

**CSU499 PROJECT
REPORT**

**FACE RECOGNITION USING BIOMIMETIC PATTERN
RECOGNITION**

*Submitted in partial fulfilment of
the requirements for the award of the degree of*

**Bachelor of Technology
in
Computer Science and Engineering**
Submitted by

RATHEESH K V	B080179CS
SANTHOSH C	B080331CS
SHANKAR V	B080032CS
SUNIT MATHEW	B080339CS

Under the guidance of
Ms. Lijiya A



DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING
NATIONAL INSTITUTE OF TECHNOLOGY CALICUT
NIT CAMPUS PO, CALICUT
KERALA, INDIA 673601
April 16, 2012

Abstract

In this paper, we present a face recognition system using the new concept of Biomimetic Pattern Recognition (BPR), which uses Optimal Coverage Surfaces (OCS). BPR uses the concept of matter cognition instead of matter classification as in traditional pattern recognition methods. This new system can reduce the false acceptance rate of the samples and enhance the correct acceptance rate.

Keywords: *Pattern cognition, Biomimetic Pattern Recognition, Face recognition, Optimal Coverage Surface, Hyper-sausage structure, Homology-continuity, Horizontal and Vertical integral projections, Corner Detection.*

Contents

1	Problem Definition	2
2	Introduction	3
2.1	Background and Recent Research	3
2.1.1	Traditional face recognition	3
2.1.2	Biomimetic Pattern Recognition	4
2.1.3	Principle of Homology-Continuity (PHC)	5
2.1.4	k-Nearest Neighbor Algorithm	5
2.1.5	Face recognition using Biomimetic Pattern Recognition	6
2.2	Motivation	6
3	Work Done	7
3.1	Input to the system	8
3.2	Facial feature extractor	9
3.3	Face recognizer	12
3.4	Training of the Samples	14
3.5	Sample Recognition	15
3.6	Output	15
3.7	Experiment Results and Analysis	15
4	Future Work	17
5	Conclusion	18
	References	19

Chapter 1

Problem Definition

To build a highly reliable face recognition system using Biomimetic pattern recognition(BPR) and Optimal Coverage Surfaces (OCS).

Current face recognition methods, which derive from the idea of "division" in the traditional pattern recognition, including methods based on face geometrical features, template-matching or neural networks, are all based on dividing existing face types in the face recognition systems, therefore can not avoid the following two drawbacks:

The first, these methods are unable to solve the problem of the high false acceptance rate for untrained samples. If a face sample of untrained type is introduced, the system will place the sample into one of the divided sample subspaces, thus recognized it falsely.

The second, when a new type of face samples is added into a face recognition system deriving from the idea of "division" of the traditional pattern recognition, it is necessary to retrain the entire system.

The new system recognizes the input images based on the similarity and continuity of samples of the same class. Hence it can overcome these drawbacks and produce more accurate results. The system is first trained with a set of sample images for each class. An RGB image of fixed size is given as input to the system. The system recognizes the image if it belongs to any of the trained classes. It is rejected otherwise.

Chapter 2

Introduction

2.1 Background and Recent Research

Face recognition has been a very active research field in the recent years and many techniques for facial recognition have been developed. Most of these techniques use pattern classification as the main principle.

2.1.1 Traditional face recognition

There are predominantly two methods which are employed: geometric (feature based) and photometric (view based). In geometric pattern recognition method, face recognition software recognizes and measures various features of the face. Every face has distinguishable landmarks, some of them are^[5] :

1. Distance between eyes
2. width of nose
3. depth of eye socket
4. shape of cheekbones
5. length of jaw line

These are measured and numerical code (faceprint) is created that represents the face in database. During recognition process, faceprint of an image that needs to be recognized is compared with faceprints in the database.

Here we take a look at three major algorithms used in this field: PCA (Principal Component Analysis)^[5], LDA (Linear Discriminant Analysis)^[5], EBGM (Elastic Bunch Graph Matching)^[5].

Principal Component Analysis (PCA): This technique was put forth by Kirby and Sirovich in 1988. It requires that the gallery images and the probe must be same size. Data compression techniques are

used to remove noise or useless data and a low dimensional effective facial pattern is obtained. The image is retained in orthogonal and uncorrelated structures known as eigenfaces. These are then stored in a 1-D array and compared against an image gallery to get a match. The major advantage of this method is that the data required to identify someone is very low, typically $1/1000^{th}$ of the data presented. The major disadvantage is that it requires a full frontal photo to work with.

Linear Discriminant Analysis (LDA): Unlike PCA, LDA is a statistical approach to facial recognition. It works on the principle of classifying samples of unknown classes based on samples with known classes. It requires that between classes variance is maximized and within class variance is minimized. The major advantage is that a range of facial patterns belonging to the same user can easily be recognized. The major disadvantage is that in high dimensional data, this technique faces the small sample size problem (when there isn't enough sample training data compared to the dimensionality of the sample space).

Elastic bunch graph matching (EBGM): Linear analysis like the two given above, however, does not address some real-world characteristics that are present in images. EGBM realizes these taking into factors like illumination, posture, facial expression etc. They use Gabor wavelets that project the face onto an elastic grid using a dynamic link architecture. Gabor jets are nodes on the elastic grid that describe image behavior around a given pixel. It is the result of a convolution of the image with a Gabor filter. Recognition is based on the response of the Gabor filter at each node.

2.1.2 Biomimetic Pattern Recognition

Pattern cognition is a new concept that deals with the process of identifying patterns in a manner similar to the way we humans perceive objects. Traditional methods use pattern classification and optimal separation. Pattern cognition uses similarities between samples of the same class to find an optimal covering. Pattern cognition is based on the continuity of samples of given classes in the feature space. Mathematically speaking the method will involve a topological analysis of a higher dimensional feature space. Hence it is also called Topological Pattern Recognition (TPR). Another common name for this process is Biomimetic Pattern Recognition (BPR). The word biomimetic emphasizes that the process closely mirrors the similarity it possesses with how a human being interprets images^[1].

Distinction between Biomimetic Pattern Recognition and Traditional Pattern Recognition:

Traditional Pattern Recognition	Biomimetic Pattern Recognition
Optimal classification of many classes of sample	Cognition of different classes of sample one by one
Distinction between one class of sample and limited classes of known sample	Distinction between one class of sample and unlimited unknown classes of sample
Based on distinct of samples in different classes	Based on connection of samples in the same class
To find the optimal classification hypersurface	To find the optimal covering of samples in the same class

2.1.3 Principle of Homology-Continuity (PHC)

In real-world scenarios, any two sample of the same class will have between them gradual changes i.e. abstracted features are continuously mapped. This principle of continuity among samples of the same class is called Principle of Homology-Continuity. Images of sample in the original sample space are mapped onto a closed set A of the feature space. The task of Biomimetic Pattern Recognition system is to ensure whether the mapped image of the object belongs to a set P where P is the covering set for the cognition^[1].

2.1.4 k-Nearest Neighbor Algorithm

k-NN is one of the traditional pattern recognition method for classifying object based on closest training samples in the featur space. k-NN is the simplest of all machine learning algorithm. An object classified by a majority vote of its neighbors, with the object assigned to the class most common amongst its k nearest neighbors, k is positive integer and small. The neighbors are taken from a set for which the correct classification is known.

The training examples are vectors in a multidimensional feature space, each with a class label. The training phase of the algorithm consists only of storing the feature vectors and class labels of the training samples. In the classification phase, k is a user-defined constant, and an unlabeled vector is classified by assigning the label which is most frequent among the k training samples nearest to that query point. Usually Euclidean distance is used. A drawback to the basic "majority voting" classification is that the classes with the more frequent examples tend to dominate the prediction of the new vector, as they tend to come up in the k nearest neighbors when the

neighbors are computed due to their large number.

The best choice of k depends upon the data; generally, larger values of k reduce the effect of noise on the classification, but make boundaries between classes less distinct. A good k can be selected by various heuristic techniques.^[7]

2.1.5 Face recognition using Biomimetic Pattern Recognition

Existing face recognition methods using the concept of division in traditional pattern recognition cannot avoid two important drawbacks: the first, they are unable to solve the problem of the high false acceptance rate for untrained samples, and the second, adding a new type face sample into system cause repeated retraining that need long training time. Face recognition using biomimetic technique can overcome these drawbacks^[2].

Face recognition using biomimetic pattern recognition includes face area detection, facial feature extraction and mapping of the image sample into the n - dimensional feature space. The task of BPR is to determine whether the mapped image belongs to any of the Optimal Coverage Hyper-Surfaces.

2.2 Motivation

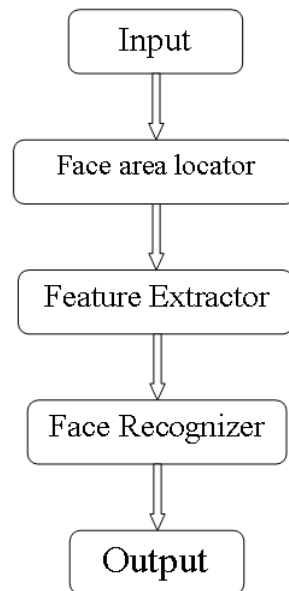
Pattern recognition is a fast developing area of computing with a wide variety of real world applications. Our group has always been keen to develop something relevant and substantial in the field of pattern recognition. We see this project as continuation of our mini project in which we implemented a simple image processing system. However it is our interest in working with the latest technologies that directed us to Biomimetic Pattern Recognition.

Biomimetic recognition is based on a very recent development which could be used to garner better results in systems that implement pattern recognition.

Chapter 3

Work Done

We have successfully implemented and tested a five stage face recognition system based on the design presented earlier. We were able to successfully locate the face area from a given input image and extract the required features from the same. We were also able to use these features from samples of different classes to train the system and also test various input images against this trained sample set. We have implemented the same in C++ using OpenCV libraries in a Visual Studio environment.



3.1 Input to the system

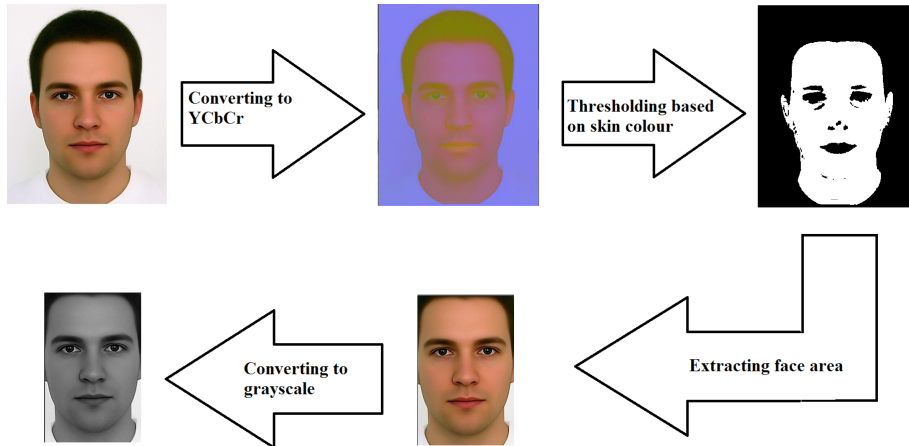
The input to the system is an RGB image of fixed size. The image contains a face that is both obverse (both the eyes are visible) and upright (both the eyes are in the same horizontal level). The image is then converted to YCbCr colour space. The reason we use this colour space is because RGB components are subject to the lighting conditions and thus the face detection may fail if the lighting condition changes. In the YCbCr colour space, the luminance information is contained in Y component and the chrominance information is in Cb and Cr. Therefore, the luminance information can be easily de-embedded. The RGB components were converted to the YCbCr components using the following formula.

$$Y = 0.299R + 0.587G + 0.114B$$

$$Cb = -0.169R - 0.332G + 0.500B$$

$$Cr = 0.500R - 0.419G - 0.081B$$

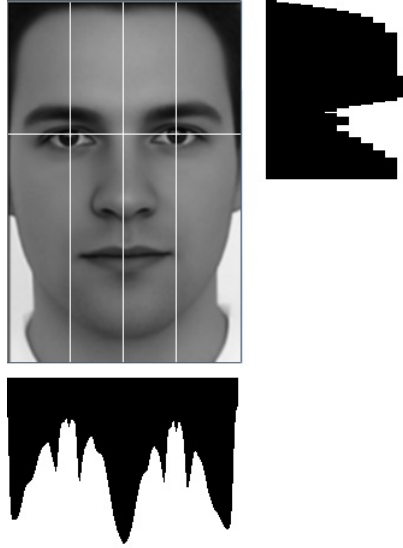
In OpenCV the built-in function that performs this operation is `void cvCvtColor()`. On this image a threshold is then applied based on the skin colour. This is done using the function `cvInRangeS()`. From the resultant image, we identify the largest segment as the face area using the functions `cvFindContours()` and `cvContourArea()`. The bounding box for this area is determined and it is used to extract the face area from the image. This is done using the function `cvBoundingRect()`. This image is then converted to grayscale using the function `cvCvtColor()`. A smooth filter is then applied on the resultant image using the function `cvSmooth()` and given to the facial feature extractor.



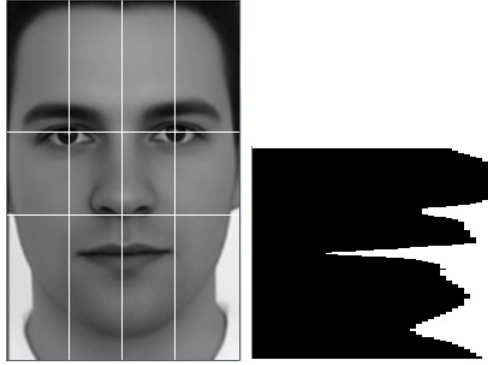
3.2 Facial feature extractor

For facial feature extraction we used a method based on vertical and horizontal integral projections and Harris corner detection operator.

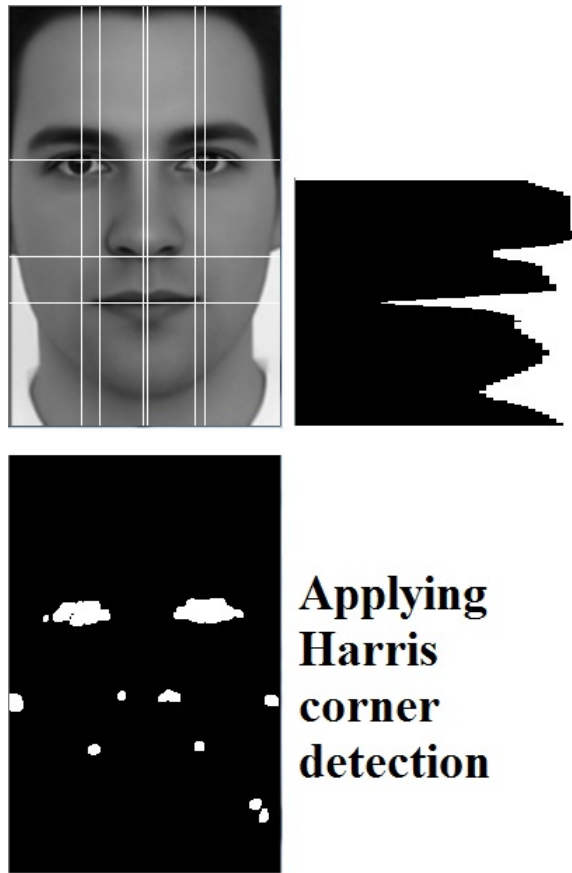
1. **Locating the eyeballs:** The centers of eyes are located by searching the valley points in the local luminance image. By projecting the image in the top area of the face, and then normalizing the histogram got by directional integral projection, we located the probable vertical coordinates of the eyes from the second valley point in vertical integral projection image. Similarly, by using the horizontal integral projection, we found the second valley points on both sides from the center, and probable horizontal coordinates were determined. The valley points are located by finding the first derivative of the histograms obtained by integral projection. The detected points are taken as centers of two eyes. The midpoint between the two eyeballs is also determined.



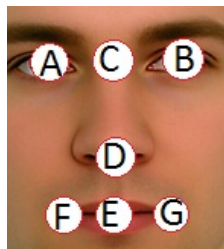
2. **Locating the feature point of the nose:** The strip region of two eyeballs width is taken to get integral projection curve in vertical direction. Then we search along the projection curve down from the vertical coordinates of eyeballs to find the first valley point. This is taken as the vertical coordinates of nostrils. The horizontal coordinate of the midpoint of the two eyeballs is taken as the horizontal coordinate of the midpoint of the nostrils. The midpoint of two nostrils is taken as the feature point in nose-area.



3. Locating the mouth corners: Vertical coordinate of the mouth region is obtained from valley points from vertical projection of mouth area and by using a HARRIS corner detection operator mouth corners are obtained. The mid-point of two mouth corners is taken as the center of the mouth. Total seven facial features are extracted, two eye balls and its mid-point, feature point from nose area, two mouth corners and its midpoint. Total seven facial features are extracted, two eye balls and its midpoint, feature point from nose area, two mouth corners and its midpoint.^[6] Following figure shows the steps of locating the mouth corners.



We then take base points representing the seven facial features got in the above steps and extract the face features referring to the different parameters. Doing so we get a 705 dimensional vector representing the input image. The orientations of the parameters are 0, 45, 90, 135, 180, 225, 270, 315 degrees, respectively. The feature numbers represent the numbers of the features extracted by calculating the difference of the gray scale values of the two adjacent points in the orientation, and the base points represent the start points of the facial feature extraction.



Parameters for Feature Extraction

Base points	Orientations	Numbers
A, B, C and E	0	15
	1	15
	2	15
	3	15
	4	15
	5	15
	6	15
	7	15
D	0	15
	1	15
	2	15
	3	15
	4	15
F	0	15
	1	15
	2	15
	6	15
	7	15
G	2	15
	3	15
	4	15
	5	15
	6	15
Total		705

For example, if $K(m,n)$ represents the gray scale value of the point at (m,n) , and for extracting three features in the orientation of 0 degree with the point at (m, n) as the base point, the three features should be

$$\begin{aligned} &K(m+1,n)-K(m,n), \\ &K(m+2,n)-K(m+1,n), \\ &K(m+3,n)-K(m+2,n), \end{aligned}$$

Similarly, the three features extracted in the orientation of 45 degrees with the point at (m, n) as the base point should be

$$\begin{aligned} &K(m+1,n+1)-K(m,n), \\ &K(m+2,n+2)-K(m+1,n+1), \\ &K(m+3,n+3)-K(m+2,n+2), \end{aligned}$$

and so on.

3.3 Face recognizer

In our system we consider the recognition of basically upright and obverse faces. Hence, the angles of elevation of the faces basically remain constant (small changes of the angles are regarded as the system noises), and only

small rotations in horizontal level are permitted. Since the rotations from left to right (or from right to left) of the faces are continuous processes, the variations of the corresponding images (feature points, which are the images formed by mapping the faces to the multidimensional space) will also be continuous. It thus obeys the basic principle of BPR-the continuity law of the whole samples of the same type in the feature space. Considering the small disturbances in other orientations, the coverage form of a certain type of samples in the feature space should be the topological product of line segments and a 705-dimensional hypersphere, and thus the close subspace of such type of samples is formed. Let A be the line segment and R be the radius of the hypersphere, then the subspace of this type of samples P_a can be written as:^[2]

$$f = \{x | \min(\rho(x,y)) < R, y \in A, x \in R^{705} \}$$

Assuming the number of trained samples of each type (each person) is K, the trained sample set can be written as:

$$s = \{x | x = S_1, S_2, S_3, \dots, S_k \}$$

Here $S_1, S_2, S_3, \dots, S_k$ are the samples collected in the sequential orientations.

To cover the subspace P_a with limited Optimal coverage surfaces, we utilize several lines to approximate the line segment A, and thus get a new line segment B. Then, we acquire P_b , the topological product of a 705-dimensional hypersphere and B, and which is the approximation of P, and the final subspace acquired. Because there are K trained samples, we can use K-1 lines, each of which is represented by B_i ($i = 1, 2, \dots, k-1$), to approximate A, thus we have:

$$B_i = \{x | x = \alpha s_i + (1-\alpha)s_{i+1}, \alpha \in [0,1], s_i \in S, x \in R^{705} \}$$

$$B = \bigcup_{i=1}^{k-1} B_i$$

The coverage of each line segment B_i is:

$$P_i = \{x | \min(\rho(x,y)) \leq R, y \in B_i, x \in R^{705} \}$$

To cover P_i , the following structure of the OCS is adopted:

$$y_i = f[\phi(S_i, S_{i+1}, x)]$$

In the equation above, S_i, S_{i+1} is the feature vector of the i th and $(i+1)$ th trained sample, respectively, x is the input vector, in other words, the feature vector of the sample to be recognized, and y_i is the output of the i th OCS. ϕ is a function with multi-vector inputs, one scalar quantity output and determined by the OCS, and it can be written as:

$$\phi(s_i, s_{i+1}, x) = \min(\rho(x,y)), y \in \{z | z = \alpha s_i + (1-\alpha)s_{i+1}, \alpha \in [0,1]\}$$

Here $\phi(s_i, s_{i+1}, x)$ is the distance of x from the line segment $\overline{s_i s_{i+1}}$. Then

$$\phi^2(s_i, s_{i+1}, x) = \begin{cases} \|x - s_i\|^2, & q(x, s_i, s_{i+1}) < 0 \\ \|x - s_{i+1}\|^2, & q(x, s_i, s_{i+1}) > \|s_{i+1} - s_i\| \\ \|x - s_{i+1}\|^2 - q^2(x, s_i, s_{i+1}) & \text{otherwise} \end{cases}$$

$$q(x, s_i, s_{i+1}) = (x - s_i) \cdot \left(\frac{s_{i+1} - s_i}{\|s_{i+1} - s_i\|} \right)$$

Then the Optimal coverage surface(OCS) can be written as,

$$f_{OCS}(x) = g\left(\frac{\phi^2(\overline{s_i s_{i+1}}, x)}{R^2} - 1\right)$$

And f is a nonlinear transfer function; here we adopt the step function:

$$g = \begin{cases} 1, & x \leq 0 \\ 0, & x > 0 \end{cases}$$

The sample subspace consisting of the coverage of all K-1 Optimal Coverage Surface(OCR) is:

$$P_b = \bigcup_{i=1}^{k-1} P_i$$

Thus the Optimal Coverage Surface(OCR) form an hyper-ellipsoid or “hyper-sausage” shape. Any point that falls within this region is recognized as that class.^[4]

3.4 Training of the Samples

According to the principle of BPR - determining the subspace of a certain type of samples basing on the type of samples itself, the training of the type of samples needs only the samples of the type itself, and if a new type of samples is added, it is not necessary to retrain anyone of the trained types of samples. The training procedure of a certain type of samples (faces of a specific person) is as following:

Extract the features of each face and acquire 705 feature vectors;

Train the OCS covering the spaces P_1 (corresponding to the line segment consisting of the 1st and the 2nd vectors), P_2 (similarly, corresponding to the line segment consisting of the 2nd and the 3rd vectors), ..., P_i , ..., P_{k-1} in sequence. Store the parameters of the K-1 OCS, and end the training.^[2]

3.5 Sample Recognition

It can be concluded that the feature subspace of each type of faces consists of K-1 OCS, which can be written as:

$$y_i = f[\phi(S_i, S_{i+1}, x)]$$

And the discriminant function of this type is:

$$F_m(x) = F\left(\sum_{i=1}^{k-1} y_i\right)$$

Note: here m is the symbol number of this type, and F is the step function

$$F = \begin{cases} 1, & x > 0 \\ 0, & x \leq 0 \end{cases}$$

Therefore, if the output of $F_m(x)$ is 1, sample x belongs to type m, if not, sample x doesn't.^[2]

3.6 Output

The system correctly recognizes the sample input image if it is cognized by one of the trained sample, else the sample will not recognize or it will get rejected.

3.7 Experiment Results and Analysis

In our experiments, we collected four types of samples (faces of four persons), trained three of them, and tested all. We also do experiments with K-Nearest Neighbor Rules using the same samples. The data of the experiment results are showed as follows in table.

Results of Experiment with BPR

Type	Trained Samples	Samples in this type			Samples not in this type		
		Total	Correct	Refuse	Total	False	Refuse
A	5	10	9	1	25	1	24
B	5	10	9	1	25	1	24
C	5	10	7	3	25	0	25

Results of Experiment with KNN

Type	Trained Samples	Samples in this type			Samples not in this type		
		Total	Correct	Refuse	Total	False	Refuse
A	5	10	4	6	25	3	22
B	5	10	10	0	25	4	21
C	5	10	7	3	25	2	23

By analyzing the data in the tables, the following results can be acquired : In the face recognition system based on BPR, the correct acceptance rate for samples of the same type reaches 83.33%, and the refusal rate is 16.67%, while the two elements of KNN are 70% and 30% respectively. On the other hand, the refusal rate of samples of different types reaches 97.33% and the false acceptance rate is 2.67% in BPR, while the two elements of KNN are 88% and 12% respectively. The results show that the face recognition system based on BPR has a very high correct acceptance rate and a very low false acceptance rate and therefore it is much more advanced than those based on traditional pattern recognition methods, such as KNN.

Chapter 4

Future Work

We have implemented an efficient face recognition system using BPR. Further developments can be made by using multithreading for training the samples and testing the input samples to improve their efficiency. An efficient data structure can also be designed and used to store the samples of different classes and also a suitable scanning algorithm can be applied so as to reduce the time complexity.

Chapter 5

Conclusion

We have successfully implemented a Face Recognition System according to the design presented earlier. We have used a feature extraction method based on integral projection, corner detection and differential methods that can efficiently extract the required characteristic facial features. We used these features from samples of different classes to train the system for finding the Optimal Coverage Surface for each class. We then used Biomimetic Pattern Recognition to test various input images against this trained sample set. We also tested the same sample set and input images with KNN, a traditional pattern recognition method and compared the results.

From our experiments, the following results were obtained :

1. In our experiments, the training data must be sequential and continuous, which is the prerequisite of the face recognition system based on BPR.
2. In the face recognition system based on BPR, each type of samples is trained and recognized independently, and addition of a new type will not influence the trained ones.
3. The false acceptance rate of untrained samples of the face recognition system based on BPR is very low as compared to traditional methods. If a lower threshold value is adopted, the false acceptance rate can be reduced to nearly zero, however, the refusal rate of trained samples will increase.
4. In our experiments, the application of BPR on face recognition was researched and satisfying results were acquired. It shows that the application of BPR on face recognition is a new and promising research field.

Bibliography

- [1] Wang Shou-jue and Chen Xu *Biomimetic (Topological) Pattern Recognition- A new Model of Pattern Recognition Theory and Its Application*, Acta Electronica Sinica Vol.30 No. 2002.
- [2] Wang Zhi-hai, Mo Hua-yi, Lu Hua-xiang and Wang Shou-jue, *A Method of Biomimetic Pattern Recognition for Face Recognition*, Acta Electronica Sinica Vol.30 No.10 2002.
- [3] Shoujue Wang, *A New Development on ANN in China Biomimetic Pattern Recognition and Multi Weight Vector Neurons*
- [4] Wenming Cao¹, Jianqing Li, and Shoujue Wang *Continuous Speech Research Based on HyperSausage Neuron*, Institute of Intelligent Information System, Zhejiang University of Technology, Institute of Semiconductors, Chinese Academy of Science
- [5] *Face Recognition*, National Science and Technology Council subcommittee on biometrics, <http://www.biometrics.gov>
- [6] Hua Gu, Guangda Su and Cheng Du, *Feature Points Extraction from Faces*, Research Institute of Image and Graphics, Department of Electronic Engineering, Tsinghua University, Beijing, China.
- [7] Wikipedia <http://www.wikipedia.org>