

## Original Research Article

# Comparative Analysis of Self-Organizing Feature Map and Counter Propagation Network in Face Recognition

### ABSTRACT

**Aim:** Face recognition systems have gained substantive attention from researchers due to its applications in security and access control. In this study, comparative analysis of SOFM and counter propagation CPN techniques in face recognition was carried out.

**Problem/Study Design:** In lieu of threat to global peace and criminal activities in our society today, it is then imperative to adopt techniques to recognize face. A comprehensive evaluation of two selected artificial neural network techniques was performed to address these challenges.

**Place and Duration of Study:** Ladoke Akintola University of Technology (LAUTECH), Ogbomoso, Nigeria and was done during the period of the Master Study.

**Methodology:** A database of 240 face images was created by capturing six face images from each of 40 persons with a digital camera. Image pre-processing was carried out using MATLAB imaging tool and each normalized using histogram equalisation method. Principal Component Analysis (PCA) was used to extract distinctive features and reduce the dimensionality of each image from 600 x 800 pixels to four different dimensions; 50 x 50, 100 x 100, 150 x 150 and 200 x 200 pixels. SOFM and CPN techniques were used as classifiers for face recognition then evaluated using 140 images for training and 100 images for testing with similarity threshold value of 0.8. The two techniques were evaluated using recognition accuracy and computation time as performance metrics.

**Results:** The results of evaluation showed that, at 50 x 50 pixels, SOFM had 81% accuracy with computation time of 243s while CPN gave 84% accuracy in a time of 174s. Correspondingly, at 100 x 100 pixels, SOFM had 83% accuracy with a time of 244s whereas CPN had 88% accuracy with a time of 179s. Similarly, at 150 x 150 pixels, SOFM gave accuracy of 87% with a time of 245s while CPN generated 90% accuracy with a time of 190s. Furthermore, at 200 x 200 pixels, SOFM resulted in accuracy of 92% with a time of 249s, however, CPN had 95% accuracy with computation time of 234s respectively.

**Conclusion:** This research has shown that CPN outperformed SOFM techniques in face recognition based on recognition accuracy and computational time.

**Keywords:** (Self-Organizing Feature Map SOFM, Counter Propagation Network CPN, Principal Component Analysis PCA, Face Recognition)

### 1. INTRODUCTION

Face recognition has been studied for many years and it has practical applications in areas such as security systems, identification of criminals. Face recognition is an active area of research which has aroused interest of researchers from security, psychology, neuroscience and image processing to computer vision. It is one of the biometric techniques that identify people by "who they are" and not by "what they have" or "what they know" [1]. Face recognition was defined as a pattern recognition task performed specifically on faces and carries the characteristics of a typical pattern recognition system. This system was summarized in modules, namely; face acquisition, image pre-processing, feature extraction, classification module. Image acquisition module is the entry point of the face recognition process. It is the module where the face image under consideration is presented to the system [2].

As a result of global security threat and criminal activities, there is need of adopting techniques coupled with some security measures to recognize face. Self-Organizing Feature Map (SOFM), Principal Component Analysis (PCA), and Independent Component Analysis techniques have been used individually on face recognition system and other pattern recognitions and compared based on some performance metrics. Self-Organizing Feature Map is an unsupervised learning technique and Counter Propagation Network is a supervised learning technique with fast fused clustering network. Self-Organizing Feature Map (SOFM) and Counter Propagation Network (CPN) are two techniques that have been used previously individually on pattern recognition but have not been compared in order to determine their overall accuracy in face recognition systems. This research work conducts a comparative analysis of SOFM and CPN techniques to recognize face images in the database and establish the more efficient between the two techniques.

This work focuses on the use of self-organizing feature map (SOFM) and counter propagation network (CPN) techniques for face recognition. Other related areas such as face detection are not considered.

Summarily, SOFM and CPN were used as classifiers. The more efficient of these two techniques was checked and their recognition rate was evaluated.

## 2. Related Work

Feature extraction is a type of dimensionality reduction that efficiently represents interesting parts of an image as a compact feature vector. This approach is useful when image sizes are large and a reduced feature representation is required to complete tasks such as image matching and retrieval. Researcher interest in face recognition accrued, thereby, providing different algorithms such as Discrete Cosine Transform (DCT), Principal Components Analysis (PCA), Linear Discriminant Analysis (LDA), and Elastic Bunch Graph Matching (EBGM). DCT was explained as an accurate and robust face recognition system and with certain normalization techniques, its robustness to variations in facial geometry and illumination can be increased. An alternative holistic approach to face recognition is discrete cosine transform [3]. PCA was described as a useful statistical technique that has found application in fields such as face recognition and image compression, and is a common technique for finding patterns in data of high dimension. It is a way of identifying patterns in data, and expressing the data in such a way as to highlight their similarities and differences. It was discovered that having found these patterns in the data, and being compressed i.e. then PCA reduced the number of dimensions, without much loss of information [4]. Bolme described LDA as a statistical approach for classifying samples of unknown classes based on training samples with known classes. This technique aims to maximize between-class (i.e., across users) variance and minimize within-class (i.e., within user) variance [5]. Image graphs was used to represent faces in order to handle larger variations in pose. They tested the method in a scenario where recognition is performed based on a single image per person present in the gallery set. Faces are represented by labelled graphs where edges are labelled with distance information and nodes are labelled with wavelet responses locally bundled in jets [1].

Feed-Forward Neural Network (FFNN) and Counter-propagation Neural Network (CNN) classification methods are discovered to be non-optimal in terms of computational time and complexity. Their classification performance is bounded above by that of the eigenface but is more costly to implement in practice [6]. SOFM is used to classify Discrete Cosine Transform DCT-based vectors into groups to identify if the subject in the input image is "present" or "not present" in the image database [7]. SOFMs can be one-dimensional, two-dimensional or multi-dimensional maps. The number of input connections in a SOM network depends on the number of attributes to be used in the classification [8]. A modified Counter Propagation Neural Network (CPN) is employed by Fenwa in 2012 for handwritten character recognition, which proves to be faster than the conventional CPN. In the modified CPN model, there was no need of training parameters because it is not an iterative method like backpropagation architecture which took a long time for learning. This paper implemented a modified Counterpropagation neural network for recognition of online uppercase (A-Z), lowercase (a-z) English alphabets and digits (0-9). The system is tested for different handwritten character. The performances of the techniques were evaluated based on recognition rate and total recognition time. [9]

The Counter Propagation Network (CPN) is a supervised learning algorithm that combines the Grossberg

learning rule with the SOFM. Graupe said CPN has good properties of generalization that allow it to deal well with partially incomplete or partially incorrect input vectors, and serves as a very fast clustering network [10].

[1] Presented an experiment based on black African faces (with and without tribal marks) using the optimized Fisher Discriminant Analysis. In the experiment, different sizes of gray scale images were used and recognition accuracy between 88 and 99% were obtained. Also, taking into consideration was the rate of identifying an image using the same number of images to test the face recognition system.

The performance evaluation of three selected PCA-based techniques was conducted for face recognition. Principal Component Analysis, Binary Principal Component Analysis (BPCA), and Principal Component Analysis –Artificial Neural Network (PCA-ANN) were selected for performance evaluation. A database of 400, 50x50 pixels images consisting of 100 different individuals, each individual having 4 images with different facial expressions was created. Three hundred images were used for training while 100 images were used for testing the three face recognition systems. The systems were subjected to three selected eigenvectors: 75, 150 and 300 to determine the effect of the size of eigenvectors on the recognition rate of the systems. The performances of the techniques were evaluated based on recognition rate and total recognition time. The performance evaluation of the three PCA-based systems showed that PCA-ANN technique gave the best recognition rate of 94% with a trade-off in recognition time. Also, the recognition rates of PCA and B-PCA increased with decreasing number of eigenvectors but PCA-ANN recognition rate was negligible [6].

[11] Implemented three different algorithms and methods in FacelVQA to extract the faceness, pose, illumination, contrast and similarity quality attributes using an objective full-reference image quality assessment approach. Structured image verification experiments were conducted on the surveillance camera (SCface) database to collect individual quality scores and algorithm matching scores from FacelVQA using three recognition algorithms namely principal component analysis (PCA), linear discriminant analysis (LDA) and a commercial recognition SDK. FacelVQA produced accurate and consistent facial image assessment data. The Result shows that it accurately assigns quality scores to probe image samples. The resulting quality score can be assigned to images captured for enrolment or recognition and can be used as an input to quality-driven biometric fusion systems. A general trend of increase in performance with increase in samples/character has also been observed in the case of character recognition [12].

A comparison of three unsupervised techniques was made which were done along with a technique in which the two techniques SOFM and PCA were combined together for dimensionality reduction and feature selection. The simulation results indicate that the performance of face recognition system decreases as the number of classes (subjects) is increased. This is true for all the three methods i.e. SOFM, PCA, ICA (I & II), SOFM & PCA combined and local and global processing as well [4]. The novel face recognition technique that uses features derived from DCT coefficients, along with a SOFM-based classifier was presented by [10]. The system was evaluated in MATLAB using an image database of 25 face images, containing five subjects and each subject having 5 images with different facial expressions. After training for approximately 850 epochs the system achieved a recognition rate of 81.36% for 10 consecutive trials. Self-organizing feature map technique was used which involve stages such as integration of input image, feature extraction, training and mapping. The highest average recognition rate achieved using SOFM was 92.40%, obtained for 40 persons' 400 images of AT&T database. Thus, the experimental results made them conclude that the complexity of face recognition system decreases dramatically by using SOFM [7].

The classification result for satellite image of Modified Counter Propagation network (MCP) with the result by the Self-Organizing Feature Map SOFM was compared. MCP was noticed to be superior to the SOFM and has the qualitative method for the classification [8]. In CPN models used, it was discovered that there was neither need of training parameters nor an iterative method like back-propagation architecture which

took a long time for learning.

[19] Experimented based on black African faces using Principal Component Analysis (OPCA) and Fisher Discriminant Analysis (OFDA) techniques were carried out. The design of the face recognition system was separated into three major sections-image acquisition and standardization, dimensionality reduction, training and testing for recognition. Under static mode, experiments were performed on single scaled images without rotation, OPCA and OFDA both give recognition accuracies of between 89% and 97%; and, 88% and 98% respectively.

### 3. METHODOLOGY

In this study, face images were acquired with a camera and passed into the system for preprocessing. Conversion of face images into grayscale and histogram equalization were two preprocessing techniques employed. These techniques created a platform for image enhancement. Principal Component Analysis was used as feature extraction and dimensionality reduction. Finally, classification of individual images based on input image was tested, by using SOFM and CPN classifier. The stepwise procedures to achieve this research work is shown in Figure 1.

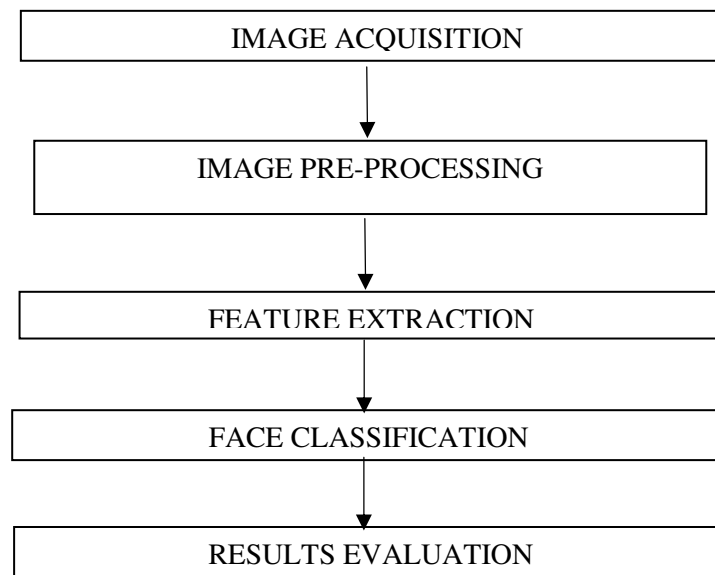


**Fig. 1. Components of a Face Recognition System**

#### 3.1 Acquisition of Face Images

Image acquisition module is the entry point of the face recognition process. It is the module where the face image under consideration is presented to the system. An acquisition module can request a face image from several different environments.

Two hundred and forty neutral face images were captured with a digital camera with a default size of 1200 x 1600 pixels. The original face images were downsized into 50 x 50, 100 x 100, 150 x 150 and 200 x 200 pixels. One hundred and forty images were used for training the system while 100 images were used to test the system.

#### 3.2 Image pre-processing

In this study, image pre-processing was carried out by converting face images into grayscale and

application of illumination normalization such as histogram equalization method.

The images acquired from the digital camera are color images in three-dimensional form (3-D) and is converted into grayscale (two-dimensional form (2-D)) with pixel value between 0 and 255, that is, image in black and white. Each of the grayscale images are expressed and stored in form of matrix in MATLAB which eventually is converted to Vector image for further processes.

The normalization used was histogram equalization which ensured that the input pixel intensity,  $X$  was transformed to new intensity value,  $x'$  by  $T$  as shown in equation 1. The transform function,  $T$  was the product of a cumulative histogram and a scale factor. The scale factor was needed to fit the new intensity value within the range of the intensity values

$$x' = T(x) = \sum_{i=0}^r n_i \cdot \frac{\text{max intensity}}{N} \quad (1)$$

where  $n_i$  is the number of pixels at intensity  $i$ ,  $N$  is the total number of pixels in the image.

### 3.3 Feature Extraction

In this study, Principal Component Analysis was used as feature extraction which converts the set of correlated face images into set of uncorrelated eigenfaces and was also used for dimension reduction of the face vector space. It is the transformation of normalized face vector space into lower dimensional subspace, that is, the dimensionality of the original training set is reduced before eigenfaces were calculated. Eigenfaces (eigenvectors) are the principal components of the training set of face images generated after reducing the dimensionality of the training set. PCA eigenface method considers each pixel in an image as a separate dimension, that is,  $N \times N$  image has  $N^2$  pixels or  $N^2$  dimensions.

To calculate eigenvector, there is a need to calculate the covariance matrix  $C$  as

$$C = A \cdot A^T \quad (2)$$

Where,  $A = N^2 \times M$ ,  $N$  here is the dimension of the image,  $M$  is the number of column vector. If eigenvector is calculated from a covariance matrix before dimension reduction, the system will slow down terribly or run the system out of memory, due to huge computations. In order to overcome this problem, the solution is to calculate eigenvectors from the covariance matrix with reduced dimensionality. Therefore, the covariance matrix is calculated for the eigenvector in the inverse form as  $C = A^T \cdot A$ , Where,  $A = M \times N^2$ . This gives room for dimension reduction. The eigenvectors is sorted according to their corresponding eigenvalues from high to low. Then, the eigenvectors corresponding to zero eigenvalues are discarded while those associated with non-zero eigenvalues are kept [1]. Consequently, the eigenface is formed.

The original images in Figure 2 (a) are trained by undergoing preprocessing stage as explained above through conversion into grayscale, getting its histogram equalization, that is, enhancing the intensity of the image and using PCA to reduce the dimension of the images as shown in Figure 2 (b) and extracted features are critically seen in Figure 2 (c).



Fig. 2(a). Original Image

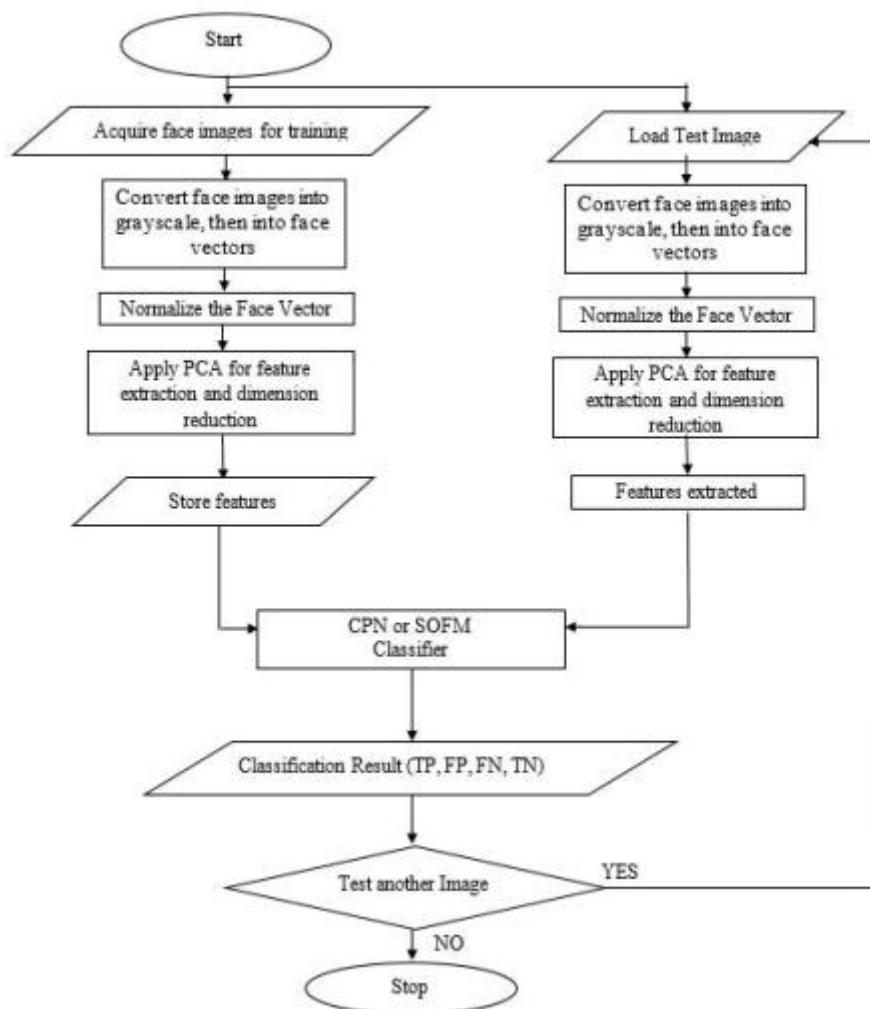


Fig. 2(b). Pre-processed Images

### 3.4 Face Classification

Self-Organizing Feature Map and Counter Propagation Network classifiers were used after feature extraction. They involve learning and classifying, either as unsupervised or supervised. SOFM classified as unsupervised whereas CPN classified as supervised. Face recognition classifiers took place by setting

260 a threshold value for the system. Threshold is a user setting for facial recognition systems for  
 261 authentication and verification. Threshold is the acceptance or rejection of a facial template match which  
 262 is dependent on the match score falling above or below the threshold.



263  
 264  
 265 **Fig. 3. Flowchart showing trained and tested faces with SOFM or CPN**  
 266

### 267 3.5 Performance Measures of SOFM and CPN

268 The performance of Self-organizing feature map (SOFM) and counter propagation network (CPN) on  
 269 trained and recognized faces was measured against recognition accuracy and computation time.  
 270

$$271 \text{ Overall Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \% \dots\dots\dots (3)$$

272  
 273 Where, TP= True Positive, TN= True Negative, FP=False Positive, FN= False Negative  
 274

$$275 \text{ Computation Time=Total Recognition Time} \dots\dots\dots (4)$$

## 277 4. Evaluation Results and Discussion

278 Results acquired by SOFM and CPN techniques using face recognition system with respect to the  
 279 performance metrics used, such as, training time, recognition accuracy and computation time are  
 280 evaluated as follows.

The total training time generated by SOFM with 50 x 50 pixel resolution was 193 sec, 100 x 100 pixel resolution took 206 sec, 150 x 150 pixel resolution was 223 sec, 200 x 200 pixel resolution was 246 sec whereas CPN at 50 x 50 pixel resolution had 169 sec, 100 x 100 pixel resolution was 183 sec, 150 x 150 pixel resolution was 198 sec, 200 x 200 pixel resolution was 221 sec as presented in Table 1.

Table 1 deduced that the training time of Counter Propagation Network had lesser time as a result of the unsupervised nature of the Network compared with the supervised self-organizing feature map.

**Table 1:** SOFM and CPN training time at different resolutions

| Dimension Size | SOFM Time (sec) | CPN Time (sec) |
|----------------|-----------------|----------------|
| 50 X 50        | 193             | 169            |
| 100 X 100      | 206             | 183            |
| 150 X 150      | 223             | 198            |
| 200 X 200      | 246             | 221            |

Recognition accuracy obtained by SOFM and CPN were compared and determined at different threshold values of 0.20, 0.40, 0.60, 0.80 and the study discovered that CPN has better performance in accuracy than SOFM as enumerated in Figure 2. The recognition accuracy at 200 x 200 pixel resolution with CPN generated 91% at 0.20 threshold, 92% at 0.40 threshold, 94% at 0.60 threshold, and 95% at 0.80 threshold, whereas, SOFM obtained 89% accuracy at 0.2 threshold, 90% accuracy at 0.40 threshold, 91% accuracy at 0.60 threshold, and 92% accuracy at 0.80 threshold. Table 2 deduced the performance of CPN against SOFM at different pixel resolutions pixel resolutions of 50 x 50, 100 x 100, 150 x 150, and 200 x 200.

The average recognition time produced at 200 x 200 pixel resolution with CPN are 350s at 0.2 threshold, 249s at 0.4 threshold, 161s at 0.6 threshold, 234s at 0.8 threshold, however, SOFM produced 390s at 0.2 threshold, 252s at 0.4 threshold, 263s at 0.6 threshold and 249s at 0.8 threshold. Summarily, CPN was noticed to classified faster than SOFM. Table 2 shows that values generated in terms of computation time by CPN was lesser than that of SOFM at different pixel resolutions used.

The results were determined based on 0.8 threshold value was selected because of its outstanding performance to other threshold values. Consequently, CPN generated high recognition accuracy at a less time with SOFM.

Finally, the results of evaluation showed that CPN distinctively outperformed SOFM in terms of recognition accuracy and has faster computation time.

**Table 2:** Table showing combined results with SOFM and CPN at threshold value of 0.80

| Pixel Resolutions | Algorithm | Accuracy (%) | Recognition Time (sec) |
|-------------------|-----------|--------------|------------------------|
| 50 x 50           | SOFM      | 81           | 243                    |
|                   | CPN       | 84           | 174                    |
| 100 x 100         | SOFM      | 83           | 244                    |
|                   | CPN       | 88           | 179                    |
| 150 x 150         | SOFM      | 87           | 245                    |

|           |      |    |     |
|-----------|------|----|-----|
|           | CPN  | 90 | 190 |
| 200 x 200 | SOFM | 92 | 249 |
|           | CPN  | 95 | 234 |

## 5. CONCLUSION

This research work evaluated the intrinsic features of CPN and SOFM algorithms on face recognition system in other to determine their effectiveness on the developed system. The face recognition system was preprocessed and its feature was extracted by using principal component analysis for dimensionality reduction. Each of the algorithms (CPN and SOFM) was employed for classification.

One hundred and forty (140) images were trained and 100 images were tested at different resolutions. The experimental results obtained revealed better recognition accuracies in respect of CPN over SOFM for all the resolutions considered. Also, CPN recorded better and less recognition time than SOFM. In view of this, CPN algorithm-based system would produce a better security surveillance than SOFM algorithm-based face recognition system.

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