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Classification using Adaptive Multiscale Retinex and Support Vector Machine for Face Recognition System

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Abstract: This study presents an efficient face recognition system based on Support Vector Machine. A lighting correction method, i.e., Adaptive multiscale retinex is introduced to reduce various lighting conditions before performing the classification task. The performance of this method is evaluated using the Yale and ORL databases. The recognition rate of the proposed method achieved up to 92% compared to the principal component analysis method with 73.7%.

Key words: Face recognition, support vector machine, adaptive multiscale retinex, principal component analysis

INTRODUCTION

Face recognition is a subject in pattern recognition study for machine learning applications. Although, other biometrics system such as fingerprint, iris and others reported to be more accurate, the research in face recognition has significantly increase for the past 20 years because of its non-intrusive characteristic (Angle *et al*., 2005). Furthermore, face recognition systems require minimal participation from users in order to perform identification tasks. Despite of these advantages, to build a face recognition system is not an easy task. Several constraints that usually confront researchers are varying poses, lighting conditions and facial expressions.

There are certain techniques used in face recognition study (Zhao *et al.,* 2000). One of it is the statistical pattern method which has been extensively adopted in many face recognition commercial products (Jain *et al.,* 2000). A statistical method is defined as a method which analyzes a pattern data with D dimensional input vector. The representation of the input data are usually the pre-processed by reducing the dimensionality, extract the relevant information from the data and remove noise before the recognition task is performed. One of the earliest statistical methods is by Turk and Pentland (1991), who has proposed the eigenfaces or also known as Principal Component Analysis (PCA) method. The classification is done using the simple Euclidean distance equation. The PCA usually became a benchmark method to the others and it is extensively used in many research papers (Duan *et al*., 2008; Mong *et al*., 2009).

Support Vector Machine (SVM) is a classifier derived from statistical learning theory. The SVM is a popular method because of its ability to solve many non-linear classification problems with good results. One of the initial relevance using SVM regarding vision computing applications is for face detection, where the discrimination is between two classes; face and non-face (Osuna *et al*., 1997). Then, the research in SVM extended to multiclass problems which suit the application of a face recognition task, i.e., to recognize more than two person face images and described as K class problems (Philips, 1999). The research of SVM for ORL database using global and local SVM is done by Heisele *et al.* (2003). Guo *et al.* (2001) also applies the same experiments; i.e. using the ORL database but compares uses Nearest Center Classification (NCC) method. The results have proven SVM performs better than NCC. Another approach uses Kernel Principal Component Analysis (KPCA) as feature extraction method and combines it with SVM to classify face image (Li *et al*., 2005). Mazanec *et al*. (2008) did an experiment by applying Linear Discriminant Analysis (LDA) and SVM for face recognition algorithm.

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In this study, we proposed SVM method for a face recognition system using Yale (Georghiades *et al.*, 2001) and ORL (Samaria and Harter, 1994) databases. The conditions held in these databases are images with various facial expressions and illuminations. Therefore, we introduce a modified illumination correction method, i.e., Adaptive Multiscale Retinex (AMSR) to lessen the illumination effects. This study outline is as follows; a description on the illumination correction method, AMSR is explained followed by the SVM theory and multiclass SVM method. After that is the experimental setup and results. Finally, is to conclude the findings on this study.

ILLUMINATION CORRECTION METHOD: ADAPTIVE MULTISCALE RETINEX (AMSR)

An illumination correction method is needed in a face recognition system due to variance lighting conditions in human faces. In this study we implement a modified method, based on the multiscale retinex by Jobson *et al.* (1997a, b) to reduce the effect of illumination in a face image. The original Multiscale Retinex algorithm is obtained from single scale retinex as:

$$R(x,y) = \log I(x,y) - \log[F(x,y) * I(x,y)] \tag{1}$$

where, I(x,y) is the input image, R(x,y) is the retinex output and F(x,y) is the Gaussian surround function. Symbol (*) denotes convolution. Gaussian surround function is given by:

$$F(x,y) = K \cdot e^{-(x^2+y^2)/c^2} \tag{2}$$

where, c is the Gaussian shaped surrounding space constant. The value of c is related to visual angle in the direct observation which is determined through experiments. K is selected such that:

$$\iint F(x,y)\,dx\,dy = 1. \tag{3}$$

Until this stage the single scale retinex would only provide tone reproduction and dynamic range compression at a certain scale in an image. The image would have only one of the important characteristics. Thus, to overcome this limitation, superposition of different scales at a certain weight would solve this problem as shown in Eq. 4, where N is number of scale and R_{ni} is the different scale of single scale retinex. ω_n is the weight of each single scale retinex with equal value.

$$R_{MSRi} = \sum_{n=1}^{N} \omega_n R_{ni}. \tag{4}$$

According to Herscovitz and Yadid-Pecht (2004) a method need to be applied to restore the information in different regions to smoothen the global contrast in the image according to which region is darker or brighter. The information here is different intensity in different regions in the original picture. For this reason, recombination is needed to restore the information as:

$$R_{MSRi} = \sum_{n=1}^{N} \omega_n R_{ni} + \omega_{original} \cdot \log(\text{original}) \tag{5}$$

After recombination with weighted original picture, adjustment is made on the histogram by performing a constant shift which helps improve the entire global brightness of the image. To shift the histogram is a simple task, since the image pixels should be in certain range. In order to allocate the pixels in the range, we set the initial maximum pixel as MinVal and the minimum pixel as MaxVal. Then we evaluate the entire image pixels one by one (PixVal) and update the new pixel value (New Val) as:

$$\text{NewVal} = \left[\frac{\text{PixVal} - \text{MinVal}}{\text{MaxVal} - \text{MinVal}}\right] \times 255. \tag{6}$$

Next, we execute a local image enhancement technique because we notice that, the image lost important features from the original image although the face image intensity is homogenous. This technique divides the image into rectangular blocks. Usually how many blocks should be used is determine through experiments. First, obtain the cumulative density function of the small region histogram. Then the centre pixel of the region is equalized using histogram equalization and moved to the adjacent pixel in the rectangular region. This process is called Adaptive Histogram Equalization (AHE). Further explanation on AHE can be found in Zhiming and Jianhua (2006).

BASIC SVM THEORY

Here, the SVM theory which is a statistical classification method proposed by Corinna and Vladimir (1995) is explained. It is a popular machine learning algorithm because it can solve a non-linear classification problem in higher dimensional space with an encouraging result.

For two classes problem, we assume that we have a dataset, which given m as the amount of the labeled training samples, x_i are the training samples while y_i are the targets or labels in N-dimensional space as:

$$\{x_i, y_i \mid x_i \in R^N, y_i \in \{-1,1\}, i = 1 \ldots m\} \tag{7}$$

In SVM, the results in a linearly separable problem correspond to a decision function:

$$f(x) = \text{sign}((w \cdot x) + b) \tag{8}$$

The set of samples is said to be optimally separated by the hyperplane if it is separated without error and the margin is maximal. This hyperplane bisects the shortest line between the convex hulls of the two classes, thus, it must satisfy the following constrained minimization as:

$$\text{Min}: \frac{1}{2} w^T w, \qquad y_i(w.x_i + b) \geq 1 \tag{9}$$

This hyperplane can be constructed by solving quadratic optimization problem which is the solution of w and expand with $w = \sum_i \alpha_i y_i x_i$ in terms of a subset of training patterns that lie on the margin. These training patterns x_i are called support vectors, which provide the important information of classification problems. Then the decision function can be formulated as:

$$f(x) = \text{sign} \sum_i \alpha_i y_i (x \cdot x_i) + b \tag{10}$$

For the linearly non separable case, a modification on previous minimization problem needs to be done to recover the misclassified data points. A new penalizing error variable is introduced; ξ_i as the measurement of violation of the constraints:

$$\text{Min}: \frac{1}{2} w^T w + C \sum_{i=1}^{L} \xi_i \quad y_i (w \cdot x_i + b) \geq 1 - \xi_i \tag{11}$$

C is used to weight the penalizing parameter ξ_i. The SVM separate a non-linear separable classification problem by mapping the data into a feature space via a non-linear map. This solution is done by using kernel, K. By using kernel, the non-linear separated samples input space will be turn out to be linearly separated after being mapped in feature space. The decision boundaries function for non-linear problems can be formulated as:

$$f(x) = \sum_i \alpha_i y_i K(x, x_i) + b \tag{12}$$

There are a lot of kernel functions. Some of them are shown in Table 1. Any type of kernel can be chosen according to experiments as it is dependent on the sample data.

Multiclass SVM: The original SVM is a binary classification method, i.e., it classifies two classes problems. However, in a face recognition system requires multiclass classification. There are some techniques to solve multiclass SVM problems. However, one versus one method is the most reliable thus, it is more suitable for practical use than others (Hsu and Lin, 2002). For this reason, one versus one method is chosen for face recognition task (Chang and Lin, 2001).

Table 1: Types of kernel function

Kernel function	Classifier
$K(x,x_i) = \exp(-\|\|x-x_i\|\|^2/2\sigma^2$	RBF
$K(x,x) = (x^T x_i+1)^d$	Polynomial
$K(x,x) = x^T x_i$	Linear

In one versus one method, every two pairs of classes is trained using one classifier. Each subject or person is considered as one class and the total value is k classes. Overall, the number of classifier used will be k(k-1)/2. The training data, x_i is trained using binary classifier with the mth and nth classes:

$$\frac{1}{2}\left(w^{mn}\right)^T w^{mn} + C \sum_i \xi_i^{mn} \tag{13}$$

Based on a voting scheme called Max Win strategy, the procedure is to test x binary scheme with all mth to nth class with the amount of k(k-1)/2 testing. If the output, x is in mth class then a vote will be added to the class. The other classes in decreased by one vote. Then the prediction result will be made based on the largest voted class.

RESULTS AND DISCUSSION

We test the algorithm using Yale database which contains 165 grayscale images of 15 individuals. There are 11 images per subject, one per different facial expression or configuration including with and without glasses, different illumination variation and changes in facial expression. The images size are about 96×106. Note that this size is the cropped face images. The examples of the images in Yale database are shown in Fig. 2a, b. We also evaluate the algorithm using ORL database, which contains 40 persons. Each person has 10 different images, taken at different times. We show the examples of the images in Fig. 3. There are variations in facial expression such as open/closed eyes, smiling/non-smiling and with and without glasses.

For SVM, the number of classes is 15 classes for Yale database and 40 classes for ORL database. Thus, the testing is done with 15(15-1)/2 = 105 and 40(40-1)/2 = 780 classifier for Yale and ORL database, respectively. The data are divided into 50% training and 50% testing data by selecting the images randomly. We use RBF kernel function and implement 5 fold cross validation technique to obtain the best C and g parameter.

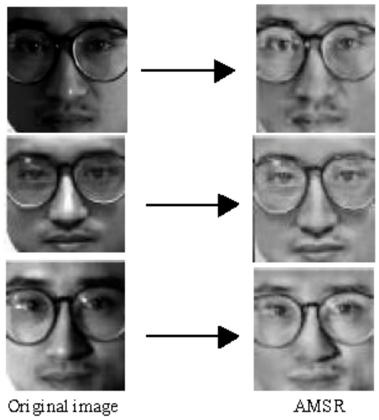

Fig. 1: The comparison of face image after processed with AMSR

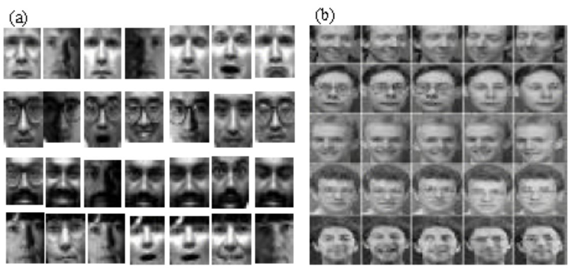

Fig. 2: Examples of faces in (a) Yale and (b) ORL database

Several experiments were carried out to examine the performance of illumination correction method and classifier. The overall process of the experiment is in Fig. 3. This system consists of two modes, i.e., user enrollment and recognition mode. The first mode procedure is that, a set of individuals in Yale/ORL database were used as an input to AMSR and the data later were train using SVM. The same procedures were implemented in the recognition mode which includes SVM testing process. The next experiment was done to determine the performance of the system using PCA as feature extraction method. The objective is to know the relevancy of PCA in the process as done in Guo *et al.* (2001) and Faruqe and Hasan (2009).

The results for Yale database are presented in Table 2. The recognition rate without using illumination correction method using PCA is 45%, while using SVM is 74%. After we applied AMSR, SVM achieved 89.9% while PCA is 61.2% recognition rates. This indicates including AMSR has increased the recognition rate because most of the illumination factor is reduce as in Fig. 1. This result also proved using SVM is better than the PCA method. The processing time for PCA is higher than our proposed method.

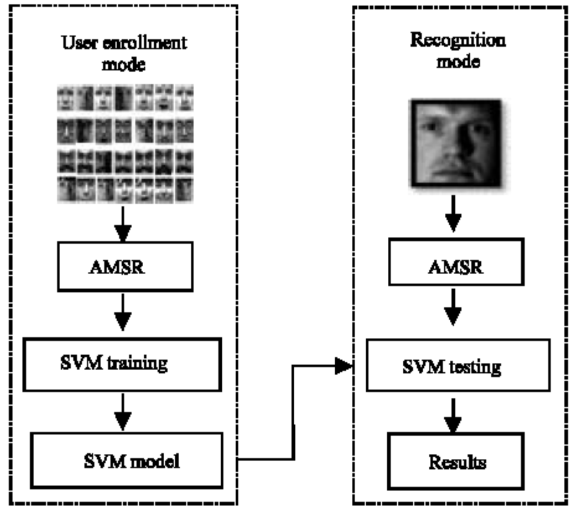

Fig. 3: Block diagram of the proposed face recognition system

Table 2: Comparison of recognition rates and processing time for Yale database

Methods	Recognition rates (%)	Processing time (sec)
SVM	74	0.181
PCA	45	0.673
SVM+AMSR	89.9	0.354
PCA+AMSR	61.2	0.923

Table 3: Comparison of recognition rates and processing time for ORL database

Methods	Recognition rates (%)	Processing time (sec)
SVM	86.5	0.244
PCA	73.7	0.869
SVM+AMSR	92	0.457
PCA+AMSR	71.5	1.25

Next are the results for ORL database which presented in Table 3. We can observe that the results trends are same as the Yale database; however, the recognition rates and processing time for this database is higher. Implementing SVM on a larger compound database has outcome better results, i.e., up to 92% recognition rate. Using PCA and AMSR achieved 71.5% recognition rates.

From above explanations, several assumptions summarized such as:

- SVM able to extract relevant discriminant information from the training data. From Table 2 and 3 using SVM without any feature extraction and lighting correction method could attain recognition rate of 74% for Yale database and 86.5% for ORL database
- AMSR could mitigate the impact of lighting for face image. The results proved that when AMSR is added as pre-processing, the recognition rates increased. In

Yale database, the recognition rate has increased from 74 to 89.9% when AMSR is included. While in ORL database, the recognition rate increased from 86.5 to 92%. However, the processing time is longer when AMSR is added as a pre-processing step due to calculation involving the weight scale, ω_n in Eq. 4

- PCA is not sensitive for highly illuminated data. When PCA is included as feature extraction method, the recognition rates became lower. Then after we add AMSR as lighting correction method, the recognition rates. This indicates using PCA must add lighting correction method before classification task is done
- SVM loose it superiority when the image data is represented by feature extraction technique, the cause is, the data may be over train and this made SVM unable to get the right SV points to separate the data

CONCLUSION

This study addresses a classification method for a face recognition system. Some of the complexity of this system involves various illumination condition of the face image. To deal with this problem, we proposed an illumination correction method i.e., Adaptive multiscale retinex. The algorithm is designed to provide better tonal rendition as well as pixels adjustment based on local features of the face image. Our experiment uses Yale and ORL databases and compare the results using PCA method which achieved only 73.7% while our proposed technique accomplish 92% recognition rate.

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