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A ROBUST FACE RECOGNITION APPROACH THROUGH DIFFERENT LOCAL FEATURES

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ABSTRACT

In this paper, we proposed method is a robust face recognition approach through different local features has been implemented. We used YALE face database in this paper. First the images are partitioned into different sub bands using discrete wavelet transform. Kernel methods are widely used for to extract the features from the different sub bands for non linear methods. sub band methods are used for extract the local features from the all sub bands. Then the all local features are formed as global features to improve the recognition efficiency. As compared to linear methods most of the researchers use non linear methods for real time applications. In this paper we proposed face recognition approach through different local features gives better results as compared to existing techniques

Keywords: *K-mean algorithm, K-medoids algorithm and classifier.*

I. INTRODUCTION

With the recent endeavor of computer vision researchers, lots of features have been designed to characterize various aspects of an object. Taking advantage of multiple features can provide more information for face recognition (FR), and the advantages of jointly analyzing multiple features are demonstrated in the literature [1–4]. Although it is widely believed that recognition performance can benefit from multiple features, in front of the developed multi-feature approaches, it remains an exploratory task to design a more effective and more efficient method to exploit multiple features. In recent years, several FR methods [5–7] have been developed based on the dictionary learning (DL) framework, and achieved very promising results. These DL-based FR methods are mainly developed in the following two tracks [8]:

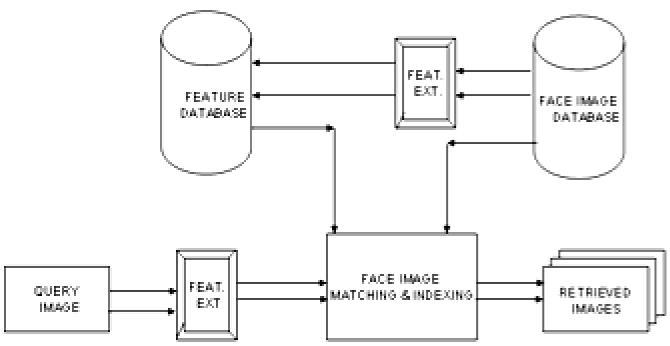
1. Directly making the dictionary discriminative, such as learning a class-specified sub-dictionary for each class;
2. Making the sparse coefficients discriminative to propagate the discrimination power to the dictionary.

Even though DL-based recognition methods achieve very promising and even state-of-the-art performances, they only work on a single feature type, e.g. the original grayscale facial image or facial outline image, rather than multiple informative features. In other words, they cannot exploit multiple features of one face image and their possible semantic relationships to enhance FR performance. Aware of the limitations of these DL-based methods that they cannot deal with multiple features, researchers have proposed several methods to tackle this problem [9–11]. Yuan and Yan propose a multi-task joint sparse representation based classification method (MTJSRC), which treats the recognition with multiple features as a multi-task problem, locality preserving projection (LPP) [16,17], local linear embedding (LLE) [18], and other manifold learning methods [19,20]. Most traditional subspaces election methods assume that the data obeys the Gaussian distribution, which satisfies the case that the data just suffers from the change of one factor. While the tensor subspace analysis considers the facial image as a linear combination of multiple factors, such as identity, expressions, poses illumination conditions, and provides ways of analyzing their influences [21–24]. Compared to these methods mentioned above, non negative matrix factorization (NMF) projects the facial image into the subspaces with non-negativity constraints [25–27]. The performance of the holistic matching methods obviously degrades with variations in expressions, poses, illumination conditions, partial occlusions, etc. Increasing attention recently has been put into the local matching methods.

Extraction and representation of contours in images are vital for many image processing applications. A contour is an ordered set of points with edges connecting them into a piecewise defined curve. Representation of the extracted contour in a simple form is extremely useful in solving various problems such as character recognition, shape matching and retrieval, and medical image analysis. Both extraction and representation problems are chal- lenging due to noise, artifacts, and occlusion. In this study, we are interested in extracting the contour in an image and representing it with a small number of points by down-sampling the points found on the contour. Many application domains, such as object detection [1,2] and shape matching [3], require the use of contour information. Can and Duygulu [4] used polygonal approximation techniques for line-based representation of word images. Arandjelovic and Sezgin [5] proposed a method to do recognition of human-drawn sketches using temporal and image based features. Similarly a method for contour- based shape matching between hand-drawn engineering shapes was presented by Hou and Ramani [6]. Boundary-based representation was used for object detection in many studies [1,2] including human body modeling [7]. Compact point representations are important for these applications, since processing and analysis algorithms depend on point or feature correspondences [8–10]. A widely used method to build a shape model is to create a subset of points by picking equally spaced points [11]. However, such representations can lose important shape information while reducing the number of points. An accurate boundary representation will also help reduce the time complexity of atlas-based registration and segmentation methods which involves object contour matching.

Basics concepts of k-mean algorithm and k-medoids are discussed in section II. Proposed method is discussed in section III. Experimental results are presented in section IV. Concluding remarks are discussed in section V.

II. FACE RECOGNITION METHOD



(FEAT EXT -FEATURE EXTRACTION)

Block Diagram

III. PROPOSED METHOD

Proposed Algorithm

Proposed method is presented below:

1. Each image is decomposed as sub band. And Sub band is resized to the original image size.
2. Each resized image is partitioned into sub images.
3. Convert the each sub image into column data matrix. Each of them can be expressed in the order of a D-by-N. Ci = {ci1+ci2+ci3+…ciN} with i = 1, 2,…….. K. here N is the total number of images
4. Calculate mean value for each sub image.
5. Subtract the mean value from column data matrix of each sub image then obtain vertically centered column data matrix Cvi = {ĉi1+ĉi2+ĉi3+…ĉiN},i = 1, 2,……...K.
6. Rearrange the elements to get square matrix.

7. Collect Eigen values, Eigen vectors, and diagonal values of the square matrix and Repeat the same procedure for row data matrix.
8. Reduce the feature size as per the requirement as feature 1.
9. Above steps are repeated for the whole image without DWT to generate the feature 2.
10. Feature 1 and 2 are combined to get the global feature.
11. Minkowski distance is used to retrieve the relevant images.
12. Minkowski distance is concentrated on Euclidean space, which can be considered as a generalization of both Euclidean and Manhattan distance for getting more recognition efficiency.

IV. EXPERIMENTAL RESULTS

A. Feature Extraction Process

Method comparisons have been also performed. The recognition technique proposed here is much faster and provides better results for large face sets than non-automatic approaches. Also, our SIFT-based method produces better recognition results than unsupervised techniques using other face features, such as the Eigen faces [3,4] or the 2D Gabor filtering based characteristics [12]. Also, we have considered some other automatic classification algorithms to be applied for the face feature vectors. Thus, it is possible to use other clustering procedures, instead of the described region-growing algorithm, in combination with the validation indexes. Therefore, we have tested K-means algorithms and their variants [20], and Self-Organizing Feature Maps (SOFM), on the same facial feature vector sets and obtained weaker recognition results and also slower execution times. The performance parameters of several face recognition techniques are compared in the next table. The parameter values are registered for this SIFT-based unsupervised recognition method, the Eigenface algorithm of Turk & Pentland [3], the Eigenface-based method of Barbu [4], the 2D Gabor filtering approach [12], and an algorithm using SIFT features with K-means clustering. As it results from Table 1, the recognition technique provided here achieves the highest values for Precision, Recall and F1, which means it outperforms the other methods

Table 1: Recognized efficiency on face database

	No. of top recognized matches				
	1	***3***	***5***	***7***	***10***
Mean	*100*	*58.5*	*50.5*	*44.2*	*36.25*
Variance	*100*	*60*	*54.5*	*48.2*	*42.25*
KPCA	*100*	*77.5*	*71*	*65*	*58*
KERNEL LDA	***100***	***93***	***89***	***86***	***68.9***

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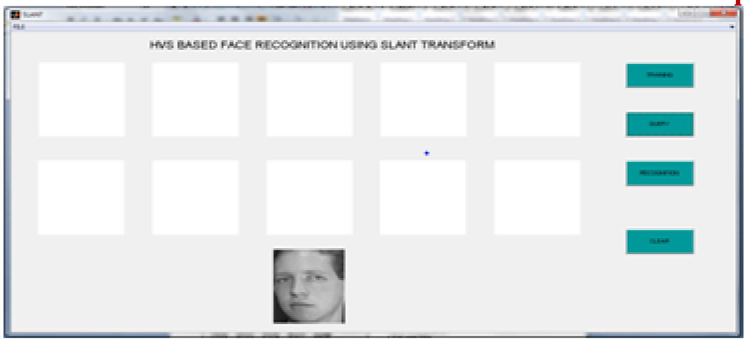

Figure2: Query image

Figure3: Retrieval result

To verify the effectiveness of the proposed approach, the overall average retrieval accuracy obtained by assigning different weights to the global-based and regional-based similarity scores is shown in Fig. 9, where G and R, respectively, represent global and regional weights. It also clearly shows the effectiveness of our fusion approach (G:R = 3: 7) as it achieves the best accuracy. Additional experiments using the same test bed, the same 150 query images, and the 20 returned images are performed on several variants of our proposed method to experimentally illustrate the validity of our method. These variants include: The experimental results on 5000 images from the COREL database demonstrate that the proposed algorithm achieves good retrieval accuracy with fast speed due to the small feature vector size (i.e., 3 elements for color, 6 elements for texture, 5 elements for global EHDs, and 25 elements for semi-global EHDs). Shape or spatial information is not considered in our implementation for the efficiency consideration. It may be further integrated into the retrieval system to improve the accuracy with a compromised efficiency. Next we compare the recognition performance of IMED- embedded EFM and PEFM without normalization using the PolyU palmprint database. Fig. 7 shows the recognition rates of these two methods over different LDA dimensions. From Fig. 7, we can see that PEFM without normalization can achieve higher recognition rate than IMED-embedded EFM. This performance difference can also be explained by that, for PEFM, IMED is only embedded in the testing stage. These experimental results also indicate that, in the training stage, IMED-embedded methods even decrease the recognition performance sometimes.

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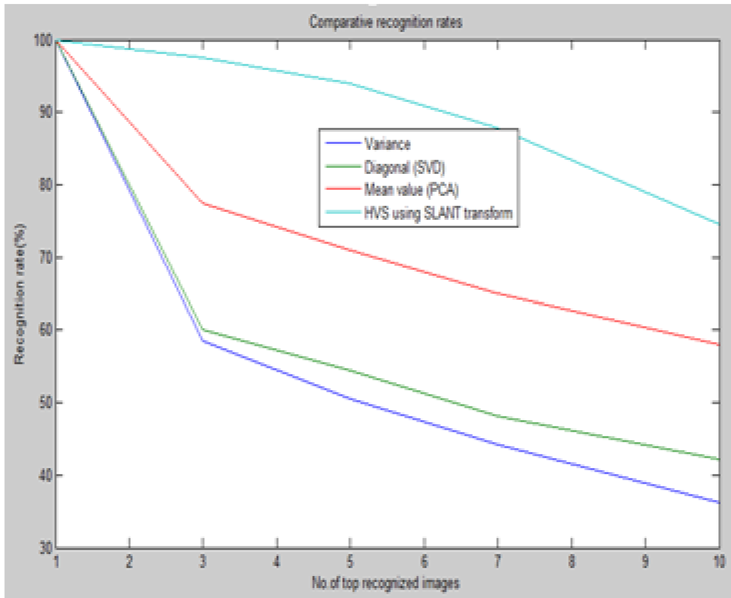
B. Comparative Recognition Rates



V. CONCLUSIONS

In this paper, we proposed method is a robust face recognition approach through different local features has been implemented. We used YALE face database in this paper. First the images are partitioned into different sub bands using discrete wavelet transform. Kernel methods are widely used for to extract the features from the different sub bands for non linear methods. sub band methods are used for extract the local features from the all sub bands. Then the all local features are formed as global features to improve the recognition efficiency. As compared to linear methods most of the researchers use non linear methods for real time applications. In this paper we proposed face recognition approach through different local features gives better results as compared to existing techniques.

REFERENCES

1. *W. Zhao, R. Chellappa, P.J. Phillips, A. Rosenfeld, Face recognition: a literature survey, ACM Computing Surveys 35 (4) (2003) 399–458.*
2. *W. Shu, D. Zhang, Automated personal identification by palmprint, Optical Engineering 37 (8) (1998), 2659–2362.*
3. *D. Zhang, W. Kong, J. You, M. Wong, On-line palmprint identifica- tion, IEEE Transactions on Pattern Analysis and Machine Intelli- gence 25 (9) (2003) 1041–1050.*
4. *P.N. Belhumeour, J.P. Hespanha, D.J. Kriegman, Eigenfaces versus Fisherfaces: recognition using class specific linear projection, IEEE Transactions on Pattern Analysis and Machine Intelligence 19 (7) (1997) 711–720.*
5. *X. Wu, D. Zhang, K.Wang, Fisherpalms based palmprint recognition, Pattern Recognition Letters 24 (2003) 2829–2838.*
6. *D.L. Swets, J. Weng, Using discriminant Eigenfeatures for image retrieval, IEEE Transactions on Pattern Analysis and Machine Intelligence 18 (8) (1996) 831–836.*
7. *K. Liu, Y.Q. Cheng, J.Y. Yang, X. Liu, An effective algorithm for Foley- Sammon optimal set of discriminant vectors by algebraic method, International Journal on Pattern Recognition and Artificial Intelli- gence 6 (5) (1992) 817–829.*
8. *L.F. Chen, H.Y. Mark Liao, M.T. Ko, J.C. Lin, G.J. Yu, A new LDA-based face recognition system which can solve the small sample size problem, Pattern Recognition 33 (10) (2000) 1713–1726.*

[Yohanu, 4(9): September 2017] ISSN 2348 – 8034
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9. H. Yu, J. Yang, A direct LDA algorithm for high-dimensional data with application to face recognition, Pattern Recognition 34 (10) (2001) 2067–2070.
10. J. Lu, K.N. Plataniotis, A.N. Venetsanopoulos, Face recognition using LDA-based algorithms, IEEE Transactions on Neural Networks 14 (1) (2003) 195–200.
11. R. Huang, Q. Liu, H. Lu, S. Ma, Solving the small sample size problem of LDA, in: Proceedings of 16th International Conference on Pattern Recognition, August 2002, pp. 29–32.
12. J.Yang,D.Zhang,J.Y.Yang, A generalized K-L expansion method which can deal with small sample size and high-dimensional problems, PatternAnalysis and Applications6(2003)47–54.
13. H.Cevikalp,M.Neamtu,M.Wilkes,A.Barkana, Discriminative common vectors for face recognition, IEEE Transactions on Pattern Analysis and Machine Intelligence27(1)(2005)4–13.
14. J.Yang,J.Y.Yang,Why can LDA be performed in PCA transformed space, Pattern Recognition36(2)(2003)563–566.
15. J.Yang, F.Frangi,J.Y.Yang, D.Zhang, Z.Jin, KPCA plus LDA: a complete Kernel Fisher discriminant framework for feature extraction and recognition, IEEE Transactions on Pattern Analysis and Machine Intelligence27(2)(2005)230–244.
16. K.Wang,W.Zuo,D.Zhang, Post-processing on LDA's discriminant vectors for facial feature extraction, in:T.Kanade, A.Jain, N.K.Ratha (Eds.), Audio-and Video-based Biometrics Person Authentication (AVBPA'05),2005,pp.346–354.
17. W.Zuo, K.Wang, D.Zhang,J.Yang, Regularization of LDA for face recognition: a post-processing method, in:W.Zhao, S.Gong, X.Tang (Eds.), IEEEInternationalWorkshoponAnalysisandModelingof FacesandGestures,2005,pp.377–391.
18. C.Liu,H.Wechsler,EnhancedFisherlineardiscriminantmodelsfor face recognition,in:Proceedings of 14th International Conference on PatternRecognition, August1998,pp.1368–1372.
19. C.Liu,H.Wechsler,Gabor feature based classification using the enhanced Fisher linear discriminant model for face recognition, IEEE Transactions on Image Processing 10(4)(2002)467–476.
20. Wang,X. Tang, A unified framework for subspace facerecognition, IEEETransactions on Pattern Analysis and Machine Intelligence 26(9)(2004)1222–1228.
21. L.Wang,Y.Zhang,J.Feng,On the Euclidean distance of images, IEEE Transactions on Pattern Analysis and Machine Intelligence 27(8) (2005)1334–1339.
22. A.C.Bovik, Basic tools for image Fourier analysis ,in:A.C.Bovik(Ed.), Handbook of Image and Video Processing, seconded, Elsevier, Singapore, 2006,pp.57–73.
23. P.J.Philips,The Facial Recognition Technology (FERET) Database, /http://www.itl.nist.gov/iad/humanid/feretS.
24. P.J.Philips,H.Moon,S.A.Rizvi,P.J.Rauss,The FERET evaluation methodology for face-recognition algorithms, IEEE Transactionson Pattern Analysis and Machine Intelligence 22(10)(2000) 1090–1104.
25. Poly U Palmprint Palmprint Database, (version2) (online), available: /http://www.comp.polyu.edu.hk/_biometrics/S.
26. D.Zhang, W.-K.Kong, J.You, M.Wong,Online palmprint identification, IEEE Transactionson PatternAnalysis and Machine Intelligence 25(9)(2003)1041–1050.
27. J.Yang,J.Y.Yang,A.F.Frangi,Combined Fisher faces framework, Image andVisionComputing 21(2003)1037–1044.
28. J.Hao,W.Zuo,K.Wang,Theoretical investigation on post-processed LDA for face and palmprint recognition, in:International Conference on Computational Intelligence and Security (CIS2007), 2007,pp.301–305.
29. T.Hastie, A.Buja, R.Tibshirani, Penalized discriminant analysis, Annals of Statistics 23(1995)73–102.
30. D.Cai, X.He,Y. Hu,J.Han, T.Huang,Learning aspatially smooth subspace for face recognition,in:IEEE Conference on Computer Vision and Pattern Recognition, 2007(CVPR2007),June2007.