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PERFORMANCE OF FACE RECOGNITION WITH PRE-PROCESSING TECHNIQUES ON ROBUST REGRESSION METHOD

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ABSTRACT: The Robust Regression method has been used successfully in face recognition problems. Based on empirical experiments on some standard face image databases, the method shows very high accuracy. The method used the histogram equalization technique to normalize illumination such that the effect of illumination factors is reduced substantially on the image. In this research, some contrast adjustment techniques are used in the pre-processing stage to determine how far those techniques affect the face recognition performance. There are three contrast adjustment techniques used, i.e. Histogram Equalization (Histeq function), Contrast-limited Adaptive Histogram Equalization / CLAHE (Adapthisteq function) and Imadjust function. In addition, it is also used the no-pre-processing technique (not using pre-processing techniques). The experiments were performed on three standard face image databases, i.e. CMU-PIE Face Database, Extended Yale Face Database B, and AR Face Database. The experimental results show that the use of Adapthisteq function in the pre-processing stage of the Robust Regression method produces the highest average accuracy of 97.69%. This result is better than the accuracy of Histeq, Imadjust, or no-pre-processing technique, which are 94.53%, 90.59%, and 93.43% respectively.

Keywords: Face Recognition, Robust Regression, Pre-processing, and Contrast Adjustment.

1. INTRODUCTION

The face recognition technology used to identify a person's identity has many advantages over other biometric-based techniques such as fingerprint, palm, retina, iris, voice, behavior, and other body parts recognition. In face recognition, the object recognition process does not need an individual's active role so it can be used for surveillance or security monitoring effectively. The process of obtaining facial image data can also be done more easily [1], for example, using a simple camera can already be used to acquire images.

The researchers have developed many face recognition methods to solve the emerging problems and achieve the best performance of face recognition. The problems that often arise in face recognition are related to factors that influence it, such as variations of illumination, variations of expression, position changes, or the addition of attributes on the face. One of the face recognition methods developed was the Robust Regression [2]. Based on the previous research conducted by Naseem, Togneri, and Bennamoun [2], where experiments were performed using 3 standard face database, i.e. Yale Face Database B [3], CMU-PIE Database [4]-[5], and AR Database [6], the Robust Regression method showed better face recognition performance compared to other face recognition methods.

The Robust Regression method was developed to solve face recognition problems that are influenced by illumination factor. Illumination variation is one of the important factors affecting the reliability of a face recognition technique [7]. Even in the research conducted by Hu [8], the factor of illumination variation gives a higher influence on face recognition performance than other factors. Furthermore, face recognition problems affected by illumination variation have not been fully resolved, especially in complex lighting conditions [9].

In the pre-processing stage, the Robust Regression method used the Histogram Equalization technique [10], one of the most used Histogram Remapping techniques currently, for normalizing the face image by adjusting contrast and reducing the facial image variation caused by the influence variations of illumination. In this research, some contrast adjustment techniques are used in the pre-processing stage to find out how far they affect face recognition performance. There are 3 contrast adjustment techniques used, i.e. Histogram Equalization (histeq function), Contrast-limited Adaptive Histogram Equalization / CLAHE (adapthisteq function) and imadjust function. In addition, experiments were also performed by eliminating contrast adjustment techniques on pre-processing stage. Experiments were performed using 3 standard face image databases, i.e. CMU-PIE Face Database, Extended

Yale Face Database B, and AR Face Database. Theoretically, where the various contrast adjustment techniques are intended to set the contrast of the image, these techniques will produce the equally good performance. Through this research, where empirical experiments are conducted, we will know the performance produced in more detail, as well as which techniques present the best results.

2. METHODOLOGY

This section explains the Robust Regression approach, pre-processing techniques, datasets, and evaluation techniques used in this research. There are 3 contrast adjustment techniques used in the pre-processing stage of Robust Regression, i.e. Histogram Equalization (Histeq function), Contrast-limited Adaptive Histogram Equalization / CLAHE (Adapthisteq function) and Imadjust function. The experiment is also done by eliminating pre-processing technique (no-pre-processing technique).

The experiment was performed on 3 standard face image databases (datasets), i.e. CMU-PIE Face Database, Extended Yale Face Database B, and AR Face Database. Furthermore, the experiment, based on the evaluation techniques, is conducted to determine how far those pre-processing techniques affect face recognition performance.

2.1 The Robust Regression Approach

In the Robust Regression Method, the pre-processing phase is performed for each face images. In the previous research [2], a pre-processing technique used is Histogram Equalization, which is intended for normalization of illumination in images. In the training process, each grayscale face image of $a \times b$ is represented as a vector $a \cdot b$ and then downsampled becomes a smaller dimensional vector. This training process is performed to generate a regressor or predictor for each class/individual, formed from a combination of multiple face image vectors of the same individual. Each test data will be classified into one of the classes using the predictor that has been created during the training process.

As in the training process, for each of the test images to be tested, it also enhances the contrast of its image in the pre-processing phase by using the Histogram Equalization technique. Next, each image matrix is converted into a vector and downsample becomes a smaller-sized vector. For each class I, the value of $\beta(i)$ is estimated by using the Robust Huber Estimation [11]-[12] and further predicts the response vector. Then, the Vector Distance is determined and the class is predicted with the smallest distance [2].

The Robust Regression approach was developed to overcome the problem of illumination variation. Therefore, experiments were performed for face image data affected by variations of illumination.

2.2 Pre-processing Techniques

In the pre-processing stage of the Robust Regression method in this research, some techniques of Contrast Adjustment will be implemented and will be compared to the results. There are 3 contrast adjustment techniques used, i.e. Histogram Equalization (Histeq function), Contrast-limited Adaptive Histogram Equalization / CLAHE (Adapthisteq function) and Imadjust function. Experiments were also performed by not using the contrast adjustment technique at the pre-processing stage (no-pre-processing technique).

The contrast adjustment technique is used to get a new image with better contrast than the contrast of the original image. A low contrast image may occur due to lack of illumination, lack of dynamic field of the image sensor, or errors in the setting of the lens opener during the image capture process. The use of contrast adjustment technique is intended to increase the dynamic field of gray level in the image to be processed.

2.3 Datasets

The experiments in this research used 3 standard face image databases that are widely used by researchers in the field of face recognition i.e. CMU-PIE Face Database, Extended Yale Face Database B [13], and AR Face Database. The face images used in the experiment are the frontal images (front view) with the neutral expression. This experimental approach is performed according to the characteristic of the Robust Regression Method effectively used in relation to the illumination factor.

2.3.1 CMU-PIE Face Database

The CMU-PIE Face Database contains 68 individuals with 13 positions, 4 expressions, and 21 illumination variations. The original image size is 640×486. In the Robust Regression approach, each face image is downsampled to 50×50. In this research experiment, some images of each individual become training data and some other images become testing data in accordance with evaluation techniques that are also used in many other studies including the previous Robust Regression research.

In the research, the image data used consists of 68 individuals with 1 position (frontal position), 1 expression (neutral expression), and 21 variations of illumination. Figure 1 shows the illumination variation on one individual at the CMU-PIE Database with the frontal position.

Fig.1 One of the individual in illumination variation at CMU-PIE Database with frontal view

2.3.2 Extended Yale Face Database B

The Extended Yale Face Database B is a face image database developed from Yale Face Database B, with more individuals and changes in illumination variations. The database consists of 38 individuals and 64 illumination conditions per individual. The original image size is 168×192. In the research, the image data used consists of 38 individuals with 1 position (frontal position), 1 expression (neutral expression), and 64 variations of illumination. Figure 2 shows the illumination variations on one individual at the Extended Yale Face Database B with the frontal position.

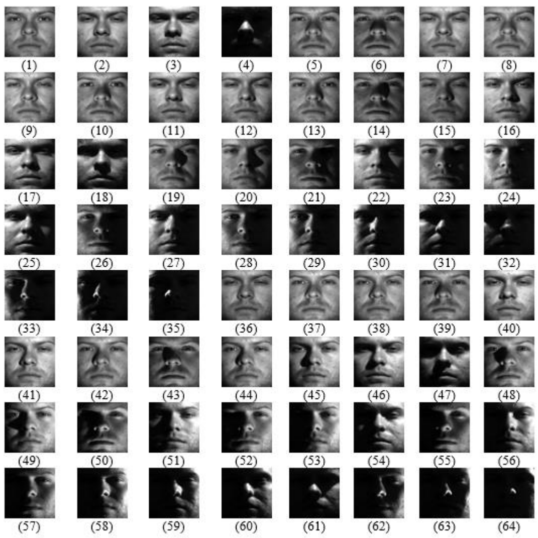

Fig.2 One of the individual in illumination variation at Extended Face Database B with frontal view

2.3.3 AR Face Database

The AR Face Database consists of 126 individuals with 26 conditions (variations of illumination, expression, and addition of accessories). In the research, facial images used are frontal images with neutral expressions and 8 image conditions that are affected by variations of illumination. Figure 3 shows 8 illumination variations from one individual.

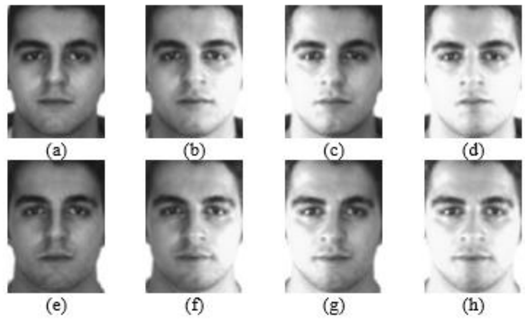

Fig.3 One of the individual in illumination variation at AR Face Database with frontal view

2.4 Evaluation Techniques

The evaluation technique in the research is a testing technique in the process of the empirical experiment which is used to measure the accuracy level of a face recognition method that has been determined and used in various studies on the same problem domain. This evaluation technique is different for each image database.

Table 1 Evaluation Technique on the CMU-PIE Database

Evaluation Techniques	Training Images	Testing Images
1a	5, 6, 7, 8, 9, 10, 11, 18, 19, 20	All Images
1b	5, 6, 7, 8, 9, 10	All Images
1c	5, 7, 9, 10	All Images
1d	7, 10, 19	All Images
1e	8, 9, 10	All Images
1f	18, 19, 20	All Images
2a	3, 7, 16	All Images
2b	1,10, 16	All Images
2c	2, 7, 16	All Images
2d	4, 7, 13	All Images
2e	3, 10, 16	All Images
2f	3, 16	All Images

The evaluation techniques in the CMU-PIE Database are shown in table 1. There are 2 experimental techniques performed. In the experimental technique 1, the training process is performed on images with frontal lighting conditions (light source from the front of the picture) and the testing process is performed on all images, as shown in the evaluation technique 1a-1f. Whereas in the experimental technique 2, the training process is carried out on images with extreme lighting conditions and the testing process is performed on all images, as shown in the evaluation technique 2a-2f.

In the Extended Yale Face Database B, Evaluation Techniques are performed on the images grouped into 4 subsets (subset 1-4). Subset 1 consists of images that receive light from the lighting angle of 0-25°. Subset 2 consists of images that receive light from the lighting angle of 26-50°. Subset 3 consists of images that receive light from the lighting angle of 51-77°. Whereas subset 1 consists of images that receive light from the lighting angle >77°. The evaluation technique is carried out in the following way: the training process is performed on subset 1 drawings and the testing process is performed on the other subset images (subset 2-4), as shown by table 2.

Table 2 Evaluation Technique on the Extended Yale Face Database B

Evaluation Techniques	Training Images	Testing Images
1	Subset 1	Subset 2
2	Subset 1	Subset 3
3	Subset 1	Subset 4

Table 3 Evaluation Technique on the AR Face Database

Evaluation Techniques	Training Images	Testing Images
1	1, 14	5, 6, 7, 18, 19, 20
2a	1	5, 6, 7
2b	14	18, 19, 20
3a	1	5
3b	1	6
3c	1	7

Experiment in the AR Face Database is performed on each individual with 8 illumination variations divided into 2 sessions (each session consisting of 4 images). Based on figure 3, session 1 includes the image of types (a)-(d) and session 2 covering the images of type (e)-(h). There are 3 techniques used for evaluating. In the evaluation technique 1, as shown in table 3 (evaluation technique 1), the training process is performed on images of type (a) and (e), while the testing process is performed on images of type (b), (c), d), (f), (g) and (h). In evaluation technique 2, as shown in table 3 (evaluation techniques 2a and 2b), the training process is performed on images of type (a) or (e) images. While the testing process is done on images of type (b), (c), and (d) for training images of type (a) and images of type (f), (g), and (h) for training images of type (e). In evaluation technique 3, as shown in table 3 (evaluation techniques 3a, 3b, and 2b), the training process is performed on images of type (a). While the testing process is done on images of type (b) or (c) or (d).

3. RESULTS

In the research, several techniques of Contrast Adjustment are used in the pre-processing stage of the Robust Regression method for face recognition. There are 3 techniques of Contrast Adjustment used, i.e. Histogram Equalization (Histeq function), Contrast-limited Adaptive Histogram Equalization / CLAHE (Adapthisteq function) and Imadjust function. An empirical experiment was conducted to compare the face recognition performance of the Robust Regression method using some of the Contrast Adjustment techniques in its pre-processing. The testing is also done by eliminating pre-processing techniques. The experiment is done using CMU-PIE Face Database, Extended Yale Face Database B, and AR Face Database.

The experiment results of the research on the CMU-PIE Face Database are shown in Table 4(a) and 4(b), where the use of Adapthisteq technique produces the best performance of face recognition, better than the use of other techniques.

Table 4(a) The Experiment Results on the CMU-PIE Face Database

Evaluation Techniques	Histeq Technique	Adapthisteq Technique
1a	100 %	100 %
1b	99.41 %	100 %
1c	99.85 %	100 %
1d	99.93 %	100 %
1e	99.41 %	100 %
1f	100 %	100 %
2a	100 %	100 %
2b	100 %	100 %
2c	100 %	100 %
2d	100 %	100 %
2e	100 %	100 %
2f	99.93 %	100 %
Average Accuracy	99.88 %	100 %

While the experiment results of the research on the Extended Yale Database B are shown in Table 5(a) and 5(b), where the use of Adapthisteq technique also produces the best performance of face recognition, better than the use of other techniques.

Table 4(b) The Experiment Results on the CMU-PIE Face Database

Evaluation Techniques	Imadjust Technique	Without Pre-processing
1a	100 %	100 %
1b	99.86 %	99.86 %
1c	99.86 %	99.44 %
1d	95.45 %	86.27 %
1e	99.86 %	99.86 %
1f	100 %	100 %
2a	100 %	100 %
2b	100 %	99.93 %
2c	100 %	99.93 %
2d	100 %	100 %
2e	100 %	99.93 %
2f	99.86 %	98.74 %
Average Accuracy	99.57 %	98.66 %

Table 5(a) The Experiment Results on the Extended Yale Database B

Evaluation Techniques	Histeq Technique	Adapthisteq Technique
1	99.89 %	100 %
2	94.92 %	99.44 %
3	93.68 %	94.74 %
Average Accuracy	96.17 %	98.06 %

Table 5(b) The Experiment Results on the Extended Yale Database B

Evaluation Techniques	Imadjust Technique	Without Pre-processing
1	98.79 %	98.46 %
2	92.67 %	96.99 %
3	81.05 %	89.47 %
Average Accuracy	90.84 %	94.97 %

The last, the experiment results of the research on the AR Face Database are shown in Table 6(a) and 6(b). The same as the experimental results on the CMU-PIE Face Database and the Extended Yale Database B previously, the use of Adapthisteq technique on the AR Face Database also produces the best performance of face recognition that the use of other techniques.

Table 6(a) The Experiment Results on the AR Face Database

Evaluation Techniques	Histeq Technique	Adapthisteq Technique
1	90.33 %	96.00 %
2a	86.00 %	95.33 %
2b	91.00 %	92.67 %
3a	87.00 %	97.00 %
3b	80.00 %	95.00 %
3c	91.00 %	94.00 %
Average Accuracy	87.56 %	95.00 %

Table 6(b) The Experiment Results on the AR Face Database

Evaluation Techniques	Imadjust Technique	Without Pre-processing
1	84.50 %	88.00 %
2a	79.33 %	86.33 %
2b	86.33 %	86.67 %
3a	82.00 %	88.00 %
3b	79.00 %	87.00 %
3c	77.00 %	84.00 %
Average Accuracy	81.36 %	86.67 %

Table 7(a) The comparison of Experiment Results

Evaluation Techniques	Imadjust Technique	Without Pre-processing
CMU-PIE Face Database	99.88 %	100 %
Ext Yale Face B	96.17 %	98.06 %
AR Face Database	87.56 %	95.00 %
Average Accuracy	94.53 %	97.69 %

Based on experimental results in the research on 3 standard face databases, as shown in table 4(a), 4(b), 5(a), 5(b), 6(a) and 6(b), the average accuracy of face recognition is calculated to determine which technique shows the best result, as shown in table 7(a) and 7(b). Based on table 7(a) and 7(b), the use of the Adapthisteq technique produces the best performance of face recognition, better than the use of other techniques (Histeq technique, Imadjust technique, and no-pre-processing technique).

Table 7(b) The comparison of Experiment Results

Evaluation Techniques	Imadjust Technique	Without Pre-processing
CMU-PIE Face Database	99.57 %	98.66 %
Ext Yale Face B	90.84 %	94.97 %
AR Face Database	81.36 %	86.67 %
Average Accuracy	90.59 %	93.43 %

4. CONCLUSION

Based on the experiments conducted in this research, the use of Adapthisteq function (CLAHE technique) in the pre-processing stage of the Robust Regression method produces the highest average accuracy (97.69%), better than using Histeq technique that produces average accuracy of 94.53% or Imadjust technique (90.59%) or without pre-processing (93.43%). Thus, the use of the Adapthisteq function (CLAHE technique) in the pre-processing stage of the Robust Regression method for face recognition is recommended more than any other pre-processing technique.

However, this conclusion needs to be reexamined on other face recognition methods, whether showing the same or not the same results, that can be done in future research.

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