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IMAGE PREPROCESSING WITH SYMMETRICAL FACE IMAGES IN FACE RECOGNITION AND REGRESSION CLASSIFICATION

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ABSTRACT: Face recognition with variations in lighting is a significant thing than the physical characteristics of each individual in facial recognition problems. The difference in illumination from the right and left can affect the face image. A face image is an axis-symmetrical object. There are many studies on face recognition, but only a little attention is paid to this issue and few studies to explore and exploit the axis-symmetrical property of faces for face recognition are conducted. In this paper, we take the axis-symmetrical nature of faces then take the side of the face that is not exposed to dark light for pre-processing that will then be done by robust regression classification. The results of this experiment got an average accuracy of 92.8%. Using the proposed method on data with a 51 to 77- degree illumination angle produces better accuracy.

Keywords: Preprocessing, Face Recognition, Symmetrical Face, Regression Classification

1. INTRODUCTION

Biometric system is a recognition technology by using body parts or human behavior that has uniqueness. Biometric identification is based on the natural characteristics of humans, namely physiological characteristics such as the face, fingerprint, voice, palms, and eye retina. Biometric identification has the advantage of not being easy to use by unauthorized users. Biometric identification is owned by one person and not the same as another. In information technology, biometrics usually refers to technology to measure and analyze the characteristics of the human body to be used as an authentication process. Biometric systems become an option to recognize a person's identity e.g. face. The face can identify a person. The face is a dynamic object that has a high level of variability [1]. One part of the widely used biometric system is facial recognition. Facial data is relatively easy to get just by using the camera.

Face recognition is one of the most popular issues in the field of pattern recognition, computer vision, etc. Face recognition with the most challenging illumination variations and important issues in face recognition. Variations caused by lighting are a matter more significant than the individual's own physical features[2]. Lighting variations reduce face matching performance and face detection accuracy. Lighting the image is the first step in a face recognition system [3]. Various methods have been proposed to perform face recognition with poses, illuminations, and facial expressions to reduce the disadvantageous effect on face recognition[4]. In a few years, researchers have found several ways in facial recognition with variations of illumination. The shape of the symmetrical face image is useful to overcome the various poses and illumination problems [5].

Various lighting conditions have two approaches to this problem. it's model-based, and preprocessing based[6]. The model-based approach makes an attempt to model the light variation. This approach requires a large amount of training data and sometimes fail when there is a complicated lighting configuration[7]. The preprocessing-based approach using preprocessing for removes lighting influence effect without any additional knowledge. Pre-processing based will change the image directly without assumptions or prior knowledge. Therefore, they are usually used in practical systems for their simplicity and efficiency[7]. Some traditional pre-processing method such as histogram equalization (HE), histogram specification (HS), logarithm transformation (LOG), Gamma Intensity Correction (GIC) and self-quotient image (SQI) [8] have been proposed recently with impressive performance improvement for illumination problem.

Face symmetry perception is critical for identifying in the social environment. In general, the face has a symmetrical structure. All human faces are objects that have similar, symmetrical, two eyes, a nose, and a mouth aligned in a fixed arrangement. When humans recognize faces often utilize facial geometry information. Not only the facial structure but also the facial expression is symmetry[9]. The symmetry property has been successfully applied to face detection[10]. In face detection, the symmetry property of the human face is very useful to quickly locate the candidate's faces. The faces have a symmetry section between right and left if it is divided into exactly two parts at the midpoint. In other words, the left-half face is almost always the "mirror image" of the right-half face. Some face recognition algorithms have used the symmetric structure of the face to solve this problem. It has been proven that the performance of some tasks such as face recognition can be developed using the symmetric structure of the face[11].

Many approaches have been taken to solve this facial recognition problem. One of them is the Robust Regression. Robust Regression is the basic concept of a class model from a set of facial images in a linear subspace. Robust Regression develops a linear model of the test image to be recognized as a linear combination of the training images. Robust Regression is a classification algorithm for facial recognition problems in random pixels, which show better results than some other approaches. In the Robust Regression, the pre-processing stage using Histogram Equalization to normalize the illumination on the face image shows a fairly high degree of accuracy[12]. Histogram Equalization is a process of generalizing a histogram to distribute the gray level of an image. In this method will be used to widen the range of gray levels, thus increasing the contrast of the image. Some experimental results on the Robust Regression approach have resulted in better accuracy rates than other approaches. However, there are still some test results that show less accurate accuracy. However, this method still has some less accurate test results. So it is possible to do further development to get a better level of accuracy.

This paper proposes a method of pre-processing of facial images by exploiting symmetric facial geometry information. Assuming the face has a symmetrical side. The left half of the face is almost always a "mirror image" of the right face. This research uses images with symmetrical structures, which will be used in pre-processing and image classification. After pre-processing, the image will be classified using a robust regression method.

2. THE PROPOSED METHOD

Pre-processing image techniques have a very important role in face recognition systems, which have a major impact on the performance and reliability of facial recognition processes. Pre-processing illumination is an effective and efficient approach to overcoming illumination in face recognition. Combining image pre-processing can help improve the information obtained to facial images and also ensure that illumination effects on facial image extraction processes do not affect the nature of the face. Many pre-processing techniques can handle well if lighting is clear and flat but reduces performance when handling unbalanced and uncontrolled lighting. Some pre-processing methods that help the recognition process by minimizing extreme light. In this study, we use a symmetrical face function to help the process of face recognition with the impact of additional light or light coming from a certain angle

In this subsection, we will propose the results of this research as a pre-processing stage. In this study, this method represents a "symmetrical face image". The proposed method can be presenting an approximately axis-symmetrical face image from an original face image. This method can reduce the illumination effect on the uneven face lighting recognition with the assumption that one's face is the same between right and left.

This study uses image data from the Yale Face Database B 50x50. From Figure 1, there is unbalanced illumination between right and left. The distance between the left-half and right-half faces through the mid-point shows the distance differences between the left-half and right-half faces of the Yale face images shown in Fig.1

Fig.1 Original image from the Yale Face Database B 50x50 axis-symmetrical face image

An analysis is performed for the vertical line position to be used as a mirror line. In this research, the process of mirroring using the midpoint of the face is considered symmetry. The mirror line used as the reference of the mirroring process is the vertical line in the middle position based on the horizontal axis. The position of the mirror line based on the x-axis is obtained by using the following formula

$$MP = Round\ (CW/2) \quad (1)$$

Where MP is the position of Mirror based on the x-axis which is the midpoint of the x-axis. CW is Citra-Width which is the size of image length based on the horizontal line or x-axis.

MP value will be used as a reference line to reflect the new matrix. The face matrix with dark lighting will be replaced with a bright face matrix with the assumption that the face image is symmetry.

Researchers observe ordinary mathematical models to find 2-dimensional image symmetry. This experiment considers the face as a square shape in 2-dimensional images. This research divides the two parts vertically, it will be divided into two identical parts. This method is shown in Fig. 2.

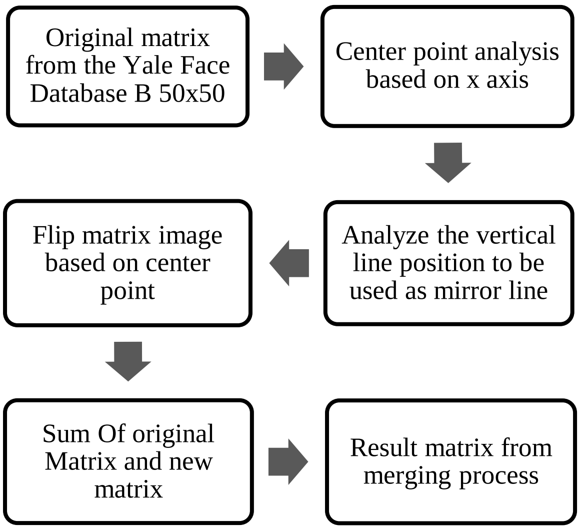


Fig. 2 Steps on this method

The image of the proposed method will be used as a dataset for robust regression classification.

3. ROBUST REGRESSION

Simple linear regression analysis is a linear correlation between one independent variable (X) and a dependent variable (Y). This analysis is to identify the relationship between independent variable with dependent variable either positive or negative. Equation 2 shows linear regression model.

$$Y = bX + e \tag{2}$$

Where Y is the dependent variable, b is regressor or predictor variable, the independent variable is X, and error term is e. The problem of robust estimation is to estimate the vector of parameters $\hat{X}$ so as to minimize the residual

$$r = a - \hat{a}\ ;\ \hat{a} = b\hat{X} \tag{3}$$

$\hat{a}$ is the predicted response variable. In statistics, the error term e is conventionally taken as a noise. However, M-estimators have shown superiority due to their generality and high breakdown point. Primarily M-estimators are based on minimizing a function of residuals

$$\hat{X} = \arg\min\{Y\hat{X} = \textstyle\sum_{i=1}^{j} \rho(r(\hat{X}))\} \tag{4}$$

Where $\rho(\gamma)$ is a symmetric function with a unique minimum at zero[14]:

$$\rho(\gamma) = \begin{cases} \frac{1}{2\text{ɣ}}\gamma^2 \\ |\gamma| - \frac{1}{2}\text{ ɣ} \end{cases} \tag{5}$$

ɣ is tuning constant called the Huber threshold. Many algorithms have been developed for calculating the Huber M-estimate in Eq. (5).

This method utilizes pattern recognition with linear regression to solve facial recognition problems. The basic concept of this method has a class model of a set of facial images in a linear subspace. The linear model of the test image should be recognized as a linear combination of the training image. Training image and test image used are small dimension image. This problem is solved by using the Robust Regression Classification. This method uses Huber's estimation to determine its class.

The face image will be represented as a small-dimensional vector in *a x b* space. The small-dimensional vector must be able to represent the face of each subject as well. Two different facial images are from the same person should be recognized as the same class[12].

Training phase in this method will produce a predictor for each class. For image, *a x b* is converted grayscale process for each image *m*. The m image will be changed down-sample process to reduce the number of pixels resulting in a smaller size. The down-sample result is converted into a vector *w (i, m)*. Each vector image will be normalized image *w (i, m)* so that the maximum value of a pixel is 1. Thereafter for each class i are joined the vectors *w (i, m)* into *X (i) = [w (i, 1) w (i, 2) ... w (i, p (i))]* where *p (i)* Is the amount of image data trained for class *i*. From the composite, it will produce a predictor for each class *X (i).*

The second stage is called testing which aims to classify test data into one class using a model (predictor) that has been built in the training phase. In testing, the z-face image with *a x b* size is changed to grayscale and down-sample process. Next from the image is converted into vector *y.* The image matrix will be normalized so that the maximum value of the pixel is 1. Using the *X (i)* predictor of each class from the training stage results, the matrix regression will be performed with the vector image testing using Huber estimation. The general equation of the linear model

$$Y = X(i) * \beta(i) \tag{6}$$

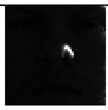
For each class i, a prediction of response vector will be generated where the predicted image *ypred(i) = X(i)*β(i).* For each class i, estimate the value of *β (i)* using Robust Huber.

After the prediction of the response vector where the predicted image *ypred(i) = X(i)*β(i).* Then the predicted *ypred(i)* image will be calculated by the distance between the input image y and the predicted image *ypred(i)* for each class i is generated *d(i) =||y-ypred(i)||.* So we will get the prediction of the class of image y with the smallest distance *arg min i(d(i)).*

4. EXPERIMENTAL EVALUATION

The data used in this study is Yale Face Database B 50x50. Yale Face Database B 50x50 is a dataset consisting of facial image data taken with various lighting conditions. Facial image used is a face image taken with a straight position to get the image of the face right in the middle. Yale Face Database B 50x50 consisted of 10 individuals and 64 Illumination conditions per individual.

Table 1 Example one of the illumination variations

Subset 1		
Subset 2		
Subset 3		
Subset 4		
Subset 5		

This research uses Yale Face Database B 50x50 image data with some lighting conditions and angle shown in Fig. 3. Some pictures on Yale Face Database B 50x50 have poor lighting so the facial image is only partially visible and part of the other image is dark. This dataset requires several different scenarios due to different lighting conditions and angles. The test scenario at Yale Face Database B 50x50 is based on the number and angle of illumination shown in Table 2.

Table 2 Divide the subset image data for the test scenario

Subset Image	1	2	3	4	5
Image Number	01-07	08-19	20-31	32-45	46-64
Angle of Degree	0-12	13-25	26-50	51-77	>77
Sum Of Images	7	12	12	14	19
Scenario	Train	Test	Test	Test	Test

Experiments in this study were conducted with several stages of training and trial process. The training process uses a subset of Figure 1 where the angle of lightning is 0 to 12 degrees. The testing process uses subset 2, subset 3, subset 4, and subset 5 which has a lightning angle of more than 77 degrees. Subset 5 has the most extreme lighting than any other subset shown in Table 1.

This research proposes pre-processing to improve image data using symmetric reflective methods. Assuming the image used actually divides the frame into two equal parts between the left and right sides. The image data used is a gray image with a two-dimensional matrix.

The process in this study begins with the process of reading image data. Image data used has some angle of lighting. The next process reads the image, next the process is continued by identifying the gray value stored in each matrix element. The image size identification process is performed to analyze the vertical line position to be used as a mirror line. In this research, the mirroring process uses all parts of the image either the right or left of the image. The mirror line used as the reference of the mirroring process is a vertical line in the middle position based on the horizontal axis. The vertical line value will be used as the reference line to mirror so that a new matrix will be obtained. The new matrix value of the mirroring result is the flip of the original matrix corresponding to the vertical line. The proposed method can be seen in the example matrix A.

$$A = \begin{bmatrix} 1 & 2 & 3 & 4 & 5 & 6 \\ 6 & 5 & 4 & 3 & 2 & 1 \\ 1 & 2 & 3 & 3 & 2 & 1 \end{bmatrix}$$

Matrix A obtains the midpoint 3.5, so that point becomes a vertical line for reflection. The reflection result will be shown in matrix B.

$$B = \begin{bmatrix} 6 & 5 & 4 & 3 & 2 & 1 \\ 1 & 2 & 3 & 4 & 5 & 6 \\ 1 & 2 & 3 & 3 & 2 & 1 \end{bmatrix}$$

A new matrix B has been obtained. The next process is matrix A and B are combined. The merging process is by doing the sum of the matrices. The matrix A and B are summed to obtain the matrix C as the new value matrix of the image.

$$\left.\begin{matrix} \begin{bmatrix} 1 & 2 & 3 & 4 & 5 & 6 \\ 6 & 5 & 4 & 3 & 2 & 1 \\ 1 & 2 & 3 & 3 & 2 & 1 \end{bmatrix} \\ + \\ \begin{bmatrix} 6 & 5 & 4 & 3 & 2 & 1 \\ 1 & 2 & 3 & 4 & 5 & 6 \\ 1 & 2 & 3 & 3 & 2 & 1 \end{bmatrix} \end{matrix}\right\} \boldsymbol{C} = \begin{bmatrix} \mathbf{7} & \mathbf{7} & \mathbf{7} & \mathbf{7} & \mathbf{7} & \mathbf{7} \\ \mathbf{7} & \mathbf{7} & \mathbf{7} & \mathbf{7} & \mathbf{7} & \mathbf{7} \\ \mathbf{2} & \mathbf{4} & \mathbf{6} & \mathbf{6} & \mathbf{4} & \mathbf{2} \end{bmatrix}$$

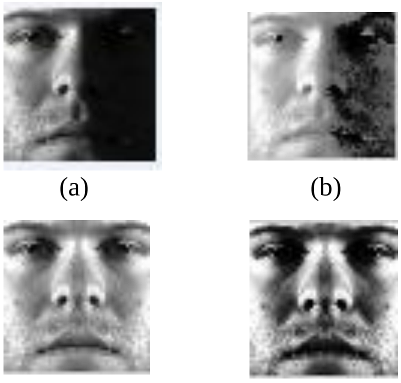
Figure 3 shows the results of the merging process of one of the data on Yale Face Database B 50x50. Figure 3 (a) is the original image of a dataset having a partial dark side. Figure 3 (b) is the image of the result of the proposed method. In Figure 3 can be seen a new image that has a balanced illumination level on the left and right. Figure 3 (b) is the result of the symmetrical face process. The original image has a dark part on the left side and a mirroring process is done to reduce the dark side. This process can be done with the assumption that the face has a symmetrical side between the right and the left.

(b) (a)

Fig. 3 (a) Original image, (b) Results of the proposed method

The results of the proposed method will be used as the dataset of the facial recognition process. Image data will be processed with Histogram Equalization (HE) to obtain optimum lighting values. Equalization Histogram is a generalization process of the histogram to flatten the distribution of gray images. HE is used to obtaining a uniform spread of histograms, so each degree of gray has a relatively equal number of pixels. This method will be used to widen the range of gray levels, thus increasing the contrast of the image.

This experiment will compare the results of the linear regression classification using the original image and image data from the proposed method. Figure 4 shows the difference between the original image and the image with the proposed method. Figure 4 (a) is the original image from Yale. Figure 4 (b) is an original image with a pre-processing HE. Figure 4 (c) is the proposed method of "symmetrical face images". Figure 4 (d) is symmetrical face images with pre-processing HE.



(a) (b)

(c) (d)

Fig. 4 (a) original image, (b) original image with histogram equalization, (c) the proposed method “symmetrical face images”, (d) symmetrical face images with histogram equalization

Figure 4 (a) is an original image having a different illumination seen as one part having a dark side. Figure 4 (d) uses the proposed method "symmetrical face images" and HE produces a clearer picture output and can minimize the dark side of the face.

Table 3 shows the results of this experiment comparing accuracy using original images and symmetrical face images. Each subset has varying results depending on the angle of the illumination. Subset 4 contains images with a 51-77 degree illumination angle and different illumination between the right and left sides. Subset 4 obtained 93.5% accuracy using image data from the proposed method. The result is better than the classification with the original image.

The average accuracy of all test subsets using the proposed method has a better accuracy of 92.8% compared to the original image classification having 89.2% accuracy. Table 3 shows an improved face recognition accuracy process. This experiment uses robust regression classification as the core process and HE as pre-processing. This study uses 2 image data that is the original image and image of the proposed method called symmetrical face images. Table 3 shows that the proposed method can improve face recognition results in straight and symmetrical face data. The proposed method consistently has high accuracy results for all experiments.

Table 3 Average Accuracy (%) on the Yale Face Database B 50x50

Subset Image	Original Image with HE	Symmetrical Face Image with HE
Subset 2	100	100
Subset 3	95	100
Subset 4	72.1	93.5
Subset 5	90	77.8
Average	89.2	92.8

The test scenario on that subset can be seen in the graph shown in Figure 5. Figure 5 shows the accuracy of the images using the symmetrical face better than the original image except for subset 5.

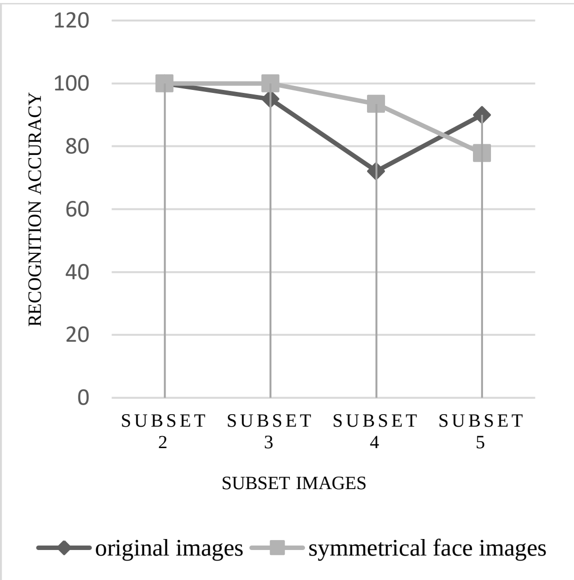


Fig. 5 Performance curves for the Yale Face database B 50x50

Table 3 and Figure 5 show that the proposed method has a better accuracy rate than the original image data except subset 5. Subset 5 has an illumination angle of more than 77 degrees. This angle has an extreme illumination so the whole face looks dark. The proposed method has high accuracy if the data used has unbalanced illumination between right and left. Subset 5 has lower accuracy because the original image is dark overall so the method is not very influential.

5. CONCLUSION

Experiments using image data from the proposed method have a better average accuracy of 92.8% compared to the original image having an accuracy of 89.2%. The proposed method works very well for image data that has a 51 to 77-degree illumination angle. This method removes half the dark face and replaces it with half the face that looks bright by employing a symmetrical facial image.

6. ACKNOWLEDGMENTS

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