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Image Based Face Detection Using Probabilistic Neural Network

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***Abstract*— This paper presents an image based face detection using probabilistic neural network. 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 Probabilistic Neural Network (PNN) was used to distinguish between face and non-face images. Probabilistic neural networks can be used for classification problems. The performance of the PNN face detection system will be based on the detection rate, False Acceptance Rate (FAR) and the False Rejection Rate (FRR) criteria.**

***Keywords*— Face Detection, Image Processing, Probabilistic 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 Probabilistic Neural Network for face detection. PNN is used to distinguish face and non-face images. The output of the network can be optimized by setting suitable values of the center and the spread of the PNN.

II. Probabilistic Neural Networks

Probabilistic neural networks can be used for classification problems. When an input is presented, the first layer computes distances from the input vector to the training input vectors and produces a vector whose elements indicate how close the input is to a training input. The second layer sums these contributions for each class of inputs to produce as its net output a vector of probabilities. Finally, a complete transfer function on the output of the second layer picks the maximum of these probabilities, and produces a 1 for that class and a 0 for the other classes. The architecture for this system is shown in Fig 1 [13].

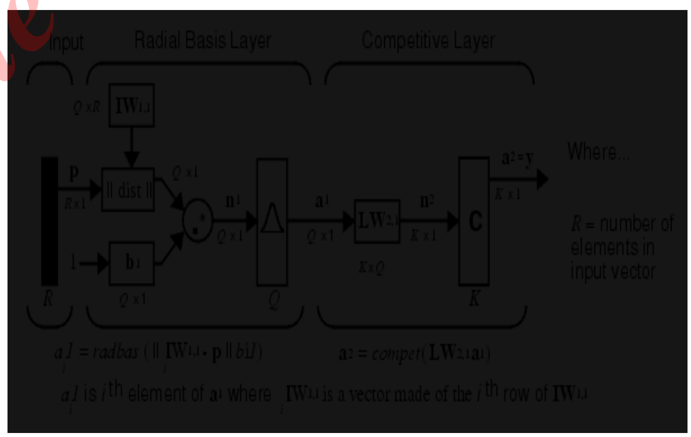

Fig 1: Architecture of PNN [13]

Q = number of target pairs

K = number of classes of input data

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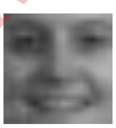
It is assumed that there are Q input target vector pairs. Each target vector has K elements and one of these elements is 1 and the rest are 0. This means that each input vector is associated with one of K classes.

The first-layer input weights, IW1,1(net.IW{1,1}), are set to the transpose of the matrix formed from the Q training pairs, P'. When an input is presented, the || dist || box produces a vector whose elements indicate how close the input is to the vectors of the training set. These elements are multiplied, element by element, by the bias and sent to the radial basis transfer function. An input vector close to a training vector is represented by a number close to 1 in the output vector a1. If an input is close to several training vectors of a single class, it is represented by several elements of a1 that are close to 1 [13].

The second-layer weights, LW1,1(net.LW{2,1}), are set to the matrix T of target vectors. Each vector has a 1 only in the row associated with that particular class of input, and 0's elsewhere. Function ind2vec was used to create the proper vectors. The multiplication Ta1 sums the elements of a1 due to each of the K input classes. Finally, the second-layer transfer function, compete, produces a1 corresponding to the largest element of n2, and 0's elsewhere. Thus, the network classifies the input vector into a specific K class because that class has the maximum probability of being correct [13].

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. Fig 2 and 3 show the conversion of image into matrix form.



$$\Rightarrow \begin{pmatrix} A_{11} & A_{12} & A_{13} \cdots & A_{1n} \\ A_{21} & A_{22} & \cdots & A_{2n} \\ A_{n1} & A_{n2} & \cdots & A_{nn} \end{pmatrix}$$

Grayscale Image

Fig 2: Convert Image to Matrix

$$\begin{pmatrix} A_{11} & A_{12} & A_{13} \cdots & A_{1n} \\ A_{21} & A_{22} & \cdots & A_{2n} \\ A_{n1} & A_{n2} & \cdots & A_{nn} \end{pmatrix} \Rightarrow \begin{pmatrix} A_{11} \\ A_{21} \\ A_{n1} \\ \cdots \\ \cdots \\ A_{nn} \end{pmatrix}$$

Matrix Form Column Matrix

Fig 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 PNN 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 were 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.

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 2.

IV. Results

Table 1, Table 2, Fig 4 and Fig 5 shows the performance of the PNN face detection using 999 face data and 899 non-face data taken from the CBCL train datasets used as the test input. The system can detect 100% face and non-face using spread from 0.1 to 2.5. Table 2 and Fig 5 shows the FAR and FRR of the system. Spread 0.1 to 2.5 gives 0 FAR and FRR.

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Table I

Detection rate of PNN face detection with different spread setting

Spread	Face	Non-face
0.1	100	100
0.3	100	100
0.5	100	100
0.7	100	100
0.9	100	100
1	100	100
2	100	100
2.5	100	100
3	96.8969	98.8877
3.5	85.8859	97.7753
4	76.6767	96.3293
4.5	62.8629	97.6641
5	45.5455	98.4427
5.5	27.3273	99.2214
6	13.5135	99.6663
6.5	4.1041	100
7	0.6006	100
7.5	0	100
8	0	100
8.5	0	100
9	0	100
10	0	100
13	0	100
15	0	100
17	0	100
19	0	100
20	0	100

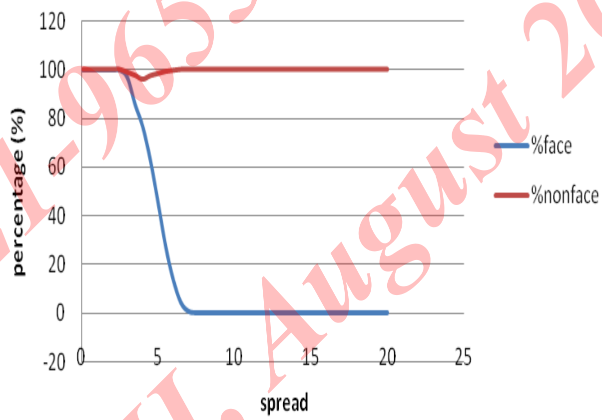

Fig 4: Detection performance on face & non-face with different spread

Table II

FAR and FRR of PNN Face Detection

Spread	FAR	FRR
0.1	0	0
0.3	0	0
0.5	0	0
0.7	0	0
0.9	0	0
1	0	0
2	0	0
2.5	0	0

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3	0.0314	0.0115
3.5	0.1444	0.0259
4	0.2421	0.04799
4.5	0.3803	0.0372
5	0.5532	0.0342
5.5	0.7324	0.0576
6	0.8678	0.027
6.5	0.959	0
7	0.994	0
7.5	1	∞
8	1	∞
8.5	1	∞
9	1	∞
10	1	∞
13	1	∞
15	1	∞
17	1	∞
19	1	∞
20	1	∞

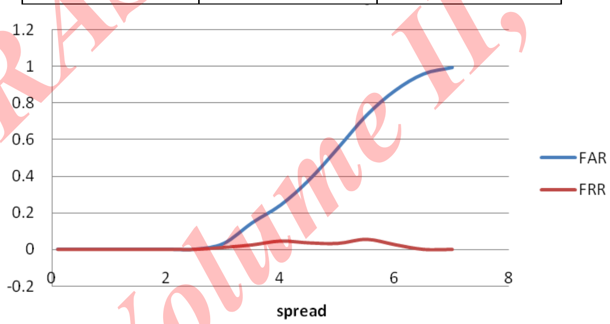

Fig 5: FAR and FRR

As for detection multiple faces in a single image, the value of spread ranging from 2 to 3 gives the best result as there is no false accept at all and the system can detect all faces in the image. This can be seen in Fig 6 to 12. In Fig 6, the system give lots of false accept for spread = 0.1. The system give no false accept for spread =4.5 but not all faces will be detected as in Fig 11. The system does not detect any face at all for spread = 6 as in Fig 12.

Fig 6: PNN with spread 0.1

Fig 7: PNN with spread 0.3

Fig 8: PNN with spread 0.7

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Fig 9: PNN with spread 2

Fig 10: PNN with spread 3

Fig 11: PNN with spread 4.5

Fig 12: PNN with spread 6

V. Conclusions

In [10] and [11], 999 face data and 899 non-face data taken from the CBCL train datasets used as the test input while the classification was done using RBFNN. The best result for the RBFNN system is 97% face detection and 99% non-face detection. Table 1 and 2 shows that using PNN in face detection with the value of spread = 2 gives improves the result as the system can detect 100% face and non-face while the FAR and FRR = 0.

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