THE EFFECT OF OVERLAPPING SPREAD VALUE FOR RADIAL BASIS FUNCTION NEURAL NETWORK IN FACE DETECTION

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Abstract

In this paper, the effect of overlapping spread value for Radial Basis Function Neural Network (RBFNN) in face detection is presented. The reason for taking the overlapping factor into consideration is to optimize the results for using variance spread value. Face detection is the first step in face recognition system. The purpose is to localize and extract the face region from the background that will be fed into the face recognition system for identification. General preprocessing approach was used for normalizing the image and a Radial Basis Function (RBF) Neural Network was used to distinguish between face and non-face images. RBFNN 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. The performance of the RBFNN face detection system will be based on the False Acceptance Rate (FAR) and the False Rejection Rate (FRR) criteria.

Keywords: *Face detection, Radial Basis Function, Neural Network.*

I. INTRODUCTION

Face can be defined as the front part of head from the forehead to the chin [1]. Biometrics deals with the identification of individuals based on their biological or behavioral characteristics [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 [2]. Face detection is the first step in face recognition system. Face detection can be regarded as a more general case of face localization. In face localization, the task is to find the locations and sizes of a known number of faces. One of the methods for face detection is Neural Networks which lies under the category of image based approach. In this paper, we focus on optimizing the RBF Neural Network for face detection. RBFNN is used to distinguish face and non-face images.

II. RADIAL BASIS FUNCTION NEURAL NETWORK

The 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' [9]. 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]. Figure 1 illustrates the architecture of the RBFNN used in this work.

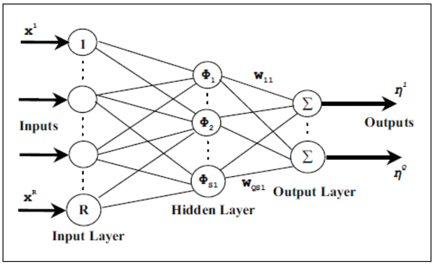

Figure 1: RBF Neural Network

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 1 is calculated according to

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

where $x \in \Re^{Rx1}$ is an input vector, $\phi(.)$ is a basis function, $\|.\|$ denotes the Euclidean norm, w_{1k} are the weights in the output layer, *S1* is the number of neurons (and centers) in the hidden layer and $c_k \in \Re^{Rx1}$ are the RBF centers in the input vector space. Equation (1) can also be written as

$$\eta(x,w) = \phi^T(x)w \qquad (2)$$

where

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

and

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

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

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

where 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.

III. NETWORK TRAINING

The image that to be fed into the network whether for training or testing will be normalized using a preprocessing step, adapted from [4].

In this project, image is first converted into double class in matrix form. The matrix is the converted into column matrix 1 x n. This input will be fed into the RBF network for the next process. Figure 2 and 3 show the conversion of image into matrix form.

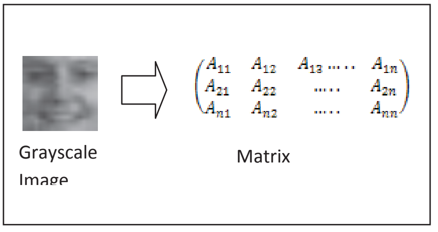

Figure 2: Convert Image to Matrix

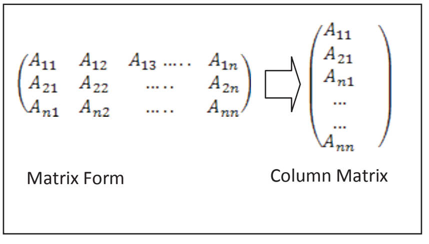

Figure 3: Convert Matrix to Column Matrix

The network is trained using 2429 face data and 4548 non-face data from the CBCL (Center For Biological and Computation Learning) train datasets [5].

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 we use K-means clustering.

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.

In [11] the spread values are the same for all centers. In this paper, the value of vector that is the closest to all vectors in the cluster will be the spread value. 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 face will be given the value of 1 while the input of non-face will be given the value of -1.

IV. TESTING

In [11], 999 face data and 899 non-face data taken from the CBCL train datasets used as the input. Different centers are chosen ranging from 2 to 200 with the spread value from 1 to 40. Apart from the previous testing, the system will also detect many faces in large image. If 100 centers are chosen, each will have the same spread value.

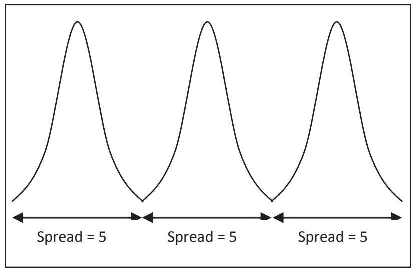

Figure 4 Same Spread For All Centers

As in [12], the same training and test datasets are used. Different centers are ranging from 2 to 350 and the spread values for every center will be variance according to the algorithm. The algorithm will calculate the best value for every center chosen where it will find the distance from all vectors in the cluster and give which vector is closest to the center. Euclidean Distance will be used to find the distance between two vectors. This means that if 100 centers are chosen, the network may have 100 different spread values for every cluster.

Apart from the previous testing, the system will also detect many faces in a large image as in [11]. The image for testing is taken from [10]. Sliding window will run inside the image and identified whether there is a face inside the current window. In [10] they are using new reduced set method for Support Vector Machines (SVMs).

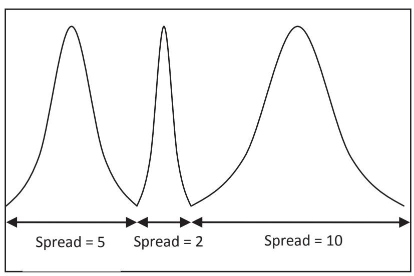

Figure 5 Variance Spread For All Centers

In this paper, the overlapping factor for RBFNN spread value is taken into consideration. Different overlapping values are chosen from 2 to 10 and the results were analyzed.

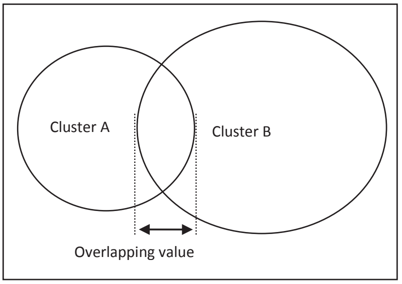

Figure 6 Overlapping value for RBFNN

As for the result, the ultimate measure of utility of a biometric system for a particular application is recognition or detection rate [12]. This can be described by two values that are False Acceptance Rate (FAR) and False Rejection Rate (FRR). FAR classifies non-face data as face data while FRR classifies face data as non-face data [13].

FAR, FRR and detection rate can be described as,

$$FAR = \frac{number\ of\ incorrect\ detected\ \ falses}{total\ number\ of\ actual\ \ faces} \quad (7)$$

$$FRR = \frac{number\ of\ incorrectly\ detected\ \ faces}{total\ number\ of\ actual\ \ faces} \quad (8)$$

$$Detection\ \ Rate = \frac{number\ of\ correct\ detection}{total\ number\ of\ input} \times 100\% \quad (9)$$

V. RESULTS

Figure 7 shows that the RBFNN response to face and non-face data nicely where it can discriminate faces and non-faces even though not completely. The system can detect 97.29% face and 97.99% non-face. The FAR and FRR are also low that is 0.027 and 0.020. The error rate using various centers is shown in Figure 8.

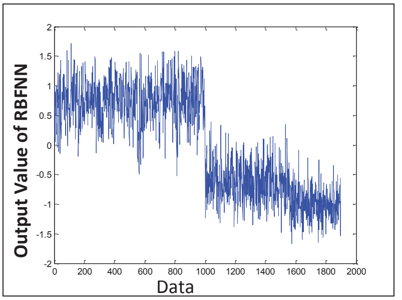

Figure 7 Output response of the trained RBFNN for CBCL training datasets as input for 300 centers and Overlapping value equal to 10

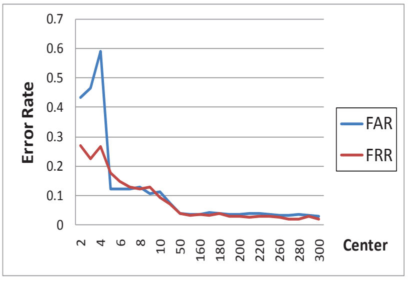

Figure 8 Error rate using various centers

Figure 9 Using RBF with the value of Centre 200 and Overlapping value equal to 5

Figure 10 Using RBF with the value of Centre 300 and Overlapping value equal to 5

Figure 11 Using RBF with the value of Centre 200 and Overlapping value equal to 10

In Figure 9, the system can detect all faces in the image but there are 2 false accept. Using overlapping value equal to 5 for 300 centers gives 4 false accept as in Figure 10. Increasing the overlapping value to 10 for 200 centers will still give 2 false accept but all face are detected. Increasing the center to 300 for overlapping value equal to 10 will ensure all faces are detected without any false accept as shown in Figure 12.

Figure 12 Using RBF with the value of Centre 300 and Overlapping value equal to 10

VI. DISCUSSIONS

The results in [11] and [12] shows that using fixed spread gives better result compare to variance spread. As the overlapping factor is taken into consideration, the result for using variance spread is improved. The best setting for the RBFNN in this paper is using 300 centers with overlapping value equal to 10. It gives 97.29% face detection and 97.99% non-face detection rate. The FAR and FRR are also low with this setting that is FAR = 0.027 and FRR = 0.020. Compare with the results in [12], this is much better. As we can see in Figure 9 to Figure 12, the result for detection of many faces in single image also improves. The system can detect all faces in the image with no false accept at all. This shows that taking the overlapping value of spread into consideration increases the performance on the system in [12].

VII. CONCLUSION

The result shows that taking the overlapping factor of RBFNN spread value into consideration improve the performance of face detection. The best setting for the RBFNN in this paper is using 300 centers with overlapping value equal to 10 where it gives 97.29% face detection and 97.99% non-face detection rate while the FAR and FRR are also low with this setting that is FAR = 0.027 and FRR = 0.020.

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