British Journal of Mathematics & Computer Science
14(3): 1-12, 2016, Article no.BJMCS.22588
ISSN: 2231-0851

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Performance Evaluation of an Improved Self-organizing Feature Map and Modified Counter Propagation Network in Face Recognition

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Authors' contributions

This work was carried out in collaboration between all authors. Authors IAA and OOA both designed the study and carried out software implementation of the algorithm as well as statistical analysis. Author EOO supervised entire process of the design and implementation of the study. Author OOA wrote the first draft of the manuscript while authors IAA and EOO managed the literature searches and edited the manuscript. All authors read and approved the final manuscript.

Article Information

DOI: 10.9734/BJMCS/2016/22588
Editor(s):
(1) Victor Carvalho, Polytechnic Institute of Cávado and Ave, Portuguese Catholic University and Lusiada University, Portugal.
Reviewers:
(1) Gholamreza Anbarjafari, University of Tartu, Estonia.
(2) Ravi Narayan, Thapar University, Patiala, India.
(3) Anonymous, Jadavpur University, India.
(4) Yue-Dar Jou, Republic of China Military Academy, Taiwan.
(5) Anonymous, The John Paul II Catholic University of Lublin, Poland.
Complete Peer review History: http://sciencedomain.org/review-history/13195

Original Research Article

Received: 12th October 2015
Accepted: 29th December 2015
Published: 6th February 2016

Abstract

Aim: To carry out performance evaluation of an Improved Self-Organizing Feature Map (SOFM) and Modified Counter Propagation Network (CPN) techniques in face recognition. These two techniques were examined, implemented and evaluated by using metrics such as recognition accuracy, sensitivity and computation time.
Problem/Study Design: In lieu of threat to global peace and criminal activities in our society today, it is then imperative to adopt a non-linear techniques that might improve the recognition performance of face recognition system because of their intrinsic characteristics. A comprehensive evaluation of these two

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selected artificial neural network techniques was performed to address these challenges and to estimate the preferred technique that had manifested an improved system.

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

Methodology: An Africa database of 240 face images was created by capturing six face images from 40 persons with a digital camera. Image pre-processing was carried out using MATLAB and normalized using local histogram equalization for contrast enhancement. 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 best selected similarity threshold value. 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 243 s while CPN gave 84% accuracy in a time of 174 s. Correspondingly, at 100 x 100 pixels, SOFM had 83% accuracy with a time of 244s whereas CPN had 88% accuracy with a time of 179 s. Similarly, at 150 x 150 pixels, SOFM gave accuracy of 87% with a time of 245 s 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 249 s, however, CPN had 95% accuracy with computation time of 234 s 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 provoked 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 that could enhance the recognition performance of the system. Features extraction algorithms and classifiers had been researched upon to have contributed to the performance of the system. Some linear and non-linear techniques had been used overtime as feature extraction and classifier in pattern recognition system either individually or comparably to ascertain the performance of the system. At the same time, evaluation of the system with some selected metrics such as recognition accuracy, sensitivity, computation time etc have been considered. Previously, comparison of unsupervised learning techniques like PCA, SOFM and Independent component analysis (ICA) has been carried out [3].

There are two non-linear techniques embraced and used as classifier in this study, they are SOFM and CPN. SOFM is an unsupervised learning technique having a clustering network and CPN is a hybrid of unsupervised and supervised learning technique (Outstar rule) [4]. SOFM and CPN are two techniques that have been used previously individually on pattern recognition but might not have been modified and compared in order to determine their overall accuracy in face recognition systems. This research work conducts a performance evaluation of an improved SOFM and modified CPN techniques to recognize face images with black African face database and establish the more efficient between the two techniques. Modification in this study depicts the fact that a linear algorithm (PCA) was used to extract features at the initial process before the application of either of the non-linear classifiers. SOFM and CPN had been used as feature extraction and at the same time used as classifier in previous studies which means non-linear approach was adopted throughout the pattern recognition processes. But this study used linear technique approach (PCA) to extract features and finally classified by using a non-linear approach technique.

This work focuses on the use of improved SOFM and modified 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 were evaluated.

2 Related Work

The interest of researchers in face recognition ensued, thereby, providing different algorithms such as Discrete Cosine Transform (DCT), PCA, Linear Discriminant Analysis (LDA), and Elastic Bunch Graph Matching (EBGM) in pattern recognition. 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. DCT was used as an alternative holistic approach to face recognition [5]. PCA was described as a useful statistical technique which has been used in application such as face recognition and image compression, and was a common technique for finding patterns in data of high dimension. It was 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, then conclusively, PCA was said to have reduced the number of dimensions, without much loss of information [6]. 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 [7]. Image graphs was used to represent faces in order to handle larger variations in pose. They tested the method in a scenario where recognition was performed based on a single image per person presented in the gallery set. Faces were represented by labelled graphs where edges were labelled with distance information and nodes were labelled with wavelet responses locally bundled in jets [1].

Feed-Forward Neural Network (FFNN) and CPN 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 [8]. SOFM was used to classify DCT-based vectors into groups to identify if the subject in the input image is “present” or “not present” in the image database [9]. SOFMs can be one-dimensional, two-dimensional or multi-dimensional maps. The number of input connections in a SOFM network depends on the number of attributes to be used in the classification [10]. A modified CPN was 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 was not an iterative method like backpropagation architecture which took a long time for learning. This paper implemented a modified CPN for recognition of online uppercase (A-Z), lowercase (a-z) English alphabets and digits (0-9). The system was tested for different handwritten character. The performances of the techniques were evaluated based on recognition rate and total recognition time [11].

The CPN was defined as 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 [12].

Omidiora presented an experiment based on black African faces (with and without tribal marks) using the optimized Fisher Discriminant Analysis (FDA). 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 [1].

The performance evaluation of three selected PCA-based techniques was conducted for face recognition. PCA, Binary PCA, and PCA–Artificial Neural Network (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 [8].

Omidiora implemented three different algorithms and methods in FaceIVQA to extract the faceness, pose, illumination, contrast and similarity quality attributes using an objective full-reference image quality assessment approach [13]. Structured image verification experiments were conducted on the surveillance camera (SCface) database to collect individual quality scores and algorithm matching scores from FaceIVQA using three recognition algorithms namely PCA, LDA and a commercial recognition SDK. FaceIVQA 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 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 indicated that the performance of face recognition system decreases as the number of classes (subjects) was increased. Independent Component Analysis (ICA) was used and described as a computational method for separating a multivariate signal into additive subcomponents. This was true for all the three methods i.e. SOFM, PCA, ICA (I & II), SOFM & PCA combined with local and global processing as well [6]. SOFM 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', that is, 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 [9].

Omidiora experimented based on black African faces using Optimized PCA and Optimized FDA 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 [14].

Nilesh presented a face and non-face recognition system using feature recognition from DCT, that is, image compression factors, along with a SOFM neural network based classifier. This system was developed in MATLAB using 25 face images in database, containing five different subjects and each different subject having 5 images with facial expressions. The neural network was trained for 1000 epochs then the system achieved a recognition rate of 98.87% for approximately 800 epochs for 10 consecutive trials. The advantage of this technique was that, it is suitable for low cost real time hardware and software implementations [15].

In a new technique for human face recognition. PCA was used for dimensionality reduction and for feature extraction. SOFM was used as classifier to identify whether the subject was present or not present in the image database. Recognition with SOFM was carried out by classifying intensity values of grayscale pixels into different groups. Evaluation of the procedure was performed in MATLAB using an image database of 20 people containing 4 subjects and each subject have 5 diverse facial expressions. After training about 500 epochs system achieved approximately 98.31% recognition rate for consecutive 5 trials. The main advantage of this technique was its low computational requirement and high speed and better recognition rate [16].

In a performance evaluation of three selected PCA based techniques for face recognition. PCA, BPCA, and PCA-ANN were selected for performance evaluation. A database of 400, 50 by 50 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 [17].

Adedeji carried out an evaluation of OPCA and Projection Combined PCA techniques based on following parameters, such as recognition accuracy, total training time, average recognition time. Overall results indicated that OPCA performed better than $(PC)^2A$ [18].

Muhammad, Dzulkifli, and Razib [19] used CPN technique singly in character recognition and measured the system with metric such as false recognition (FR). The study discovered that the lower the false recognition rate, the more reliable the system. On the other hand, performance of the system increases without threshold but at cost of more FRs. But CPN performances were found out to reduce the challenges of character recognition.

A comparison of unsupervised techniques (SOFM) alongside two linear technique (PCA and ICA) were made. SOFM and PCA were combined together for dimensionality reduction and feature selection. The simulation results of SOFM and ICA indicated that the performance of face recognition system decreases as the number of classes (subjects) was increased. SOFM, PCA, ICA also gave the same result. The decrease was more in case of SOFM and PCA compared to other methods. It was deduced that the decrease in performance of recognition system was as a result of increase in the number of classes (subjects), which gave chances of more mismatch faces because of more similar faces [20].

Shamla used SOFM in face recognition. SOFM was called sheet-like artificial neural network (i.e. non-linear techniques), the cells of which become specially tuned to various input signal patterns or classes through an unsupervised learning process. SOFM reduced dimensions and displayed similarities and discovered that SOFM were topologically ordered, which led to good extracting feature ability. SOFM achieved highest average recognition rate of 92.40%, obtained for 40 persons of AT&T database. Thus, the experimental results made them conclude that the complexity of face recognition system decreases dramatically by using SOFM [21].

Jawad presented a novel face recognition technique that uses features derived from DCT coefficients (linear algorithm), along with a SOFM-based classifier (non-linear algorithm). 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 [22].

Anbarjafari proposed a face recognition system based on local binary pattern (LBP) using the probability distribution functions (PDFs) of pixels in different mutually independent color channels. The illumination of faces were enhanced by using discrete wavelet transform (DWT and singular value decomposition (SVD), that is, state-of-the-art techniques. After equalization, face images were segmented by using local successive mean quantization transform followed by skin color-based face detection system. Kullback–Leibler distance between the concatenated PDFs of a given face obtained by LBP and the concatenated PDFs of each face in the database was used as a metric in the recognition process. The proposed system was tested by using FERET, HP, and Bosphorus face databases. The proposed system was also compared with conventional and the state-of-the-art techniques. The recognition rates obtained using FVF approach for FERET database was 99.78% compared with 79.60 and 68.80% for conventional gray-scale LBP and PCA-based face recognition techniques, respectively [23].

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. PCA 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 Fig. 1.

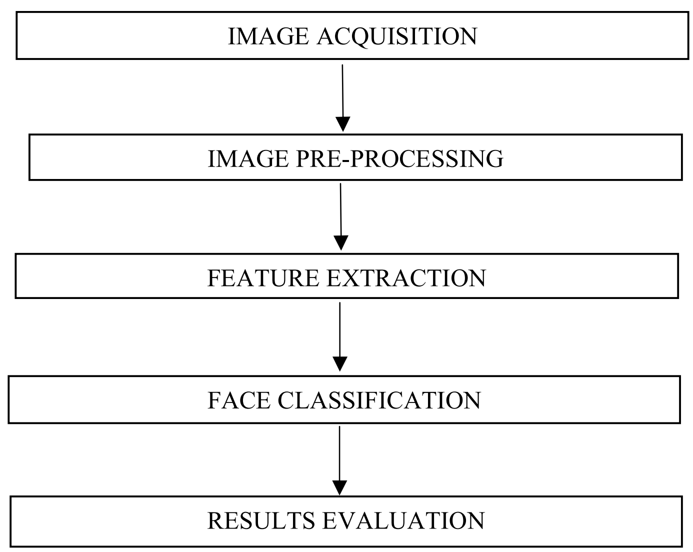

Fig. 1. Components of a face recognition system

3.1 Acquisition of face images

Two hundred and forty neutral face images were captured with a digital camera from JAF Comprehensive College, Ogbomoso, Oyo State, Nigeria with a default size of 1200 x 1600 pixels. The original face images were downsized manually 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 and 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 were color images and were converted into grayscale with pixel value between 0 and 255, that is, image in black and white. Each of the grayscale images were expressed and stored in form of matrix in MATLAB which eventually was 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

$$x' = T(x) = \sum_{i=0}^{r} n_i \, . \, \frac{\max intensity}{N} \tag{1}$$

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, a linear technique (PCA) 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 was reduced before eigenfaces were calculated. Eigenfaces (eigenvectors) were the principal components of the training set of face images generated after reducing the dimensionality of the training set. PCA eigenface method considered each pixel in an image as a separate dimension, that is, N x N image has N^2 pixels or N^2 dimensions.

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

$$C=A * A^T \tag{2}$$

where, A $=\{ \begin{matrix} a_{1,1} & \cdots & a_{1k} \\ \cdot & \cdot & \cdot \\ aj_1 & \cdots & a_{jk} \end{matrix} \}$. 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

$$C=A^T * A \tag{3}$$

where, A$=\{ \begin{matrix} a_{1,1} & \cdots & a_{1k} \\ \cdot & \cdot & \cdot \\ aj_1 & \cdots & a_{jk} \end{matrix} \}$. 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 Fig. 2a 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 Fig. 2b.

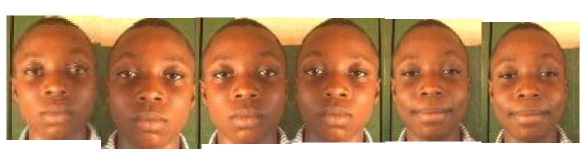

Fig. 2a. Original image

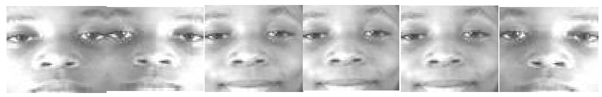

Fig. 2b. Pre-processed images

3.4 Face classification

Non-linear techniques such as SOFM and CPN 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 a threshold value for the system. Threshold is a user setting for facial recognition systems for authentication and verification. Threshold is the acceptance or rejection of a facial template match which is dependent on the match score falling above or below the threshold.

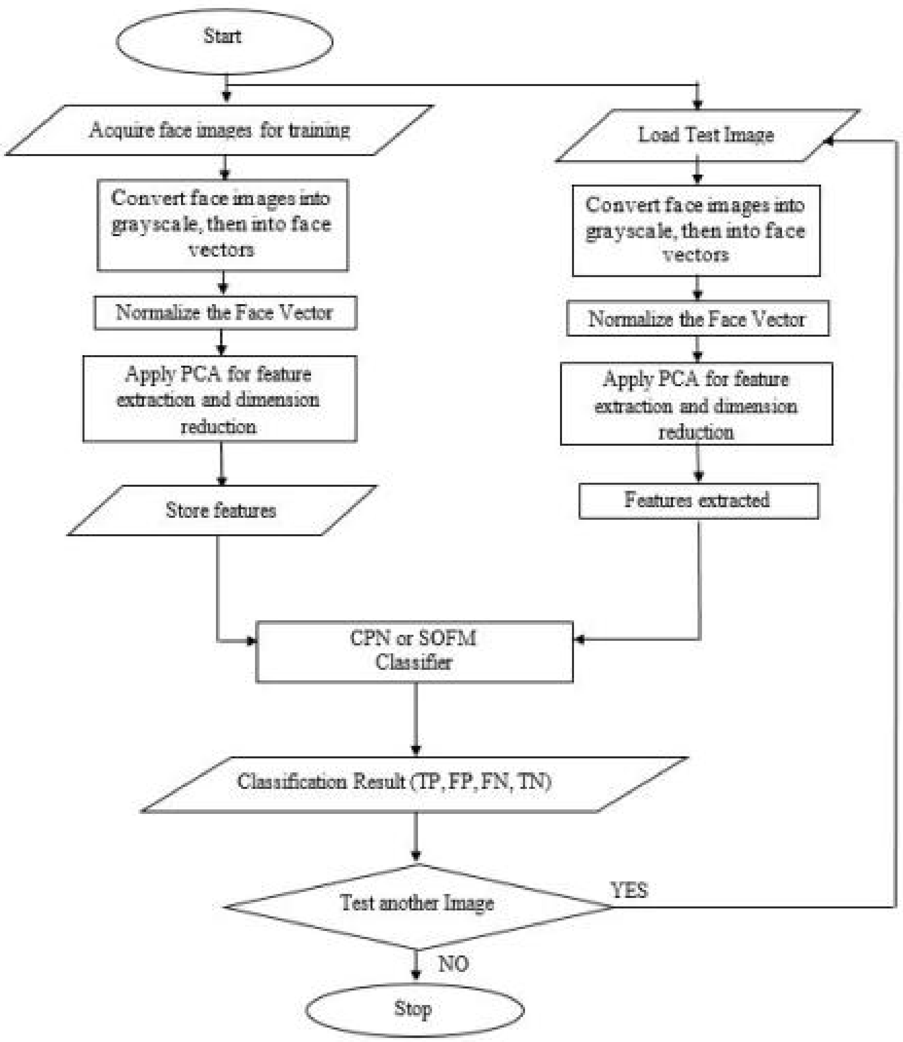

Fig. 3. Flowchart showing trained and tested faces with SOFM or CPN

3.5 Implementation of face recognition system in MATLAB

An interactive Graphic User Interface (GUI) was developed with a black African database consisting of 40 subjects of face images. The implementation tool used was MATLAB R2012a version on Windows 7 Ultimate 32-bit operating system, Intel®Pentium® CPU B960@2.20GHZ Central Processing Unit, 4GB Random Access Memory and 500GB hard disk drive.

The database was formed from black African database consisting of 40 frontal neutral face images. The system was experimented with a total of 240 images, out of which 140 images were used in training the dataset meaning 4 images per 35 subjects and 100 images to test the face recognition system meaning 2 images per 35 subjects plus 6 images per the remaining untrained subjects.

Black African faces were employed because they were not commonly used. Oftentimes researchers made use of standard database such as FERET, ORL database etc. but not much researches have been conducted on black faces.

3.6 Performance measures of SOFM and CPN

The performance of improved SOFM and modified CPN on trained and recognized faces were measured against recognition accuracy, sensitivity, false positive rate and computation time.

4 Evaluation Results and Discussion

Results acquired by SOFM and CPN techniques using black faces database with respect to the aforementioned metrics were evaluated as follows.

The training time were taken five times using Intel®Pentium® CPU B960@2.20GHZ Central Processing Unit, 4GB Random Access Memory System. SOFM took 193 s averagely with 50 x 50 pixel resolution, 206 s with 100 x 100 pixel resolution, 233 s with 150 x 150 pixel resolution, 246 s with 200 x 200 pixel resolution whereas CPN at 50 x 50 pixel resolution had 169 s averagely, 183 s with 100 x 100 pixel resolution, 198 s with 150 x 150 pixel resolution, 221 s with 200 x 200 pixel resolution as presented in Table 1.

Table 1 deduced that the training time of CPN had lesser time as a result of the hybridized unsupervised and supervised nature of the Network compared with the unsupervised SOFM.

Table 1. SOFM and CPN average training time at different resolutions

Database	Dimension size	SOFM time (sec)	CPN time (sec)
Black African faces	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 Fig. 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 of 50 x 50, 100 x 100, 150 x 150, and 200 x 200.

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

Furthermore, Table 2 shows that CPN in terms of sensitivity at different resolutions had an increase value compared with SOFM.

The results were determined based on the best selected threshold value because of its outstanding performance over 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 best selected threshold value

Database	Pixel resolutions	Algorithm	Sensitivity (%)	Accuracy (%)	Computation time (sec)
Black African faces	50 x 50	SOFM	83	81	243
		CPN	89	84	174
	100 x 100	SOFM	88	83	244
		CPN	95	88	179
	150 x 150	SOFM	95	87	245
		CPN	97	90	190
	200 x 200	SOFM	100	92	249
		CPN	100	95	234

5 Conclusion

The study has presented a performance evaluation of modified hybrid of unsupervised-supervised (CPN) and an improved unsupervised (SOFM) learning algorithms as well as their application with neutral face recognition. Modification and improvement in this study depicts the fact that a linear algorithm (PCA) was used to extract features at the initial process before the application of SOFM and CPN classifiers. SOFM learned with the ability to organize information without providing an error signal and learned the distribution of set of patterns without any class information while CPN learned by adjusting its interconnection weight combinations with the help of error signals then learned the distribution of set of patterns with class information.

This study shows that illumination of faces was enhanced by using local histogram equalization technique compared with DWT and SVD employed by [23]. Euclidean distance in SOFM and CPN between the input faces obtained by PCA and the weight of features of each face in the database was used as metric in the recognition process which is contrary to Kullback –Leibler distance used between the concatenated PDFs of a given face obtained by LBP and the concatenated PDFs of each face in the database by [23]. No fusion techniques was adopted in this study. A Black African database was engaged in this study whereas FERET face database was used by [23].

This research work implemented and evaluated the intrinsic features of CPN and SOFM algorithms in face recognition system in order to determine their effectiveness in 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.

Consent

The consent of all participants, whose photos were taken as part of our data acquisition process, was sought and obtained before being used in our experiments. They were no minors among the participants. Also, another specific consent was sought from the participant whose face is shown in Figs. 2a and 2b as regards using his face as a sample image in our publication.

Competing Interests

Authors have declared that no competing interests exist.

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