

Original Research Article**NORMALIZED INDEPENDENT COMPONENT
ANALYSIS FOR FACE RECOGNITION****ABSTRACT**

Face recognition has received substantial attention from researches in biometrics, pattern recognition and computer vision community. Face recognition has been applied mostly in security measures and access controls in restricted areas. Over the time, various approaches have been developed for face recognition; Independent Component Analysis (ICA) tends to outweigh others e.g. local feature analysis, Principal Component Analysis and Linear Discriminant Analysis (LDA) in terms uniqueness in handling dependency that exists among feature which slow down classification process and reduce the recognition accuracy but still suffer some drawbacks in ranking the independent feature. In a bid to overcome this drawback, this study presents the development of a Normalized-ICA based Face Recognition System. The FRS combines Artificial Neural Network and ICA techniques by computing the normalized power recognition which serves ANN targeted output to compute prediction for individual instances forming Normalized ICA face space for testing. In conclusion, the NICA-based recognition system developed has a better recognition accuracy and better recognition time when compared to conventional ICA-based FRS.

Keywords: {Normalized, Independent Component Analysis, face recognition}

1.0 Introduction

In recent times, the need of biometric security system is heightened for providing safety and security against terrorist attacks, robbery, etc. The demand of biometric system has risen due to its strength, efficiency and easy availability. One of the most effective, highly authenticated and easily adaptable biometric security systems is facial feature recognition (Omidiora, 2006).

The recent advance in computer vision, pattern recognition and image processing, face recognition is one of the most popular research topics. The reason behind this is that among the various biometric security systems based on finger print, iris, voice or speech, signature, etc., face recognition seems to be the most universal, non-intrusive, and accessible system (Oladipo, 2014). It is easy to use, can be used efficiently for mass scanning which is quite difficult in case of other biometrics, and also increases user-friendliness in human-computer interaction.

The earliest works on this subject were made in the 1950's in psychology. There are other issues like face expression, interpretation of emotion or perception of gestures. In the past 20 years, significant

advances have been made in design of successful classifier for face recognition using template matching algorithm (Amir 2008). However the diversity of the face image patterns makes it difficult to create robust recognition systems and the complexity of the algorithms makes them tedious to implement (Omidiora, Fakolujo, Ayeni, Olabiyisi & Arulogun, 2008). A successful face recognition methodology depends heavily on the particular choice of the features used by the (pattern) classifier. Feature selection in pattern recognition involves the derivation of salient features from the raw input data in order to reduce the amount of data used for classification and simultaneously provide enhanced discriminatory power. This research work developed a Normalized Independent Component analysis in image processing, with particular reference to human faces and then compares its results with the convectional Independent Component Analysis in terms of recognition accuracy and recognition time.

Independent Component Analysis (ICA) has emerged recently as one powerful solution to the problem of blind source separation i.e. different features classification. ICA is an unsupervised feature extraction technique whose goal is to find which components are statistically independent from each other as possible. ICA is the generalization of Principal Component Analysis (PCA). In high-dimensional applications (set of features), the ICA pipeline actually contains PCA process (for dimension reduction), whitening process (for scaling), and pure ICA process.

In a task such as face recognition, much of the important information may be contained in the high-order relationships among the image pixels. PCA is only sensitive to the second order statistics by de-correlating the input data using second-order statistics and thereby generates compressed data (dimension reduction) with minimum mean-squared reprojection error using Eigen faces (Turk and Pentland, 2006) for representation. ICA minimizes both second-order and higher-order dependencies in the input.

The Normalized Independent Component Analysis (NICA) uses the K-means nearest neighbor method for finding similar train instances to each test sample which helps in determining the energies of the different independent components and then computes some measures to determine the Power Recognition Factor (PRF) whose results are passed to the Artificial Neural Network system for training. This is done to combat the problem of the convectional ICA which includes its inability to determine the

order of the independent components and also lack capacity to determine the variances (energies) of the independent components.

Facial Biometrics has been implemented using various approaches such as local feature analysis, Independent Component Analysis, and Principal Component Analysis and Linear Discriminant Analysis (LDA) but the algorithms can be further enhanced to provide reliable face recognition, maximize recognition rate; regardless of the facial orientation, face expression, illumination variation and face dressing. This research work presents the development of a Normalized -Independent Component Analysis algorithm and investigates its performance viz a viz a conventional ICA-based system with respect to recognition time and recognition accuracy.

2.0 Literature review

The growing use of the Internet by individuals and organizations has presented opportunities for identity fraud, organized crime, money laundering, theft of intellectual property and a myriad of cybercrimes. The world has also witnessed an increase in bio-security incidents, border control incidents and terrorism. With this background, the ability to positively identify people is becoming more and more important. One key tool in this area is the use of biometrics. Humans have always identified each other by recognizing faces, voices or some other physical characteristic. Personal recognition or identification by a witness is also entrenched in our law and commercial structures. Now the use of biometric technologies is providing a means to positively identify or authenticate large numbers of people without having to primarily rely on human to human identification. (Birgit, 2005)

Whatever biometric technology, or combination of technologies are used, there are common basic procedures: this include Capture, extract, create template and compare.

Capture is also known as the enrolment or registration process. In this process the individual provides a sample of the appropriate biometric, for example provide a fingerprint, repeats a phrase for a voice recognition system or provide an image for a face recognition system. This sample is analysed and key features extracted to create a template. In some cases, several samples are provided and the key features aggregated into the template, sometimes also known as a reference template. During Extraction, Ideally the sensors will extract sufficient data to ensure the key characteristics do not vary over time or with changes in the environment (such as a poorly presented fingerprint or poor lighting for facial

recognition sensors). Devices typically take multiple samples of the presented biometric and average the results to produce the template. To minimize the size of the template and storage requirements and to speed searches, the sensors usually extract only features that tend to be unique. Ideally some form of "liveness" test should also be incorporated to minimize or defeat attempts to circumvent or compromise the system.

The template is the data representing the captured biometric and the reference against which later samples are checked. Templates are only data representing key or distinctive features of a biometric and are not a complete image or record of the original biometric (such as a fingerprint, voice recording or digital image). One analogy used is that biometrics is the body's passwords. They are usually small, which facilitates processing and speeds response times when referenced. The ease of enrolment and quality of the template are often the determining factors in the successful implementation and use of a biometric system. The comparison of the sample to templates and its ability to successfully discriminate between samples and templates is, perhaps, the most important part of a biometric system. Systems for matching have been used in a wide variety of applications for some time. Sometimes described as pattern matching, it can use a variety of techniques such as minimal distance, probabilistic analysis and neural networks. The comparison process can also add the current sample to the template, thus averaging results over a long period of use.

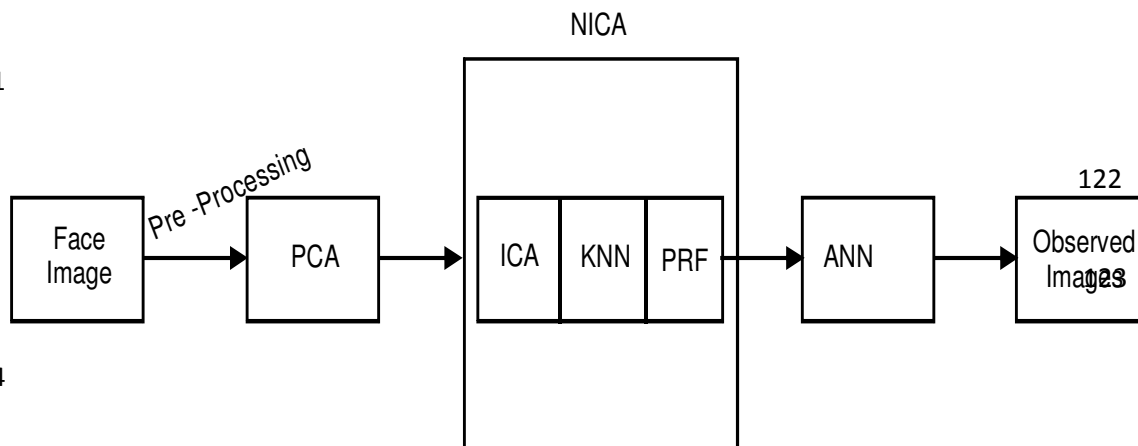
3.0 Methodology

This study presents the development of a Face Recognition System (FRS) by combining; ICA and ANN. The ICA uses the Principal component Analysis (PCA) for dimension reduction by considering the eigenvector associated with higher Eigen values in features extraction and the Artificial Neural Network (ANN) algorithm remove unimportant features in the eigen face space. This ensures that only relevant features are passed to the testing stage. The developed system used the Euclidean distance as similarity measure to determine if the face is recognized or not. The model diagram for the FRS developed is shown in Figure 1. The face database used in this simulation consists of 400 images. Ten (10) different images of 40 distinct individuals were taken and some subjects' images were taken at different times. The sequence of the steps involved in developing the system is described in the flow charts as shown in

Figure 2 and 3 respectively. The implementation proceeds in two stages namely the training and testing stage.

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Figure 1: FRS model.

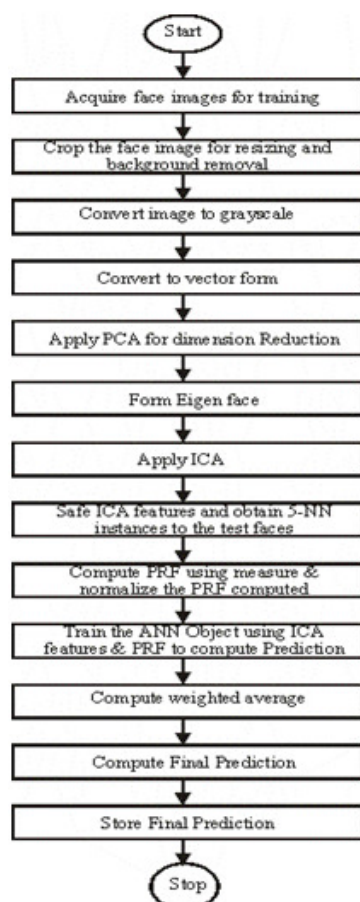


Figure 2 : Training Stage

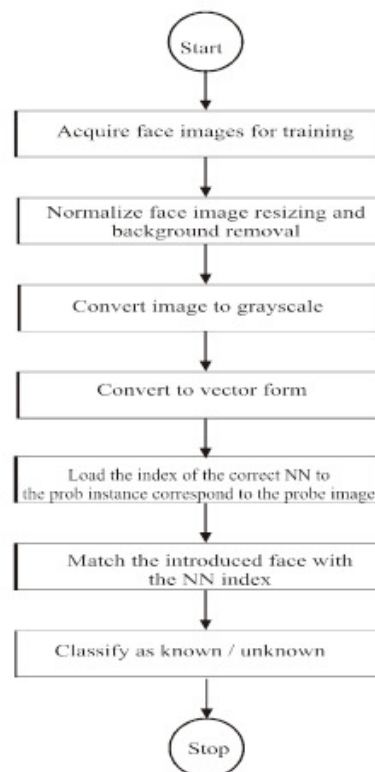


Figure 3: testing Stage

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127 The training stage is preceded by series of pre-processing stage which includes: image cropping to
 128 remove background and unwanted parts of the image, image grayscale conversion and conversion of
 129 image data to vector form. Independent component Analysis uses the Principal Component analysis on
 130 the vector form to ensure that the face image dataset is represented by a reduced number of effective
 131 features and yet retains the most intrinsic information of the image data. The face database used has 200
 132 images for training and each image has minimum resolution of $92 * 92$ (8464) and maximum of $112 * 92$
 133 (10304) pixel with 30 and 60 selected principal components after background removal. Sample images
 134 are shown in Figure 4. It should be noted that only first 30 and 60 principal components were selected for
 135 the simulation. Independent component analysis was then applied on the eigen values to make the
 136 feature vector independent of another and to be able to handle the dependency that exists among feature
 137 which slow down classification process and reduce the recognition accuracy. The Independent features
 138 are then saved for further processing. During this study it was seen that ICA lacks the capacity to know
 139 the order (i.e. energies) of each independent component, this was also stated in Mehran and Mansourv
 140 (2007). In a bid to overcome this shortcoming the already trained and saved Independent Components
 141 was then given back to the Independent component analysis (ICA) as test faces to obtain 5-nearest
 142 neighbors for all the 200 training datasets. Six (6) different measures were applied to the nearest
 143 neighbor feature set generated from the previous stage to compute the Power Recognition Factor (PRF),
 144 this was carried out to train ICAs in different classification regions. The measures include
 145 $P1$ = Number of correct recognized results in the first K results
 146 $P2$ = the first incorrect result index
 147 $P3$ = Distance between the first correct and the first incorrect result
 148 $P4$ = Distance between the first incorrect result and its previous
 149 $P5$ = Number of times that the instance is placed in a positive situations
 150 $N6$ =Number of times that the instance is placed in a negative situations
 151 The PRFs were normalized to form $nP1$ - $nP5$ and $nN6$ respectively. Which serves as the targeted output
 152 of artificial neural network. ANN objects were trained using Independent component Analysis features as
 153 the input and the computed normalized power recognition Factor (PRF) as targeted outputs. ICA features
 154 were then simulated with created ANN objects to obtain predictions for each of the training instances. The

155 weighted average of each training instances were also computed. The product of the predictions and the
 156 weighted average calculated formed the final predictions which were saved as NICA face space to be
 157 used during testing.

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Figure 4: Sample Image after background removal

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161 During testing, images were projected into NICA face space after it has been pre-processed and the task
 162 of determining whether the image was recognized or not was carried out. This was achieved by
 163 performing distance measure using Euclidean distance between the projected test image and the index of
 164 the correct nearest neighbor (NN) to the instance corresponding to the probe or test image in the created
 165 NICA face space. The image that has the minimum Euclidean distance to the test image is selected. In
 166 this case the image was classified as “known” and if the image that aren't in the same class with test
 167 image was selected as having the minimum Euclidean distance to the test image, the image is said to be
 168 “unknown”.

169 All the 400 images acquired were used in this research work. Five (5) images from each class of 10 are
 170 chosen for training while the other five were used in testing the system. The test images were introduced
 171 one at a time specifying the file name, to see if it will be classified as being “known” or “unknown” to the
 172 FRS. The performance metrics used are Average recognition accuracy, average recognition time and

total training time. These were investigated as it varies with cropped image dimension to deduce optimum dimension for the face recognition system and the results were evaluated with the performance of a convolutional ICA based recognition system.

4.0 Simulation output and Discussion

The simulation process precedes in two stages namely the training stage and testing stage. At the training stage, the system used five (5) of the 10 images samples to form NICA feature space. This was done by iteration through the faces in the f1 to f40 folder of the project directory and training the files names 1jpeg, 2jpeg, 3jpeg, 4jpeg and 5jpeg respectively. The testing image sample were arranged thus; 5jpeg, 6jpeg, 7jpeg, 8jpeg, 9jpeg and 10jpeg were the five remaining images of the first subject, 15jpeg, 16jpeg, 17jpeg, 18jpeg, 19jpeg and 20jpeg as the remaining sample of the second subject respectively. These were all stored and arranged in the project directory of the system's local drive local drive. The dimension of the cropped image influences the performance of both NICA and ICA-based FRS. Table 1 shows the summary of the effect of increase in the cropped dimension from 92*92 through 92*112 for both NICA and ICA-based systems. The recognition accuracies at dimension 92*92 are 86.00% and 95.00% for ICA and NICA-based system using 30 principal components, 86.50% and 96.00% using 60 principal components at the same dimension respectively. At dimension 92*112 a recognition accuracy of 90.00% and 98.00% was obtain for ICA and NICA-based system, 91.00% and 98.00% using 60 principal components at the same dimension respectively. This implies that recognition accuracy of both systems increases with increase in crop dimension. This is because more features will be available to identify the face image with an increase in cropped image dimension. The NICA-based system was found to have better recognition accuracy; this is due to the fact that the only relevant features were made available for recognition in the NICA feature matrix.

Table1: Recognition Accuracy for both NICA-and ICA-based System

Dimension of Cropped face images	Number of PCs used	Average recognition Accuracy for NICA (%) (G)	Average recognition Accuracy for ICA (%) (P)	Increment in recognition accuracy (G-P)	Percentage Increment in Recognition Accuracy (%) $((G-P) * 100/P)$
92*92	30	95.00	86.00	9.00	10.46
	60	96.00	86.50	9.50	10.98
92*100	30	97.00	87.00	10.0	11.49
	60	97.50	88.50	9.00	10.16
92*112	30	98.00	90.00	8.00	8.88
	60	98.00	91.00	7.00	7.69
Cumulative Increment in Recognition accuracy				52.50	

The time of recognition of images introduced to the system was well captured, as the program evaluates the difference between the time image was recognized and the time the search commences. The system was made to iterate through images 5jpeg, 6jpeg, 7jpeg, 8jpeg, 9jpeg and 10jpeg through 396jpeg, 397jpeg, 398jpeg, 399jpeg and 400jpeg in the project directory; which were the equivalent testing images. The time to recognize each image was captured and cumulated to calculate the average time it takes to recognize a test face image. At cropped dimension 92*92 it took an average of 0.0096s and 0.0095s using 30 principal components to recognize a test image in ICA-and NICA-based, 0.0086s and 0.0085s using 60 principal components at the same dimension respectively and at cropped dimension of 92*112 it took an average of 0.0102s and 0.0098s using 30 principal components, 0.0106s and 0.0099s using 60 principal components at the same dimension respectively as shown in Table 2. This shows that NICA-based system optimizes search time better than the ICA counterpart. This is due to the fact that the feature matrix presented for NICA search has only relevant feature to search through.

Table 2: Average Recognition time for both NICA-and ICA-based System

Dimension of Cropped face images	Number of PCs used	Average recognition time for NICA system (Sec)(t1)	Average recognition time for ICA system (Sec)(t2)	Recognition time gained (Sec) $T=(t1-t2)$	Percentage Increment in Recognition time (%) $((t1-t2)* 100/t2)$
92*92	30	0.0095	0.0096	0.0001	1.041
	60	0.0085	0.0086	0.0001	1.041
92*100	30	0.0093	0.0095	0.0002	2.105
	60	0.0089	0.0099	0.001	10.10
92*112	30	0.0098	0.0102	0.0004	3.921
	60	0.0099	0.0106	0.0007	6.603
Cumulative recognition time gained				0.0025	

The time incurred while training the NICA-based system was captured as the difference between the cpu-time at the commencement of the first training and cpu-time at the conclusion of the last training image. At dimension 92*92 a total time of 20.7481s and 26.3174s using 30 principal components was incurred while training the ICA-and NICA-based system, 41.5743s and 47.1435s using 60 principal components was incurred at the same dimension respectively while at dimension 92*112 a total time of 22.1677s and 27.9398s using 30 principal components was incurred while training the NICA- and ICA- based system, 45.2403s and 49.1091s using 60 principal components was incurred at the same dimension respectively as shown in table 3. This indicated that the ICA- based system trains faster than the NICA counterpart. This could be explained by the time incurred in ANN training and normalization process in removing irrelevant features in the NICA feature space.

Table 3: Training Time for both NICA-and ICA-based System

Dimension of Cropped face images	Number of PCs used	Total training time for NICA system (Sec) (t1)	Total training time for ICA system (Sec) (t2)	Extra training time (Sec) (T=t1-t2)	Percentage Increment in Recognition time (%) $((t1-t2) * 100 / t2)$
92*92	30	26.3174	20.7481	5.5693	26.842
	60	47.1435	41.5743	5.5692	13.395
92*100	30	27.9398	22.1677	5.7721	26.038
	60	49.1091	45.2403	3.8688	8.551
92*112	30	29.7026	23.2129	6.4897	27.957
	60	55.8172	50.6691	5.1481	10.160
Extra time incurred in NICA training				32.4172	

5.0 Conclusion

In conclusion the simulation reveals that the NICA- based system developed had a better recognition accuracy and better recognition time than the convectional ICA- based system but ICA- based system trains faster than the NICA- based system. Generally recognition accuracies increases with increase cropped face image dimension used.

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