FACE RECOGNITION USING FIXED SPREAD RADIAL BASIS FUNCTION NEURAL NETWORK FOR SECURITY SYSTEM

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Abstract

This paper presents face recognition using spread fixed spread radial basis function neural network for security system. The face recognition system can be applied to security system such as door lock system etc. Acquired image will be going through image processing process. General preprocessing approach is use for normalizing the image. Radial Basis Function Neural Network is use for face recognition and Support Vector Machine is used as the face detector. RBF Neural Networks offer several advantages compared to other neural network architecture such as they can be trained using fast two stages training algorithm and the network possesses the property of best approximation. The output of the network can be optimized by setting suitable values of the center and spread of the RBF but in this paper fixed spread is used as there is only one train image for every user and to limit the output value.

Keywords: *component; Face recognition, Radial Basis Function Neural Network, Image Processing.*

I. INTRODUCTION

Biometrics deals with the identification of individuals based on their biological or behavioral characteristics [1]. Face can be defined as the front part of head from the forehead to the chin [2]. A number of biometrics have been proposed, researched and evaluated for identification applications. Face is one of the most acceptable biometrics because it is one of the most common methods of identification which humans use in their interactions [1]. Face recognition is one of many possible approaches to biometric identification therefore many biometric systems are based on face recognition in combination with other biometric features such as voice or fingerprints. The human face is a dynamic object but with a standard configuration of facial features which can vary within a limited range such as using only the frontal view. It is a difficult problem to detect such dynamic objects and considering the changes in faces over time (facial hair, glasses, wrinkles, skin color, bruises) together with variations in pose, developing a robust face detection algorithm is still a hard problem to solve in computer vision systems [9].

II. IMAGE PROCESSING

In this project, the acquired image is first converted into double class in matrix form. The matrix is then converted into column matrix 1 x n. This input will be fed into the RBF network for the next process. Figure 1 and 2 shows the conversion of image into matrix form. The image that to be fed into the network whether for training or testing will be normalized using a preprocessing step, adapted from [4].

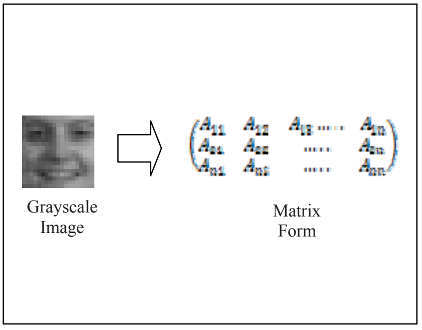


Figure 1: Convert Image to Matrix

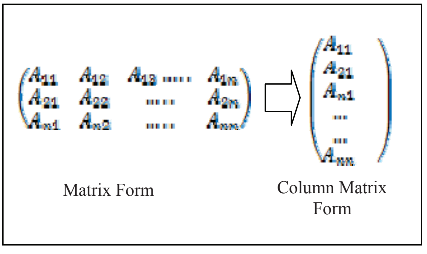


Figure 2: Convert Matrix to Column Matrix

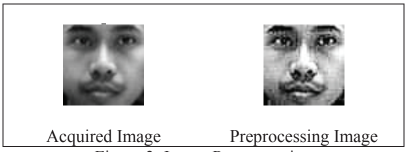


Figure 3: Image Preprocessing

III. RADIAL BASIS FUNCTION NEURAL NETWORK

RBFNN offers several advantages compared to the Multilayer Perceptrons. Two of these advantages are:

1. They can be trained using fast 2 stages training algorithm without the need for time consuming non-linear optimization techniques.

2. ANN RBF possesses the property of 'best approximation' [11]. This means that if in the set A of approximating functions (for instance the set *F*(*x*, *w*) spanned by parameters *w*), then the RBFNN has the minimum distance from any given function of a larger set, *H*.

RBFNN had been successfully used in face detection such as in Mikami, *et.al.*, 2003[3] and K. A. A. Aziz, *et.al.* [12][13][14]. Figure 4 illustrates the architecture of the RBFNN used in this work.

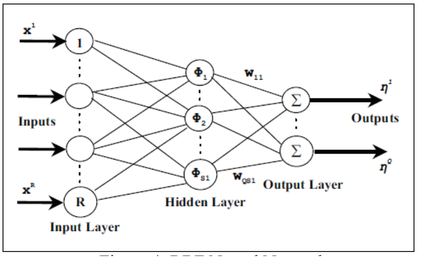


Figure 4: RBF Neural Network

The network consists of three layers: an input layer, a hidden layer and an output layer. Here, *R* denotes the number of inputs while *Q* the number of outputs. For *Q = 1*, the output of the RBFNN in Figure 4 is calculated according to

$$\eta(x,w)=\sum_{k=1}^{S1} w_{1k}\phi(\| x-c_k \|)_2 \qquad (1)$$

where $x \in \Re^{R\,1}$ is an input vector, $\phi(.)$ is a basis function, ||.|| denotes the Euclidean norm, w_{1k} are the weights in the output layer, S_1 is the number of neurons (and centers) in the hidden layer and $c_k \in \Re^{R\,1}$ are the RBF centers in the input vector space. Equation (1) can also be written as

$$\eta(x,w) = \phi^T(x)w \tag{2}$$

where

$$\phi^T(x) = [\phi(\| x - c_1 \|)\ldots\ldots\phi_{S1}(\| x - c_{S1} \|)] \tag{3}$$

and

$$w^T = [w_{11} w_{12} \ldots w_{1S1}] \tag{4}$$

The output of the neuron in a hidden layer is a nonlinear function of the distance given by:

$$\phi(x) = e^{\frac{-x^2}{\beta^2}} \tag{5}$$

β is the spread parameter of the RBF. For training, the least squares formula was used to find the second layer weights while the centers are set using the available data samples.

IV. NETWORK TRAINING

The network is trained using one image for every user. The simplest procedure for selecting the basis function centers ck is to set the center equal to the input vectors or a random subset of the input vectors from the training set but this is not an optimal procedure since it leads to the use of unnecessarily large number of basis function [6]. Broomhead *et.al.* [8] suggested strategies for selecting RBF centers randomly from the training data. The centers of RBF can either be distributed uniformly within the region of input space for which there is data. In this paper K-means clustering was used.

K-means clustering is one of the techniques that was used to find a set of centers where the technique is more accurately reflects the distribution of the data points [6]. It is used in research such as in [3] and [7]. In k-means clustering, the number of desired centers, K, must be decided in advance. The difference between two n-dimensional vectors, $\overline{V_i}$ and $\overline{V_j}$ will be the spread value given by:

$$E_{ij} = \sqrt{\sum_{k=1}^{n} \left\{ w_k \cdot (v_{ik} - v_{jk})^2 \right\}} \tag{6}$$

For the training, supervised learning is used where training patterns are provided to the RBFNN together with a teaching signal or target. As for the input of the user's face will be given the value of 1.

V. TESTING

Testing the network divided into two parts. The first part is using the same person as the input image and the second part is using different person. For both part, the output values are recorded.

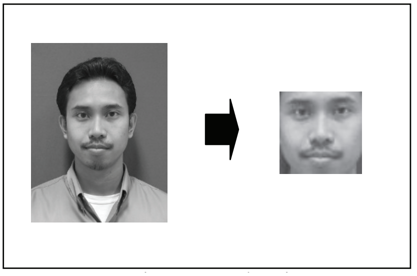


Figure 5: Face detection

Face detection use the new reduced set method for Support Vector Machines (SVMs) taken from [9].

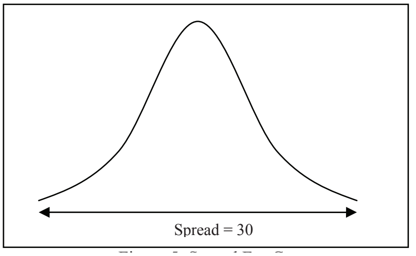


Figure 5: Spread For Center

In this paper, fixed spread value of RBFNN is used and spread ranging from 10 to 30 is used to find the best spread setting.

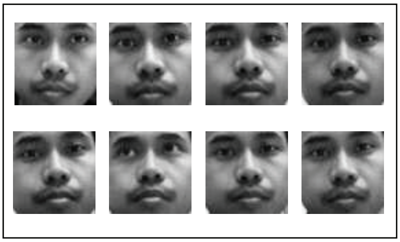


Figure 6: Face image using same person as input

VI. RESULTS AND DISCUSSIONS

Table 1 shows the output using 10 images with spread ranging from 10 to 30.

Table 1: Output using different spread value

Image No.	Spread Value				
	10	15	20	25	30
1	0.12177	0.47407	0.65204	0.76677	0.86208
2	0.09497	0.46838	0.62428	0.74399	0.81019
3	0.15841	0.44032	0.62468	0.72568	0.80599
4	0.37757	0.42894	0.62910	0.76942	0.79489
5	0.30389	0.46488	0.61575	0.73994	0.79581
6	0.38865	0.43339	0.64862	0.73414	0.80894
7	0.29739	0.46123	0.63516	0.82496	0.79308
8	0.40463	0.46402	0.59523	0.83513	0.80746
9	0.35306	0.42466	0.60791	0.70033	0.78928
10	0.36185	0.45722	0.74761	0.74080	0.77571

The results of testing the face recognition system using RBFNN are shown in Table 2 and Table 3. The RBFNN used fixed spread setting that is equal to 30. As for the face detection, SVM from [14] was used. The first image in Table 2 is the training image for the RBFNN and the target value is 1. As we can see in the table, the values for imposter or other than the user were less than 0.8. Table 3 is the result of testing the system using only the user's face as the input. Here we can see that values given by the network are more than 0.85.

Table 2: Testing using different person image as input

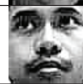
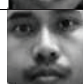
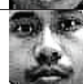
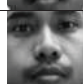
Acquired Image	Preprocessing Image	Value
		(Training Image)
		0.8603 (user)
		0.6421
		0.7232
		0.7827

Table 3: Testing using user image as input

Acquired Image	Preprocessing Image	Value
		(Training Image)
		0.9155 (recognize)
		0.8966 (recognize)
		0.8921 (recognize)
		0.8542 (recognize)

VII. CONCLUSION

The results in Table 1, 2 and 3 shows that the system can recognize a person using 30 spread value and the threshold for output is more than 0.85. Other than the user or imposter will get the value of output less than 0.8. This system can be applied in security system such as door lock. Nowadays many door lock system using pin code for authorize person to enter a restricted room. The pin code system can be changed with face recognition system.

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