An Exploration of V-HOG on W-Quartette Space for Multi Face Recognition Issues

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Abstract Illumination, Pose, and Expression variations are the major factors that put down the performance of face recognition system. This paper presents a dewy-eyed withal efficient hypothetical description for complex face recognition based on combination of w-Quartette Colorspace with Variant Hoglets (v-HOG) in sequel of our earlier work of fSVD [1]. Firstly, face image is mapped onto w-Quartette Colorspace to effectively interpret information existing in the image. Further variant Hoglet is employed to extract substantive features exhibiting linear properties to map line singularities and at the same time to derive tender features of face contortions. To foster the extracted features, the features are projected to a lower dimensional space for efficient face recognition. Five distinct distance measures are adopted as classifier to obtain appreciable recognition rate.

Keywords fSVD · w-Quartette Colorspace · v-HOG · r-HOG · Similarity measures

1 Introduction

Faces are complex ophthalmic inputs which cannot be depicted by elementary shapes and patterns. Face Recognition is a domain wherein dynamic research and assorted methods have been purported to execute this chore. Image gradients with schur decomposition are invariant to changes in illumination and pose variations [2]. Face images can be represented in terms of Eigen faces [3], which facilitates gradual changes in face and also simple to compute. A better and unquestionable 2DPCA algorithm proposed in [4], used statistical intercellular data using basic image intercellular data. In [5], volume measure was used as classifier with 2DPCA, which

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outperformed classical distance measure classifiers. For effectual face representation [6], (2D) 2PCA was coined which works on row and column directions of face images with much diluted coefficients for face representation. Multiple Kernel Local Fisher Discriminant analysis (MKLFDA) was proposed [7] to delineate the nonlinearity of face images. Independent component neighborhood preserving analysis [8] (IC-NPA) was proposed to retain the inviolable incisive potential of LDA and at the same time upholding the intrinsic geometry of the within-class information of face images. As stated earlier, combining the features always aids in improved efficiency, in [9] Eigen and Fisher face are combined using wavelet fusion, and 2FNN (Two-Feature Neural Network) is used for classification to improve the recognition rate. To surmount the problem of small sample size, an unsupervised nonlinear Spectral Feature Analysis (SFA) [10] was minted, which extracts discriminative features out of a small sample-sized face image. In [11], the author proposed a method for the recognition of facial expressions in face images using landmark points in linear subspace domain.

Nonlinear kernel sparse representations [12] aids in robustness of face recognition against illumination and occlusion by developing pixel-level and region-level kernels hiring local features. Immix of DWT, DFT, and DCT, expeditiously educe pose, translation, and illumination invariant features [13]. Decimated redundant DWT was proposed in [14] to cauterize the effect of translation of face image. Gabor jets [15] feature extractor improves accuracy rate and also reduces the computational time with the facilitation of Borda count classifier. Gray scale Arranging Pairs (GAP) [16] delineates the holistic data in the whole face image and demonstrates mellowed raciness against illumination changes. Combination of two effectual local descriptors Gabor wavelet and enhanced local binary pattern with generalized neural network [17] is insensitive to small changes in input data and is robust-to-slight variation of imaging conditions and pose variations. A more versatile improved Quaternion LPP [18] was purported to exlploit the color information in face images.

2 Proposed Methodology

In this section, we key out the proposed face image depiction and classification technique. We take into account the primal issues of face recognition and reduce the effect of these in improving the accuracy of recognition. Firstly, face image is mapped onto w-Quartette Colorspace to effectively interpret information existing in the image. Further variant Hoglet extracts discriminative features exhibiting linear properties to map line singularities and at the same time to derive tender features of face contortions. To foster the extracted features, the features are projected to a lower dimensional space for efficient face recognition. Finally, for classification, five different similarity measures are used to obtain an average correctness rate.

2.1 W-Quartette Colorspace

Different Color models possess different discriminative index. Compared to greyscale images, a color image embeds in it much more utile information for improving face recognition performance [19]. Making use of these properties, we derive an image from the original image by mapping it on Quartette Colorspace. The color face image F(x, y, z) of size (p × q × 3) is mapped as given below,

$$F_{ci}(x, y, z) = \{F(x, y, z) \rightarrow \{a * Lab, b * LUV, c * YCgCr, d * YUV\}\} \tag{1}$$

where i = 1, 2, 3, 4 and a, b, c, d are weights for colorspace

The weights for the Quartette Colorspace are set based on the behavior of the Colorspace with fSVD.

$$I_{fi}(x, y, z) = \frac{(F_{ci}(x, y, z) + \xi_1 * D_i(x, y, z))}{(1 + (\xi_1, \xi_2, \xi_3, \xi_4))} \tag{2}$$

$$\text{where } D_i(x, y, z) = U * \Sigma^{\gamma_i} * V^T$$

$$[U, \Sigma, V] = SingularValuedecomp(Inorm(x, y))$$

$$\xi_1 = 0.07, \xi_2 = 0.05, \xi_3 = 0.05, \xi_4 = 0.5, \gamma_1 = 0.695, \gamma_{2,3,4} = 0.895$$

2.2 Variant Hoglets

HOG features were first introduced by Navneed Dalal and Bill Triggs [20]. The essence of the histogram of oriented gradient descriptor or signifier is that local

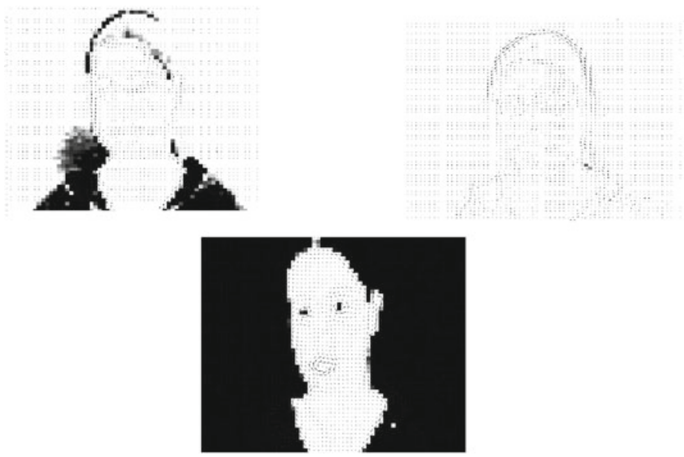

Fig. 1 v-HOG image in LAB space

object appearance and shape within an image can be described by the distribution of local intensity gradients or adjoin directions. The effectuation of these signifiers can be achieved by dividing the image into small colligated regions called cells, and for each cell amassing a histogram of gradient directions or adjoin orientations for the pixels within the cell. The combination of these histograms then represents the signifiers. The HOG signifiers has few crucial advantages like invariance to geometric and photometric transformation, which are helpful in face recognition applications. Gradient orientation preserves the important structure of the image and is much useful in face recognition [21]. To improve the face recognition accuracy, in our work we propose variant Hoglets by adopting HOG with various gradient filters which is adopted based on the colorspace. In an attempt to imbibe the behavior of wavelets with HOGs under different colorspace, we have incubated daubechies as filter kernels

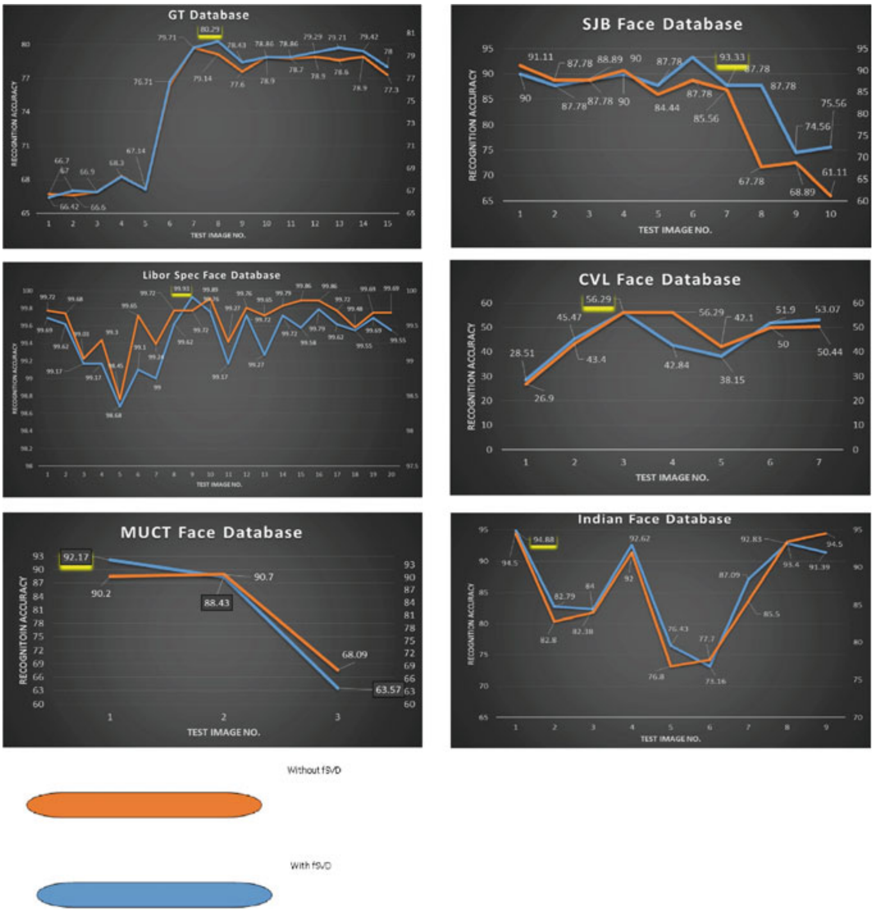

Fig. 2 Recognition accuracies for six databases

for HOG which are defined below.

$$\text{dbn} = \text{Coeff1}, \text{Coeff2}, \ldots, \text{Coeffn},$$

where n = 7 and 9, are used in combination with YCgCr and LAB colorspace.

Furthermore, the below filter kernels are also adopted with LUV and YUV colorspace, respectively.

$$[-1, 0, 1]\,\mathit{and}\,[-1, 0, 1]^T, [0.707, 0, -0.707]\,\mathit{and}\,[0.707, 0, -0.707]^T$$

Below is an example of v-HOGs under different planes of LAB colorspace:

The features obtained from the above proposed method is further compressed by projecting them on to the lower dimensional subspace and classified using an aggregate of five different distance measures (Figs. 1 and 2).

3 Result

This section acquaints the results primly on six different widely used databases. We embark into the recognition system by mapping face image onto w-Quartette Colorspace, which prepares the image for recognition in the best possible way. fSVD is then applied to normalize the mapped image. Further to extract the shape descriptors, v-HOG is applied to the derived face image and is projected onto the reduced dimensionality eigen subspace. We have used five different distance measures to formalize the inquiry face image.

To appraise our proposed technique, we have incorporated six different database viz., Georgia Tech, Dr. Libor Spacek Faces94, CVL, MUCT, Indian face and SJB face database. GTech consists of 50 persons × 15 images/person. This database shows frontal face with variations in expressions, lighting conditions, cluttered background, and scale. Libor consists of 152 × 20 images with tilt of head and considerable expression changes. CVL consists of 114 × 7 with pose and expression variations. MUCT consists of 3755 out of which we have used 199 × 12 images, and it has diversity of lighting, age, and ethnicity. Indian face database has 671 images out of which we have used 61 × 7 images, and it has considerable variations in pose and expression. SJB face database is our own face database which consists of 10 persons × 10 images/person. This also has substantial variations in expression, pose, and illumination.

To assess our algorithm, single image from every class is used for training and rest of the images are entailed for testing purpose. We performed experiments with different γ and ξ in both training and test phase. Finally, the value is set to $\xi_1 = 0.07, \xi_2 = 0.05, \xi_3 = 0.05, \xi_4 = 0.5, \gamma_1 = 0.695, \gamma_{2,3,4} = 0.895$, to achieve appreciable results.

3.1 Experiment-I—Effect of fSVD on the Extracted Features

In this experiment, we have found the correlation coefficients for features of images with and without fSVD. For experimentation purpose, only two database have been considered.

Below table suggests that the correlation coefficient is high for features extracted using fSVD than without fSVD. It also says that fSVD has better ability to discriminate within and between class features (Tables 1 and 2).

3.2 Experiment-II—Comparision of v-HOG and rHOG

In this experiment, we have compared the invidious ability of within and between class images by regular HOG (rHOG) and variant HOG (v-HOG). In this experiment, fSVD is retained in both the cases. The results suggests that v-HOG has better correlative feature extraction capacity than rHOG. v-HOG decorrelated the between-class images and at the same time upholds the correlative coefficient of within-class images.

Table 1 Average correlation coefficient

Database	With fSVD		Without fSVD	
	Within	Between	Within	Between
CVL	0.9719	0.9426	0.9616	0.9485
GT	0.9584	0.9213	0.9490	0.9229

Table 2 Comparison of v-HOG and rHOG

Database	rHOG		v-HOG	
	Within	Between	Within	Between
GT	0.9477	0.9374	0.9584	0.9213
SJB	0.9867	0.9228	0.9973	0.8702
Dr Libor	0.9965	0.9607	0.9977	0.9274
CVL	0.9697	0.9593	0.9719	0.9462
Muct	0.9898	0.9509	0.9856	0.9378
Indian	0.9837	0.9729	0.9911	0.8962

3.3 Experiment-III—Effect of v-HOG on Recognition Accuracy with and Without fSVD

In this section of experiments, we have found the recognition accuracy for with and without fSVD for all six face databases. In every database, only one image is trained per person and rest of the images are used as query images. The result suggests that the proposed method has the ability to correctly recognize the face image. The result also evoke that the proposed method has the ability to subdue the effect of single sample per person (SSPP), Illumination, expression, and pose in face recognition to a larger extent. Below figures shows the recognition accuracies of six different databases with fSVD and without fSVD.

4 Conclusion

This paper has developed an efficient algorithm for complex face recognition based on combination of w-Quartette Colorspace with Variant Hoglets (v-HOG) in coaction fSVD. w-Quartette Colorspace has the ability to effectively interpret information existing in the image. Further to it variant Hoglet extracts substantive features exhibiting linear properties to map line singularities and at the same time to derive tender features of face contortions. The simulation experiments suggest that the proposed technique yields overwhelming results under single sample per person, variation in pose, illumination, and expression.

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