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Local Binary Pattern and Ant Colony Optimization Based Feature Dimensionality Reduction Technique for Face Recognition Systems

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Abstract

Feature dimensionality reduction is the process of minimizing the number of features in high dimensional feature space. It encompasses two vital approaches: feature extraction and feature selection. In face recognition domain, widely adopted face dimensionality reduction techniques include Principal component analysis, Discrete wavelet transform, Linear discriminant analysis and Gabor filters. However, the performances of these techniques are limited by strict requirement of frontal face view, sensitivity to signal shift and sample size, computational intensiveness amongst others. In this paper, a feature dimensionality reduction technique that employed Local binary pattern for feature extraction and Ant colony optimization algorithms for the selection of optimal feature subsets was developed. The developed technique identified and selected the salient feature subsets capable of generating accurate recognition. The average training time, recognition time and recognition rate obtained from the experiment on locally acquired face data using cross-validation evaluation approach indicate an efficient performance of the potential combination of both methods in a two-level technique for dimensionality reduction.

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Keywords: *Feature selection; feature extraction; dimensionality reduction; local binary pattern; ant colony optimization; face recognition.*

1 Introduction

Dimensionality reduction refers to algorithms and techniques which create new attributes as combinations of the original attributes in order to reduce the dimensionality of a data set [1]. Dimensionality reduction is important in many domains because it mitigates the curse of dimensionality and other undesired properties of high-dimensional spaces. The main focus of dimensionality reduction is to present features in such a way that the informative part is preserved the most and eliminates extra data or components which are redundant to classification process [2]. Feature extraction and feature selection are the duo to perform efficient dimensionality reduction [3]. Feature extraction is a process that involves transformation of data [4]. The original set of features is transformed to provide a new set of features [5]. These features could be certain face regions, or distances and angles between the parts of the face [6]. The goal of feature extraction is to represent samples accurately in a lower dimensional space [7]. There are various feature extraction methods such as knowledge-based method which depends on generic visual and statistical knowledge of facial components to extract features [8] and mathematical transform method which uses Karhunen-Loeve transform [9] and Discrete Cosine transform [10] to extract features of an image. On the other hand, Feature selection problem consists in making good predictions with as few variables/features as possible. The optimality of a feature subset is measured by an evaluation criterion [11]. The main purpose of feature selection is to reduce the number of features used in classification while maintaining acceptable classification accuracy [6]. Finding an optimal feature subset is usually very difficult and many problems related to feature selection have been shown to be non-deterministic polynomial (NP) time hard [12]. The reasons for performing feature selection as stated by [13] include: improving performance prediction, reducing computational requirements, reducing data storage requirements, reducing the cost of future measurements and improving data or model understanding.

Dimensionality reduction had been carried out using different approaches by face recognition researchers. Some research did feature extraction alone, in which only the extracted features were used for recognition of faces (one-level dimensionality reduction) [14,15,16]. Dimensionality reduction had also been achieved in a two-level approach whereby feature extraction as well as optimal feature subset selection was carried out in [17,3]. Commonly researched dimensionality reduction algorithms are Principal Component Analysis (PCA), Discrete Wavelet Transform (DWT), Linear Discriminant Analysis (LDA) and Gabor filters amongst others.

The limitation of PCA is that the principal components which are the largest Eigen vector of the co-variance matrix generated are not often the optimal features in a lower dimension. It also requires full frontal faces; else the performance of the recognition process degrades [18,19,20,21]. However, there have been some improvements in the performance of PCA with modification of the Eigen vectors selected by selecting principal components using the discriminant weight given by separating hyperplanes in [22]. In DWT, images are treated as a 2D signal which changes horizontally and vertically. The coefficient of the wavelets obtained are large, unpredictable and difficult to interpret as a result of tilting of head or facial expression changes which result in signal shift. Hence it lack the information that can describe non-stationary signal behaviour [23,24,25]. Gabor requires computation of biorthogonal wavelet which is time consuming [26]. In addition, the performance of LDA is degraded when sample size becomes large [3,10]. Hence, the need for an improved feature dimensionality reduction technique that projects the face data unto a spatial distribution of pixel values to obtain both shape and texture features [16]. This can be achieved with the use of Local Binary Pattern (LBP) which gives the global description of the face.

LBP is a texture descriptor which gives a facial representation that is independent of expression and pose artifacts. It is a non-parametric texture classification method which summarizes the local structures of an image efficiently [27]. The most important properties of LBP features are tolerance against the monotonic illumination changes and computational simplicity. Due to its texture discriminative property and its very low computational cost, LBP is becoming very popular in pattern recognition [28]. LBP operators are easy to compute, hence they are suitable for real time applications. A face image can be seen as a composition of micro-patterns which are described by LBP [29]. The histogram of LBP computed over the whole face image encodes the occurrences of the micro-patterns. To obtain the local information of faces, face images were equally divided into small sub-regions to extract LBP histograms. The LBP features extracted from each sub-region are concatenated into a single, spatially enhanced feature histogram. The extracted feature histogram represents the local texture and global shape of face images. These features are the statistics of gray differential features representing the tonal variation of the gray value of pixels.

The salient subset of these features can then be obtained using Ant Colony Optimization (ACO) Metaheuristics. The collective behavior which emerges from a group of social insects has been called “swarm intelligence”. The ACO algorithm is based on a computational paradigm inspired by real ant colonies and the way they function. Ants are capable of finding the shortest route between a food source and the nest without the use of visual information, and they are also capable of adapting to changes in the environment [30]. An Ant Colony system involves simple agents (ants) that cooperate with one another to achieve an emergent, unified behavior for the system as a whole, producing a robust system capable of finding high-quality solutions for problems with a large search space. The ACO metaheuristic is characterized as being a distributed, stochastic search method based on the indirect communication of a colony of artificial ants, mediated by artificial pheromone trails. The pheromone trails in ACO serve as distributed numerical information used by the ants to probabilistically construct solutions to the problem under consideration. The ants modify the pheromone trails during the algorithm’s execution to reflect their search experience [31].

ACO gives a local description of the face which represents the optimal subset of features to efficiently recognize faces. The choice of ACO is in its uniqueness as a constructive search optimization algorithm that optimizes features using indirect communication with its search environment via pheromone in a phenomenon called stigmergy which is not found in any other metaheuristic. Our aim is to develop a more promising dimensionality reduction technique which could result in better face recognition. LBP is a robust texture feature descriptor that gives a global description of the face using structural and statistical features. There is need for optimizing the global features, so as to obtain a reduced form of features. Hence, with ACO a local description of the face which represents the salient subset of features to recognize the face is realized.

2 Related Works

Globally, many feature dimensionality reduction techniques have been investigated and some of them have outstanding performance. An assessment of PCA and DCT algorithms for access control system was carried out in [32]. It was discovered that PCA proved to be a better algorithm for access control and recognition system based on the high percentage (90.43%) of correctly classified faces and its strict attendance to both FAR and FRR (0.1077, 0.0609) respectively. Also, [17] developed an ACO-based feature selection for face recognition system that uses discrete cosine transform (DCT) to extract features and ACO for face recognition. The work uses k-Nearest Neighbour classifier to evaluate the selected feature subsets in a wrapper mode. The result obtained when evaluated on AT&T database was 98.50% recognition accuracy. However the recognition time for the tested faces using the system was not reported. Similarly, a face recognition system using a hybrid of GA and ACO algorithms was developed in [33]. The two algorithms were used to perform feature extraction and the fused features were passed unto GA for recognition of unknown face. The work produced a recognition accuracy of 93.3%. The recognition time achieved was 5.2 secs. The database used was not specified.

Furthermore, [15] developed an algorithm for one-sample face recognition using Hidden Markov Model of fiducial areas. It uses two dimensional discrete wavelet transform (2D DWT) to extract features from images and hidden Markov model (HMM) was used for training and recognition. 90% correct recognition, false acceptance rate of 0.02% and a recognition time of 0.15secs were achieved on still frontal face images locally acquired and on a subset of the AT&T database. Harmony Search Algorithm (HSA) was used by [6] to select an optimal subset of features that gives a better accuracy result in solving face recognition problem. This approach was compared with the standard PCA over a set of images from the AT&T face database. The results obtained with the HSA gives an accuracy of 94% in face recognition with the recognition time not indicated. The time requirement in terms of training time and recognition time are crucial parameters in achieving a face recognition system that mimic real-time scenario. Hence this research addresses the time requirement as well as accuracy of the face recognition system by considering the training time, recognition time and the recognition accuracy obtained using the developed technique.

3 Materials and Methods

3.1 Database Acquisition and Normalization

The locally acquired face database (LAFDAB) contains photographs of 120 randomly selected students of Kwara State University, Malete. Nigeria. The pictures of the students were captured between October 2013 and July 2014, with HD genx 300 Camera. The students were contacted and with their consent, the pictures were captured for the purpose of this research. There are 6 different images per student, as shown in Fig. 1, giving a total of 720 coloured (RGB) faces having a resolution of 1080x1920. The images were taken with variation in upright position, tolerance of some tilting and rotation of about 13 degrees as indicated by the camera. There were variations in facial expression, closed eyes, glasses worn; presence of mustache, illumination variation was achieved by capturing at different times of the day, also with indoor and outdoor capture. This makes the LAFDAB faces different from most available face dataset which are mostly captured under a controlled environment with little variation in expression and illumination.

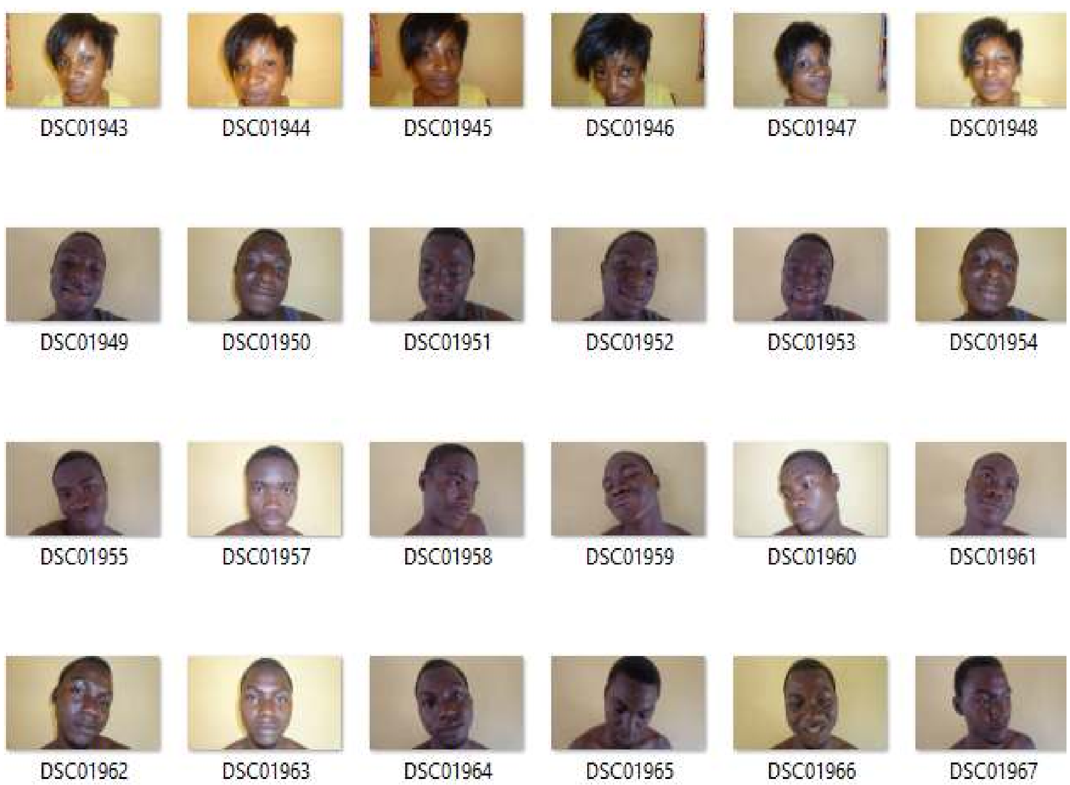

Fig. 1. Sample faces from LAFDAB

The normalization of faces was done by cropping the faces, so that the output reveals the prominent parts of the face such as eyebrow, eyelid, eyes, nose, lips and region below the lips. The intent is that the resultant face is made up of regions vital for face recognition. The number of these vital features in terms of size is varied by resizing the cropped images into arbitrarily chosen size of 70x70 pixels. These were carried out in Matlab R2012a, using the image processing toolbox. The colored images (three-dimensional) in the database were converted into grayscale images having pixel values of between 0 (black) and 255 (white).

3.2 Experimentation of the Technique

Face images have an inherent property of high dimension; pixels are highly correlated, leading to redundant information which causes computational burden in terms of processing speed and memory utilization. As earlier stated in Section 1, Local Binary Pattern was employed in this research to extract 2D distributions of local binary pattern and local contrast measurement. This enables texture information to be extracted from the face. The resultant feature representation serves as a suitable platform for selecting the optimal feature subsets. The texture descriptors were converted to image data matrix so as to be able to reference each image by its matrix. Optimal feature subset selection was done by applying ACO algorithm on the image data matrix from the feature extraction stage. This research employs filter-based feature selection using ACO, the filter criterion is taken as heuristic information. The heuristic value, η, for each feature generally represents the attractiveness of the feature. Correlation is one of the most common and useful statistics that describes the degree of relationship between two variables. If two random variables are linearly dependent, then their correlation coefficient is close to ±1. If the variables are uncorrelated the correlation coefficient is 0. The correlation coefficient $\mathcal{C}_{i,j}$ between two features xi and xj is

$$\mathcal{C}_{ij} = \frac{\sum_n (xi-\bar{xi})(xj-\overline{xj})}{\sqrt{\sum_n (xi-\overline{xi}\,)^2}\sqrt{\sum_n (xj-\overline{xj})^2}} \tag{1}$$

where n= no of features (pixels) in the input space. The terms in the numerator represents the covariance between pixels xi and xj, $\overline{xi}$ and $\overline{xj}$ are the mean values of xi and xj respectively. The two squared terms in the denominator are the standard deviations of each pixel. $\mathcal{C}_{ij}$ = correlation coefficient between feature xi and xj. From equation (1), the correlation coefficient is defined as a covariance between two pixels xi and xj divided by the product of standard deviations of each pixel. If the correlation coefficient is close to 1 or -1, then the two pixels are much related to each other and if the value is 0, then the pixels are hardly related. The more the value is close to 1, for a pixel, the higher the pixel is correlated to the class labels and thus the feature is considered important and selected. Pixels that are uncorrelated are discarded and considered unimportant. Artificial ants were simulated and they move randomly over the face in a clique to construct a pheromone matrix. The heuristic information (η) for this experiment which is the measure of attractiveness of a feature (pixel) based on the local statistics of the image was obtained using equation (1) by computing the correlation between pairs of pixels. The process of construction of solution by the ant was carried out by adopting the probabilistic transition rule in equation (2).

$$P_{i,j}^{\boldsymbol{k}}(t) = \frac{[\tau_{i,j}(t)]^{\propto}[\eta_{i,j}]^{\beta}}{\sum_{j \in \boldsymbol{J}^{\boldsymbol{k}}}[\tau_{i,j}(t)]^{\alpha}[\eta_{i,j}\,]^{\beta}} \text{ , if } i \in J^k \tag{2}$$

Where J^k is ant k's unvisited features, η_i is the heuristic desirability of choosing feature i, τ_i is the pheromone value at feature *i*, α determine the importance of pheromone value β determine the importance of heuristic information. J_i^k is the neighborhood of ant *k* when in feature *i*. α determines the extent to which pheromone information is used as the ants build their solution. β determines the extent to which heuristic information is used by the ants. Optimization by ACO formulates the problem in form of a graph where edges connect nodes; here nodes are pixels (feature). The neighborhood of a feature *i* contains all the features directly connected to feature *i* in the graph *G = (N, A)*, except for the predecessor of feature *i*, that is, the last feature the ant visited before moving to *i*. In this way the ants avoid returning to the same feature they visited immediately before feature *i*. Only in case N_i^k is empty, which corresponds to a dead end in the graph, feature *i*'s predecessor is included into N_i^k.

Global and Local Pheromone update were carried out by adopting equation (3) and equation (4) respectively.

$$\tau_{i,j}^{k} \leftarrow (1-\rho).\tau_{ij} + \rho.\Delta(i,j)^{k} \tag{3}$$

where $\rho \in (0,1)$ is the pheromone update parameter, $\Delta\tau^k$ is the amount of pheromone on arc and $\Delta(i,j)$ = $\sum_{k=1}^{n} \Delta\tau_{i,j}^{k}$

$$\tau^{(n)} = (1-\varphi).\tau^{k} + \varphi.\tau^{(0)} \tag{4}$$

where φ is the decay coefficient.

When this is done to every pixel in the image, a subset of pixels is obtained which represents the optimal set of features on the face image. Once the pixels are being selected they are stored in a variable and at the end of the feature selection procedure, we obtain the size of the content of the variable in rows and columns which gives the window size of the subset of pixels. This represents the subset of ACO as seen in Fig. 2. The Process Flow of the developed technique is shown in Fig. 2.

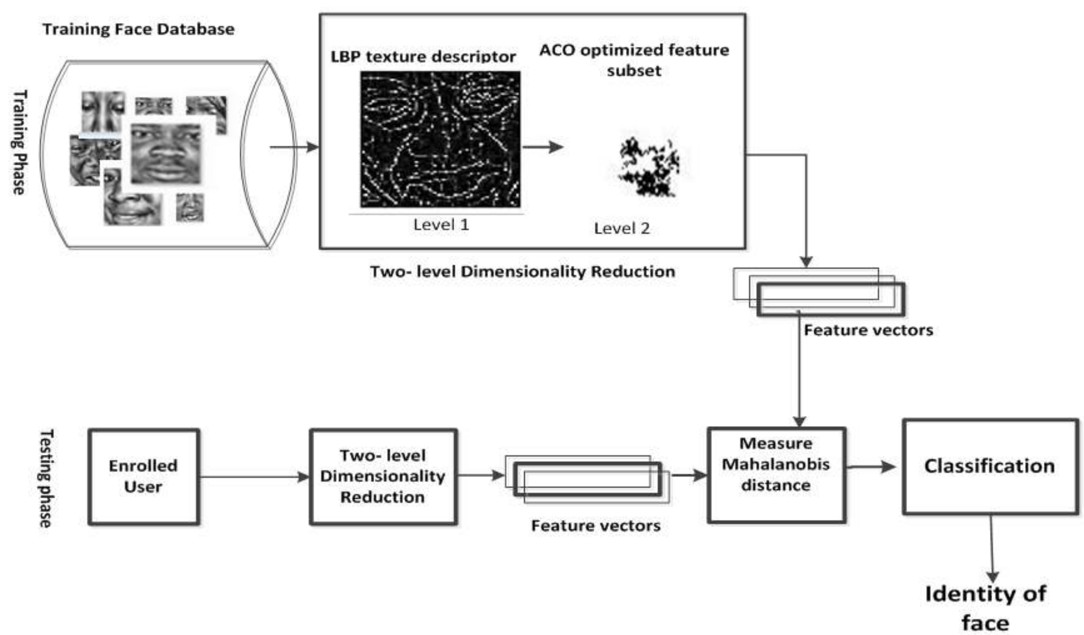

Fig. 2. Process flow of the feature dimensionality reduction technique for face recognition system

The Process flow shows the training and testing phases. The training phase comprises the face database that was trained, and a two-level dimensionality reduction component which generates the feature vectors that serves as template used for matching. The training face database which is the first component of the training phase stores the face data captured. The two-level dimensionality reduction component comprises the feature extraction and feature selection in level 1 and level 2. In level 1, feature extraction was done and LBP texture descriptor was obtained. In level 2, feature selection was done and ACO optimized feature subset was obtained.

Furthermore, from the dimensionality reduction, the feature vectors generated were saved for comparison. On the other hand, the components of the testing phase include the enrolled user to be identified, which passes through the dimensionality reduction, and the feature vectors generated which is then compared with the feature vectors in the training database by measuring the Mahalabolis distance between the two vectors in a component connecting the training and testing phase. The choice of Mahalanobis distance is due to the fact that it overcomes the blindness to correlation problem of Euclidean distance. The next component is the classification process in which the recognition of face is done based on the distance between the test and trained vectors. The identity of the enrolled user is displayed as the last component of the framework indicating a recognized face or unrecognized.

The face recognition system presented in this paper was developed, trained, and tested using MATLAB R2012a. The computer system used is a Windows professional edition with a 2.4 GHz Intel Core ‘i3 processor, 64bit OS and 8 GB of RAM. Figs. 3 and 4 shows the sample graphical user interface in MATLAB results obtained by simulating the technique on LAFDAB. From a query face, the local binary pattern is obtained, the optimal feature subset and the image in the database corresponding to the test face is displayed as the equivalent match found which indicates a recognized face as shown in Fig. 3 and misclassified face as shown in Fig. 4. There are very few cases of mismatch whereby equivalent image displayed does not indicate a correct match.

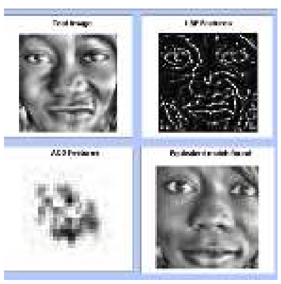

Fig. 3. Face correctly recognized

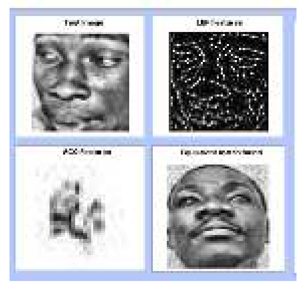

Fig. 4. Face incorrectly recognized

4 Results and Discussion

The technique was simulated in MATLAB on locally acquired face database (LAFDAB) using cross-validation**.** Cross validation method gives an honest assessment of the true accuracy of our system. The 720 images in the LAFDAB were divided into 6 folds due to the fact that there are 6 samples of each individual in the database. The cross-validation procedure is as follows:

- The images were divided into 6 folds
- Put one image of a person into a fold
- Each fold consists of 120 images, each one image corresponds to a different person
- In each experimental run, 5 folds were used to train and remaining 1 fold was used for testing
- The training and testing sets consists of 600 and 120 images respectively in a particular experimental run
- Obtain recognition rate for all 6 runs and compute the average.

The result obtained is shown in Table 1. The average training time obtained was 589.50 secs for the 6 folds. Dividing this value by 600 gives 0.98secs per image. Similarly, the average recognition time obtained was 43.09secs, divided by 120 gives 0.36secs per image.

Table 1. Result of 6-fold cross-validation procedure

Image fold	Training time (secs)	Recognition time (secs)	Number of images recognized	Recognition rate%
Fold 1	588.04	43.28	115	95.8
Fold 2	578.92	43.01	117	97.5
Fold 3	577.38	43.33	114	95.0
Fold 4	581.16	42.89	116	96.7
Fold 5	583.87	42.91	111	92.5
Fold 6	582.41	43.15	113	94.1
Average for 6 folds	589.5 0.98 secs/image	43.09 0.36 secs/image		95.3

From Table 1 the recognition rate obtained using the cross-validation evaluation with 6-fold was 95.3%. The training time per face image was 0.98 secs and recognition time was 0.36 secs per face. It can be concluded that the developed FRS is suitable for real-time face recognition considering the minimal recognition time achieved from the experiment. The result was compared with state of the art methods as shown in Table 2. The developed face recognition system (FRS) took far less period in both training and recognition of faces when compared with some existing FRS. Earlier techniques (Sawalha and Doush, (2012), Parsi, Salehi and Doostmohamadi, (2012) and Parli and Bhaiya, (2013)) did not report any training time while recognition time reported by Parli and Bhaiya, 2013 (10-20 mins) was too high for a robust face recognition system to be realized. Also, the recognition rate achieved by the developed system is far more than the 80% performance benchmark prescribed in [34].

Table 2. Comparison of existing dimensionality reduction with developed technique

Feature extraction	Feature selection	Training time	Recognition time	Recognition rate	References
PCA	HS	N/a	N/a	94%	Sawalha and Doush (2012)
PCA	GA	N/a	N/a	97.7%	Parsi Salehi and Doostmohamadi (2012)
PCA+LDA	GA	N/a	10-20mins	97.5%	Parli and Bhaiya (2013)
LBP	ACO	0.98secs	0.36secs	95.3%	Developed (2015)

5 Conclusion and Further Work

In this research, a local binary pattern and ant colony optimization (LBPACO) based feature dimensionality reduction technique was developed for face recognition system. The technique extracted local patterns from a face image using an advanced image processing technique called texture analysis using LBP. From this texture, ACO was used to obtain the salient features from the face image. These were done to reduce the dimension of features in a face for efficient recognition. The performance of ACO was optimized by LBP in a two-level form. The results of the experiment revealed that the two-level algorithm (LBP-ACO) is a very good combination with very high performance that produced a robust and reliable face recognition system. Further evaluation of the technique on other robust face databases is one of the future intension of the research.

Competing Interests

Authors have declared that no competing interests exist.

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