

3.2 Preprocessing

Preprocessing uses individual components such as green and blue binary components, which are merged. Based on the grouping of pixels with higher intensities; the coordinates near to boundary are noted. Eight pixel adjacency is used to group the different connected pixels. Finally the facial part of original image is cropped.

Homomorphic filtering [10] is applied on preprocessed images to compress different range of gray-levels and for enhancing the contrast. The approach decomposes each image into illumination and reflectance component. The processing is carried out in frequency domain using logarithm and Fourier transform. Finally, the output image is retrieved using inverse operations. It helps in sharpening and also smoothens the variations in light of an image. It is an optional step and the performance is observed for both with and without homomorphic filtering.

3.3 Feature Extraction

The different methods used for dimension reduction to yield unique features are discussed in this section.

3.3.1 Basic Local Phase Quantization (BLPQ)

Discrete Fourier Transform (DFT) is applied on smaller portion of images to name it as local. The phase of DFT is quantized for each pixel location and arranged in histogram form. LPQ [11] is insensitive to blur in an image for classifying textures. The local phase information is extracted using Short Term Fourier Transform (STFT) computed over a rectangular neighborhood at each pixel position using equation (1) for input f(x). The phase information of each STFT output is encoded to binary values and finally all values are concatenated to yield histogram of BLPQ. One hundred significant BLPQ histogram features are considered in further step.

$$\mathrm{F(u,x)} = \sum_{\mathrm{y \in N_x}} \mathrm{f(x-y)}.\, \mathrm{e}^{-\mathrm{j2\pi yu}^{T}} \qquad (1)$$

where, *u* is frequency variable, *y* belongs to neighborhood mask (Nx) of specified size at each pixel *x*.

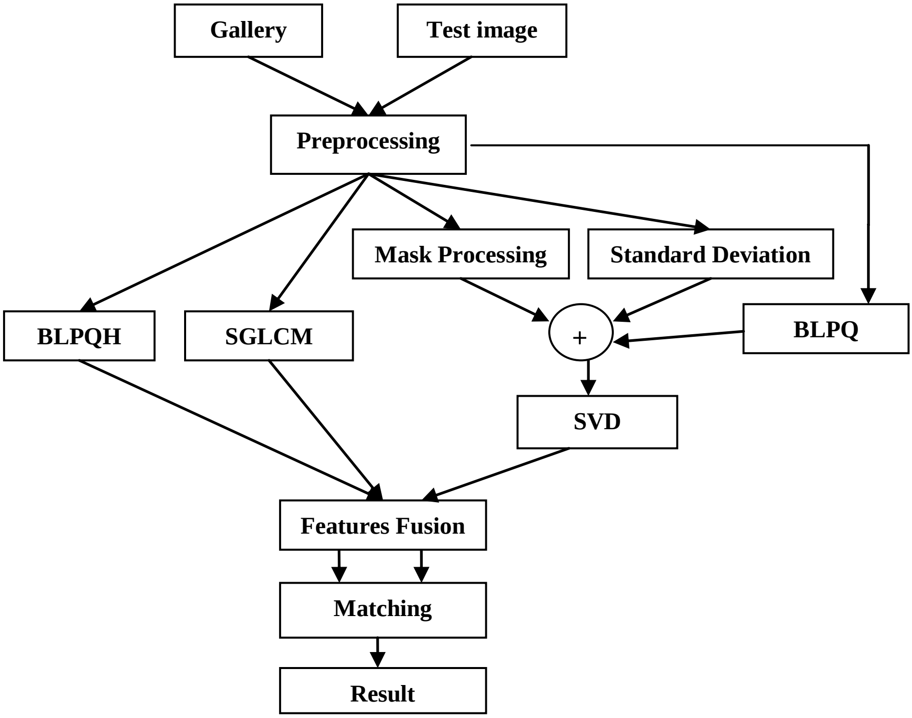

Figure 1. Block diagram of the Proposed BSS FR model.

3.3.2 Scaled Gray Level Co-occurrence Matrix (SGLCM)

SGLCM [12], [13] is computed for each preprocessed image. It is obtained by accumulating the number of times each pair or combination of pixels present in the image. As the gray levels vary with minimum to maximum value of class support and the pixels ranging from 100 to 200 are scaled to 9, 10 and 11 gray levels to produce a square matrix of corresponding gray level. Any combination of pixels in four different directions 0^0, 45^0, 90^0, and 135^0 from reference pixel is computed and vice versa. For each direction one co-occurrence matrix is produced and then all the four matrices are added. One hundred spatially dependent dominant coefficients from final matrix are derived.

3.3.3 Others

The mask processing is performed on each 3*3 overlapping block of preprocessed image. Each pixel in the output image contains the difference between maximum and minimum intensity values within each 3*3 mask. Similarly standard deviation of entire image is computed for each 3*3 segment of image. Another one hundred features are extracted by applying Singular Value Decomposition (SVD) [14] on added matrices of mask processing, standard deviation and BLPQ image. These features in turn added with BLPQ histogram, SGLCM features to get final one hundred features per image and fed as one input to next step. Similar operations are performed on test or query image to get another set of one hundred features per image which are used as another input to next step.

3.4 Matching

Fused final features of database and query images are compared to obtain to complete recognition process. The Euclidean Distance (ED) measure is computed and the image with minimum value is decided as recognized. Non matched count of persons with in database is used to compute False Rejection Rate (FRR) and the percentage accepted count of out of database persons is the False Acceptance Rate (FAR).

4 . ALGORITHM

The proposed system identifies human faces using proposed BLPQ, SGLCM and SVD based Face Recognition (BSS FR) model. It is depicted in Table 1 with the two objectives.

(i) To improve Recognition Rate (RR).
(ii) False Acceptance Rate (FAR) and False Rejection Rate (FRR) are to be reduced.

5 . RESULT ANALYSIS

The available CMU-PIE database is modified by selecting 5 images for each of expression, lights and talking cases with an additional image for testing purpose. Totally, 1088 images database of 68 persons with 16 images per person is used to test the proposed algorithm. The MATLAB Version 7.12.0.635 (R2011a) is used to develop the method. The results obtained are in Table 2 without homomorphic filtering. The performance of proposed algorithm is better for expression class compared to talking and lights class.

The maximum % RR of 95.23 is obtained for expression case, as compared to talking and lights class it is 80.95 for each of them. With the quest of improving the % RR by reducing error rates, the homomorphic filtering is used on preprocessed images by retaining rest of the algorithm as it is i.e. except homomorphic filtering everything is same. It is observed that no change in the maximum % RR, but it is able to achieve better FAR e.g. at 0.5 threshold the values of FAR are 100 and 65.38 respectively for without and with homomorphic filtering. It is encouraging, further by using homomorphic filtering the number of final fused features are varied. Performance is tested for the number of features varied is 81, 100, and 121 as in Table 3. It is observed that between 81 and 100 features case, the maximum %RR is 90.47 and 95.23 respectively. The maximum %RR has no variation among 100 and 121 features case, but once again the value of FAR has some improvements for most of values of threshold in 121 features case as compared with 100 features case. Finally Table 4 compares the maximum value of % RR with other methods [15], [16], and [17]. It is clear that the proposed algorithm is better with the parameter considered.

The reasons for results improvement are; (i) the BLPQ yield features which are insensitive to blur and useful in classification and also improves the contrast of an image, (ii) the SGLCM features are robust and yield discriminating features (iii) Fusion of all features makes them still unique in representing original images.

Table 1. Algorithm of the Proposed BSS FR Model

Input: Database and probe images of face
Output: Recognition / Rejection of a person.

1. Preprocessing uses components of input image to detect and elicit facial fart with or without homomorphic filtering
2. All preprocessed images are converted to gray scale and resized to 100*100 uniformly.
3. One hundred each of BLPQ histogram and gray level co-occurance features are derived and added.
4. Mask processing and standard deviation is applied on preprocessed image and linearly averaged with BLPQ image.
5. SVD is applied on the output of step 4 to get 100 singular values & fused with 100 features of step 3 to obtain final features.
6. Euclidean Distance between database and test image feature vectors is computed.
7. Matching is decided for an image with minimum distance.

Table 2. Performance of Different Classes on CMU-PIE database without Homomorhic filtering

Threshold	Expression			Lights			Talking		
	% FRR	% FAR	% RR	% FRR	% FAR	% RR	% FRR	% FAR	% RR
0.0	100	0	0	100	0	0	100	0	0
0.1	0	38.46	95.23	0	61.53	80.95	0	30.76	80.95
0.2	0	57.69	95.23	0	88.46	80.95	0	38.46	80.95
0.3	0	76.92	95.23	0	96.15	80.95	0	42.3	80.95
0.4	0	92.3	95.23	0	100	80.95	0	65.38	80.95
0.5	0	100	95.23	0	100	80.95	0	84.61	80.95
0.6	0	100	95.23	0	100	80.95	0	92.3	80.95
0.7	0	100	95.23	0	100	80.95	0	100	80.95
0.8	0	100	95.23	0	100	80.95	0	100	80.95
0.9	0	100	95.23	0	100	80.95	0	100	80.95
1.0	0	100	95.23	0	100	80.95	0	100	80.95

Table 3. Results of Different Feature sizes on CMU-PIE database with Homomorhic filtering

Threshold	81 features			100 features			121 features		
	% FRR	% FAR	% RR	% FRR	% FAR	% RR	% FRR	% FAR	% RR
0.0	100	0	0	100	0	0	100	0	0
0.1	11.9	0	88.09	11.9	0	88.09	11.9	0	88.09
0.2	9.52	0	90.47	11.9	0	88.09	11.9	0	88.09
0.3	0	19.23	90.47	0	11.53	95.23	0	3.84	95.23
0.4	0	38.46	90.47	0	46.15	95.23	0	19.23	95.23
0.5	0	57.69	90.47	0	65.38	95.23	0	50	95.23

Table 4. Maximum % RR Comparison on CMU-PIE database

Method	Maximum % RR
N-2DPCA+LDA- 12 images per subject [15]	94.63
WSRC - 5 images per subject [16]	94.86
LVP - 6 images per subject [17]	95
Proposed BSS FR model - 5 images per subject	95.23

6. CONCLUSION

Unlimited number of issues exists in the arena of proposing a robust face recognition system. The techniques such as BLPQ, SGLCM and SVD are used in the proposed system. A cognitive face detection method is used in preprocessing. Mask processing and standard deviation on preprocessed image is derived and amalgamated with BLPQ image. The singular values of SVD on amalgam image of three components are used to fuse in next step. One hundred final features are obtained by fusing one hundred features each of BLPQ histogram; SGLCM and Singular values. The results are computed using ED measure. Performance of the proposed algorithm on CMU-PIE face dataset is superior compared to other methods for different cases considered. In future, the algorithm is tested by creating our own database and applying runtime input.

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