International Journal of Soft Computing 11 (1): 36-44, 2016
ISSN: 1816-9503

Face Recognition System for Blur Image Using Backpropagation Neural Networks Approach and Zoning Features Extraction Method

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Abstract: Applications of face recognition systems have been fairly well-established. However, since Facial Image Recognition System basically depends on the source images as object recognition and methodology, good analysis results from abnormal images containing a blur or noise have still problems. It is therefore, important to develop efficient method to recognize these abnormal images. To analyze the abnormal image, we used introduction of Backpropagation Neural Networks called BNN. Prior to using BNN approach, segmentation as pre-processing and image extraction using zoning method through filtering, grayscaling, thresholding and zoning calles FGTZ were conducted. To confirm the effectiveness of our study, blur images were varied from level 1-5 with 10 variations including variations of poses and lighting. The results showed that pre-processing techniques and extraction methods can generate representative facial features whereas the overall of system containing various blur levels and poses can distinguish well between male and female. Further, the system developed has been successfully recognize faces with an average accuracy above of 79% under various blur levels and variation poses.

Key words: Recognition approach, exstaction methods, blur levels, variaty poses, effectiveness

INTRODUCTION

Recently, face recognizition system has been well-known for detecting or analyzing image which has been applied for Closed-Circuit Television (CCTV) and system login. Although, this system has been already established, there are still several limitations. The system basically depends on image sources as object recognition and methodology. Therefore, quality of the system is determined by various factors such as lighting, motion and distance (Bayesian and Liu, 2007). Good recognition rate will be gained only when using normal face recognition without any noise. In fact, the common tools (such as CCTV) as a receptor for getting face image cannot avoid either blur or noise (Shapiro and Stockman, 2001). It is therefore, important to develop an effiecient method to recognize image from abnormal images that containing blur and noise.

To meet the demand for minimizing the effect of blur and noise, many techniques have been reported. Face recognition using segmentation and Pulse-Coupled Neural Networks, the results arepart of the face can be easily distinguishable (Ranganath and Kuntimad, 1994). Face recognition with translation, rotation, scale, distortion and intensity invariance have not been successful (Johnson, 1994a). Face recognition in a complex back ground using motion and color information showed better results than the previous studies. While (Lee *et al*., 1996). However, from the current method, some weaknesses still persist: the level of illumination, the shadow of another object, changes inpose and limitation recorder (Fairman *et al*., 1994). Therefore, it is important to develop efficient techniques to identify abnormal images.

This study reported a new technique for recognizing blur images using Backpropagation Neural Networks (BNN) Method. Prior to using BNN Method, we used segmentation of pre-processing and image extraction step using Filtering, Grayscaling, Thresholding and Zoning (FGTZ) were conducted. The aim of filtering, grayscaling, thresholding and zoning are for reducing blur or noise, converting red greed and blue color to grayscale, converting to binary and producing a unique of facial features. Different from other methods, our technique was simpler to isolate main image from background without eliminating essential information such as facial characteristics. We also found that the ability of face recognition system is also determined by the features of the face that will be used in the process of categorization or recognition. The more unique feature of the face, the better the performance of the system.

Filtering: The filter method used is a Gaussian filter which is based on previous studies that the optical image noise can be approximated by a Gaussian models

(Shapiro and Stockman, 2001). The 1D Gaussian filter having impulse response expressed by the following function:

$$g(x) = \frac{\sqrt{a}}{\pi} . e^{-\alpha x^2} \quad (1)$$

The frequency response is given by the Fourier transform here:

$$g(f) = e^{-\frac{\pi^2 f^2}{\alpha}} \quad (2)$$

where, f is the natural frequency. Equation 2 can be expressed by the standard deviation of the parameters as follows:

$$g(x) = \frac{1}{\sqrt{2\pi . \sigma}} . e^{-\frac{x^2}{2\sigma^2}} \quad (3)$$

and the frequency response can then be expressed as Eq. 4:

$$\hat{g}(x) = e^{-\frac{f^2}{2\sigma f^2}} \quad (4)$$

By writing α of Eq. 2 as functions σ and equations $g(x)$ for and as a function σ_f. The two equations to $\hat{g}(f)$ can be shown that the dot product of the standard deviation and the standard deviation in the frequency domain is expressed as Eq. 5:

$$\hat{\sigma} . \sigma_f = \frac{1}{2\pi} \quad (5)$$

where, the standard deviation is expressed in physical units, for example in terms of time and frequency in seconds and hertz. In 2D, it is the product of two Gaussians where each one for each direction become Eq. 6:

$$g(x, y) = \frac{1}{2\pi\sigma^2} . e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (6)$$

Where:

x = The distance of the point of origin in the horizontal axis
y = The distance of the point of origin on the vertical axis
σ = The standard deviation of the Gaussian distribution
G(x, y) = The pixel blur on the x and y coordinates in the image

The value of the standard deviation σ in the Gaussian filter determines the amount removed frequency by the filter. The larger value of σ, the greater frequency is wasted and the opposite (Gao, 2003).

Grayscalling: Grayscalling is conversion procces of pixels from initial image with different variations of the value of RGB (Red, Green and Blue) into gray image. Image of grayscale image is a single sampleof each pixel, the intensity information with variations gradation 0-255. To convert a color from the color space based on the model RGB into grayscale representation, calculated in linear RGB space as Eq. 7 is 128 (Johnson, 1994b):

$$C_{linear} = \begin{Bmatrix} \frac{C_{linear}}{12.92} & C_{argb} \le 0.04045 \\ \left(\frac{C_{argb}+0.055}{1.005}\right)^{2.4} & C_{argb} > 0.04045 \end{Bmatrix} \quad (7)$$

where, C_{srgb} is one of three RGB (R_{srgb}, G_{srgb} and B_{srgb}, each in the range [0, 1]) and C_{linear} corresponding to intensity values (R, G and B in the range [0, 1]). Then, the lighting is calculated as a sum of weigh of three linear intensity values. RGB color space is defined in the CIE (Commission Internationale de l'Eclairage) 1931 linear luminance Y which is expressed as Eq. 8 (Paola and Schowengerdt, 1997):

$$Y = 0.2126R + 0.7152G + 0.0722B \quad (8)$$

The constant indicates the size of a typical human perception of intensity, depending on the components used in particular, human vision is most sensitive to green color and are less sensitive to blue. To encode the grayscale intensity in linear RGB each of the three components can be adjusted to match the Y linear lighting (replacing the R, G, B by Y to obtain a linear grayscale). A linear luminance usually requires gamma compressed to get a conventional non-linear representation (Paola and Schowengerdt, 1997). For RGB, each of the three axes are arranged with the same gamma-compressed Y_{srgb} given by the inverse gamma expansion above as follows:

$$Y_{argb} = \begin{Bmatrix} 12.92Y & Y \le 0.0031308 \\ 1.055Y^{1/2.4}\text{-}0.055 & Y > 0.003130 \end{Bmatrix} \quad (9)$$

In practice, because of the three RGB components are the same, it only needs to store all the values in RGB-compatible format that supports the single channel representation. Web browsers and other software that accepts RGB images usually produce the same arrangement as grayscale images because it has the same value in all color channels.

Thresholding: Thresholding is the process of converting a gray image into a black and white imageor binary image can be written mathematically as follows:

$$g(x, y) = \begin{cases} 1 & \text{if} \quad f(x, y) \geq T \\ 0 & \text{if} \quad f(x, y) < T \end{cases} \tag{10}$$

With g (x, y) is a binary image from a grayscale image f (x, y) and T is the threshold value. Thresholding the image is a simple but effective way to isolate objects in binary image. This technique need to consider the threshold value based on some similarities between the original image and the the binary image version. This attribute can clarify edge shape, sharpness or one that can generate a grayscale image similar to the binary.

Zoning: Zoning technique to perform facial feature extraction to retrieving information that most relevant to be categorized in a way to minimize the variation between patterns in same category and maximize the variation between raw data available in different categories (Mori *et al*., 1992).

Zoning extraction method calculate the percentage of black pixels of an area (Suen *et al*., 1994). For example, the 5×7 area zoning method an image which is initially sized 35×35 pixels, so it is only compacted into 5×7 areas where each area consists of 5×7 pixels. With the implementation of this method, the original image size of 35×35 pixels and has a pixel value of information as much as 1,225 pieces into a 5×7 area is represented only by the number of 35 pieces of information. This will reduce the amount of information that must be included in the initial BNN without losing information contained on the original image (Suen *et al*., 1994). With the lower left corner as the origin (0, 0), the phase angle of each pixel at (x, y) is calculated as follows:

$$\theta = \tan^{-1}\left(\frac{y}{x}\right) \tag{11}$$

A feature value calculated from the pixel values to produce a unique contribution. For example, feature box with the bottom left corner as (0, 0), the coordinates for the pixel distance k in bth box at location (i, j) is calculated as follows:

$$d_k^b = (i^2 + j^2)^{1/2} \tag{12}$$

If the sum of the distances of all black pixels divided by the total number of pixels as features (λ) for each of the following boxes:

$$\lambda = \frac{1}{N}\sum_{k=1}^{n_b} d_k^b \tag{13}$$

Where:
N = The total number of pixels of a box
n_b = The number of black (pattern) pixels in bth box

then, the box feature modification is calculated as follows:

$$\lambda_{mod} = \lambda\alpha\cos\theta \tag{14}$$

where, α is a multiplier factor taken as $\cos\theta$ range is 0 to 1, thus the average pixel density is calculated as follows:

$$\beta = \frac{1}{N}\sum_{k=1}^{n_b} \alpha\cos\theta \tag{15}$$

Where:
N = The total number of pixels in a box
n_b = The number of black (pattern) pixels in bth box

Backpropagation neural networks: Backpropagation Neural Networks (BNN) is a method to conduct a competitive learning layer in supervised (Dhaneswara and Moertini, 2004). In this method, each output unit represents a particular category or class. Learning or training process is done in advance by the given input vector will automatically classifiable. If several input vectors have a very close distance, then the input vectors will be grouped in the same class. After learning is finished, the next step is testing that is calculates the distance between testing input with the final weights respective of output classes. Class that has the closest distance to the input vector will be the winner (Ranganath *et al*., 1995). This is an architecture of Backpropagation Neural Networks (BNN).

Figure 1 is a model of architecture in this study has 35 nodes of input layer, 140 nodes of hidden layer and 20 nodes of output layer. Input units denoted by X, hidden units denoted by Z and output units denoted by Y. The weights between X and Z is denoted by v while the weights between Z and Y is denoted by w. Backpropagation network consists of two stages: learning or training stage which BNN given amount of training data and the target and the testing or aplication stage after BNN finished learning stage.

Training algorithm of BNN: Training algorithm is used to find the closest output to the input vector. The training consists of three steps: input data is inserted into the network (feed forward), calculation and propagation of the error and renewal (adjustment) weights and biases (Fausett, 1994). In feed forward, each unit of input (X_i) will receive an input signal and propagate to each hidden unit (Z_j). Each hidden unit then calculate the activation and

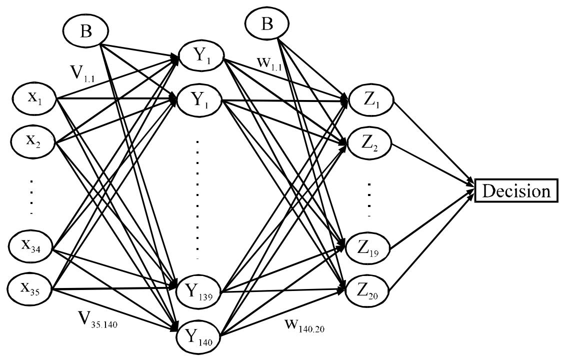

Fig. 1: Network architecture of BNN

send a signal (z_j) to output unit. Then, each output unit (Y_k) calculate the activation (y_k) to generate a response to a given input network. In the training process, each unit of output compare activation (y_k) with a target value (t_k) to determine value of the error. Based on this error, calculated factor δ_k where these factors are used to distribute the error from the output to the hidden layer. In the same way, δ_k factors also counted on hidden units Z_j where this factor is used to update the weights between the input layer and the hidden layer. After all factor δ is determined, the weight for all layers refurbished (Fausett, 1994).

Training steps:

Step 0: Initialize the weights and biases
Both of weights and biases can be set to any number (random) and usually numbers around 0 and or -1 (positive or negative bias)

Step 1: If the stopping condition is not fulfilled, execute steps 2-9

Step 2: For each training data, perform steps 3-8

Feed forward:

Step 3: Each unit of input (X_i, i = 1, ..., n) receives input signals x_i and propagate the signal to all units in the hidden layer. The input x_i is the training input data that has been scaled

Step 4: Each hidden unit (Z_j, j = 1, ..., p) will sum input signals that have been weighted including bias with:

$$z\_in_J - v_{oJ} + \sum_{i=1}^{n} x_i v_{ij}$$

and use an activation function to calculate the output signal of hidden units with:

$$Z_j = f(z\_in_j)$$

This output signal then sent to all units in the unit of output layer.

Step 5: Each unit of output (Y_k, k = 1, ..., m) will sum input signals that have been weighted including bias:

$$y\_in_k - w_{ok} + \sum_{j=1}^{p} Z_j w_{jk}$$

and use an activation function to calculate the output signal from the output unit with:

$$y_k = f(y\_in_k)$$

Backpropagation error:

Step 6: Each unit of output (Y_k, k = 1, ..., m) receive a targeted (expected output) to be compared with the output generated:

$$\delta_k = (t_k - y_k) f'(y\_in_k)$$

δ_k factors used to calculate the error correction (Δw_{jk}) which will be used to renew w_{jk} with:

$$\Delta w_{jk} = \alpha \delta_k z_j$$

It also calculated bias correction Δw_{0k} which will be used to renew w_{0k} with $\Delta w_{0k} = \alpha\delta_k$
δ_k factor then sent to the layer in front of hidden unit

Step 7: Each hidden unit (Z_j, j = 1, ..., p) sum input delta (which is sent from the layer in step 6) which has been weighted:

$$\delta\_in_j = \sum_{k=1}^{m} \delta_k w_{jk}$$

Then, the result is multiplied by the derivative of the activation function which is used to generate a network error correction factor δ_j where:

$$\delta_j = \delta\_in_j f'(z\_in_j)$$

δ_j factor is used to calculate the error correction (Δv_{ij}) which will be used to renew v_{ij} where:

$$\Delta v_{ij} = \alpha \delta_j x_i$$

It also calculated bias correction Δv_{0j} which will be used to renew v_{0j} where:

$$\Delta v_{0j} = \alpha \delta_j$$

Updates weights and biases:

Step 8: Each unit of output (Y_k, k = 1, ..., m) will renew bias and weight with each hidden unit, w_{jk}(baru) = w_{jk}(lama)+Δw_{jk}.
Similarly, for each hidden unit will renew bias and weight with each unit of input with:

$$v_{ij}(\text{new}) = v_{ij}(\text{old}) + \Delta v_{ij}$$

Step 9: Check the stopping condition
If the stop condition has been gotten then the network training stopped. To determine the stopping condition, commonly used is restrict iteration to do. If there are as many as m training data then to calculate the Mean Square Error (MSE) is used the following equation:

$$MSE = 0.5 \times \{(t_{k1} - y_{k1})^2 + (t_{k2} - y_{k2})^2 +, ..., + (t_{km} - y_{km})^2\}$$

MATERIALS AND METHODS

Face recognition system: Face recognition system developed consists of five modules that are reading the images, segmentation preprocessing, extraction, training of BNN, testing images, recognition results as shown in Fig. 2.

Source of images is a digital face image of the RGB Color Model (Red, Green, Blue) with extensions JPEG (Joint Photographic Experts Group). After segmentation

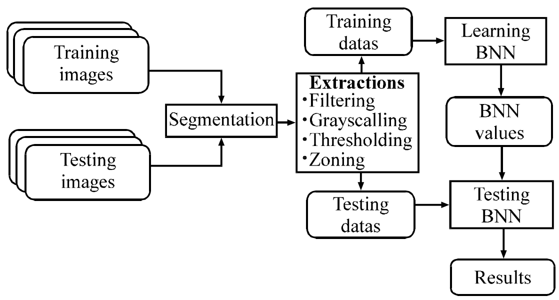

Fig. 2: Steps of research

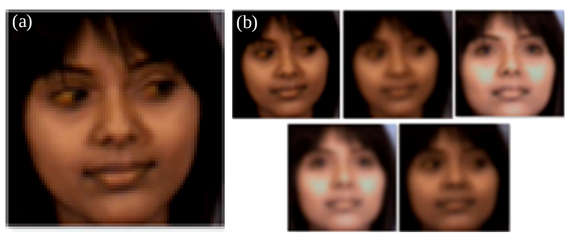

Fig. 3: a) Normal image and b) Blur and variations position image

Fig. 4: Face image with variation poses

pre-processing then extraction feature that consists Filtering, Grayscaling, Thresholding and Zoning (FGTZ) is done. Training process conducted for Backpropagation Neural Networks (BNN). Learning process produces parameter values BNN, especially weights to be used in the testing process.

Resources datas: The resources datas used in this study were taken from http://www.milbo.org/muct/. The data used in a number of 20 respondents (10 men, 10 women), each position or a variation on 10 different poses and 5 levels of blur (Fig. 3).

The order of 1-10 is the image of man and woman is the image sequence 11-20. Total of face image for 20 respondents are 1000 images. For training used 200 normal images (20 respondents×10 positions or poses). The size of the face image is determined automatically by cutting (segmentation) using Cascade Object Detectorre (Fig. 4).

RESULTS AND DISCUSSION

Preprocessing results: Figure 5 shows results of segmentation, filtering and grayscaling process. Figure 5a is the origin photograph image with the size is 480×480 pixels. After cutting method, the size of the segmentation process was 115×115 to 215×215 pixels. Actually, this image was used depending on the area of the face and still in RGB extension. Based on the present image, the resulting cutting image was about 15-32% of the original image. Figure 5b is the blur image segmetation result gained by separating or cutting face object from its background. This cutting method is used by Cascade Object Detector Method in which the aim was to produce face image size surrounding attributes of face.

Figure 5c is the image resulted from the filtering image. To get successful filtering process, we used Gaussian Model. Filtering is the process to remove noise or blur in the face image. In this study, the filter method using Gaussian Model. From several previous studies recommended that blur or noise from the optical image can be approximated with Gasussian Model (Haddad and Akansu, 1991). RGB filtering results are still shaped by the varied sizes ranging image filtering results appear more clear and assertive without losing information.

Figure 5d is the image resulted from grayscalling that is the process of changing the face of the RGB image into a gray. Originally, RGB face image matrix has a value of 3 layers namely the matrix R-G-B then converted into 1 layer matrix is a matrix grayscale. The resulting image is in the form of grayscale and more simple but not lose information needed. Grayscale form is also more simple in its management so it is possible to load the image data much more.

After the image is grayscale, the next process is thresholding to produce a binary image that has only two gray level values (black and white). Figure 6a shows result of grayscalling, pixels will be changed to 1 (black) if gray rate is greater than the Threshold (T) and will be converted to 0 (white) if the gray level less than or equal to the value of T. Threshold (T) can use a grayscale intensity value of the center is 128 (Johnson, 1994a). Figure 6b is result of binary code. Binary image still retains the characteristics of the face clearly but increasingly for easily processed because it involves only values 1 and 0.

Figure 7 is the result of face image resulted of features extraction to obtain the characteristics of an object that is able to distinguish a character or pattern of other patterns. These characteristics are used to retrieve relevant information from the input face image that can be understood easily by the system. The process of feature extraction on research using zoning techniques that

Fig. 5: a) Origin image; b) Segmented image; c) Filtered image and d) grayscalled image

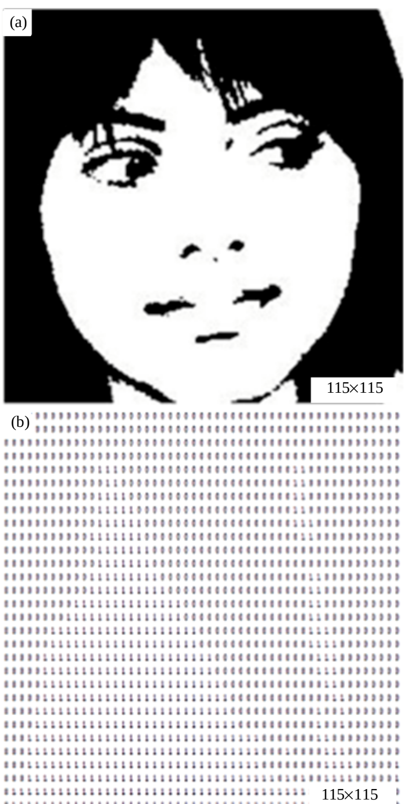

Fig. 6: a) Binary image and b) Binary code

transform a face image into N×M region desired. In this study, the dimensions of the desired face image is 7×5 region. Each region will calculate the pixel density that is dividing the sum of the values of pixels by the number of pixels in the region.

$$7\left\{\underbrace{\begin{array}{ccccc} 1.00 & 0.93 & 0.97 & 1.00 & 0.82 \\ 1.00 & 0.63 & 0.38 & 0.85 & 0.99 \\ 0.74 & 0.55 & 0.00 & 0.39 & 0.78 \\ 0.49 & 0.04 & 0.00 & 0.00 & 0.56 \\ 0.58 & 0.00 & 0.05 & 0.01 & 0.65 \\ 0.86 & 0.05 & 0.14 & 0.12 & 0.88 \\ 1.00 & 0.43 & 0.02 & 0.36 & 0.91 \end{array}}_{5}\right.$$

Fig. 7: feature values of face images

The results of feature extraction is more simple but have a good level of uniqueness. With this simplicity, the system load becomes smaller and it is possible to accommodate a large capacity of data. On the other hand, the unique features resulted make the system has a high ability. This is an advantage of previous research wich using eigen face feature.

Recognition process of Backpropagation Neural Networks (BNN): The objectives of training process to find the weights of each class where the weights are placed in a file for use on the stage of introduction. BNN training process using supervised (direction) to obtain the weight vectors that will perform vector quantization of the input (Fausett, 1994). After determining the weight vectors and biases during training process, then with supervised learning, the weight vector will identify targets that have been given together with the input. BNN supervised to determine the output unit with the most appropriate betwen target and input vectors by shifting the position of the weight vector. After the training is complete, BNN is considered to have smart so when the network given inputs, the network will produce output as expected. How to get the output is to implement the backpropagation method the same as the process of learning but only on the part of the forward with the following steps (Fausett, 1994) (Table 1):

Step 0: Initialize the weights according to the weight that has been produced on the training process above
Step 1: For each input, do steps 2-4
Step 2: For each input i = 1, ..., n numbers in the range of the activation function as is done in the training process
Step 3: for j = 1, ..., p:

$$z\_in_j - v_{os} + \sum_{i=1}^{n} x_i v_{ij}$$

$$Z_j = f(Z\_in_j)$$

Step 4: For k = 1, ..., m:

$$y\_in_k = w_{ok} - \sum_{j=1}^{p} Z_j W_{jk}$$

$$y_k = f(y\_in_k)$$

y_k is the output variables that are still in the scale according to the range of the activation function. To get the real value of output, y_k must be restored

The rate of face recognition: The the distribution falses in the face recognition based gender show in Table 2 (1-10 male and 11-20 female).

The recognition false spreads forming a diagonal area. No false face recognition of man group to women and the opposite. Recognition false of man among and also of women's groups. Thus, the system is able very well to distinguish between classes of man and women from blur images. By gender, following the introduction of the average results of all of blur and variations in poses in Table 3.

The level of recognition rate of men and women almost the same, although, there are relatively small differences in value the recognition of the man image of class 0.3% higher. This suggests that in the context of image blur and variations inpose both genders have the same complexity but system developed very accurate to distinguish gender. In general, the average of recognition system is 79.67% as good qualification. The highest recognition in the 10th image class of men is 88.64% and the lowest recognition in 14th image class of women with a recognition rate of 71.67%.

There are four classes image of men and five classes image of women under the average recognition rate but others are above average. The highest recognition rate in the group of men is 88.64 and 88.10% for women groups, the lowest recognition rate of man 74.07 and 71.67% of women groups. Recognition rate of image based on the level of blur in various poses can be shown in Table 4.

The recognition rate of systems generally highest in class image number 8 (men) and class image of the number 17 (women) were 80% whereas the lowest numbers shown in image class 2 (men) is 60%. The highest recognition rate in the group of man same with the women were 80% and the lowest recognition rate is 60% for men and 70% for women. There are two classes of men's groups who are low extremly is class 2 and 4 at blur level 5 with the recognition rate is 50%. Based on the results of these observations can be mentioned that the blur is more disturbing to the recognition rate of man. The recognition rate generally decrease based on blur level of for image class of men and women. The higher blur an image, the more difficult to recognize.

Blur level 1 still produce a maximum recognition rate 100% of class image 10 (men) and 16 (women). The average of recognition rate in blur level 1 is 84 or 10% above of average. While the blur level 5 the most difficult to recognize with the the average of recognition rate is 66%. Table 5 is the results of face recognition based on the blur level and pose variation.

In general, variations of the poses can be overcome with this system models developed, so that the recognition rate is relatively good qualificchtion. Pose which the most easily recognizable is the pose 1 with an average recognition rate is 82% and pose wich the most difficult to recognize is the pose 6 with an average accuracy of 68%. While on every blur level, pose wich the most recognizable is pose 5 in blur-1 that is 100%. Pose which the most poorly recognized is pose 3 (down) to blur-4 and 5, respectively 60%.

Table 1: Data results of training process

Parameters	Values
Input neurons	35
Hidden neurons	140
Output neurons	20
Learning rate	0.018
Learning time	3.22 min
Learning cycle	5.000 epoch
Weights	Updated

Table 2: Distribution recognition falses

Persons	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	Sum	Accurasy (%)
13	9	2	-	4	-	-	-	1	1	3	-	-	-	-	-	-	-	-	-	-	50	78.00
2	-	40	3	-	1	2	4	-	1	2	-	-	-	-	-	-	-	-	-	-	53	75.47
3	1	3	41	4	3	-	-	2	-	-	-	-	-	-	-	-	-	-	-	-	54	75.93
4	-	-	-	41	-	1	4	2	2	1	-	-	-	-	-	-	-	-	-	-	51	80.39
5	3	-	3	-	40	3	-	-	3	2	-	-	-	-	-	-	-	-	-	-	54	74.07
6	-	2	2	-	-	40	-	3	3	-	-	-	-	-	-	-	-	-	-	-	50	80.00
7	-	3	1	1	3		38	-	-	1	-	-	-	-	-	-	-	-	-	-	47	80.85
82		-	-	-	1	4		40	-	2	-	-	-	-	-	-	-	-	-	-	49	81.63
9	4	-	-	-	-	-	4	-	40	-	-	-	-	-	-	-	-	-	-	-	48	83.33
10	1	-	-	-	2	-	-	2	-	39	-	-	-	-	-	-	-	-	-	-	44	88.64
11	-	-	-	-	-	-	-	-	-	-	41	-	-	-	3	1	-	2	-	-	47	87.23
12	-	-	-	-	-	-	-	-	-	-	-	37	-	2	-	-	2	-	2	2	45	82.22
13	-	-	-	-	-	-	-	-	-	-	2	-	42	-	3	2	-	-	2	3	54	77.78
14	-	-	-	-	-	-	-	-	-	-	3	2	-	43	2	4	2	3	-	1	60	71.67
15	-	-	-	-	-	-	-	-	-	-	2	4	-	-	38	-	4	1	2	-	51	74.51
16	-	-	-	-	-	-	-	-	-	-	-	2	2	-	-	4	-	1	1	2	48	83.33
17	-	-	-	-	-	-	-	-	-	-	-	3	-	2	2	1	38	2	3	2	53	71.70
18	-	-	-	-	-	-	-	-	-	-	1	-	3		1	2	2	40	1	3	53	75.47
19	-	-	-	-	-	-	-	-	-	-	1	2	-	3	-	-	1	1	39	-	47	82.98
20	-	-	-	-	-	-	-	-	-	-	-	-	3	-	1	-	1	-	-	37	42	88.10
Sum	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	793	79.67

Table 3: Face reconition based on gender

Gender	Avg. of accuracy (%)
Male	79.8
Female	79.5

Table 4: Recognition rate based on person and blur

	Percentage					
Persons	Blur-1	Blur-2	Blur-3	Blur-4	Blur-5	Avr. of person
1	60	80	60	60	60	64
2	60	70	60	60	50	60
3	80	80	80	70	70	76
4	60	80	80	80	50	70
5	90	70	70	70	70	74
6	90	70	70	70	60	72
7	90	80	70	70	70	76
8	90	80	80	80	70	80
9	90	80	80	70	70	78
10	100	80	80	80	60	80
11	90	70	70	60	70	72
12	80	80	80	70	70	76
13	80	80	70	70	60	72
14	90	80	80	70	60	76
15	90	80	70	70	70	76
16	100	70	70	70	70	76
17	90	80	80	80	70	80
18	80	70	70	70	70	72
19	70	80	70	60	70	70
20	90	70	70	70	70	74
Avr. of blur	84	77	73	70	66	74

Table 5: Face recognition based on poses

	Percentage										
Poses	1	2	3	4	5	6	7	8	9	10	Avr. of blur
Blur-1	80	75	75	90	100	75	90	95	80	75	84
Blur-2	90	75	80	75	80	70	70	70	80	75	77
Blur-3	80	75	75	70	75	65	65	70	80	75	73
Blur-4	80	75	60	70	70	65	65	65	75	75	70
Blur-5	80	75	60	70	70	65	65	65	75	75	70
Avr. of poses	82	75	70	75	79	68	71	73	78	75	75

CONCLUSION

Filtering, Grayscaling, Tresholding and Zoning (FGTZ) Methods support to Backpropagation Neural Networks (BNN) approach as the face recognition system from the image blur with a variety of poses. Zoning as a feature extraction technique able to reduce the complexity of face image become more simple and representative. The system is able to distinguish classes both of men and women in a variety of image blur and pose. System is relatively same for both class man and women for the source image blur and varied poses. Until the blur level 2, the system shows very good performance achieving 84% and good enough to blur levels 3-5. A variety of poses can be extracted properly to produce features that differentiated between image blur. However, the system performance is decreased for the ducking pose because there is information that is not complete or blocked.

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