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Comparison of Feature Extraction with PCA and LTP Methods and Investigating the Effect of Dimensionality Reduction in the Bat Algorithm for Face Recognition

Azita Mousavi [a,1], Hadis Arefanjazi [b,2], Mona Sadeghi [c,3], Ali Mojarrad Ghahfarokhi [d,4], Fatemehalsadat Beheshtinejad [e,5], Mahsa Madadi Masouleh [f,6] *

[a] School of Engineering, San Francisco Bay University, San Francisco, CA 94132, USA
[b] Department of Electrical and Computer Engineering, Binghamton University, SUNY, NY, USA
[c] Department of Industria and Mechanical Engineering, Payam Noor University, Isfahan, Iran
[d] Department of Computer and Information Science, University of Michigan, Dearborn, USA
[e] Department of Computer Engineering, Islamic Azad University, Najafabad Branch, Esfahan, Iran
[f] Department of Electrical and Computer Engineering, University of Victoria, BC V8P 5C2, Canada
[1] amousavi420@alumni.sfbu.edu; [2] harefan1@binghamton.edu; [3] sadeghi_pnu@yahoo.com; [4] mojarrad@umich.edu; [5] fa_beheshti@yahoo.com; [6] Mahsa.mmadadi@gmail.com
* Corresponding Author

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ABSTRACT

Face recognition is one of the challenging subjects of image processing. Facial recognition is often a biometric method that basically uses faces to recognize people. The face recognition system consists of three main steps: finding the face in the image, feature extraction and classification. The face recognition system faces challenges such as changes in lighting, changes in age, changes in facial expressions, etc. One of the important issues in this system is the algorithm execution speed. For this purpose, the dimensions of the feature vectors should be small enough, especially when the database is large. Since the face recognition system must be performed on a wide range of databases, dimensionality reduction techniques are required to reduce time and increase accuracy. Dimension reduction methods are used for this purpose. Two methods of dimensionality reduction, including LTP and PCA, are given in this research. In this research, first, the LTP feature vectors are extracted from the face image, and then the effective features are selected using the Bat algorithm. Therefore, this algorithm has three main phases of feature extraction, feature selection and classification. This algorithm is implemented on the ORL database, which contains 400 images of 40 different people with a size of 112×92 pixels. In addition to reducing the time required for testing, the proposed method has provided a very good accuracy of 99%.

1. Introduction

Face recognition has attracted tremendous attention during the last three decades because it is considered a simple pattern recognition and image analysis method. There are at least two reasons to understand this trend: 1- a wide variety of commercial and legal applications, and 2- the availability of relevant technologies (for example, smartphones and digital cameras). Although existing machine learning and recognition systems have matured to some extent, their performance is limited to real-world application conditions [1, 2]. For example, recognizing face images captured in an unconstrained environment, such as changes in lighting, facial expression, relative occlusion, facial expressions, or camera movements, is still challenging. In other words, the existing technologies are still far from the capabilities of the human visual system. In our daily life, the face is perhaps the most common and well-known biometric feature [3]. With the invention of photography, government departments and private institutions keep facial photos (from personal identity documents, passports, or membership cards) in their records. For example, these sets have been used in forensic investigations as a reference database to match and compare facial images of a respondent (e.g., criminal, witness, or victim). In general, facial recognition system applications are divided into the following categories: security, surveillance, general identity verification, criminal justice system, image database research, smart card and video indexing.

Face recognition has a long history and has involved neuroscientists, psychologists, and computer scientists. The human face is not an ideal method compared to other biometric features. It is usually less accurate than other biometrics, such as the iris or fingerprint, and can potentially be affected by makeup, facial changes, and lighting [4].

However, the face has advantages that make it one of the most desirable biometric features for identity recognition, such as natural features: face is a very realistic biometric feature that is used by humans to recognize a person and is probably the most important biometric feature for validation and identification purposes [5]. For example, in the field of access and control, it is very easy to monitor and evaluate people after authentication using facial features. Non-invasive: unlike fingerprint or iris images, facial images can be obtained quickly and without physical contact. When the face is used as a biometric identifier, people feel more relaxed. Furthermore, a facial recognition device can collect data in a friendly way that people generally accept [6].

Less involvement: Face recognition requires less user input compared to iris or fingerprint [7]. One of the most important fields in computer vision is face recognition, which is considered in the field of biometric systems in a wide range of applications. Face recognition is an important research direction in the field of pattern recognition. Face recognition belongs to the category of non-linear problems, so several artificial intelligence methods have been applied to face recognition in the past years. At present, artificial neural network, especially BPNN[1] neural network, is usually used in the field of face recognition [8, 9]. Due to the problem of pre-processing in the artificial neural network, the results are sometimes negatively affected. Neural networks have disadvantages, such as the need for a large data set for correct and accurate training, the need for powerful processors to perform complex network calculations, and low productivity in some cases, such as recognizing objects in images with different angles. Therefore, we need to develop a new method for face recognition [10, 11]. Finding a subset of features from a large set is a problem that occurs in many fields. Since increasing the number of features increases the computational cost of a system, the design and implementation of systems with the minimum number of features seem necessary. On the other hand, it is very important to pay attention to the fact that an effective subset of features must be selected to create acceptable performance for the system. This leads us to use search methods to find an optimal subset of features. All the classifiers provide acceptable results in low dimensions, while in high dimensions, there is a known problem called the Curse of Dimensionality [12-14]. Therefore, feature selection can have a significant effect on the correct recognition rate of the classification algorithm. In general, it is not clear which subsets of features create the most distinction for the studied model classes, and on the other hand, it is not feasible and cost-effective to examine all existing subsets. The main purpose of feature selection is to reduce the dimension of the feature vector in classification to obtain an acceptable classification rate [15].

In this section, several articles that have used evolutionary algorithms to reduce dimension in their works are briefly described. With the aim of how determining the dimensions of feature vectors in principal component analysis, Li et al. presented a new feature selection method based on the

[1] Back-propagation neural network

improved genetic algorithm (ICGA), which preserves population diversity and improves general searchability. Then, in this research, PCA has been used to extract the feature vectors of face images. The results showed that this method, in addition to reducing the dimensions of the feature space, also achieved a higher detection rate [16]. Cho et al. proposed a computationally efficient hybrid face recognition system that employs both holistic and local features. The PCA technique is used to reduce the dimensionality. After that, the local Gabor binary pattern histogram sequence (LGBPHS) technique is employed to realize the recognition stage, which is proposed to reduce the complexity caused by the Gabor filters. The experimental results show a better recognition rate compared with the PCA and Gabor wavelet techniques under illumination variations. The Extended Yale Face Database B is used to demonstrate the effectiveness of this system [17]. Moussa et al. developed a fast face recognition system based on DCT and PCA techniques. The genetic algorithm (GA) technique is used to extract facial features, which allows to remove irrelevant features and reduces the number of features. In addition, the DCT–PCA technique is used to extract the features and reduce the dimensionality. The minimum Euclidian distance (ED) as a measurement is used for the decision. Various face databases are used to demonstrate the effectiveness of this system [18].

In these conditions, features that have less discriminating power are removed, and a series of features that contain appropriate information for distinguishing model classes remain. Bats are fascinating animals, and their ability to search for predators using echolocation has attracted the attention of many researchers from other fields. Bats, mostly small bats, emit a loud sound with a short pulse, wait until it reaches an object, and after a moment, the echo reaches their ears. Therefore, bats are able to calculate their distance from an object. In addition, echolocation can help bats distinguish prey from obstacles in complete darkness. Based on the behavior of bats, an evolutionary algorithm named bat algorithm was presented [19]. This approach is modeled by mimicking the behavior of bats in search of prey. The Bat Algorithm, due to its versatility, is used in a wide range of applications, including:

1- Feature Selection: The algorithm can be used to select the most relevant features in a high-dimensional dataset, improving the performance of machine learning algorithms by reducing overfitting, improving accuracy, and reducing training time.

2- Image and Signal Processing: The bat algorithm has been applied to edge detection and image segmentation tasks in digital images. It is also used in radar signal processing.

3- Networks: In computer networking, the Bat Algorithm can be used in routing protocols to find the best path for data transmission. It's also utilized in wireless sensor networks for node localization.

4- Optimization Problems: Due to its nature, the Bat Algorithm is often used for solving various complex optimization problems, including engineering design optimization, scheduling, and logistical problems.

5- Machine Learning: The Bat Algorithm is used in training neural networks, determining the optimal weights and biases that minimize error [20, 21].

In this research, in Section 2, we have discussed the use of dimensionality reduction algorithms. Then we divided them into two linear and non-linear algorithms and explained each of the sub-sets. Dimensionality reduction methods, such as PCA and LTP, have been used to mitigate the curse of dimensionality. PCA is a linear dimensionality reduction technique that projects high-dimensional data onto a lower-dimensional space, preserving the variance of the data. LTP, on the other hand, is a non-linear method that can handle complex data structures more effectively than PCA. However, these methods can sometimes lead to a loss of relevant information, resulting in a decrease in face recognition accuracy. Therefore, there is a need for efficient feature selection techniques, such as the Bat Algorithm, that can effectively reduce dimensionality while preserving the most relevant features for accurate face recognition. In Section 3, the bat algorithm is explained. In the next parts, the effect of dimensionality reduction using PCA and LTP algorithms and its effect on the time needed to extract features are compared. In the end, the results of dimension reduction with the bat algorithm are given, and we can see that the accuracy of face recognition with this algorithm has increased significantly compared to other algorithms.

2. Dimension Reduction Algorithms

The main function of these algorithms is to show the face image by a matrix of pixels, and this matrix is often converted into feature vectors to make it easier to handle them. After that, these feature vectors are implemented in the low-dimensional space. These algorithms are sensitive to changes (face state, lighting, and facial gestures), and these advantages make these methods widely used. Also, these methods can be divided into categories, such as linear and non-linear methods, based on the method used to represent the subspace.

2.1. Linear Techniques

The most famous linear techniques used for face recognition systems are the face-specific technique (principal component analysis, PCA), Fisher Face technique (LDA linear discriminant analysis), and independent component analysis (ICA). Here the two methods, PCA and LDA, are briefly explained.

2.1.1. Special Face and Principal Component Analysis (PCA)

The special face is one of the popular methods in comprehensive approaches, which is used to extract feature points of the face image. The principal components created by the PCA technique are used as special faces or face templates. The PCA method converts a number of variables with correlated probability into a small number of incorrect variables called "principal components." The purpose of PCA is to reduce the large dimensions of the data space (observed variables) to the intrinsically smaller dimension of the feature space (independent variables) that is needed to describe the data economically. Fig. 1 shows how to represent a face with a small number of features.

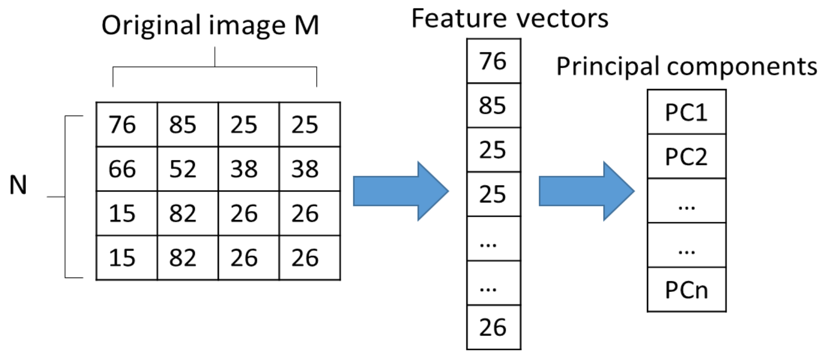

Fig. 1. Dimensionality reduction with PCA

PCA computes the eigenvectors of the covariance matrix and maps the original data onto a lower-dimensional feature space defined by eigenvectors with large eigenvalues. Fig. 2 shows the use of PCA in face representation and recognition, as well as five special faces from the ORL database.

Fig. 2. The first five featured figures from the ORL database

An image may represent an N×M vector, so a typical 4×4 image is converted to a 16-dimensional vector. The training set of images $\{X_1, X_2, X_3, \ldots, X_N\}$ is considered. The average face of the set is defined by this relation:

$$X = \frac{1}{N}\sum_{i=1}^{N} X_i \tag{1}$$

The estimation covariance matrix should be calculated to show the degree of dispersion in all the feature vectors that are related to the mean vector. The covariance matrix Q is defined by the following:

$$Q = \frac{1}{N}\sum_{i=1}^{N} (X - X_i)(X - X_i)^T \tag{2}$$

The eigenvectors and their corresponding eigenvalues are calculated using (3).

$$CV = \lambda V \qquad (V \neq 0) \tag{3}$$

where V is the set of the matrix of eigenvectors Q, which is related to its own eigenvalue, i.e., λ. All educational images of the i_{th} a person is implemented in a special subspace.

$$y_k^i = W^T(x_i) \qquad (i = 1,2, \ldots, N) \tag{4}$$

where y_k^i are the images of x and they are called principal components. They are also referred to as feature faces. Face images are represented as a linear combination of the "principal components" of these vectors. In order to extract facial features, PCA and LDA are two different feature extraction algorithms that are used. Fig. 2 shows the first five features created from the ORL database.

2.1.2. Fisher Face and Linear Discriminant Analysis (LDA)

The Fisher face method is based on the same principle of similarity as the special face method. The aim of this method is to reduce the image space with large dimensions based on the linear discriminant analysis (LDA) technique instead of the PCA method. The LDA method is usually used for dimension reduction and face recognition. PCA is an unsupervised technique, while LDA is a supervised learning method that uses information from the data. For all samples of all classes, the intra-class dispersion matrix S_W and inter-class dispersion matrix S_B are defined as follows.

$$S_B = \sum_{i=1}^{c} M_i\,(x_i - \mu)(x_i - \mu)^T \tag{5}$$

$$S_W = \sum_{i=1}^{c}\sum_{x_k \in x_i} M_i\,(x_k - \mu)(x_k - \mu)^T \tag{6}$$

where μ is the average vector of samples belonging to class i, x_i shows a set of samples belonging to class i, where x_k is the number of images of that class, c is the number of separate classes, and M_i is the number of training samples in the class i. S_B describes the scatter of features around the overall mean for all face classes, and S_W describes the scatter of features around the mean of each face class. The goal is that the ratio $det\,|s_w|/det|s_B|$ be maximized, in other words, minimizing S_W while maximizing S_B. Fig. 2 shows five special faces and the first fisher face obtained from the ORL database.

2.2. Linear Support Vector Machine

LBPs have been shown to have high-resolution features for texture classification and are robust to illumination effects and invariant to single-ion gray level changes. However, since their threshold limit is exactly the central pixel value of i_c, they are sensitive to noise and have weak luminance gradients, especially in near-uniform image regions. Many areas of the face are almost uniform, and suggestions have been made to increase resistance in these areas.

Tan et al. [22] proposed the Local Triple Pattern (LTP), which extends LDP to three core values. In LTP, each gray level in an area with a width of ± t around i_c is set to zero. One above it is assigned with + and one below it with −. That is, the indicator $S(u)$ is replaced by a 3-quantity function:

$$S(u, i_c, t) = \begin{cases} 1 & .\ u \geq \mathrm{i_C} + \mathrm{t} \\ 0 & .\ |u - \mathrm{i_C}| < t \\ -1 & .\ u \leq \mathrm{i_C} - t \end{cases} \tag{7}$$

The binary LBP code is replaced by an LTP code. t is the threshold value specified by the user. Therefore, LTP codes are more resistant to noise, but they are not invariant to changes in brightness.

3. Bat Algorithms

To model Bat Algorithm [23], a number of rules are stated below. 1) All bats use echolocation to sense distance and are magically able to distinguish between prey and obstacles. 2) A bat b_i randomly flies with speed V_i at location x_i with a constant frequency f_{min} variable wavelength λ and height A_0 to search for food. They can automatically adjust the wavelength (frequency) of the emitted pulses and adjust the pulse emission rate $r \in [0,1]$ depending on the approximation of their target. 3) Although the height can change in many ways, we assume that the height changes from a large (positive) value A_0 to a small fixed value A_{min}.

In the bat algorithm, the i-th bat updates its velocity and position to b_i using the following equations:

$$f = f_{min} + (f_{max} - f_{min})\beta_i \tag{8}$$

$$v_i^j(t) = v_i^j(t-1) + \left[\hat{x}^j - x_i^j(t-1)\right]f_i \tag{9}$$

$$x_i^j(t) = x_i^j(t-1) + v_i^j(t) \tag{10}$$

where f_i refers to the frequency of b_i . f_{min} and f_{max} are the minimum and maximum frequencies, respectively. β is a random number in the interval $(0,1)$. $v_i^j(t)$ and $x_i^j(t)$ refer to the j-dimensional velocity and location of b_i at time step t. During the search process, b_i wants to emit the pulse with the largest height and the smallest frequency. When b_i finds its prey, the height and frequency are updated as follows:

$$A_i^{t+1} = \alpha \times A_i^t \tag{11}$$

$$r_i^{t+1} = r_i^0[1 - exp\,(-\gamma \times t)] \tag{12}$$

r_i^t and A_i^t refer to pulse propagation and amplitude at time step t, respectively. γ and α are algorithm parameters. Like many evolutionary algorithms, random walk is used in BA, which improves the variability of possible solutions. BA first selects a solution from among the best bats and then uses a random move to generate a new solution for each bat.

$$x_{new} = x_{old} + \varepsilon\bar{A}(t) \tag{13}$$

where $\bar{A}(t)$ is the average height in a given repetition t and $\varepsilon \in [-1,1]$ is a randomly generated number. In Table 1, the pseudocodes of the bat algorithm are given. The parameters used in the bat algorithm are given in Table 2.

Table 1. Pseudocodes of bat algorithm

The objective function $f(x), x = (x^1, \ldots, x^N)$
1. Initialize the population $x_i, v_i,\ i = 1, 2, \ldots, m$
2. For each bat

3. Defining pulse frequency f_i, loudness A_i and pulse rate r_i
4. End for
5. As long as $t < T$
6. For each bat x_i
7. Generating new solutions using (8), (9), and (10)
8. If $rand > r_i$
9. Choosing a solution among the best solutions
10. Generate a local solution around the best solutions using (13)
11. End if
12. If $rand < A_i$, $f(x_i) < f(\hat{x})$
13. Accepting new solutions
14. Increase r_i and decrease A_i by (11) and (12)
15. End if
16. End for
17. End until

Table 2. Parameters in bat algorithm

Parameters	The amount of
Number of bats	50
Number of generations	100
Initial pulse frequency	0.9
Pulse rate	0.5
α	0.99
γ	0.01
Initial speed	0

4. Results and Discussion

LTP feature extraction has been used to measure the bat algorithm. One of the reasons for choosing this feature is its greater resistance to changes in brightness and noise compared to LBP. Also, the dimensions of the LTP feature vector are twice that of the base LBP type. Fig. 3 shows an example of LTP feature extraction with positive and negative patterns on a sample image from the ORL database. This algorithm is implemented on the ORL database, which contains 400 images of 40 different people with a size of 112×92 pixels. Sample images from the ORL database are shown in Fig. 3. In this research, the threshold value for LTP is considered to be 5. For further processing by the bat algorithm, LTP parameters must be set first. For this purpose, on the ORL database, the accuracy of LTP detection with different block sizes and PCA dimension reduction of 200 to 500 is investigated. The recognition accuracy table of the ORL database with different block sizes is given in Table 3. Execution time is the total time required to train the classifier with 90% of the ORL dataset and test the classifier with 10% of the ORL dataset images. The best detection accuracy is achieved in block sizes of 12×12 and 14×14 with a value of 97%.

Table 3. The recognition accuracy of the ORL database

Block Size	Dimensions of the Feature Vector	Execution Time (s)	Detection Accuracy
6×6	155648	2.2	96.25
8×8	86016	1.3	96.50
10×10	50688	0.66	96.75
12×12	40960	0.49	97
14×14	28672	0.34	97
16×16	21504	0.26	97.75

4.1. Examining PCA Dimension Reduction

In this step, PCA dimensionality reduction from 40 to 100 has been investigated on the ORL database. The size of the block is considered 14×14. Therefore, the initial dimension of its feature vector is equal to 28672 components. For this database, the detection accuracy without reducing the dimension was 97%, but in reducing the dimension of PCA to 100 components, in addition to greatly reducing the execution time, we faced an increase in the detection rate. The results of the detection rate and LTP execution time after dimensionality reduction on the ORL database are given in Table 4.

Fig. 3. The first five featured figures from the ORL database

Table 4. Dimensionality reduction of ORL database

PCA Dimension Reduction	Detection Rate	Execution Time (s)
40	96.75	6.69
60	97.25	6.88
80	97.25	7.17
100	97.50	7.29
120	97.25	7.42
140	97	7.64

4.2. Investigation of Dimension Reduction with Bat Algorithm

Table 5 shows the results obtained after dimensionality reduction by the proposed bat algorithm on the ORL dataset. Also, the number of references to the fitness function (NFE) when the algorithm converges to the maximum detection rate is also given. The best detection accuracy for dimension reduction with a threshold limit of 0.5 has been obtained with a value of 99.25%, which has a good increase compared to 97.5% of PCA dimension reduction. Of course, the dimension reduction in this threshold limit is about half of the original dimensions. Also, at the threshold of 0.8, an accuracy level of 99% was obtained, which, in addition to the proper detection accuracy, also has a suitable dimension reduction.

Table 5. Best detection rate after dimensionality reduction with bat algorithm

Threshold	Dimensions of the Feature Vector	Detection Rate	NFE
0.5	14319	99.5	2030
0.6	7529	99.75	1760
0.7	6484	99.25	2165
0.8	5824	98.5	3722
0.9	2864	97.25	2447
0.95	1407	97	4691
0.98	698	93.25	4798

5. Conclusion

Face recognition is an active research area with numerous challenges and opportunities. Advances in technology, such as deep learning and optimization algorithms, have significantly improved face recognition accuracy. However, challenges, such as the curse of dimensionality, remain. Future research needs to focus on developing efficient and reliable methods for feature extraction and selection, as well as improving the robustness of face recognition systems to real-world conditions. In this research, a new method for reducing the dimensions of the feature vector using the bat algorithm is presented. For this purpose, we used the ORL database, which does not require face extraction. LTP feature vector was extracted from these images. LTP feature vectors have dimensions of about 30K, which are too large and not suitable for online work. To reduce the dimensions of the feature vector, there are balanced methods such as PCA and LDA. But these methods also suffer from problems such as the number of selected features should be increased with the number of images in the database so as not to affect the accuracy of the correct diagnosis. Choosing the right number of feature vectors is one of their challenges. Also, reducing the dimensions may reduce the detection rate. Therefore, in this research, an evolutionary algorithm has been used for this purpose. In this research, first, LTP feature vectors were extracted from the face image, and then the effective features were selected using the bat algorithm. In addition to reducing the time required for testing, the proposed method has provided a very good accuracy of 99%.

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References

[1] M. P. Beham and S. M. M. Roomi, "A review of face recognition methods," *International Journal of Pattern Recognition and Artificial Intelligence,* vol. 27, no. 4, p. 1356005, 2013, https://doi.org/10.1142/S0218001413560053.

[2] T. Kamyab, A. Delrish, H. Daealhaq, A. M. Ghahfarokhi, and F. Beheshtinejad, "Comparison and Review of Face Recognition Methods Based on Gabor and Boosting Algorithms," *International Journal of Robotics and Control Systems,* vol. 2, no. 4, pp. 610-617, 2022, https://doi.org/10.31763/ijrcs.v2i4.759.

[3] A. J. O'Toole, D. A. Roark, and H. Abdi, "Recognizing moving faces: A psychological and neural synthesis," *Trends in Cognitive Sciences,* vol. 6, no. 6, pp. 261-266, 2002, https://doi.org/10.1016/S1364-6613(02)01908-3.

[4] A. Dantcheva, C. Chen, and A. Ross, "Can facial cosmetics affect the matching accuracy of face recognition systems?," in *2012 IEEE Fifth International Conference on Biometrics: Theory, Applications and Systems (BTAS)*, pp. 391-398, 2012, https://doi.org/10.1109/BTAS.2012.6374605.

[5] P. Sinha, B. Balas, Y. Ostrovsky, and R. Russell, "Face recognition by humans: Nineteen results all computer vision researchers should know about," *Proceedings of the IEEE,* vol. 94, no. 11, pp. 1948-1962, 2006, https://doi.org/10.1109/JPROC.2006.884093.

[6] A. Ouamane, A. Benakcha, M. Belahcene, and A. Taleb-Ahmed, "Multimodal depth and intensity face verification approach using LBP, SLF, BSIF, and LPQ local features fusion," *Pattern Recognition and Image Analysis,* vol. 25, pp. 603-620, 2015, https://doi.org/10.1134/S1054661815040215.

[7] G. Porter and G. Doran, "An anatomical and photographic technique for forensic facial identification," *Forensic Science International,* vol. 114, no. 2, pp. 97-105, 2000, https://doi.org/10.1016/S0379-0738(00)00290-5.

[8] J. Wei, Z. Jian-Qi, and Z. Xiang, "Face recognition method based on support vector machine and particle swarm optimization," *Expert Systems with Applications,* vol. 38, no. 4, pp. 4390-4393, 2011, https://doi.org/10.1016/j.eswa.2010.09.108.

[9] A. H. Sadeghi, Z. Sun, A. Sahebi-Fakhrabad, H. Arzani, and R. Handfield, "A Mixed-Integer Linear Formulation for a Dynamic Modified Stochastic p-Median Problem in a Competitive Supply Chain Network Design," *Logistics,* vol. 7, no. 1, p. 14, 2023, https://doi.org/10.3390/logistics7010014.

[10] A. Mousavi, A. H. Sadeghi, A. M. Ghahfarokhi, F. Beheshtinejad, and M. M. Masouleh, "Improving the Recognition Percentage of the Identity Check System by Applying the SVM Method on the Face Image Using Special Faces," *International Journal of Robotics and Control Systems,* vol. 3, no. 2, pp. 221-232, 2023, https://doi.org/10.31763/ijrcs.v3i2.939.

[11] T. Kamyab, H. Daealhaq, A. M. Ghahfarokhi, F. Beheshtinejad, and E. Salajegheh, "Combination of Genetic Algorithm and Neural Network to Select Facial Features in Face Recognition Technique," *International Journal of Robotics and Control Systems,* vol. 3, no. 1, pp. 50-58, 2023, https://doi.org/10.31763/ijrcs.v3i1.849.

[12] H. A. Firpi and E. Goodman, "Swarmed feature selection," in *33rd Applied Imagery Pattern Recognition Workshop (AIPR'04)*, pp. 112-118, 2004, https://doi.org/10.1109/AIPR.2004.41.

[13] X. Wang, S. M. Abtahi, M. Chahari, and T. Zhao, "An adaptive neuro-fuzzy model for attitude estimation and control of a 3 DOF system," *Mathematics,* vol. 10, no. 6, p. 976, 2022, https://doi.org/10.3390/math10060976.

[14] M. Sajjadi, M. Chahari, H. N. Pishkenari, and G. Vossoughi, "Designing nonlinear observer for topography estimation in trolling mode atomic force microscopy," *Journal of Vibration and Control,* vol. 28, no. 23-24, pp. 3890-3905, 2022, https://doi.org/10.1177/10775463211038140.

[15] M. L. Raymer, W. F. Punch, E. D. Goodman, L. A. Kuhn, and A. K. Jain, "Dimensionality reduction using genetic algorithms," *IEEE Transactions on Evolutionary Computation,* vol. 4, no. 2, pp. 164-171, 2000, https://doi.org/10.1109/4235.850656.

[16] M. Li, W. Du, and L. Yuan, "Feature selection of face recognition based on improved chaos genetic algorithm," in *2010 Third International Symposium on Electronic Commerce and Security*, pp. 74-78, 2010, https://doi.org/10.1109/ISECS.2010.25.

[17] H. Cho, R. Roberts, B. Jung, O. Choi, and S. Moon, "An efficient hybrid face recognition algorithm using PCA and GABOR wavelets," *International Journal of Advanced Robotic Systems,* vol. 11, no. 4, p. 59, 2014, https://doi.org/10.5772/58473.

[18] M. Moussa, M. Hmila, and A. Douik, "A novel face recognition approach based on genetic algorithm optimization," *Studies in Informatics and Control,* vol. 27, no. 1, pp. 127-134, 2018, https://doi.org/10.24846/v27i1y201813.

[19] X.-S. Yang, "Bat algorithm for multi-objective optimisation," *International Journal of Bio-Inspired Computation,* vol. 3, no. 5, pp. 267-274, 2011, https://doi.org/10.1504/IJBIC.2011.042259.

[20] N. Karlupia and P. Abrol, "Wrapper-based optimized feature selection using nature-inspired algorithms," *Neural Computing and Applications,* vol. 35, no. 17, pp. 12675-12689, 2023, https://doi.org/10.1007/s00521-023-08383-6.

[21] K. Rautela, D. Kumar, and V. Kumar, "A Systematic Review on Breast Cancer Detection Using Deep Learning Techniques," *Archives of Computational Methods in Engineering,* vol. 29, no. 7, pp. 4599-4629, 2022, https://doi.org/10.1007/s11831-022-09744-5.

[22] X. Tan and B. Triggs, "Enhanced Local Texture Feature Sets for Face Recognition Under Difficult Lighting Conditions," *IEEE Transactions on Image Processing*, vol. 19, no. 6, pp. 1635-1650, 2010, https://doi.org/10.1109/TIP.2010.2042645.

[23] A. S. Alphonse, S. Abinaya, and K. S. Arikumar, “A Novel Monogenic Sobel Directional Pattern (MSDP) and Enhanced Bat Algorithm-Based Optimization (BAO) with Pearson Mutation (PM) for Facial Emotion Recognition,” *Electronics*, vol. 12, no. 4, p. 836, Feb. 2023, https://doi.org/10.3390/electronics12040836.