A Heuristic Based RBFN for Location and Rotation Invariant Clear and Occluded Face Identification

Goutam Sarker
SMIEEE, Associate Professor
Computer Science and Engineering Department
NIT Durgapur, India

Shruti Sharma
M Tech. Student
Computer Science and Engineering Department
NIT Durgapur, India

ABSTRACT
This paper describes a robust and efficient method for rotation and location independent identification and localization of facial images using one modified Radial Basis Function Network (RBFN) which embeds a new Heuristic Based Clustering (HBC) and Back Propagation (BP) learning. HBC in RBFN determines the natural number of clusters or groups on the basis of 'person-view'. BP network learns to identify a 'person' irrespective of his view. The method successfully performs location invariant upright and rotated facial identification in different views and expressions with or without occlusion. The learning as well as identification with standard facial database is fast, efficient, effective and the accuracy as well as precision of the system with Holdout Method is moderate.

Keywords
Machine learning, HBC, BP network, RBFN, Holdout Method, Accuracy

1. INTRODUCTION
Face identification and localization has drawn considerable interest and attention in the field of pattern recognition for last two decades. This is very important because of its potential applications such as in the field of video surveillance, access control system, retrieval of an identity from a dataset for criminal investigation and person authentication etc. Designing an automated system for face identification is difficult due to high variability in facial images .Sources of variability include individual appearance, three dimensional poses, facial expression, facial hair, makeup and other factors. Furthermore the illumination condition, background, scale and occlusion are all present in facial image acquired under real world scenarios. This makes face recognition and localization a great challenging problem [1, 2].

Many methods have been proposed [19, 20, 21, 22] for face identification tasks, from which neural network approaches achieve higher accuracy in detection because they are powerful to train large number of patterns.

In one of our previous work [7], a multilayer BP Network was used for face identification and localization. The system was unable to handle rotation as well as occlusion.

In our several other previous works [12, 13, 14, 15, 18] we have developed RBFN with OCA and BP Network. These systems were more or less meant for clear faces or fingerprints without any rotation and occlusion. Also the localizations were not location invariant.

In our previous work [17] a modified RBFN was used for occluded fingerprint identification and localization, but the system was unable to deal with rotation and location invariance. In another of our work [16], a modified RBFN was used to perform location invariant face identification which was unable to deal with rotation and occlusion.

In this paper, face identification and localization is implemented using modified Radial Basis Function Network (RBFN) [23] and the system can also identify occluded and rotated images which are in single frame as well as multiple image frame. The image dataset consists of faces of different persons in three different views and Heuristic Based Clustering (HBC) [3, 4, 5, 6] Algorithm is used to cluster the image set. Back propagation (BP) Network is used in RBFN to learn to identify a person irrespective of his view and /or expression.

In section 2, HBC, BP learning and RBFN are briefly introduced. Overview of the system is given in section 3. Algorithm of present technique is introduced in section 4. Measurement of performance of the system is discussed in section 5. Experimental results based on database from Pointin'04 ICPR Workshop are reported in section 6. Related words are discussed in section 7. Finally conclusions are drawn in section 8.

2. THEORY OF OPERATION
2.1 Heuristic Based Clustering (HBC) Algorithm
Natural clustering is one in which the classifier does not know directly or indirectly from the user a priori the total number of cluster to be formed. HBC is one such algorithm. The system performs natural grouping or clustering of the input data set.

2.2 Back Propagation (BP) Learning
One of the most popular methods for training multilayer network is Back Propagation (BP) [7] Learning Algorithm.

2.3 Radial Basis Function Network (RBFN)
RBFN is a complicated Pattern Recognition Network that computes and thereafter uses radial basis function as activation function. The overall output of the network is a non linear combination of weighted sum of radial basis units.

RBFN have attracted massive research interest in the field of neural network [25, 26, 27, 28]. The basic structure of RBFN is shown in Figure 1

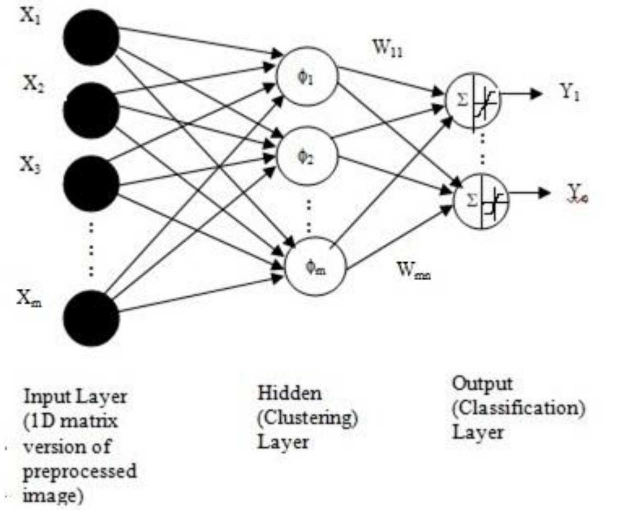

Figure 1: RBF Neural Network

The output of k^{th} RBF unit is

$$H_k(X)=H_k[||X-|/\sigma_k] \quad (1)$$

where k=1,2… , j. X is an i dimensional input vector, μ_k is the vector with same dimension as X, j is the number of hidden units and $H_k(.)$ is the RBF unit.

Typically H_k is chosen as a Gaussian function

$$H_k(X)=exp[-||X-\mu_k||^2/2\sigma_k^2] \quad (2)$$

||.|| is the Euclidean Distance between input image and central image.

The j^{th} output $Y_j(X)$ of RBF neural network is

$$Y_j(X)=b(j)+\sum_{i=1}^{n} Hi(X)*w_2(j,i) \quad (3)$$

where $w_2(j,i)$ is the weight of the i^{th} respective field to the j^{th} output and b(j) is the bias of j^{th} output.

In the following analysis, the bias is not considered in order to reduce network complexity. Hence ,

$$Y_j(X)=\sum_{i=1}^{n} Hi(X)\ *w_2(j,i) \quad (4)$$

3. OVERVIEW OF THE SYSTEM

3.1 Preprocessing

The image has to be preprocessed before learning or identification. There are several steps in pre-processing.

i) Gray Image Conversion: First step is to convert the image into gray scale.

ii) Noise Elimination: This step is done to eliminate the noise from facial images.

iii) Deblurring: This process reduces the blur of sample pattern in the noise eliminated faces.

iv) Image Normalization: This process normalizes all patterns into 75*75 pixels and stores into the training database.

v) Image Binarization: Now the image is converted into binary image.

vi) Conversion of 2D matrix of images into 1D matrix: The images in the database which are in 2D matrix of 75*75 are converted to a 1D matrix form.

Figure 2 shows the steps involved in pre-processing of images.

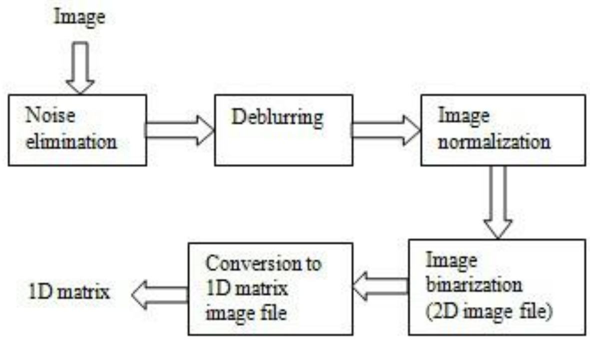

Figure 2: Image Preprocessing Scheme

4. ALGORITHM OF PRESENT TECHNIQUE

4.1 Learning Algorithm

4.1.1 Heuristic Based Clustering

Here we are presenting the HBC algorithm for computing the μ and σ for every basis unit.

Input: A facial pattern set with n faces.

Output: A cluster set C with k different clusters C_1 ,C_2, … , C_k

Steps:

i) Select an element randomly from the dataset (say a_x) and find its nearest neighbor (say a_y). Include a_x, a_y in cluster C_i.

ii) Find the nearest neighbor of a_y (say a_z) and include it in cluster C_i.

iii) Find the nearest neighbor of a_z (say a_w) and include it in cluster C_i.

iv) Find the distances between all pair of data points a_x, a_y, a_z, a_w.

v) Find the largest distance and call it the threshold.

vi) Find all the neighbors of a_x, a_y, a_z, a_w which lie within the threshold distance and include them in the cluster C_i.

vii) Repeat steps i to vi taking all the unexplored elements as the dataset for $(i+1)^{th}$ cluster.

The mean of each cluster is calculated by taking the average of all the data points which fall in one cluster. The width or Standard Deviation of each cluster is calculated by the formula

$$\sigma_i=\sqrt{\frac{1}{N}\sum_{i=1}^{N}(Xi-\mu i)^2}$$

where N is the number of data points in each cluster, X_i is the data point of i^{th} cluster, μ_i is the mean of i^{th} cluster.

4.1.2 BP Learning

Here we are presenting the modified two layer BP Network Learning.

begin

initialize η, $t \leftarrow 0$;

initialize $(w_{ji})_t$ randomly between 0 and 1 excluding 0 and including 1 through a random number generator;

do

$t \leftarrow t+1$;

$x_t \leftarrow$ sequentially chosen pattern;

calculate the error;

$(w_{ji})_{t+1}=(w_{ji})_t + \eta$.error;

until $(w_{ji})_{t+1} \approx (w_{ji})_t$

return w

end

Where

$\eta \equiv$ a constant called the rate of learning.

$t \equiv$ number of iterations

$w_{ji} \equiv$ weight of the link between i^{th} RBF unit and j^{th} output unit.

The larger the value of η, the faster is the training, but it cannot be too large to make overshooting in learning. The smaller the value of η, the slower is the learning. We have assumed η=0.1.The learning stops when no further presentation of image causes the change in the weight of any link i.e $(w_{ji})_{t+1} \approx (w_{ji})_t$.

4.2 Face Identification

The training dataset consists of faces of different persons in left, front and right views.. Each view has different expressions. After applying HBC on this dataset, clusters are formed in a manner such that each cluster has images of same person in a particular view. The BP layer output of RBFN gives the identity of an input person irrespective of his view and / or expression.

In the present method for face identification, the number of inputs are set equal to that of features (i.e. dimension of input space), while number of outputs is set to the number of classes i.e. identifiable persons. The number of basis (hidden) unit is equal to the number of clusters formed by HBC which is also equal to the number of 'person-view'.

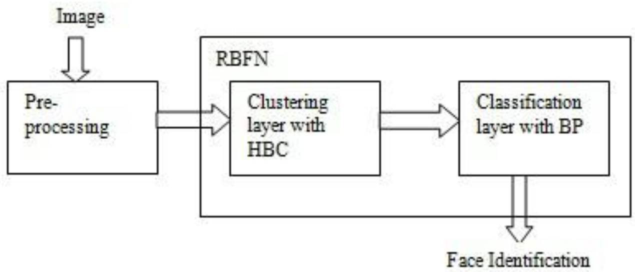

Figure 3: Identification of faces

Before the image for testing is fed to the network it is required to find the angle by which it is rotated. This can be done by finding the slope of a particular line in the rotated image which is horizontal in the upright image. For our purpose we have chosen the line which forms the base of the image. We have found the convex hull [32] of the region of the person for finding this base line. A set *A* is said to be convex if the straight line segment joining any two points in *A* lies entirely within *A*. The algorithm is presented below:

4.2.1 Convex Hull Algorithm

Here we are presenting the Convex Hull Algorithm which finds the region of the person in the image.

i) Find the points with minimum and maximum x coordinates, those are bound to be part of the convex.

ii) Use the line formed by the two points to divide the set in two subsets of points, which will be processed recursively.

iii) Determine the point, on one side of the line, with the maximum distance from the line. The two points found before along with this one form a triangle.

iv) The points lying inside that triangle cannot be part of the convex hull and can therefore be ignored in the next steps.

v) Repeat the previous two steps on the two lines formed by the triangle (not the initial line).

vi) Keep on doing so on until no more points are left, the recursion has come to an end and the points selected constitute the convex hull.

4.2.2 Algorithm to Find the Angle of Rotation

Here we are presenting below the steps to find the base line and thereby its slope to convert the image into an upright one.

i) Threshold the image to binary to filter out the region belonging to the person and complement the image to get person's region. This region is refined further by filling holes and morphological closure.

ii) Find the convex hull of the region. Find the longest line by checking each line of the convex hull separately. Normally this should be the base of the region.

iii) Calculate the slope of longest line and find its angle with horizontal axis.

iv) Rotate the original image with the angle found to get the upright image.

The above steps give a rotation corrected image, but for correct identification we need to crop this image and position it correctly.

During the testing of each and every test image, BP network produces different output activation in the output units. The output unit which shows the highest activation above a threshold value gives the class of the pattern given as input.

4.2.3 Multiple Image Frame

To find the location of different images in the frame, following algorithm is adopted.

begin

input the image frame.

threshold the image frame into binary to mask the individual image regions.

remove noise from the binarized image.

extract all connected components

for each connected component

find its bounding box.

extract the same region in the original image frame with coordinates of the bounding box.

end for

end

In the above algorithm we convert the image frame into binary keeping a threshold such that the individual image regions in the frame are masked i.e. they become completely black .After removing the noise from this binarized image we find the connected components i.e. maximal region of connected pixels which are not separated by boundary. The bounding box of connected component gives the upper left corner coordinates and its width and height. With the help of these coordinates we get the individual images from the image frame. For each image obtained from the frame, steps to find the angle of rotation are performed. The image thus obtained, after performing pre-processing steps, is then fed to the network for identification.

5. MEASUREMENT OF THE PERFORMANCE OF THE SYSTEM

5.1 Holdout method

To measure the performance of the system, Holdout method is used. The available dataset is divided into two sets: training and test. Training dataset is that portion of the available labeled examples that are used to build the classifier. Test dataset is that portion of available labeled examples that is used to measure the performance of classifier.

5.2 Accuracy

The accuracy of a classifier is the probability of its correctly classifying records in the test dataset. It is measured as the percentage of records in the test dataset that are correctly classified by the classifier.

5.3 Precision

The precision of a classifier is the probability of records actually being in Class C if they are classified as being in Class C.

If there are two classes Class1 and Class2, Fig 4 shows the confusion matrix.

Actual class →

Predicted class ↓	Class 1	Class 2
Class 1	a	b
Class 2	c	d

Figure 4 Confusion matrix

With this confusion matrix:

$$\text{Percentage accuracy of classifier} = \frac{(a+d)}{(a+b+c+d)} * 100$$

$$\text{Percentage precision for Class C1} = \frac{a}{(a+b)} * 100$$

$$\text{Percentage precision for Class C2} = \frac{d}{(c+d)} * 100$$

6. EXPERIMENTAL RESULT

Experimental results are based on database from Pointing'04 ICPR Workshop. The training dataset consists of images of 4 different persons, each in 3 views (left, right and front) and 10 expressions, thus making a total of 120 images. The test dataset consists of 80 images each of known and unknown, clear, occluded and rotated single as well as multiple image frame. Time taken for learning in this system is 19.68 seconds.

Figure 5 some images from training dataset

The figures below show the test images: single_rot_occ1 (Fig 6) and multi_rot_occ1 (Fig 7).

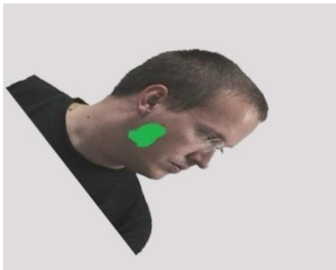

Figure 6 single image with rotated and occluded image.

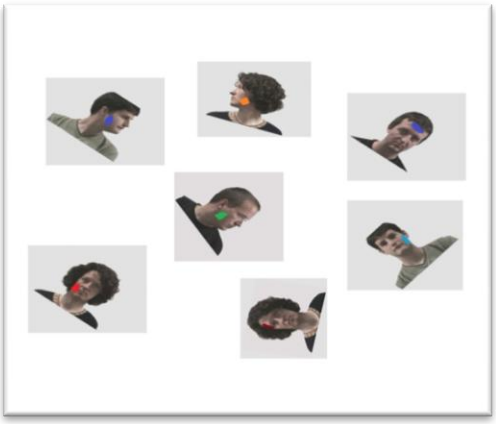

Figure 7 multiple image frame with rotated and occluded images

We took one sample rotated, noisy blurred and occluded image and the preprocessor performed evaluation of the angle of rotation of image then it performed noise elimination, deblurring of the image and finally binarization of image to ultimately get the 2D image matrix and thereafter the 1D image matrix i.e. the internal form of the preprocessed input image. This is shown below diagrammatically

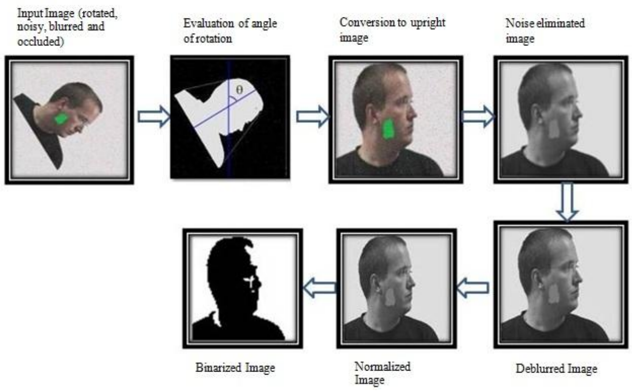

Table 1 and Table 2 present the confusion matrix for occluded rotated images in single and multiple image frame respectively.

Table 1: Confusion matrix for Occluded rotated image in single image frame

	Person 1	Person 2	Person 3	Person 4	Unknown Persons
Person 1	13	0	1	1	1
Person 2	0	15	3	0	5
Person 3	0	0	16	0	5
Person 4	0	0	0	17	3

Table 2: Confusion matrix for Occluded rotated image in multiple image frame

	Person 1	Person 2	Person 3	Person 4	Unknown Persons
Person 1	17	0	1	0	4
Person 2	0	14	1	0	4
Person 3	0	0	16	2	3
Person 4	0	0	0	15	3

Table 3 shows the accuracy and Table 4 shows the learning time of the classifier including both training and testing time, for clear and occluded faces with and without rotation in single as well as multiple images frame.

Table 3: Accuracy of classifier

Type of face	Type of Image Frame	
	Single face image	Multiple face image frame
Clear faces	98.75	92.5
Occluded faces	97.5	91.25
Clear Rotated faces	68.75	73.75
Occluded Rotated faces	78.75	77.5

Table 4: Learning time of the classifier

Type of face	Type of Image frame			
	Single face image Training time=19.68		Multiple face image frame Training time=19.68	
	Testing time	Total Learning time	Testing time	Total Learning time
Clear faces	0.2965	19.9765	2.7715	22.4515
Occluded faces	0.2863	19.9663	2.3748	22.0548
Clear Rotated faces	0.7566	20.4366	6.1547	25.8347
Occluded Rotated faces	0.6901	20.3701	6.0631	25.7431

Table 5 and Table 6 shows the precision of the classifier for single face images and multiple face images frame respectively.

Table 5: Precision of the classifier for single face images

Type of face	Person1	Person2	Person3	Person4
Clear Faces	95	100	100	100
Occluded Faces	100	100	95	95
Clear Rotated Faces	70	63.63	71.42	70.58
Occluded Rotated Faces	81.25	65.21	76.19	85

Table 6: Precision of the classifier for multiple face images frame

Type of face	Person1	Person2	Person3	Person4
Clear Faces	100	95	100	95
Occluded Faces	100	95	95	95
Clear Rotated Faces	80	69.56	72.72	73.68
Occluded Rotated Faces	77.27	73.68	76.19	83.33

The system performs well for clear and occluded images without rotation and the accuracy is above 90%, while for rotated images the accuracy drops to 68.75 % for single image frame and 73.75% for multiple images frame. Similarly the precision of classifier is more for clear and occluded images without rotation and drops to 63.63% when rotation is included in the single face images and 69.56% in multiple face images frame.

Some salient portion of user-system interactions are shown below:

```
MAIN MENU :

Name the folder for learning faces: training_dataset

Time elapsed for learning

    19.6837

IDENTIFICATION:

Enter your choice:1 for single frame image testing, 2 for frame independent testing:1

name the test image:single_rot_occ1

Face is person

     1

Time elapsed for identification 0.6901 seconds

Want to test more?

Enter y for yes or enter n for no:y

Enter your choice:1 for single frame image testing, 2 for frame independent testing:2

name the test image:multi_rot_occ1

The face is person 4 at position (271 ,852)

The face is person 3 at position (307 ,405)

The face is person 1 at position (548 ,661)

The face is unknown at position (603 ,329)

The face is person 4 at position (636 ,921)

The face is unknown at position (916 ,446)

The face is person 3 at position (910 ,738)

Time elapsed for identification 6.0631 seconds
```

7. RELATED WORKS

Many methods have been developed for face recognition and localization. The approach [31] proposed a system that localizes the face from the given input image using the skin color detection method where face is located using template matching. An approach [30] localized faces using a single grey scale image. They analyzed performance of each feature detector which shows the "non-linear SVM" reduced the number of false negatives by 32.2% in comparison with the "linear-SVM".

A face detection system using RBFN was implemented in [35] which gives 96% face detection and 97% non-face detection rate.

In [33], a retinally connected neural network examines a small window of an image, and decides whether each window contains a face or not. This system can detects only upright faces looking at the camera. Preliminary work in this area indicates that detecting profiles or semi-profiles views of face is more difficult than detecting frontal views.

A neural network based face detection system which detects faces at any degree of rotation in the image plane is described in [34]. It uses multiple networks: a 'router' to detect the orientation of image and one or more 'detector' networks which detect faces. The system is able to detect 79.6% of faces with small number of false positives.

8. CONCLUSION

A location and rotation invariant face identification system for plain as well as occluded images based on modified RBFN using a new Heuristic Based Clustering (HBC) has been designed and developed. The system is able to identify rotation invariant clear as well as occluded facial images and localize those images in image frames which are completely location invariant. The accuracy as well as precision of clear, rotated as well as occluded images with Holdout Method is moderately high. The system is efficient, effective and fast while the network size is small. Also the learning time including both training and performance evaluation is moderate.

The work may be further extended by increasing the number of identifiable persons as well as number of angle-expression combination.

9. REFERENCES

[1] G.L Marcialis and F. Roli, "Fusion of appearance based on face recognition algorithm", .Pattern Analysis and Applications,v.7.No 2,Springer-verlag London(2004) pp 151-163.

[2] W. Zhao, R. Chellappa, A. Rosenfeld, P.J. Phillips, "Face Recognition: A literature Survey", UMD CFAR Technical Report CAR-TR-948,(2000).

[3] G. Sarker, "A Heuristic Based Hybrid Clustering for Natural Classification", International Journal of Computer, Information Technology and Engineering (IJCITAE), Vol. 1 No. 2, Dec. 2007, pp. 79-86.

[4] G. Sarker, "A Heuristic Based Hybrid Clustering", Journal of the Institution of Engineers, Computer Engineering Division, Vol 89, November 2008, pp. 7- 10.

[5] G. Sarker, "A Heuristic Based Hybrid Clustering for Natural Classification in Data Mining", 20th Indian Engineering Congress, organized by The Institution of Engineers (India), December 15-18,2005,Kolkata,INDIA, paper no. 4.

[6] G. Sarker, "A Heuristic Based Hybrid Clustering for Natural Classification", International Conference of Computer & Devices for Communication CODEC-06 held on December 18-20,2006, Kolkata organized by Institute of Radio physics & Electronics, University of Calcutta.

[7] G. Sarker, "An Optimal Back propagation Network for Face Identification and Localization",International Journal of Computers and Applications,Vol. 35, Issue 2, 2013, ACTA Press, Canada.

[8] G. Sarker, "An Unsupervised Learning Network for Face Identification and Localization", International Journal if Computer, Information Technology and Engineering (IJCITAE), Vol.6, No 2, pp-83-89, Dec 2012.

[9] G. Sarker, "An Unsupervised Learning Network for Face Identification and Localization", International Conference on Communications , Devices and Intelligent Systems (CODIS), Dec 28 and 29, 2012, Kolkata pp 652-655.

[10] G. Sarker, "A Probabilistic Framework of Face Detection", IJCITAE, Vol. 4, No. 1 pp 1-17, 2010.

[11] G. Sarker, "A Multilayer Network for Face Detection and Localization", Vol. 5, No. 2 pp 41-53, 2011.

[12] G. Sarker, K.Roy, "An RBF network with Optimal Clustering for Face Identification", International Conference on Information & Engineering Science- 2013 (ICIES-2013),Feb. 21-23 2013, organized by IMRF, Vijayawada, Andhra Pradesh.

[13] G. Sarker, K.Roy, "A Modified RBF network with Optimal Clustering for Face Identification and Localization", International Conference on Advanced Engineering and Technology , held at Kolkata on 15th Feb. 2013, pp. 32-37

[14] G. Sarker, S.Kundu, "A Modified Radial Basis Function Network for Fingerprint Identification and Localization", International Conference on Advanced Engineering and Technology , held at Kolkata on 15th Feb. 2013, pp. 26-31.

[15] G. Sarker, "A competitive Learning Network for Face Detection and Localization", accepted for publication in the International Journal of Computer, Information Technology and Engineering (IJCITAE), June, 2013.

[16] K.Roy, G. Sarker, "A Location Invariant Face Identification and Localization with Modified RBF Network", published in ICCS 2013, 21-22 September, 2013, Burdwan pp 23-28.

[17] S.Kundu, G. Sarker, "A Modified Radial Basis Function Network for Occluded Fingerprint Identification and Localization", IJCITAE, 7(2), pp 103-109, 2013.

[18] D. Bhakta, G. Sarker, "A Radial Basis Function Network for Face Identification and Subsequent Localization", International Conference on Computer Science and Information Technology (ICCSIT), pp. 1-6, 10th March 2013.

[19]Ferdnand van der Heijden, "Edge and Line Feature Extraction Based on Covariance Model", IEEE Transactions on Pattern Analysis and Machine Intelligence, VOL. 11, NO. I, JANUARY 1995.

[20] Ming-Hsuan Yang, Member, IEEE, David J. Kriegman,Senior Member, IEEE, and Narendra Ahuja, Fellow, IEEE "Detecting Faces in Images: A Survey", IEEE Transactions on Pattern Analysis and Machine Intelligence, VOL. 24, NO. 1, JANUARY 2002.

[21] Haiyuan Wu, Qian Chen, and Masahiko Yachida, "Face Detection From Color Images Using Fuzzy Pattern Matching Method", IEEE Transactions on Pattern Analysis and Machine Intelligence, VOL. 21, NO. 6, JUNE 1999.

[22] M.A. Turk and A.P Pentland, "Eigen faces for Recognition", Journal of Cognitive Neuroscience, v. 3, No. 1, pp. 71-86, 1991.

[23] F. Behloul, B.P.F. Lelieveldt, A. Boudraa, J.H.C. Reiber, "Optimal design of radial basis function neural networks for fuzzy-rule extraction in high dimensional data", The Journal of the Pattern Recognition Society.

[24] M.J. Er, S. Wu, J. Lu and H.L. Toh "Face Recognition with RBF Neural Networks", IEEEtran on Neural Networks, v.13, No 3(2002), pp 697-710.

[25] J. Park and J.Wasnberg, "Universal Approximator Using Radial Basis Function Network" Neural Computation, v. 3, pp 246-257, 1991.

[26] J. Moody and C.J. Draken, "Fast Learning in Network of Locally Tuned Processing Units", Neural Computation, v. 1, pp 281-294, 1989

[27] S. Lee and R.M. Kil, "A Gaussian Potential with Hierarchically Self Organizing Learning", Neural Networks, v.4, pp. 207-224, 1991.

[28] F. Girosi and T. Poggio, "Networks and The Best Approximation Property", Biological Cybernetics, v. 63, pp. 169-176, 1990.

[29] Xianquan Zhang , Zhenjun Tang, Jinhui Yu, Mingming Guo, "A Fast Convex Hull Algorithm for Binary Image", Informatica 34 (2010) pp. 369-376.

[30] M. Hamouz, J. Kittler,J.-K. Kamarainen,P. Paalanen,H.Ka "lvia" inen, and J. Matas, Member,IEEE Computer Society "Feature-Based Affine-Invariant locaization of Faces",IEEE Transactions on Pattern Analysis and Machine Intelligence, VOL. 27, NO. 9, SEPTEMBER 2005.

[31] ShujaatAli,Jagannath University, Jaipur, Rajasthan, "Novel fast and Efficient Face Recognition Technique", International Journal of IT, Engineering and Applied Sciences Research (IJIEASR)Volume 1, No. 1, October 2012,ISSN: 2319-4413.

[32] Rafael C. Gonzalez, Richard E.Woods, "Digital Image Processing", Pearson Education, Second Edition.

[33] H. A. Rowley, S. Baluja, and T. Kanade, "Neural Network-Based Face Detection", IEEE Transactions PAMI, vol.20,no.1, pp. 23-38,Jan.,1998.

[34] H. A. Rowley, S. Baluja, and T. Kanade, "Rotation Invariant Neural Network-Based Face Detection", IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'98), 1998, pp.38.

[35] Khairul Azha A. Aziz,Ridza Azri Ramlee,Ahmad Nizam Jahari,Melaka,Malaysia,Shahrum Shah Addullah,Skudai,Malaysia "Face Detection Using Radial Basis Function Neural Network With Variance Spread Value", 2009 International Conference of Soft Computing and Pattern Recognition.