NYU TANDON SCHOOL OF ENGINEERING

Department of Electrical and Computer Engineering

EL9123 Introduction to Machine Learning

Project Report

(Fall 2017)

Local Binary Patterns for Aging Face Recognition

Student Name:	Minghao Ye
Student ID:	N14706831
Program:	Master's in Electrical Engineering
Group:	39
Submission Date:	Dec. 19th, 2017

Abstract

In the realm of Computer Vision and Pattern Recognition, face recognition became a popular issue in the late 20th century and gained huge progress during the 1990s. Despite that lots of researches were conducted to enhance the performance of facial recognition systems, the aging process remains as a problem which may reduce the recognition rate. Nowadays, people are suggested to renew their images stored in the database every few years to ensure high recognition rate in identity verification and security check. When it comes to finding missing children, or identifying criminals, it is impossible to update their current face images over years. However, unlike other factors, there are only limited researches on aging face recognition. In this project, the Local Binary Patterns (LBP) method is implemented using C++ programs to view the performance of addressing the aging issues. The preprocessed aging datasets of the experiments are selected from the largest public aging face database MORPH Album 2, and extensive experiments are conducted to obtain the 1st rank recognition rate of LBP method under different parameter settings. After the evaluation and analysis of experiment results, it is found that LBP method can achieve maximum 1st rank recognition rate of 0.7 on selected dataset.

1. Introduction

In recent years, face recognition has already become a hot topic among people. Due to the rapid development of facial recognition technology, automatic face recognition systems are widely applied in identity verification procedure and security areas. For instance, the smart phone can detect and recognize the user's face to unlock the phone. At the territorial boundaries between mainland China and Hong Kong SAR, tourists can use e-channels to pass Luohu Port with high efficiency, because the e-channel system can quickly detect the human face and classify the face image to a certain person in the database to identify the identity of each person. Indeed, automatic face recognition is becoming indispensable in our daily lives. Commonly, the face recognition process consists of three phases: Firstly, face detection is conducted to locate a face based on the input image; secondly, facial features are extracted from the face using different mechanisms; finally, face recognition can be performed based on these facial features. Acting as one of the biometric traits, human faces can represent the unique identity of each person like fingerprints, which means that face recognition technique could be applied in the verification stage of electronic payment system in the future.

Nowadays, face recognition technology has become increasingly mature, but it is still facing many challenges which are mainly caused by large intra-class variations [1]. While most of previous studies of face recognition mainly focused on neutralizing the effect of internal and external variation factors such as illumination, expression and pose, the effect of aging process on face recognition did not receive adequate attention. Recently, aging issue is receiving more and more attention in the realm of face recognition, because people realize that the aging process is also a crucial factor which can lead to large intra-class variation and thus decrease the accuracy of face recognition [2]. As time elapsed, the facial features gradually change according to time, which may bring huge difficulties to the machine-based face recognition systems. For instance, there is a realistic situation where even human themselves cannot recognize an aging face after decades. Another common situation is that everyone need to renew their passport or identity card after certain periods. When renewing the vouchers, each person should take a new photo to replace the old one, which can also reflect the huge difference between younger face and aging face. It is known that facial aging is a very sophisticated process, which can change not only the shape but also the texture of human faces.

Therefore, in this project, I implemented LBP method using C++ programs and conducted experiments on the aging databases. According to Ahonen et al. [3], the LBP operator can describe the local texture features to construct histogram-based local texture descriptors which can be combined into a global face description. Then, the face can be effectively recognized using this LBP-based face description. In the experiment, the effects of different parameter settings were discussed, and the performance LBP on aging database is carefully evaluated and analyzed.

The rest of this report is structured as follows. In section 2 “Literature Review”, several age-invariant face recognition approaches are investigated. The methodology is elaborated in detail in section 3. And then, experimental analysis and discussion on experiment results are delivered in section 4. After that, a conclusion of the whole project is given, and the further improvements of the project are carried out in section 5. At the end, the references are listed.

2. Literature Review

According to Panis et al. [4], past researchers tried to address the aging issue in face recognition from three different approaches: Facial age estimation/simulation, age progression and age-invariant face recognition. When most of the researchers mainly focus on age estimation and age simulation, age-invariant face recognition approaches are taken into account only in recent years. To better review the past literatures, the large portion of the aging-related algorithms can be divided into two sections, including generative methods and discriminative methods.

For the generative methods, age simulation is one of the most popular methods to fix aging problem rather than directly recognize images. For instance, Park et al. [5] proposed an age simulation method to build a 3D model of the probe image using face modeling and render the model of probe image to the same age as the images in the database. Ramanathan and Chellappa [6] suggested that a face growing model can be applied to face verification process for cross-age faces under 18 years old. Although these methods can address aging problems to some extent, the computational cost and information requirement are much higher. Moreover, it is a challenging task to simulate an aging face, since the life style and environment can also influence the shape and texture of human face during age progression [7]. Therefore, the performances of generative methods are unstable.

As for discriminative methods, they are suitable for age-invariant face recognition, because discriminative methods and robust feature descriptors can effectively reduce the intra-class variances caused by aging process [8]. Recent researches applied discriminative methods like GOP (Gradient Orientation Pyramid) and MLBP (Multi-scale Local Binary Patterns) so that the performance of the face recognition system can become better when dealing with aging database.

For GOP, the feature descriptor only preserves gradient orientation information, which is more robust to the aging progress than other factors [9]. Li et al. [1] also proposed a discriminative model which can combine LBP and SIFT features into face recognition process. Since the aim of age-invariant face recognition is to extract the facial features that are robust to aging process and achieve high recognition rate, these discriminative methods can satisfy the requirements with relatively low computational cost.

3. Methodology

Local Binary Patterns is one of the most effective texture descriptors to describe the facial features. According to Ali et al. [10], the LBP operator is proved to be highly discriminative since it is robust to monotonic grey-level changes with relatively low computational cost. Therefore, LBP is suitable for facial analysis and representation. Ahonen et al. [3] also propose that the LBP descriptors can be applied in the realm of face recognition, because LBP can achieve large extra-class variances and low intra-class variations, which means that it should be robust to the aging effect, illumination, and other factors. Therefore, I apply LBP descriptor into age-invariant face recognition using C++ program and conducted experiments to observe the results. Different from holistic approaches like PCA, LBP focus on the texture pattern of local facial regions, and the local LBP features can be combined into a global description of face. In the rest of this section, the principle of LBP operator and its application in representing the local texture of face images are elaborated, and then the program design of my LBP program is delivered.

3.1 The Principle of LBP Operator

The primitive LBP operator can effectively describe the local texture pattern of face images. For every pixel, the LBP operator compare its 3x3 neighborhood with the center pixel value. Given that the center pixel value is set as the threshold, if the neighboring pixel value is smaller than the threshold, it is represented as 0; otherwise, it is represented as 1. Normally, the neighborhood should be scanned in a clockwise direction, and an 8-bit binary number can be obtained for each pixel. Then, LBP label of the center pixel can be derived by converting the binary number into decimal number, ranging from 0 to 255. The detailed operation is shown in Figure 1.

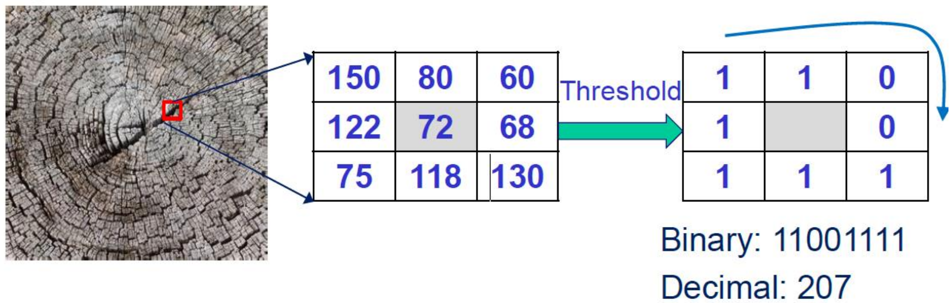


Figure 1. The principle of LBP operator.

To improve the original LBP operator in dealing with different scales of textures, Ojala et al. [11] suggest an extended form of LBP to consider the neighborhood of varied sizes, which allows it to scan random numbers of evenly distributed sampling points on a circle of any radius centered at the pixel. They also introduce a new idea called "uniform patterns", which refers to the binary patterns with at most two bitwise transitions between 0 and 1. For totally 256 binary patterns, there are only 58 uniform patterns, and the others are called non-uniform patterns. According to Ojala et al., the uniform patterns occupied an appearance of nearly 90 percent of all patterns in their experiments when scanning 8 neighbors at a circle of radius of 1. Therefore, when calculating the LBP histogram, each uniform pattern occupies one bin while all non-uniform patterns only occupy one bin. This extended LBP operator can decrease the dimension of LBP histogram from 256 to 59 while keeping texture representation by including most the variances, which is an effective improvement. This kind of extended LBP operator can be notated as $LBP_{P,R}^{u2}$, where $u2$ represents the only usage of uniform patterns, P is the number of sampling points, and R is the radius of circular neighborhood [3].

3.2 Face Representation and Recognition Based on LBP

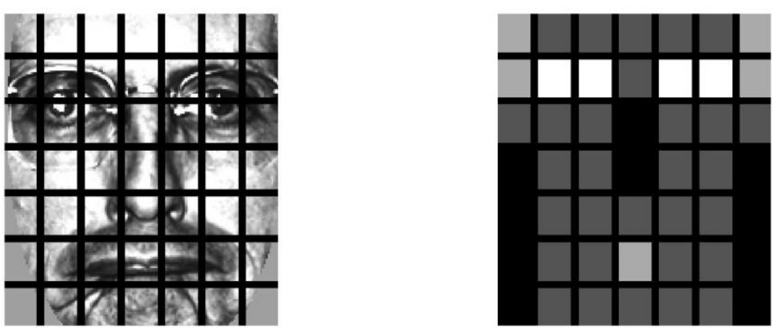
When applying LBP into face texture description, the histogram of the LBP labels can be considered as a good descriptor. According to Ahonen et al. [3], the motivation of combining local LBP histograms into the global description of face is that this kind of local approach can break the limitation of holistic methods and it is more robust to the variations in poses and illuminations. Meanwhile, for face images, it is very important to retain the spatial information of texture descriptor. Therefore, the histogram can be extended into a "spatially enhanced histogram" to describe both the facial features and the spatial relations of facial regions. The details of using LBP to represent face images are elaborated below:

(1) Divide the face image into m facial regions $R_0, R_1, \dots, R_{m-1}$.
(2) For each facial region, compute a 59-bin LBP histogram.
(3) Normalize the histograms and concatenate the histograms of each facial regions into a global description of the original face image, the spatially enhanced histogram.

This representation scheme can also be applied to face recognition. Ahonen et al. suggest that each local histogram can represent the feature of a small micropattern on the human face, thus certain local histograms may have larger contribution towards the extra-class variances. When the spatially enhanced histograms are used to recognize faces, different weights can be added to the local regions considering the importance of their containing information, as is illustrated in Figure 2. For instance, the area of eyes and mouth may have bigger weights than other regions. Thus, face recognition can be achieved by calculating the weighted Chi square distance between the global descriptions of gallery images and the probe image and then classifying the probe image to their nearest neighbor. The weighted Chi square distance can be calculated as

$$\chi_w^2(x, y) = \sum_{i,j} w_j \frac{(x_{i,j} - y_{i,j})^2}{x_{i,j} + y_{i,j}}$$

Where x and y are the normalized spatial enhanced histogram to be compared, i and j represent the i-th bin of the j-th local region, and w_j is the weight assigned to the j-th local region.



(a) (b)

Figure 2. (a) Example of an image which is partitioned into 7x7 patches. (b) The weights assigned for each patch. Brighter color represents larger value. Adapted from "Face Description with Local Binary Patterns: Application to Face Recognition," by T. Ahonen, A. Hadid, and M. Pietikainen, Dec. 2006, IEEE Trans. PAMI., vol. 28, no. 12.

3.3 C++ Program Design of LBP

In order to witness the performance of LBP-based face recognition on aging issues, I designed a C++ program to implement the LBP algorithm. In this program, an external library OpenCV 2.4.13 was applied in my design.

The whole C++ program codes can be divided into five parts:

(1) A platform which can import images from database. In the LBP program, OpenCV functions are used to import and store the training images and testing images.

(2) Configuration. To conduct experiments under different conditions, I set up a list of variable parameters at the beginning of codes. Before conducting experiments using LBP program, I can preset several parameters including the number of training samples of each person, the division setting of image, and the setting of weights.

(3) LBP function. This is the core part of LBP-based face recognition program. In this function, LBP operator can be applied to the image to obtain the LBP image. Then it can achieve the division of LBP image, calculate and normalize the 59-bin uniform local histogram, and combine these local histograms into the global description.

(4) Main program. The main program undergoes the training process and then the testing process to perform face recognition by calculating the weighted Chi square distance. Figure 3 can illustrate the program flow of my LBP program.

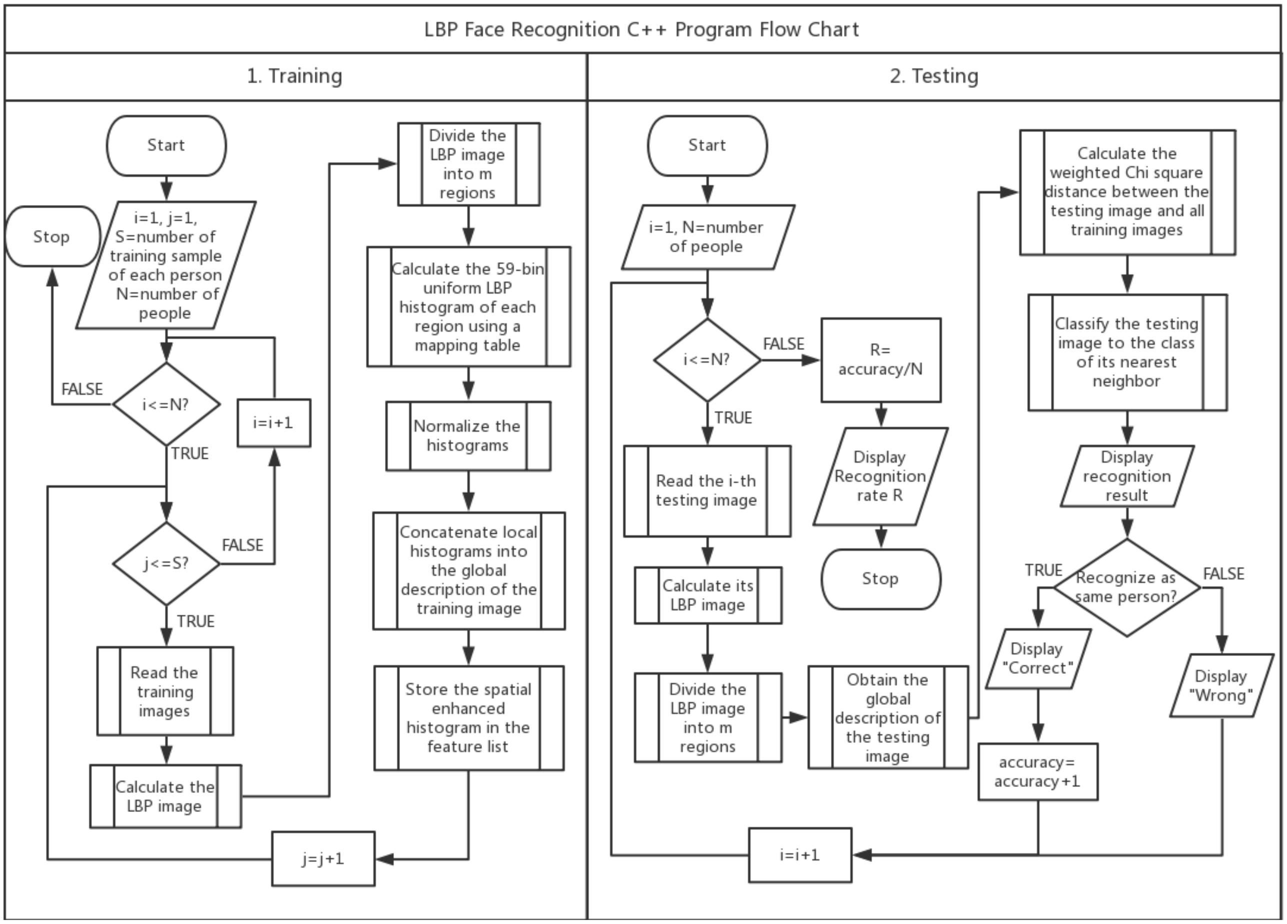


Figure 3. The program flow chart of the LBP face recognition C++ program.

Using this program, I can obtain the experiment results under different parameter settings and analyze the results. When I run the program, it can first perform the training stage, and then display the classification result of each testing image with the overall recognition rate. Therefore, all these data can be recorded to analyze the experiment results under different parameter settings, which helps us to better understand the performance of LBP on aging database. The detailed experiment data analysis will be delivered in next section.

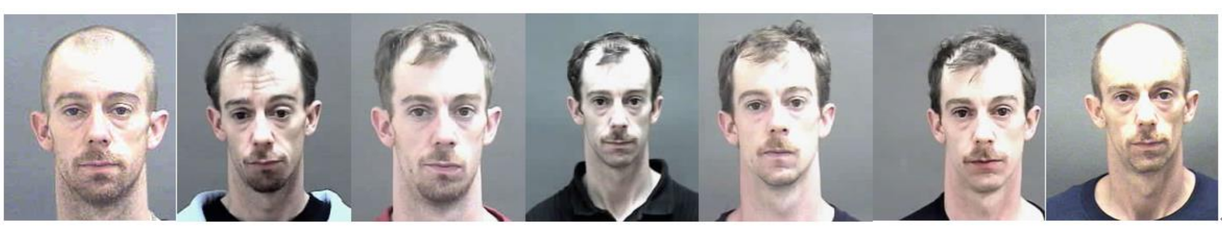
4. Experimental Analysis and Discussion

In this section, age-invariant face recognition experiments were conducted using LBP method to evaluate the performance on the aging issue. The dataset is selected from MORPH Album 2 database.

4.1 Experimental Setup of MORPH Database

In the realm of age-invariant face recognition, there is a well-known publicly available database containing aging faces: The MORPH Album 2 database. It is the largest aging database containing about 78000 longitudinal face images of more than 13000 people at different ages [12]. For each subject in the MORPH Album 2 database, the age gap is around 1 to 5.

In this case, MORPH Album 2 was chosen to be the database of experiments. However, there are still many kinds of variations between the images of the same subject at different ages, including different facial expression, poses, lighting conditions, etc. To eliminate these irrelevant factors as much as possible and emphasize on the aging effect, 700 images of 100 subjects were randomly selected from the database. Each selected subject has 6 training images at younger age and 1 testing image at older age. These selected images have relatively good quality with similar lighting conditions, facial expressions, poses, and the like. Therefore, this dataset was suitable for the aging-related experiments in this project. Figure 4 shows the example images of one subject at different ages in the selected aging dataset. The age gaps between the training images and the testing image are ranging from 1 to 5.



Age 30 30 30 30 31 31 35

Figure 4. Example images of one subject at different ages in the dataset selected from MORPH Album 2. The left 6 images are the training images with younger age, and the last image is the aging image to be tested.

However, these selected images cannot be directly used for experiments, since the background information and different resolutions may reduce the recognition rate. Before the experiments were conducted, the images in the dataset were preprocessed through my C++ image preprocess program. The details of preprocessing the dataset can be shown below:

(1) Using a duplicate checking function to detect whether there are duplicated images in the selected dataset.
(2) If no duplication, import the dataset and using a sort function to read the images in a sequence from younger faces to older faces.
(3) Apply face detection function to detect the face in the image and then cropped the image into a pure face image. ASM library is adapted in this step to detect the feature points of human faces.
(4) Transform the RGB pure face image into gray-scale image.
(5) Use median filter and histogram stretch to enhance the image
(6) Resize the image to a fixed size of 140x140.

Figure 5 is an illustration of the preprocessed images. After preprocessing the dataset, these 700 images were used to conduct experiment using LBP program under different parameter settings. In the rest of this section, the detailed experiment results are delivered and analyzed.

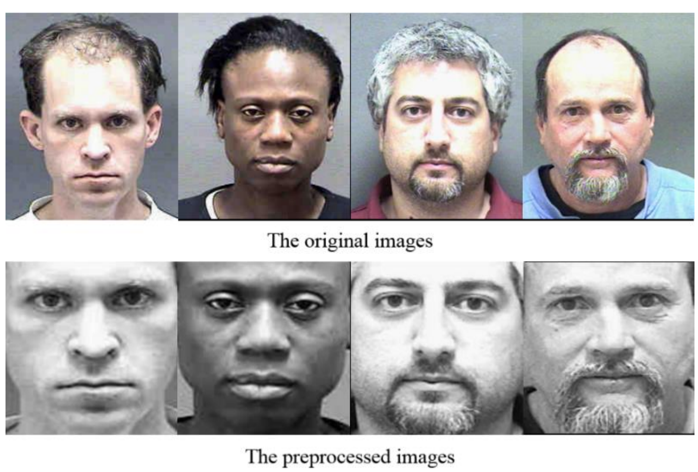
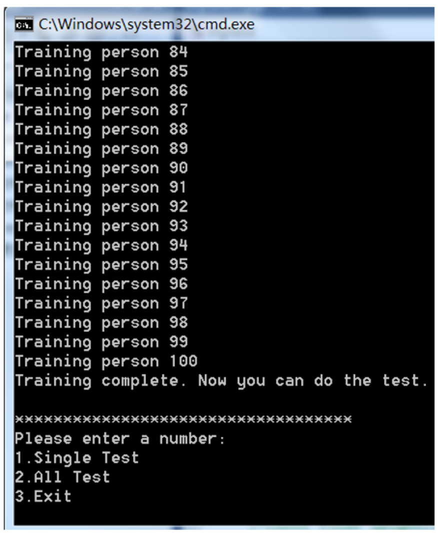


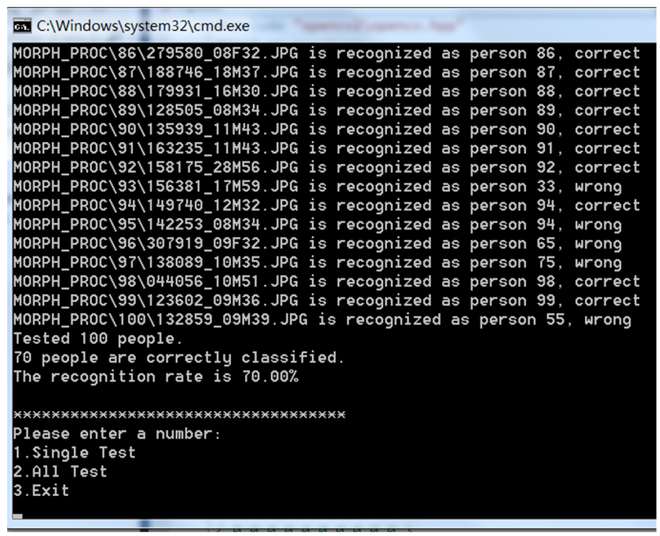
Figure 5. Example original images and the preprocessed versions.

4.2 Experiment Result and Analysis of LBP Method on MORPH Database

In this sub-section, the performance of LBP method on the selected dataset from MORPH Album 2 was evaluated, and the parameters were optimized to obtain the highest recognition rate of LBP. During the experiments, the $LBP_{8,1}^{u2}$ operator was used to extract the local texture features from the images. For the LBP program, a simple interface based on CMD was written to achieve different functions. Figure 6 can provide an illustration of the LBP program.



(a)



(b)

Figure 6. (a) The training process and the interface of LBP program. (b) The experiment results of LBP which are displayed on CMD window.

Firstly, the division scheme of the image was considered as an influential factor. Experiments were conducted with different division schemes when keeping the number of training samples per subject at 6, and the weights for each block in different division schemes were optimized through a series of experiments. According to Ahonen et al. [3], the weights of a block can be determined by the recognition rates when only one block is used for the recognition process. Thus, in the LBP experiments, each block was individually tested with its weight initialized to 1 while the other weights remained 0. After all the experiments were conducted, the recognition rate of specific block was assigned as the optimized weight of that block. Then, different distance measures are applied to the face recognition process. As is shown in Figure 7, the weighted Chi square distance can outperform the Chi square distance and the Euclidean distance, which is consistent with the comparative result stated by Ahonen et al. [3]

The Euclidean distance can be calculated as

$$\epsilon_k^2 = \|(\mathbf{\Omega} - \mathbf{\Omega}_k)\|^2$$

The Chi square distance can be calculated as

$$\chi^2(x, y) = \sum_{j,i} \frac{(x_{i,j} - y_{i,j})^2}{x_{i,j} + y_{i,j}}$$

The weighted Chi square distance can be calculated as

$$\chi_w^2(x, y) = \sum_{i,j} w_j \frac{(x_{i,j} - y_{i,j})^2}{x_{i,j} + y_{i,j}}$$

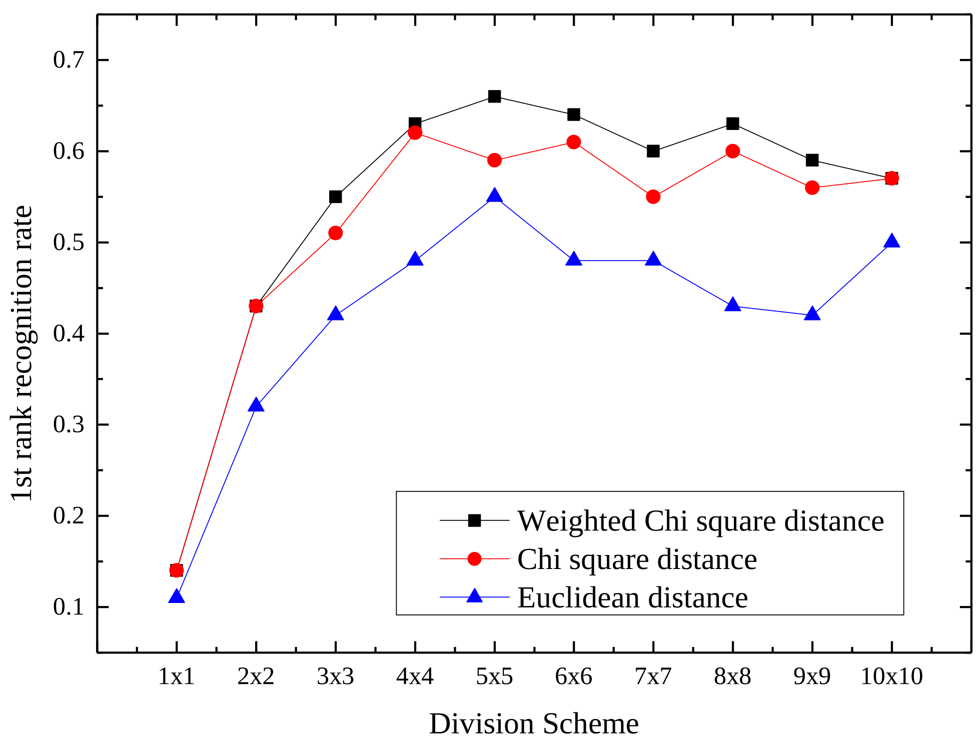


Figure 7. The 1st rank recognition rate of LBP method according to different division schemes with optimized weights, using three different distance measures.

It can be seen from Figure 7 that when the partition number increased from 1x1 to 5x5, the recognition rate increased rapidly. However, the recognition rate began to decrease as the division number continued to increase. Theoretically, smaller partitions can describe the local texture more precisely. However, the experiment result contradicts with this idea. In this case, it can be explained using two reasons. Increasing the number of partition can bring a higher-dimensional global feature, which may contain redundant information and noises to reduce the recognition accuracy. The next consideration is that if a partition is small, the histogram will become too sparse, and thus lose its statistical significance. Therefore, an optimize division was attained for the aging set by evaluating different division schemes that are similar to the 5x5 division scheme. When a partition scheme of 4x5 is adapted, a maximum face recognition accuracy of 70% can be obtained by optimizing the weights. Using this scheme, the effect of the number of training samples per subject was also measured, as is shown in Table 1. Since the recognition process was achieved by finding the nearest neighbor of the testing image and classifying it to the subject class of that neighbor, increasing the number of training samples per subject could be an effective method to improve the recognition accuracy.

Table 1

The 1st rank recognition rate of LBP method on MORPH dataset according to different number of training samples per subject

The number of samples/subject	1	2	3	4	5	6
Recognition rate with 4x5 partition scheme	0.26	0.36	0.42	0.54	0.6	0.7

From the experiments, it can be found that LBP method has a relatively low computational cost while achieving a maximum 1st rank recognition accuracy of 0.7. Indeed, LBP can address the aging issue to some extent, but it cannot achieve better recognition performance than current techniques, since LBP is not a novel method comparing to the state-of-the-art algorithms.

5. Conclusion and Further Improvements

In this project, I implemented LBP algorithm based on the selected aging dataset from MORPH Album 2. Extensive experiments are conducted using C++ program with different parameter settings to analyze and evaluate their performance in dealing with aging issues. The experimental result reveals that LBP has some advantages to address the aging problems.

As a matter of fact, there are some limitations in this work. The dataset is not large enough for aging face recognition, and the images cannot be preprocessed better to enhance the performances. Nevertheless, the performances of a local feature-based approach on aging datasets were carefully analyzed and studied. This project helps me learn more about aging face recognition through theoretical knowledge and practical works. Therefore, I would try to use larger dataset for aging face recognition, and the preprocessing program will be better modified. Furthermore, I will continue conducting research about aging recognition and try to implement more algorithms in the future.

References

[1] Z. Li, U. Park, and A. K. Jain, "A Discriminative Model for Age Invariant Face Recognition," *IEEE Trans. on Information Forensics and Security*, vol. 6, no. 3, Sep. 2011.

[2] A. K. Jain, B. Klare, and U. Park, "Face Matching and Retrieval in Forensics Applications," *IEEE Multimedia*, vol. 19, no. 1, p. 20, 2012.

[3] T. Ahonen, A. Hadid, and M. Pietikainen, "Face Description with Local Binary Patterns: Application to Face Recognition," *IEEE Trans. PAMI.*, vol. 28, no. 12, Dec. 2006.

[4] G. Panis, A. Lanitis, N. Tsapatsoulis, and T. F. Cootes, "An Overview of Research on Facial Aging using the FG-NET Aging Database," *IET Biometrics*, vol. 5(2), pp. 37-46, June 2016.

[5] U. Park, Y. Tong, and A. Jain, "Age-Invariant Face Recognition," *IEEE Trans. on Pattern Analysis and Machine Intelligence*, vol. 32(5), pp. 947-954, 2010.

[6] N. Ramanathan and R. Chellappa, "Modeling Age Progression in Young Faces," *IEEE International Conference on Computer Vision and Pattern Recognition*, pp. 387-394, 2006.

[7] N. Ramanathan and R. Chellappa, "Face Verification across Age Progression," *IEEE Conf. Computer Vision and Pattern Recognition (CVPR)*, vol. 2, pp. 462-469, 2005.

[8] D. Sungatullina, J. Lu, G. Wang, and P. Moulin, "Multiview Discriminative Learning for Age-Invariant Face Recognition," *2013 10th IEEE International Conference and Workshops on Automatic Face and Gesture Recognition (FG)*, pp. 1-6, 2013.

[9] H. Ling, S. Soatto, N. Ramanathan, and D. Jacobs, "Face Verification Across Age Progression Using Discriminative Methods," *IEEE Trans. on Information Forensics and Security*, vol. 5(1), pp. 82-91, 2010.

[10] A. Ali, V. Sagayan, A. Saeed, H. Ameen, and A. Aziz, "Age-Invariant Face Recognition System Using Combined Shape and Texture Features," *IET Biometrics*, vol. 4(2), pp. 98-115, June 2015.

[11] T. Ojala, M. Pietikainen, and T. Maenpaa, "Multiresolution Gray-Scale and Rotation Invariant Texture Classification with Local Binary Patterns," *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 24, no. 7, pp. 971-987, July 2002.

[12] K. Ricanek, Jr., and T. Tesafaye, "MORPH: A Longitudinal Image Database of Normal Adult Age-Progression," *7th International Conference on Automatic Face and Gesture Recognition (FGR06)*, pp. 341-345, 2006.