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Face Recognition Based on Multiple Region Features

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Abstract. For face recognition, face feature selection is an important step. Better features should result in better performance. This paper describes a robust face recognition algorithm using multiple face region features selected by the AdaBoost algorithm. In conventional face recognition algorithms, the face region is dealt with as a whole. In this paper we show that dividing a face into a number of sub-regions can improve face recognition performance. We use conventional AdaBoost with a weak learner based on multiple region orthogonal component principal component analysis (OCPCA) features. The regions are selected areas of the face (such as eye, mouth, nose etc.). The AdaBoost algorithm generates a strong classifier from the combination of these region features. Experiments have been done to evaluate the performance on the CMU Pose Illumination Expression (PIE) databases. Performance comparisons between single region OCPCA, our multiple region OCPCA, and published results from Visionics' FaceIt are given. Significant performance improvement is demonstrated using multiple facial region OCPCA features.

Keywords: face recognition, multiple region features, AdaBoost, Orthogonal Component PCA.

1 Introduction

In addition to popular biometric measures such as fingerprint and iris scan, the human face is another common biometric that can be used for automatic person recognition. CSIRO has developed a real time face capture and recognition system, which can automatically capture and recognise face [1]. The recognition of faces is done by finding the closest match of a newly presented face to all faces known to the system.

Popular face recognition methods include Principal Component Analysis (PCA) [2][3], Independent Component Analysis (ICA) [4], Neural Networks [5], etc. [6][7]. Generally, face recognition algorithms treat the face as one entity when performing face recognition. However, the face can be divided into a number of regions and separate features derived for each region. It would be show that such division can improve classification performance. Note that regions may overlap and hence share facial information, though the regions do not necessarily need to encompass the whole face.

By using such multiple regions, we present a method for improving face recognition performance which is an extension of a previous method, orthogonal complement principle component analysis (OCPCA) [7]. Experimental results on PIE database [11] are presented.

The remainder of this paper is organized as follows. Section 2 introduces the AdaBoost algorithm and the OCPCA face recognition method. Section 3 introduces the extension using multiple regions. Section 4 presents and discusses the experimental methodology and results, and conclusions are given in Section 5.

2 AdaBoost and OCPCA

2.1 AdaBoost Algorithm

The goal of a learning algorithm is to find a classifier with low prediction error. In recent years, there has been growing interest in learning algorithms that achieve high accuracy by voting the predictions of several classifiers. The AdaBoost algorithm [8] is a two-class classification algorithm which "boosts" the performance of an existing weak learner. By running the weak learner several times on weighted training data, adjusting the weights after each iteration and combining the hypotheses into a final hypothesis, it achieves higher accuracy than that would achieved by the weak learner.

In more details, AdaBoost assigns each example of the given training set a weight, which usually starts equal. In each round the weak learner returns a hypothesis, and the weights of all examples classified as wrong by that hypothesis are increased. Thus the weak learner is forced to focus on the more difficult examples of the training set. The final hypothesis is a combination of the hypotheses of all rounds, namely a weighted majority vote, where hypotheses with lower classification error have higher weight. AdaBoost has solved many of the practical difficulties of earlier voting algorithms [13].

AdaBoost algorithms have been successfully applied to face detection. A good example is the algorithm developed by Viola and Jones [9], which is capable of processing images extremely rapidly and achieving high detection rates. The AdaBoost algorithm is typically a two-class classifier, whereas face recognition is inherently a multi-class problem. We use differences between image pairs to convert the multi-class issue to a two-class issue. Here the two classes are difference images of "same subject" and difference images of "different subject" respectively.

2.2 Orthogonal Complement PCA

PCA [2][3] gives an optimal set of basis vectors in the sense of minimizing the mean-square error introduced by truncation of the basis. Its main purpose is to reduce the dimensionality of a data set while retaining as much as possible of the variation of the original data. However, PCA is not an optimal basis for face recognition with respect to the differentiation between images. In practice PCA does not cope well with variations in images of a single individual due to changes of expression, hairstyle, facial hair, and aging etc. Several variations of PCA have been proposed to ameliorate these difficulties [10]. In this paper we use an orthogonal complement PCA (OCPCA) [7] method. The OCPCA method redefines features that seek to account for inherent differences between individuals, whilst being relatively independent of variations between images of a single person (cf. [7] for a detailed description of OCPCA method).

3 Face Recognition Using Multiple Region OCPCA Features

3.1 Training Process

The face can be divided into many regions, for example eye, nose and mouth regions etc. However, most conventional face recognition methods such as PCA use only the face region as a whole. The basic idea of applying AdaBoost on multiple region OCPCA features is to select the best regions from the whole face image and their relative weighting for recognition.

Regions may be defined on the face in many ways. For example, figure 1 gives an example where a face is divided into 8 regions. Note that regions may overlap and hence share facial information. OCPCA features can be calculated for each region.

All the regions, or any combination of them, may be regarded as the basic weak classifiers for AdaBoost. The total number of classifiers is:

$$\boldsymbol{N} = \sum_{\boldsymbol{r}=1}^{8} \binom{8}{\boldsymbol{r}} = 255 \qquad (1)$$

To evaluate a test image against a database image, the difference image is first formed, and feature vectors for each of the regions are obtained by projecting the difference image onto the corresponding feature spaces.

A weak classifier combining a subset of the regions first calculates a value for each test image as the sum of the norms of the corresponding feature vectors. Classification is then carried out by simple thresholding. The region combinations were used as input to AdaBoost which at each stage chooses the best such combination before changing the weights for the next iteration. AdaBoost then generates a strong classifier from the combination of these region features as already discussed.

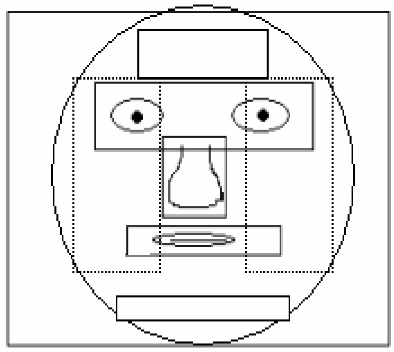


Figure1: Illustration of Multiple Regions

3.2 Recognition Process

Figure 2 describes the block diagram of multiple region face recognition system. The video sequence is input from devices such as a camera, VCR or DVD. Usually, a real-time system may use a number of attributes, such as motion, skin colour and face features, to detect faces. Once a face is detected, more accurate eye positions can be obtained using an eye detection algorithm. Then the face image is normalised in size according to this final eye position. The normalised face image is passed to the face recognition stage, whose output indicates whether the subject is recognised or not. Here, face recognition uses multiple regions of face instead of whole face region only.

For multiple regions, the recognition distance between two face images is defined as the sum of the weighted recognition distance for each region. If the distance between two face images is smaller than a threshold, then the two faces are classified as the same subject. Otherwise, different subjects are assumed.

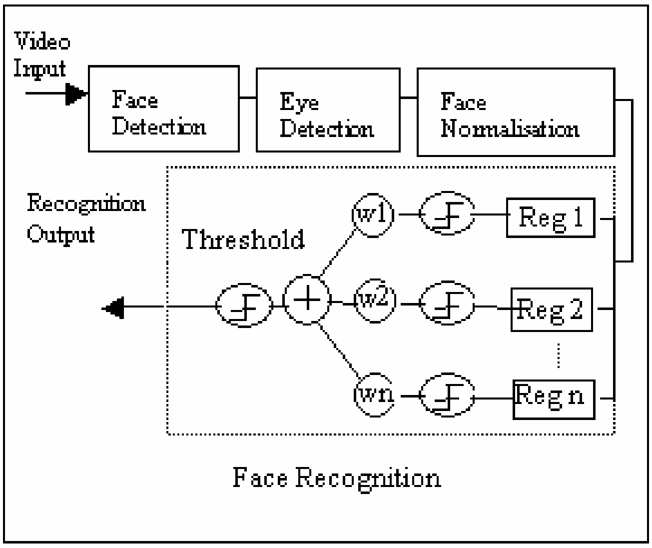


Figure 2: Block Diagram of a Multi-region Feature Face Recognition System

4 Experimental Results

4.1 Training Data and Result

The training data used is a CSIRO database. There are 105 subjects in our training database. Each subject has 7 or 8 images captured under different pose and lighting conditions. In total, we generated 2193 same-subject difference images and 2512 different-subject difference images. We divide the face into 7 rectangle regions as shown in Figure 1, with the whole face being regarded as the eighth region. Using the process described in Section 3.1, AdaBoost converged in a single iteration. The single composite region selected comprised the face, eye and nose. While it is surprising that the process converged so quickly, the good performance on test data is an indication that the solution is a good one. This performance is discussed in the following section.

4.2 Test Data

The test data used is the CMU pose illumination expression (PIE) database [11]. This database contains a total of 41368 images taken from 68 individuals. To obtain a wide variation across pose, images were taken using a set of 13 synchronized high-quality color cameras and 21 flashlights in the CMU 3D room. The resulting images are 640x480 in size, with 24-bit color resolution. The cameras and flashes are distributed in a hemisphere in front of the subject. Two cameras were placed above and below the central camera. Two cameras were placed in the corners of the room. 9 cameras were placed at roughly head height in an arc from approximately a full left to a full right profile. Each neighboring pair of these 9 cameras is therefore approximately 22.5^{o} apart.

Figure 3 shows the cameras' positions in two dimensions, where the letter c represents camera and the number represents the camera index. Figure 4 shows the images of a subject across the 13 different poses. Each subject was recorded under different expressions and illuminations.

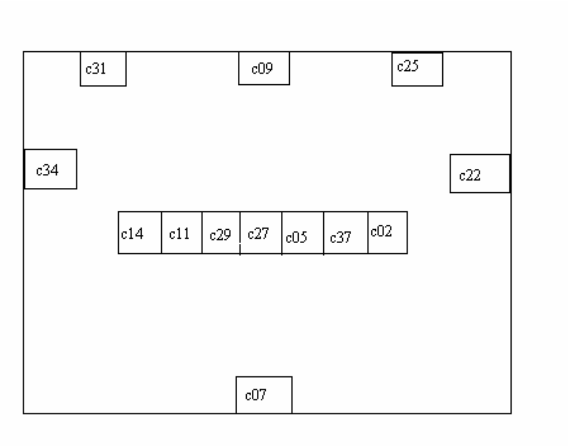


Figure 3. PIE Database Camera Positions

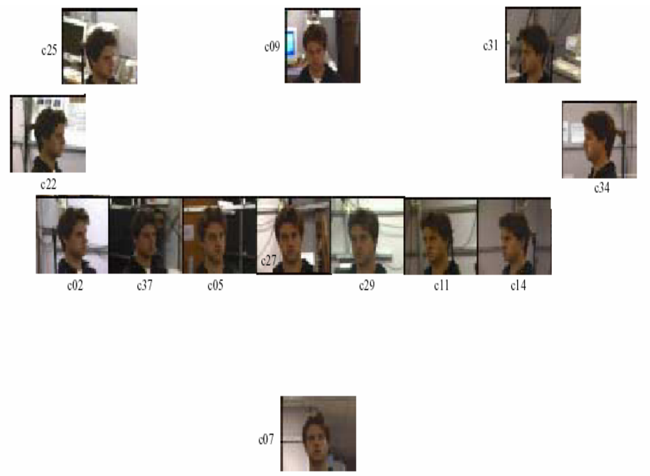


Figure 4: Images of a Subject across the 13 Different Poses

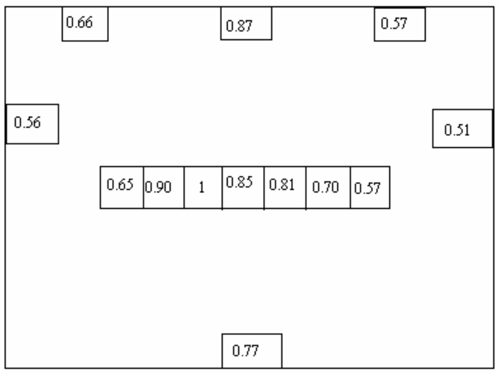
4.3 Performance on Test Data

A series of tests using two novel face recognition algorithms, MIT Bayesian Eigenface recognition algorithm [10] and Visionics' FaceIt Local Feature Analysis (LFA) recognition algorithm [14], to evaluate the effect of face pose on face recognition performance have been done in reference [12]. The results of MIT are much worse than FaceIt's. So here, we tested and compared our recognition performances with FaceIt only. In order to compare with Visionics' FaceIt recognition system, we evaluated the recognition performance of our system in the same conditions as FaceIt.

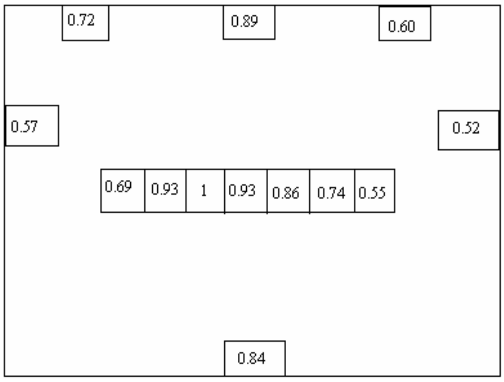
Face recognition is a two-step process consisting of face detection and recognition. In order to ensure the validity of our findings in terms of face recognition accuracy, we used manually located eye positions as in reference [12]. We evaluated and compared recognition performance with respect to pose variations.

In the PIE database, there are 13 pose images for each subject. We used images with 22.5^o pose (C29) and front pose (C27) in turn as gallery images, the remaining poses as probe images.

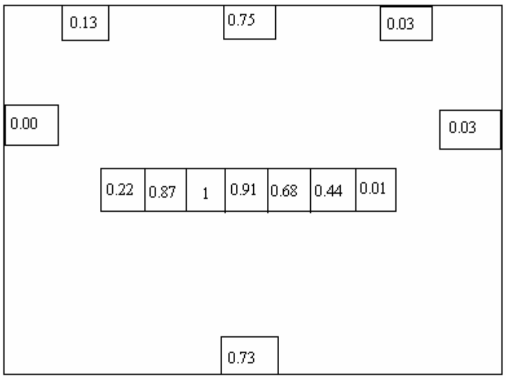
Figures 5 & 6 show the recognition rates of the three methods when the gallery images are either 22.5^o pose (C29) or front pose (C27) and the probe images vary in pose. From figures 5 & 6 we can see that comparing with the general OCPCA method, multiple region OCPCA improves the recognition performance by 1% to 8% for 22.5^o pose gallery image, and 1% to 10% for front pose gallery image. Comparing with Visionics' FaceIt recognition system, the performance of multi-region OCPCA method is much better for both 22.5^o pose and front pose gallery images. In all cases OCPCA shows most improvement for wide-pose probe images.



(a): General OCPCA

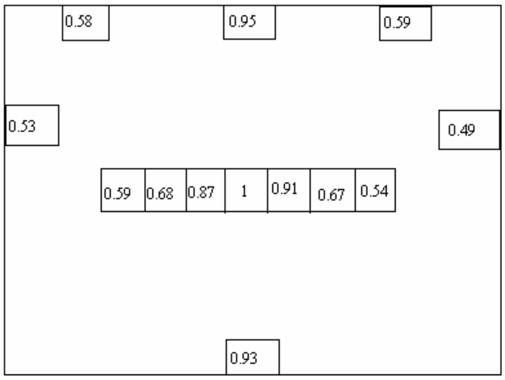


(b): Multiple Region OCPCA

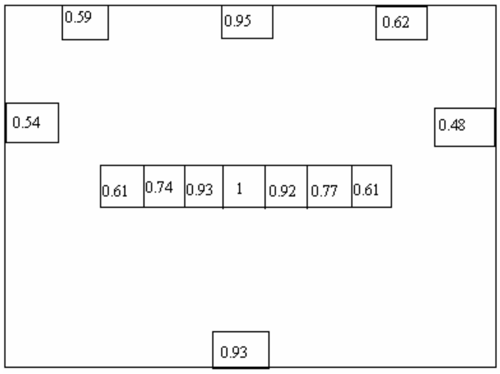


(c): Visionics' FaceIt

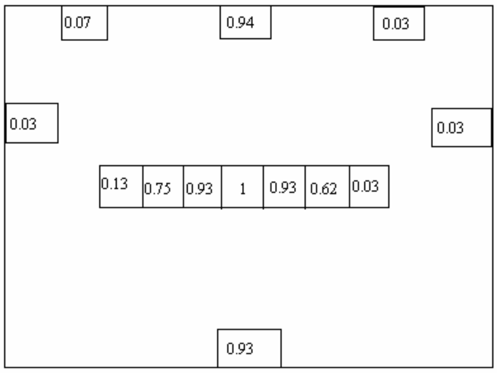
Figure 5: The Recognition Rates for 22.5^{o} **(C29) Gallery Images**



(a) General OCPCA



(b): Multiple Region OCPCA



(c): Visionics' FaceIt

Figure 6: The Recognition Rates for Front (C27) Gallery Images

5 Conclusions

We have presented a novel face recognition method based on multi-region OCPCA features selected by an AdaBoost algorithm. From the experiment results, it can be seen that the AdaBoost selecting multi-region OCPCA features is very promising. It can improve the recognition performance up to 10% comparing to general OCPCA method, and its performance is much better than Visionics' FaceIt system, especially for wide-pose probe image recognition. Through investigation on more facial regions, further improvements can be expected with the multiple-region OCPCA method.

References

1. Rong-yu Qiao, Jason Lobb, Jiaming Li and Geoff Poulton "Trials of the CSIRO Face Recognition System in a Video Surveillance Environment", Proceedings of the Sixth Digital Image Computing Techniques and Applications, Jan. 2002, pp246-251.

2. Pentland, A., Moghaddan, B. and Starber, T. "View-based and modular eigenspaces for face recognition". Computer Vision and Pattern Recognition, 1994, pp.84-91.
3. Turk, M., and Pentland, A. "Eigenfaces for recognition". Journal of Cognitive Neuroscience 3(1), 1991, pp.71-86.
4. Bartlett, M. S., and Sejnowski, T. J. "Independent components of face images: a representation for face recognition". Proceedings of the 4th Annual Jount Symposium on Neural Computation,1997, Pasadena, CA.
5. Lawrence, S., Giles, C. L., Tsoi, A. C., and Back, A. D. "Face recognition: a hybrid neural network approach". Uni. of Maryland Technical Report CS-TR-3608, 1997.
6. Samaria, F., and Fallside, F. "Face identification and feature extraction using hidden markov models". Image Processing: Theory and Applications, 2000 edited by G. Vernazza, Elsevier.
7. Poulton, G. "Optimal feature sets for face recognition". Proceedings, IASTED Int. Conf. On Signal Processing & Communications, Feb. 11-14, 1998, pp. 269-272.
8. Yoav Freund and Robert E. Schapire "A decision-theoretic generalization of on-line learning and an application to boosting", Journal of Computer and System Sciences, 55(1): 119-139, Augest 1997.
9. Paul Viola and Michael Jones "Rapid Object Detection using a Boosted Cascade of Simple Features", Computer Vision and Pattern Recognition, 2001 IEEE.
10. Baback Moghaddam, Chahab Nastar and Alex Pentland "A Bayesian Similarity Measure for Direct Image Matching", International Conference on Pattern Recognition, Vienna, Austria, August 1996.
11. T. Sim, S. Baker, and M.Bsat. "The CMU Pose, Illumination, and Expression (PIE) Database of Human faces", Technical Report CMU-RI-01-02, Robotics Institute, Carnegie Mellon University, Pittsburgh, PA, January 2001.
12. Ralph Gross, Jianbo shi and Jeffery F. Cohn "Quo Vadis Face Recognition" 2001
13. Schapire, R. "The strength of weak learnability" Machine Learning, 5 (1990) 197-227.
14. P.Penev and J. Atick. "Local feature analysis: A general statistical theory for object representation", 1996.