SURVEY

The Impact of Bio-Inspired Approaches Toward the Advancement of Face Recognition

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An increased number of bio-inspired face recognition systems have emerged in recent decades owing to their intelligent problem-solving ability, flexibility, scalability, and adaptive nature. Hence, this survey aims to present a detailed overview of bio-inspired approaches pertaining to the advancement of face recognition. Based on a well-classified taxonomy, relevant bio-inspired techniques and their merits and demerits in countering potential problems vital to face recognition are analyzed. A synthesis of various approaches in terms of key governing principles and their associated performance analysis are systematically portrayed. Finally, some intuitive future directions are suggested on how bio-inspired approaches can contribute to the advancement of face biometrics in the years to come.

Categories and Subject Descriptors: I.5.4 [**Pattern Recognition**]: Applications

General Terms: Algorithms, Security, Performance

Additional Key Words and Phrases: Face recognition, bio-inspired computing, feature selection, optimization, evolutionary algorithms, artificial neural networks, swarm intelligence

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1. INTRODUCTION

Extensive research on the face recognition (FR) problem has taken place and several surveys have been published (see, e.g., Islam et al. [2012], Abate et al. [2007], Bowyer et al. [2006], Scheenstra et al. [2005], Kong et al. [2005], and Zhao et al. [2003]), but to our knowledge, there is no survey specific to bio-inspired approaches pertaining to the advancement of FR. The motivation for employing bio-inspired optimization approaches is that not only are they intuitive but also they can effectively complement purely principled approaches. Das et al. [2008] have claimed that biologically motivated algorithms, mimicking particular features and mechanisms from biology, have experienced astonishing growth in the last few decades due to their intrinsic parallelism and simplicity in computation. Interestingly, natural computing is a recent branch in

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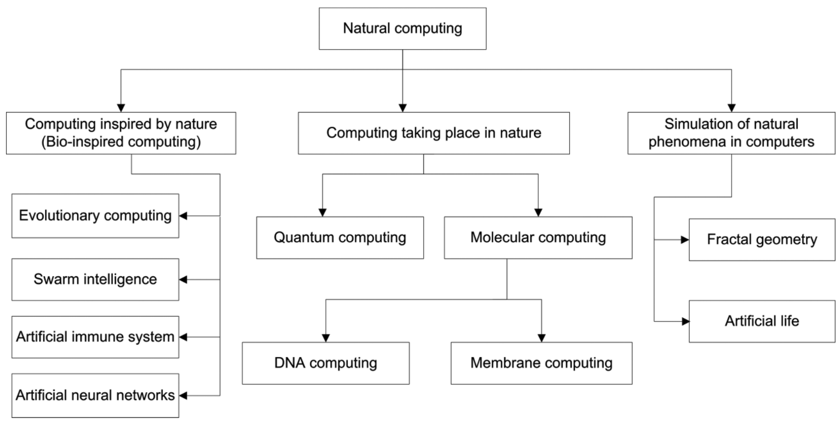

Fig. 1. Taxonomy of natural computing fields.

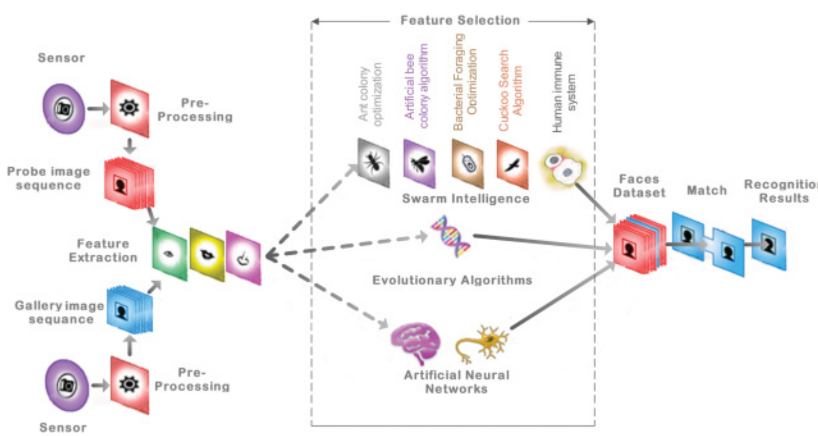

Fig. 2. General framework of bio-inspired-based face recognition systems.

computer science that takes inspiration from nature to design sophisticated computational models. Natural computing encompasses three branches, namely, computing inspired by nature, which is known as bio-inspired computing; computing taking place in nature; and the simulation of natural phenomena in computers as shown in Figure 1 [de Castro 2006a, 2006b; Rozenberg et al. 2011]. The most popular approaches within bio-inspired computing are evolutionary computation, artificial neural networks (ANNs), Swarm Intelligence (SI), and artificial immune system (AIS) [de Castro 2006a, 2006b]. Bio-inspired approaches are robust when utilized in the representation and classification of insufficient FR data, feature extraction, matching, and online updating [Zhang and Zuo 2007]. More importantly, they might have a significant impact on the advancement of automated FR systems. On that basis and due to the fact that bio-inspired computing techniques have emerged as a fascinating area of research in the last few decades, the aim of this survey is to provide a comprehensive review of bio-inspired approaches pertaining to face recognition. A general framework of the bio-inspired-based FR system consists of four main functions: the preprocessing stage, the extraction of features, optimal feature selection, and finally the recognition as shown in Figure 2. There are many articles published on bio-inspired techniques for optimizing the FR problem, and the majority of them have proven the effectiveness of these approaches

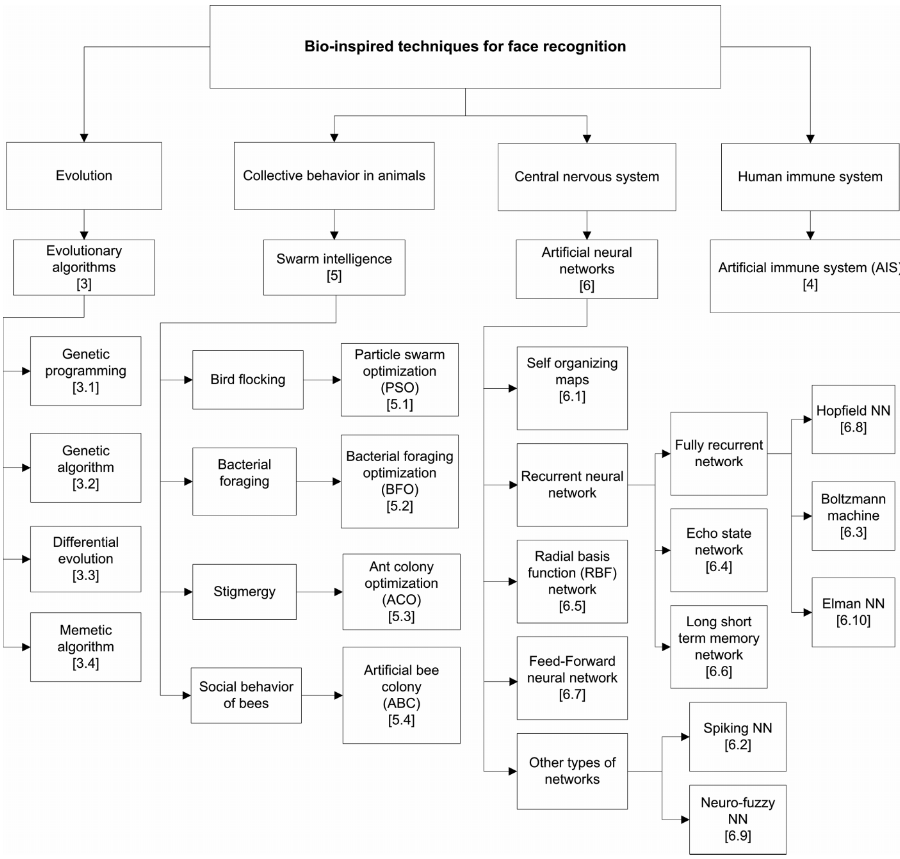

Fig. 3. A taxonomy of bio-inspired techniques for FR that are presented in this manuscript; the numbers in the parentheses represent the corresponding section numbers of these techniques.

especially when combined with traditional methods. We can classify bio-inspired FR techniques according to their source of inspiration using the taxonomy chart shown in Figure 3. An outline of the essential contributions of this article is presented as follows:

(1) An up-to-date review of state-of-the-art bio-inspired techniques for solving the FR problem is presented (as summarized in Figure 3).
(2) The methodology of how each algorithm characterizes the FR problem in terms of biological entities such as chromosome encoding, genetic operations, and performance analysis is described.
(3) A number of useful tables and diagrams of current developments, advantages, and disadvantages of typical bio-inspired-based FR techniques are synthesized cohesively.
(4) An overview of ensemble-based bio-inspired methods used in FR problem is presented.
(5) Typical bio-inspired methods that handle several key FR challenges such as pose, illumination, expression, and occlusion are summarized.
(6) A brief overview of possible future trends for enhancing the FR problem is provided.

Table I. Typical Face Recognition Databases

Database Name	# Subj.	#Images	Data	Variations
Face recognition grand challenge (FRGC) [Phillips et al. 2005]	466	50,000	2D, 3D	i,e
Facial recognition technology (FERET) [Phillips et al. 1997]	1,199	14,126	2D	p,i,e
Yale [Belhumeur et al. 1997]	15	165	2D	i,e
Yale B [Georghiades et al. 2001]	10	5,760	2D	p,i
Olivetti research laboratory (ORL) [ORL 1992]	40	400	2D	e
AR [Martinez and Benavente 1998]	126	4,000	2D	i,e,o
Carnegie mellon university pose, illumination, and expression (CMU PIE) [Sim et al. 2002]	68	41,368	2D	p,i,e
Massachusetts institute of technology - center for biological and computational learning (MIT-CBCL) [MIT 1996]	10	2,000	2D, 3D	p,i
Academy of sciences pose, expression, accessories, and lighting (CAS-PEAL) [Gao et al. 2008]	1,040	30,900	2D	p,e,o,i
University of manchester institute of science and technology (UMIST) [umi 1998]	20	564	2D	p
Extended multi modal verification for teleservices and security applications (XM2VTS) [Pigeon and Vandendorpe 1997]	37	185	2D,3D	p
Binghamton university - 3D facial expression (BU-3DFE) [Yin et al. 2006]	100	2,500	2D, 3D	p,e
University of milano bicocca database (UMB-DB) [Colombo et al. 2011]	143	1,473	2D, 3D	o,e
GavabDB [Moreno and Sánchez 2004]	61	549	3D	e,p
Bosphorus [Savran et al. 2008]	105	4,666	2D, 3D	p,e,o
KinectFaceDB [Min et al. 2014]	52	936	2D, 3D	i,o,e,p

Variations are indicated by abbreviations: Expression (e), Illumination (i), Occlusion (o), and Pose (p)

The article is organized as follows: based on the taxonomy chart given in Section 1, a summary of the frequently used FR databases is presented in Section 2. FR approaches based on evolutionary algorithms, AIS, swarm intelligence, and ANNs are presented in Sections 3, 4, 5, and 6, respectively. The summary and discussion of the approaches presented are outlined in Section 7. Ensemble-based bio-inspired FR techniques are summarized in Section 8. Typical bio-inspired methods that handle key FR challenges such as pose, illumination, and occlusion are presented in Section 9. The survey is concluded by providing potential future research directions in Section 10, followed by a list of acronyms.

2. DATABASES

Some of the variations that can considerably affect the recognition performance of FR systems are pose, illumination, occlusion, and facial expressions. The effectiveness of FR algorithms can be estimated by how well they can handle one or a combination of these variations. Toward that end, several databases that provide as many variations as possible have been built. Some of the typical databases for FR are listed in Table I. For an exhaustive list of databases, readers are referred to the Face Recognition Homepage [Grgic and Delac 2009].

3. EVOLUTIONARY-BASED APPROACHES

Evolutionary computing is a paradigm within computational intelligence that draws its inspiration from natural evolution [Simon 2013; Eiben and Smith 2008]. The basic metaphor of evolutionary computing relates the powerful natural evolution to a particular style of problem solving. It benefits from the collective phenomena in how

Table II. Performance Analysis of Evolutionary Computing-Based FR Approaches

Algorithm Name	Chromosome Encoding	Objective Function	RR	Relevant References
GA	N-bit binary vectors	To optimize the fuzzy rules To find the optimal eigenvectors	Yale B [98.59%] FERET [81.49%] CMU PIE [92.12 %]	Nam and Miura [2013] Zheng et al. [2005]
GP	Parse trees of varying sizes and shapes	To classify image groups	ORL [91.5%, 92.5%] Yale B [76%, 78.07%]	Bozorgtabar et al. [2011] Zhang et al. [2011a, 2011b]
DE	Real-valued vectors	To find the optimal subset of the PCA features To optimize the parameters of the RBFNN	Yale B [78.1%, 98.1%] Yale A [63.72%, 95.48%]	Mallipeddi and Lee [2012] Yoo et al. [2013]

populations adapt to the environment through utilization of the iterative processes, which are growth, recombination, mutation, and selection. The algorithms involved in evolutionary computing are termed as evolutionary algorithms (EAs), which are evolutionary programming (EP), evolution strategy (ES), differential evolution (DE), genetic algorithm (GA), and genetic programming (GP) [Eiben and Smith 2008; Fogel 1998]. EAs have received considerable interest in the FR domain. Performance analysis in terms of recognition rate (RR) of some of these approaches is given in Table II. The percentage of correct matches yielded by an algorithm on a benchmark dataset(s) usually represents its RR with reference to the benchmark dataset(s).

3.1. Genetic Programming (GP)

GP is an evolutionary-based algorithm proposed in 1992 [Koza 1992]. It takes its inspiration from the natural evolution to allow the exploration of the space of computer programs. GP is considered as an extension of GA; it differs from the latter in terms of chromosome representation. GP represents a nonlinear encoding of a candidate solution (in the form of a tree) in which search is applied to the solution directly. In contrast to GA, which has fixed-length encoding, GP adopts variable-length representation. GP works by defining a goal in the form of fitness function and then using this criterion to evolve a set of candidate solutions. GP uses an iterative process to gradually improve the quality of solutions by undergoing a set of genetic operators, such as crossover and mutation [Zhao et al. 2003]. Bozorgtabar et al. [2010] have used GP to cluster the features of face images. The features have been extracted by two principal component analysis (PCA)-based FR algorithm,s namely, 2DPCA and MLPCA. They performed their experiments on the ORL database using the Leave-One-Out approach, where nine training images and one testing image have been used. Leveraging GP creates one strong classifier from a number of weak classifiers. GP on its own has yielded a marginal RR, whereas leveraged GP has an improved RR comparable to that of eigenfaces. 2DPCA has an inferior RR compared with GP-based PCA because the extracted features of 2DPCA are larger than those of the GP-based PCA. The authors have concluded that using the GP algorithm on its own is not preferable because of its long training time compared to other methods. In their recent work, Bozorgtabar et al. [2011] applied leveraging GP to the FR system. PCA is utilized to extract the most representative features of the image, thus providing dimensionality reduction, and then the GP algorithm is applied in order to classify the images. They have obtained 91.5% RR where five images are selected for training. However, an RR of 92.5% is reported by applying the Leave-One-Out approach. Most recently, Ibrahem et al. [2013]

Table III. Comparison of Different Variants of Genetic Programming Algorithms

Method	Database	Recognition Rate (5 Training Images)	Recognition Rate (9 Training Images)
GP [Bozorgtabar et al. 2010]	ORL	63.5%	67.5%
Leveraged GP [Bozorgtabar et al. 2011]	ORL	91.5%	92.5%
GP [Ibrahem et al. 2013]	ORL	76%	98%
GNP-PCA [Zhang et al. 2011b]	Yale-B	76%	
GNP-MAS [Zhang et al. 2011a]	Yale-B	78.07%	

implemented an FR technique using the GP algorithm. First, significant feature vectors of the input face image are extracted and the distances among features are calculated; then GP is applied to extract a mathematical formula for face representation. Second, the input image is compared with all stored images to find the best match. Neshatian and Zhang [2009] have adapted the GP algorithm along with Naive Bayes to propose an optimal feature selection approach where a bit mask encoding is used. In their approach, the GP algorithm is exploited to select the best discriminative features of the face image. Experimental results show that the required computational time can be notably decreased using this approach.

Genetic network programming (GNP) is a novel evolutionary algorithm proposed by Katagiri et al. [2000]. In contrast to GP, solutions in GNP are represented by directed graphs rather than a string and tree structure to provide a more flexible representation of complex optimization problems. Zhang et al. [2011b] proposed a bio-inspired technique called GNP-PCA to enhance the classification accuracy and the generalization ability of the traditional PCA-based FR system under complicated illumination conditions. GNP-PCA deals with the coefficients of eigenfaces as attributes of a face database and mines the class association rules from it, which in turn are applied to construct the classifier. However, GNP-PCA is not robust enough under noisy testing environments since the characteristics of noise are not considered in the approach. Furthermore, the noisy situations are dynamic, which makes it difficult to train the model. In their recent work, Zhang et al. [2011a] proposed the GNP-based multiagent GNP-MAS framework to overcome GNP-PCA drawbacks. Experimental results on the Yale B database demonstrate the robustness of GNP-MAS over GNP-PCA. A comparison between different variations of GP is shown in Table III.

3.2. Genetic Algorithms (GAs)

GA is one of the popular population-based algorithms inspired by natural evolution and proposed by Holland [1973]. GA achieves outstanding performance when used to solve complicated optimization problems. As in the case of biological evolution, it undergoes genetic operations such as crossover, mutation, and selection. A vast amount of literature on using GA for solving the FR problem exists [Yankun and Chongqing 2002; Harand et al. 2004; Karungaru et al. 2004; Fan and Verma 2004; Zheng et al. 2005; Liu and Wang 2006; Kim et al. 2006; Tan et al. 2007; Li et al. 2010; Zhao 2010; Venkatesan and Rao Madane 2010; Valdez et al. 2011; Gamarra and Quintero 2013; Nam and Miura 2013; Shih and Liu 2005; Loderer and Pavlovicova 2014]. Generally, each chromosome encodes a feature subset of the face image. The chromosomes are encoded by n-bit binary strings. Kaungaru et al. [2004] implemented an FR system using template matching with the help of GA. In their work, GA has been used to guide the template matching to produce better recognition results. Fan and Verma [2004] used a combination of GA together with ANNs as feature selection and classification techniques in their FR system. Fisherface, which is a combination of LDA and PCA, is a well-known approach to deal with the small sample size (S3) problem. The traditional PCA method takes the biggest eigenvalues and the analogical eigenvectors for LDA.

Zheng et al. [2005] found that some small principal components should be used for dimensionality reduction. Along this line, Zheng et al. [2005] proposed a GA-Fisher method, which is an enhanced version of the traditional Fisherface method in which the effectiveness of LDA is enhanced by integrating a whitening procedure. GA has been used in their approach to select the eigenvalues to be used in LDA. In their experiments, they used the FERET database and CMU PIE database. Experimental results show that GA-Fisher outperforms the traditional Fisherface method. The major drawback of the conventional PCA is that it retains undesirable within-class variations caused by variations such as illumination and facial expressions. Within-class variations would cause a dramatic drop in the recognition performance. Thus, Liu and Wang [2006] constructed a nonlinear evolutionary weighted PCA based on GA, applying GA to select the optimal weights of the PCA. Li et al. [2010] proposed an improved chaos GA to overcome some drawbacks of the classical GA, such as inclination toward premature convergence and low efficiency. To improve the efficiency of GA, tent map has been used to generate a well-diversified population. In their experiment, they showed that their algorithm reported better classification accuracy than the other approaches. Madane [2010] proposed an FR system using a combination of GA and ant colony optimization (ACO), wherein features of the face image are extracted by means of the ACO algorithm and then GA is used for matching.

3.3. Differential Evolution (DE)

DE was first announced in 1995 by Storn and Price [1997]. DE shares some characteristics with the GA algorithm in which similar genetic operators such as crossover, mutation, and selection are used. In contrast to GA, which relies on crossover operation, the DE algorithm depends on the mutation and uses the mutation operator as a search mechanism and selection operator to direct the search toward the prospective regions in the search space. Mallipeddi and Lee [2012] implemented an FR system using the DE algorithm named FS-DE. In their work, the aim of using the DE algorithm is to select the optimal PCA features. With experimental validations on different databases (Yale, Yale B, ORL, and AR), they demonstrated that depending on the eigenvalues to select the PCA eigenvectors is not always appropriate. In another experiment, they compared the performances of their proposed FS-DE and the Fisher LDA algorithm [Belhumeur et al. 1997]. Results show that the FS-DE algorithm performs better than Fisher LDA on the AR database. The good performance of FS-DE is due to the fact that Fisher LDA operates on the PCA subspace, in which the selection of the eigenvectors depends mainly on maximizing the variation, as opposed to FS-DE, where the selection depends on class separability. In Yoo et al. [2013], DE has been used to optimize the parameters of the radial basis function neural network (RBFNN). Experimental results on the Yale database demonstrated the classification capabilities of the RBFNN.

3.4. Memetic Algorithm (MA)

MA is a population-based algorithm that applies a separate local search process to refine individuals and improve their fitness. MA is motivated by the interaction of biological and memetic evolution. In the context of cultural evolution, the term *meme* is analogous to the term *gene*, and unlike *genes*, *memes* usually undergo modifications in their representations [Dawkins 1976]. The special feature of MA is that all offsprings can gain experience during the local search before being involved in the evolutionary process. In their recent work, Kumar et al. [2009] implemented an approach for FR based on PCA and MA called PCA-MA, using PCA for the dimensionality reduction and MA for feature (eigenvector) selection. In their experiments, Kumar et al. [2009] tested their proposed work on the ORL and Yale B datasets. An RR of 98.57% is reported with only eight selected features, whereas the eigenfaces yielded an RR of

97.14% with 30 selected features. The MA algorithm has the advantage of achieving a much better RR with only a small number of features [Kumar et al. 2008]. Most recently, Zhou et al. [2011] implemented a Gabor-filter-based FR (POMA) based on particle swarm optimization (PSO) and MA. Gabor wavelets are utilized to extract the required features from the image. They deployed the comprehensive learning particle swarm optimizer (CLPSO) as the global search algorithm because of its global optimization capability. However, the CLPSO is subject to slow convergence and is trapped in local optima. In order to cope with this disadvantage, they used a local search mechanism. In their experiments, Zhou et al. [2011] evaluated their proposed algorithm using the FERET database and an RR of 90.7% was reported with a clock speed of 5.8 seconds.

4. ARTIFICIAL IMMUNE SYSTEM (AIS)

The essential function of the biological immune system is to protect living organisms from the invasion of antigens such as viruses and bacteria. The biological immune system has the capability of recognizing foreign pathogens, learning, memorizing, processing data, and discriminating between self and nonself cells [Brostoff et al. 1998]. The AIS draws its inspiration from the function and characteristics of the biological immune system. The recent advances in AIS have given rise to three fundamental theories: clonal selection, negative selection, and immune networks. According to the Jernes hypothesis, the immune system has the capability of dynamically maintaining the memory via the existence of a mutually reinforcing network of B cells [Jerne 1974]. Motivated by this theory, Luh and Hsieh [2009] proposed a PCA Immune Network (PCA-IN) algorithm. PCA was applied to the face images to calculate the eigenvectors and their corresponding eigenvalues. For the purpose of reducing the number of mathematical operations without losing any critical data, the top 20 eigenvectors with the max eigenvalues have been selected. Then the training subset was randomly chosen to be input into the immune network classifier. Luh [2011] proposed an FR method using AIS based on PCA to deal with the S3 problem. In this work, the training face images (antigens) are randomly picked and then transformed to an $N_{AG} \times n$ dimensional eigenface, where N_{AG} denotes the number of training images and n indicates the number of eigenvectors. The second step was to randomly initialize the immune network classifiers. The proposed algorithm was further optimized using GA; the subset of features of each image (chromosomes) are illustrated by a matrix of order $N_{ab} \times (n+1)$, where N_{ab} is the number of antibodies in each immune classifier. In this experiment, an RR of 99.7% has been reported on the ORL database.

5. SWARM INTELLIGENCE (SI)-BASED TECHNIQUES

SI is a relatively recent branch in natural computing that has the capability to construct fast, efficient, and precise solutions to NP optimization problems. SI algorithms are motivated by the collective behavior of organisms, such as special kinds of birds, ants, bees, and schools of fish. Even though these animals have little ability on their own, they can cooperatively carry out several complicated jobs necessary for their existence. The success of SI-based algorithms has been reported in many research papers. Several swarm-based approaches are used for the FR problem and are summarized in Table IV.

5.1. Particle Swarm Optimization (PSO)

The PSO algorithm [Kennedy and Eberhart 1995] has been effectively utilized in several fields such as ANN training, clustering, and FR. The basic idea behind PSO is based on the food-seeking behavior in organisms, such as the collective behavior of fish schooling. The main processing elements in the PSO algorithm are called

Table IV. Performance Analysis of Swarm-Based FR Techniques

Algorithm name	Chromosome Encoding	Objective	RR	Relevant References
PSO	Binary alphabetic string	To reduce the feature space by selecting the best subset of Gabor features	ORL [94.7%, 96.8%] FRGC [79.19%]	Ramadan and Abdel-Kader [2009] Raghavendra and Dorizzi [2011]
ACO	Directed graph	To select the optimal set of the extracted DWT features	ORL [99.75%]	Kanan et al. [2007]
ABC	A set of N weights	To select the best parameters to be used at the matching score level To train a weighting mask for assisting the FR system	ORL [99%] ORL [86.88%]	Tran and Liatsis [2011a] Tsai et al. [2014]
BFO	Binary vector	To find the optimal eigenvectors to be used in LDA To select the optimal features extracted by DCT	Yale [88.57%] UMIST [98.09%] FG-Net [31.2%, 64.5%]	Panda et al. [2011] Yadav et al. [2013]

particles, which are responsible for computation, where each particle encodes one possible solution of the problem. Interestingly, in contrast to the GA algorithm, PSO has no genetic operations. In the FR domain, PSO algorithms have been used to select the best discriminative features of the face image through the extracted feature space, where each particle represents one face image. PSO has been applied for the FR problem by many variations and improvements including discrete, binary, and mixed PSO (e.g., Du et al. [2007], Abdel-kader et al. [2008], Ramadan and Abdel-Kader [2009], Villegas et al. [2009], Sun and Zhou [2011], Cheng et al. [2011], Nitish Sinha [2011], Raghavendra and Dorizzi [2011], Azzawi and Al-Saedi [2010], Yan et al. [2009], Valuvanathorn et al. [2012], Darestani et al. [2013], Abdulameer et al. [2013], and Chakraborti and Chatterjee [2014]). An improved FR system based on PCA, PSO, and ANNs was developed by Du et al. [2007], wherein the face image, after reducing the dimensions using PCA, will be input to the back propagation (BP) feed-forward ANN for training. Basically, BP ANN is a multilayered feed-forward neural network, which is characterized by its good adaptability, classification, and identification. A simple three-layered BP ANN is composed of an input layer, a hidden layer, and an output layer. The PSO algorithm is used to optimize the weight values of the BP network. In Sun and Zhou [2011] and Ramadan and Abdel-Kader [2009], a PSO-based feature selection algorithm was proposed to select the optimal subset of features based on specified discrimination criteria. Yan et al. [2009] proposed a discrete particle swarm optimization (DPSO) in which a multiplicative likeness enhancement mechanism was used for the purpose of feature selection. The direct fractional-step linear discriminant analysis is employed to extract the features of the images. Each particle is related to some features that are picked according to their corresponding likeness. In binary particle swarm optimization (BPSO), particles are represented by binary strings analogous to the classical GA approach. Cheng et al. [2011] employed BPSO-based feature selection in the proposed FR system and compared their results with GA. The ORL database was used in their experiments. Their results show that the GA algorithm has more parameters and less computational time than the BPSO algorithm. However, the RR of the BPSO algorithm is higher than that of GA. Overall, the BPSO algorithm has reported an RR of 94.5%. Sinha and Priyanka [2011] enhanced the performance of the BPSO by applying image

Table V. Comparison of Different LDA-Based FR Algorithms

Name of the Algorithm	Choice of Database	Recognition Rate
Fisherfaces [Belhumeur et al. 1997]	Yale	76.20%
GA-Fisher [Zheng et al. 2005]	FERET	85.71%
EBFS-Fisher [Panda et al. 2011]	Yale	88.57%

processing techniques. They reported an RR of 97.9% and a reduction of 37% in the number of coefficients on the ORL database. Using the Yale B database, they reported a 99.3% RR. Most recently, an improved version of BPSO named adaptive inertia particle swarm optimization (AIPSO) was proposed by Raghavendra and Dorizzi [2011]. In contrast to BPSO, where the same weights have been assigned for all particles, in the AIPSO algorithm, the weight value of each particle is given iteratively based on the corresponding fitness value to avoid getting stuck in a local optimum. Experimental results show that the use of the AIPSO algorithm in feature selection has improved the RR when compared to other methods with an RR of 79.19% on the FRGC database [Phillips et al. 2005]. [Ramadan and Abdel-Kader 2009] performed experiments to compare the RR of their PSO-based approach against the GA-based approach. An RR of 94.7% was reported when adapting the discrete cosine transform (DCT) feature vector, whereas an RR of 96.8% was reported using the discrete wavelet transform (DWT) technique. They found that the PSO-based feature selection algorithm yields good classification accuracy with a small amount of features.

5.2. Bacterial Foraging Optimization (BFO)

The bacterial foraging optimization (BFO) algorithm proposed by Passino [2002] draws its inspiration from the collective foraging behavior of the so-called *E. coli* bacteria. The BFO algorithm was used in the feature selection process of FR. Jakhar et al. [2011] and Panda et al. [2011] used the BFO algorithm to reduce the extracted feature subset by removing the irrelevant features and selecting the most representative feature subset. Panda and Naik [2011] proposed an LDA-based FR called the EBFS-Fisher algorithm, which uses the E-coli bacterial foraging strategy (EBFS) to select the optimal principal components and achieve dimensionality reduction. The authors compared their results with the GA-Fisher algorithm proposed by Zheng et al. [2005]. Their results show that the EBFS-Fisher approach outperforms GA-Fisher, where the RR of EBFS-Fisher has been increased by 2.86%, from 85.71% of GA-Fisher to 88.57%. In Jakhar et al. [2011], the DCT is applied to the face images to extract the best features. The BFO algorithm selects the most representative features and removes irrelevant features. Each position of the bacteria represents one possible solution (feature subset of the face image) required for FR. Bacteria position is either one or zero, which refers to the selection or rejection of a particular feature, respectively. Their results show that the BFO algorithm can achieve good recognition rates using a small number of features. Most recently, Yadav et al. [2013] proposed a BFO-based FR system that alleviates the effect of aging by combining local and global LBP features at match score level by means of the bacteria foraging fusion algorithm. The algorithm is evaluated using the FG-Net database [Georghiades et al. 2010], where an RR of 64.5% is obtained using the oldest image as a probe, whereas an RR of 31.2% is reported when using the youngest image as a probe. A performance comparison of three algorithms, Fisherfaces, GA-Fisher, and EBFS-Fisher, is shown in Table V.

5.3. Ant Colony Optimization (ACO)

The ACO algorithm is a bio-inspired algorithm that was proposed in 2005 [Dorigo and Blum 2005]. It simulates the natural behavior of social ants seeking a path that links their nest and the food source. The capability of such insects to select the shortest paths is basically attributed to their ability to deposit a chemical substance called pheromone in their way of traversal to which other ants are attracted. The path that has a large amount of this chemical is preferred by the ants. As time goes by, this chemical decays, causing a little amount of pheromone on less popular routes. As a consequence, the shortest path will be more likely to be followed by other ants, this route will be boosted, and the remaining paths will gradually decline [Dorigo and Blum 2005]. The ACO was used as a feature selection classifier in Kanan et al. [2007]. In their work, the FR problem was formulated as a directed graph where vertices correspond to features of the face image and the arcs that link them denote the selection of the following feature. The ant traverses the graph to search for the optimal feature subset of the face image. An RR of 96% was reported on the ORL database [ORL 1992] with only 20 selected features. Dolkar and Saha [2009] introduced a new method for FR (BPN-ACO) that employs a back propagation neural-network (BPN) algorithm along with the ACO technique to find the best weight values of the BPN in the classification phase. An FR system using a combination of ACO and GA was proposed by Venkatesan and Rao Madane [2010], which has been named as ACOG. In their work, the features of the face image were extracted by means of the ACO and the recognition was done by the GA. An RR of 96% was achieved using 25 face images. Most recently, Kaur et al. [2013] applied artificial bee colony (ABC) along with the ACO for feature selection and recognition, respectively. In the feature selection task, pixels of the face image are represented by bees. Each feature extracted from the face image is a source of food, where the total number of the sources is equal to the number of the bees. The recognition has been done by ACO, where the selected features are represented by nodes and the pixels of the face images are represented by ants. The ABC algorithm iteratively matches the features with the image in the database.

5.4. Artificial Bee Colony (ABC)

The artificial bee colony (ABC) algorithm gets its inspiration from honey bees, which have two main behaviors: mating behavior and foraging behavior [Karaboga and Basturk 2007]. It was proposed by Karaboga and Basturk [2007] and is mainly based on the sophisticated behavior of honey bees, which swarm to find nectar and communicate the information related to food sources.

Tran and Liatsis [2011a] proposed a novel FR system in which the ABC-based algorithm is applied to select the optimal parameters to fuse the aforementioned information at matching score levels. In their proposed work, each scouting bee represents a candidate solution in the search space. Each individual is represented by a set of N weights. The fitness of the solution is estimated by calculating the RR based on a particular set of weights. They reported an RR of 99% on the ORL database.

Most recently, Chakrabarty et al. [2013] proposed an approach to divide the face images into patches in order to seek a nonlinear functional mapping by means of Volterra kernels, which are widely utilized to model nonlinear systems. Then the ABC algorithm is deployed to get optimal Volterra kernels, which will result in increasing the interclass scatter and minimizing the intraclass scatter. Experimental results on the Yale database have proven the effectiveness of the ABC algorithm and its ability to optimize Volterra kernels.

6. ARTIFICIAL NEURAL NETWORKS (ANNS)

ANNs are sophisticated computational tools inspired by the design and functioning of the biological neural networks in the human brain [Suzuki 2011]. The basic data processing elements of the biological nervous system are known as neurons. Hence, the way of learning by setting synaptic efficiency is the essential activity in neural networks in terms of both biological and artificial means [de Castro 2006a]. The design

Table VI. Performance Analysis of Neural-Network-Based FR Techniques

Algorithm Name	Description	RR	Relevant References
SOMs	The image is segmented into subblocks to be mapped into a lower-dimensional space.	ORL [94.06% 96.2%, 98.67%] YALE [94.44%] FERET [91%]	Kumar et al. [2005] Lawrence et al. [1997] Lefebvre and Garcia [2008] Tan et al. [2005a]
HNN	HNN works as a net with input points as image features and output points as vectors; each output point contains a feedback to its input point.	ORL [80%, 96.5%] Yale [91.30%]	Gan and fei Liu [2009]; Wang and Jia [2010] Chand [2010]
SNNs	SNNs are inspired from natural computing in the brain where neurons rely on pulses and spikes as an essential part of information transmission from one neuron to another	CAS-PEAL [51%, 71%]	Gao et al. [2008]; Muller et al. [2011]
FFNN	A neuron receives the incoming signals through its axon. The information flows from inputs to outputs in only one direction.	ORL [87.75%, 92%] Yale [60% 90.2%]	Bhati [2010] Chacon and Perea [2007] Prasad et al. [2011]
RBFNN	The RBFNN is motivated by the locally tuned response observed in the biological neurons inside the nervous system.	Yale [88.3%, 95%]	Wong et al. [2011]
LSTM	Neurons have an internal state, which serves as a short memory.	MIT-CBCL [94%]	Levada et al. [2008]
Neuro-Fuzzy ANNs	ANNs and fuzzy logic are combined to form a neuro-fuzzy system.	ORL [98.9%]	Makhsoos et al. [2009]

of any ANN consists of three main features: a set of artificial neurons, the connectivity among neurons (network structure), and a learning algorithm to determine the weight values. ANNs are adaptive systems and have the ability to modify their internal structure; these characteristics allowed them to be used in several approximation and hard problems such as feature extraction and biometric recognition. Many types of ANNs have been used in FR as summarized in Table VI.

6.1. Self-Organizing Maps (SOMs)

SOMs, created by Kohonen [1985], are one of the most sophisticated computational models that simulate the functioning of the brain. Furthermore, they are the most popular ANN approach in the unsupervised learning class that makes use of a competitive learning mechanism. SOMs are widely known for their ability to handle highly dimensional problems like feature extraction and classification [Kohonen 1985]. SOMs draw their inspiration from the computational maps of neurons in the human brain and in the nervous system of the basic cerebral cortex of monkeys and auditory cortex of bats [Suga 1977]. SOMs learn on their own without any class information. Thus, neurons compete with each other to be fired. Interestingly, the FR domain has capitalized several SOM-based approaches where SOMs have been mainly utilized as a mechanism for reducing the dimensionality and for selecting the most appropriate features [Lawrence et al. 1997; Kumar et al. 2005; Tan et al. 2005a]. An overview of various SOM-based FR applications is given in Chen et al. [2010]. Lawrence et al. [1997] designed an FR system using both a conventional neural network and an SOM classifier. This approach was evaluated using the ORL database and resulted in an RR of 96.2%. The major limitation of this technique is that it is not able to come up with a generalized representation for the S3 problem [Chen et al. 2010]. Kumar et al. [2005] proposed an approach that integrates SOMs with PCA to reduce the dimensionality and to extract the best discriminative characteristics of the face images. In their work, the face image is segmented into several blocks and mapped into a lower-dimensional space, thus providing dimensionality reduction. PCA is then applied to the matrix that has been created by SOMs and the system discards all the eigenvectors that have smaller values and retains only those with the biggest eigenvalues. In their experiments, they compared the performance of PCA, SOMs, and their proposed work, which combines the two techniques together (PCA and SOMs). In another work, Lefebvre and Garcia [2008] constructed an FR system using label SOMs to measure image similarity. Each local feature vector of the face image is used as an input to the SOMs, forming a neural map that consists of all the winning cells. In order to specify the likeness between a probe image and the global model, a probabilistic-based strategy is used. An RR of 98.67% is reported on the ORL database and 94.44% on the YALE database. Tan et al. [2005a] proposed an SOM-based FR approach to handle the small size problem, wherein it has been stated that SOMs can extract the best discriminative features despite having one single image per subject owing to their unsupervised learning ability. This approach was evaluated using the FERET database, where an RR of 91% was reported. However, the performance of this technique was tested with frontal faces only, where few variations have been taken into consideration. In the case of using more complex variations like facial aging, lighting, and pose, achieving a good RR might not be guaranteed [Wang et al. 2006]. Aly et al. [2008] presented an SOM-based FR approach and evaluated its robustness against illumination variation. In the traditional approach of SOMs, Euclidean distance is used to quantify the similarity between the probe and gallery image; this approach suffers from being very sensitive to lighting variations. Along this line, Aly et al. [2008] proposed a modified version of SOMs, which uses Mahalanobis distance rather than the conventional Euclidean distance. The robustness of the proposed approach was proven using the Yale B [Georghiades et al. 2001] and CMU-PIE [Sim et al. 2002] face databases. Lanzarini et al. [2013] designed an FR technique by using a combination of a competitive SOM and a fuzzy probabilistic decision criterion. The efficiency of the proposed approach was demonstrated using the ORL and Yale databases. According to the authors, the major limitation of the approach lies in the inability to operate a rejection when the subject to be identified is not in the database. In this case, the use of a threshold to make a decision does not guarantee obtaining a correct result. Aly et al. [2010] proposed a nonlinear projection mechanism using a set of SOMs to handle the nonlinear formation of the information acquired from the Gabor response. Furthermore, a regional matching method that depends on the similarity between local facial features is presented to arrange the data without a label. The performance of the proposed approach was evaluated using the FERET database, where an RR of 93.4% was reported using 1,196 gallery images. Sagheer [2010] proposed an appearance-based FR approach based on SOMs for feature extraction and SVM for classification, conducting experiments using the CMU-PIE database, where an RR of 89.4% was reported on variations of pose and illumination, while an RR of 38.9% was reported across different pose and illumination conditions.

6.2. Spiking Neural Networks (SNNs)

SNNs are the third generation of ANNs consisting of networks of spiking neurons and inspired by the computational mechanisms in the brain. They derive their computational power from the synaptic interactions between neurons while considering the time of spike emission. In contrast to the traditional ANNs, which model the average firing rate of the neurons, SNNs model the precise timing of spikes [Paugam-Moisy and Bohte 2009]. Using SNNs for FR has demonstrated its effectiveness with both the Integrate and Fire ($I\&F$) neuron model [Shin et al. 2010; Delorme and Thorpe 2001] and the spike response model (SRM) [Hafiz and Shafie 2012]. In contrast to the $I\&F$ model, SRM can accept spikes as inputs; hence, converting analog values into spikes is important. In Shin et al. [2010] and Wysoski et al. [2008], images were converted to spikes by inserting all the pixel values into a neural network using the $I\&F$ model, which requires more input neurons. Hafiz and Shafie [2012] implemented Leaky $I\&F$ to encode face images into spikes, and the generated spikes will be input to the SRM neural model for FR. Shin et al. [2010] introduced an FR system using SNNs to deal with occlusion and rotation using a hierarchal SNN based on the $I\&F$ model. The architecture of their network consists of three layers including the input layer that comprises excitatory neurons, the extraction layer that comprises both excitatory and inhibitory neurons, and finally the matching layer that comprises excitatory neurons. In their experiments, Shin et al. [2010] demonstrated that raising the number of neurons in the recognition layer to a particular level will notably improve the recognition rate [Shin et al. 2010].

6.3. Boltzmann Machine Neural Network

Boltzmann machine was proposed by Hinton et al. [1985]. It belongs to the category of stochastic recurrent ANNs. Its parallel computational architecture makes it suitable to be used in constraint satisfaction tasks [Ackley et al. 1985]. While Boltzmann machine has been successfully used for unsupervised learning of images, it suffers from being sensitive to noise. Robust Boltzmann machine (RoBM), an improved version of Boltzmann machine, was recently introduced by Tang et al. [2012]. RoBM has the ability to effectively handle partial occlusions and noise. In their first experiment, Tang et al. [2012] used the Yale database to demonstrate the robustness of the proposed approach. Interestingly, the RoBM learning algorithm can be effectively used for learning from noisy data without having any information about the original image. In their next experiment, they used the Yale database to test whether the RoBM algorithm can accurately recognize partially occluded and noisy faces. Results justify that as the amount of noise increases, RoBM outperforms the benchmark systems.

6.4. Echo State Neural Network (ESNN)

ESNN is a kind of recurrent ANN that was proposed by Jaeger [2001]. It is motivated by the complicated neural system. The ESNN model consists of a hidden layer, which is basically formed of a random state reservoir [Deng and Zhang 2006]. Madane et al. [2008] proposed an FR system using ESNN. The network learns the features of the face obtained using the Fisher linear discriminant plan. In their experiment, a classification accuracy of 95% was reported using the faces of five persons with different orientations.

6.5. Radial Basis Function Neural Network (RBFNN)

RBFNN is a type of feed-forward ANN. The use of RBFNN in neural network applications has been increasing recently [Suzuki 2011]. One of the main problems that the conventional FR systems suffer from is the extension of the classifier for the newly included subjects. Traditional methods attempt to tackle this problem by retraining the whole system, which requires expensive computational complexity. Wong et al. [2011] addressed this problem more efficiently by using RBFNN with a novel incremental learning approach on the basis of the regularized orthogonal least square (ROLS) algorithm presented by Chen et al. [1996]. The IROLS algorithm is proposed to avoid retraining the network when a new class is introduced to the existing classes. The IROLS algorithm has the ability of constructing a small RBFNN, which has a good generalization ability and requires less computational time. Compared to the incremental learning algorithm proposed by Masip et al. [2009], IROLS allows the addition of new data as well as the new updating samples to the existing data. Based on their experiments, Wong et al. [2011] concluded that their algorithm outperforms the conventional ROLS-based RBF neural network. Meng et al. proposed a high-speed FR system using RBFNN and DCT [Er et al. 2005]. Experimental results on the ORL and Yale databases demonstrate that their proposed approach achieves a high RR with high training and recognition speed.

6.6. Long Short Term Memory (LSTM)

The LSTM neural network is a type of recurrent ANN that is related to the biological memory model in the cerebral cortex [Graves et al. 2004]. Levada et al. [2008] introduced a new methodology for FR based on template matching and the LSTM classification algorithm. To evaluate the effectiveness of the LSTM, Levada et al. [2008] selected 50 different faces that were used as classes. PCA was used to reduce the dimensionality of the input images. The MIT-CBCL dataset was used in their experiments. An RR of 96% was obtained using 10 principal components, while an 88% RR was reported using 20 principal components.

6.7. Feed Forward Neural Network (FFNN)

FFNN is a variant of ANNs with feed-forward topology, where information must flow in one direction from input to output with no back loops. The number of layers in FFNN is not limited, nor is the type of transfer function used [Suzuki 2011]. A combination of multilayer FFNN and PCA was utilized for feature extraction and recognition by Prasad et al. [2011] and Bhati [2010]. In the first experiment, Bhati [2010] tested the effect of varying the learning rate on the recognition accuracy using the ORL database. An RR of 87.75% was reported with 40% training images. In the next experiment, Bhati [2010] tested the impact of varying the number of hidden neurons on the RR and found that 100% classification accuracy was achieved when the number of hidden neurons was between five and 65. When the number of neurons exceeded 65 neurons, a lower RR and higher training time were obtained. Prasad et al. [2011] reported a classification accuracy of 96.5% using 40 images and 90.2% using 60 images from the Yale database. Chacon and Rivas-Perea [2007] proposed an FR system based on FFNN and compared the performance of the system with an SOM-based FR approach. An RR of 92% was reported on the ORL database for the FFNN, whereas an RR of 90% was reported for the SOMs. However, an RR of 60% was reported for the FFBP network, whereas an RR of 70% was reported for the SOMs using the Yale database.

6.8. Hopfield Neural Network (HNN)

HNN is a type of recurrent neural network with a single layer [Hopfield 1982]. HNN draws its inspiration from the associated biological memory characteristics in the brain [Suzuki 2011]. Gan and Liu [2009] implemented an FR system using wavelet packet and HNN. In their experiment, an RR of 80% was reported using only one sample image per subject using the ORL database. In another study, Chand [2010] constructed a face and gender recognition system using eight parallel HNNs and they compared their result with GA. An RR of 91.30% was obtained using the Hopfield neural network, while an RR of 82.61% was obtained using GA. Wang et al. [2010] proposed an HNN-based FR system. First, the Gabor filter was applied for facial feature extraction. Second, Hopfield NN was used to further achieve dimensionality reduction. Finally, for face classification, the no-balance binary tree support vector machine (NBBTSVM) was used, where an RR of 96.5% was reported on the ORL database.

6.9. Neuro-Fuzzy ANNs

ANNs and Fuzzy Logic are complementary approaches in the design of intelligent systems. The combination of these two approaches into an integrated system is called Neuro-Fuzzy NN. Neuro-Fuzzy NN is a promising approach capable of capturing qualities characterizing the biological human brain. Makhsoos et al. [2009] introduced an FR system using fuzzy mixture of experts, which is a combination of fuzzy logic, mixture of experts (ME), and multilayer perceptron networks. In their proposed system, PCA was applied for facial feature extraction and the fuzzy mixture of experts was utilized for classification. In their experiments, an RR of 98.9% was reported using the ORL database with 40 principal components and four simple MLPs in the mixture architecture.

6.10. Elman Neural Network (ENN)

ENN is a simple kind of recurrent ANN with a back loop from the output of its hidden layer to the input layer through the so-called context unit [Suzuki 2011]. Esbati and Shirazi [2011] proposed an FR system using PCA and KPCA methods for dimensionality reduction and ENN for modeling storage systems. They used an ENN that consists of eight neurons in its hidden layer and only one neuron in the output layer. In their experiments, Esbati and Shirazi [2011] compared ENN with support vector machine (SVM), and the results showed that by using 110 PCA components, an RR of 77.17% was obtained using ENN, whereas an RR of 96.16% was reported using SVM. The experimental results demonstrated that using KPCA improves the RR of the SVM-based system to 97.451%. In another recent work, Kumar and Singh [2012] compared the performance of Feed-Forward NN and ENN-based FR in terms of RR and recognition time. Their experiments revealed that the Feed-Forward ANN-based FR system had a higher RR and less training time than ENN.

7. SUMMARY AND DISCUSSIONS

The essential problem encountered when modeling real-time FR systems is the complex nature and nonlinearity of the data. The adaptive nature of bio-inspired algorithms enables it to be effectively used in modeling complex biometric systems, thereby avoiding the need of completely knowing the accurate mathematical model [Zhang and Zuo 2007]. In this regard, Shieh et al. developed a real-time FR system using PSO and SVM [Shieh et al. 2014]. In their work, PSO esd used in the feature selection phase, whereas SVM was used as a fitness function of PSO in the classification phase. The experimental results proved the ability of the PSO algorithm to speed up the recognition time and improve the performance of the FR system. Interestingly, Balasubramanian et al. proposed an automatic real-time FR system using Radial Basis Function Neural Networks [Balasubramanian et al. 2009]. The efficiency of the proposed approach was tested in real time in the laboratory environment, where an RR of 99% was reported for 50 subjects. Furthermore, an RR of 100% was reported using the XM2VTS database. In this article, existing bio-inspired approaches for FR are systematically classified and summarized. Generally, EAs have several advantages over classical search and classification approaches. The former requires less domain-specific information and is adaptive and easy to use [Fraga and Coello Coello 2011]. However, the main drawbacks of such approaches are premature convergence, low accuracy, slow convergence, and that the population size is problem contingent and crucial for the search capability [Chen and Mahfouf 2009]. Using GP on its own to solve the FR problem is reported to be not suitable since the training time and computational overhead are larger than those of the other approaches. On that basis, Bozorgtabar et al. [2011] solved this problem by using a leveraging algorithm along with GP, which will

Table VII. Comparison of Accuracy and Speed of Bio-Inspired FR Algorithms Using the ORL Database

Algorithm	Accuracy	Speed (sec)	References
GA	86.17%	1.334	Li et al. [2010]
GP	63.5%	–	Bozorgtabar et al. [2010]
DE	63.12%	6.4	Mallipeddi and Lee [2012]
ABC	99%	160	Tran and Liatsis [2011b]
PSO	94.5%	160	Cheng et al. [2011]
BFO	100%	272.11	Jakhar et al. [2011]
ACO	96%	960	Kanan et al. [2007]
FFNN	87.75%	441	Bhati [2010]
HNN	94%	2.14	Gan and fei Liu [2009]
ENN	77.17%	28.6	Esbati and Shirazi [2011]

significantly increase the RR. GA can recognize the face images within a short period of time. However, GA suffers from the problem of converging toward local optima if the fitness function is not set properly [Li et al. 2010]. Memetic algorithms are very promising for multiobjective optimization problems. However, the use of local search to improve their performance requires a considerably high memory expense [Coello et al. 2006]. A summary of the methodologies and performance analysis of evolutionary-based approaches are given in Table II, Section 2. FR systems based on the BFO algorithm result in excellent classification rates with a lesser number of facial features [Jakhar et al. 2011]. However, BFO-based feature selection is computationally expensive since it requires a long training time. The ACO algorithm can find optimal facial features without any prior knowledge of features [Kanan et al. 2007]. In contrast to ACO, the PSO algorithm requires less training time, which means that it is computationally effective. The AIS algorithm can handle the S3 problem, which is one of the challenging problems that exist in critical FR applications. A summary of the methodologies and performance analysis of swarm-based approaches are given in Table IV, Section 4. In general, ANN-based algorithms can achieve good recognition rates; however, they are computationally expensive and time consuming as they require a long training time. The number of weights in FFNN is large, and as a result, the time for training the algorithm is quite long [Svozil et al. 1997]. Moreover, ANNs are not applicable for the systems with a small sample size [Kong et al. 2005]. Interestingly, Tan et al. [2005a] presented an SOM-based FR system to tackle the one training sample problem. The fusion of several ANN classifiers has been proved to improve the overall performance of FR [Kumar et al. 2008]. A summary of the methodologies and performance analysis of ANN-based approaches are illustrated in Table VI, Section 2. Importantly, the advantages and disadvantages of typical bio-inspired approaches presented in this article are summarized in Table VIII. A comparison of several bio-inspired algorithms in terms of recognition rates has been given in Figure 4. Bio-inspired algorithms have been proven to be robust and powerful in the FR domain, as depicted in Figure 4. In Table VII, we have compared the accuracy and speed of typical bio-inspired algorithms using the appropriate dataset available in the literature. With respect to the evolutionary algorithms, we can observe that GA-based FR has achieved a higher speed and reasonable accuracy, whereas DE and GP have moderate accuracies. Swarm-based techniques are more accurate and slower than evolutionary algorithms. Owing to their iterative nature, most of the ANNs, such as FFNN, are computationally expensive; however, the Hopfield neural network yields high accuracy and speed.

Another important metric for evaluating the performance of bio-inspired algorithms is the scalability criterion, that is, how well they perform on larger datasets. GA, PSO, and SOM algorithms reported good performance when they were tested using the FERET database [Zheng et al. 2005; Kim et al. 2006; Wei et al. 2011]. Similarly, the

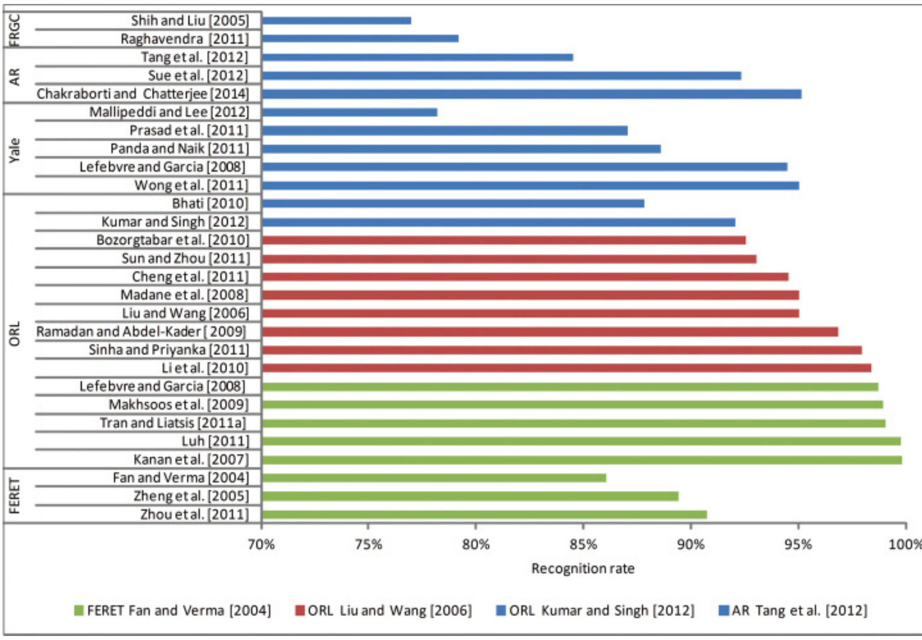

Fig. 4. Summary of the recognition rates of some typical bio-inspired FR algorithms.

Boltzmann Machine Neural Network algorithm showed good performance when evaluated using the AR database [Tang et al. 2012]. However, the DE algorithm exhibited a considerable performance degradation when evaluated using the AR database. The RBFNN algorithm yielded an RR of 92.1% on the FRGC database [Masip et al. 2009].

8. ENSEMBLE-BASED BIO-INSPIRED FACE RECOGNITION

The small sample size (S3) problem is usually encountered in subspace-based FR systems, especially when the images are high-dimensional and the within-class variations are relatively large. In many FR systems, the number of available training images is smaller than the dimensionality of the samples. Accordingly, it is hard to depict all the variations of the images due to illumination, scale, and expressions. In such conditions, the classifier is relatively biased with big variance and low performance. To tackle this problem, one approach is to fuse different classifiers so as to exploit their complementary information, which will result in constructing a more efficient and sophisticated model than any single classifier. It has been verified experimentally that the fusion of an ensemble of classifiers can achieve better classification rates than the individual classifier [Ho et al. 1994; Kittler et al. 1998]. In this context, a number of bio-inspired ensemble-based FR systems have been reported in the literature (e.g., Zhao et al. [2007], Sedai and Rhee [2007], Choi et al. [2009], Meins et al. [2012], and Mallipeddi and Lee [2012]).

Bagging, bootstrapping aggregation, is a popular ensemble method proposed by Breiman [1996]. The bagging algorithm creates a classifier using a combination of base classifiers. In contrast to boosting, which iteratively reweighs the instances before each call of the base learner, bagging creates a replicate dataset by sampling from the original dataset with replacement. One single classifier has been constructed from each of the replicates. The outputs of classifiers are combined using a majority

Table VIII. Advantages and Disadvantages of Typical Bio-Inspired FR Techniques

Algorithm Name	Advantages	Disadvantages
GA	—Low computational cost [Palod et al. 2011] —Suitable to large-scale and high-dimensional data due to its parallelization ability [Zhang and Zuo 2007].	—Convergence toward local optima —Low efficiency [Li et al. 2010]
DE	Fast convergence; uses few parameters [Mallipeddi and Lee 2012]	DE stagnates at suboptimal point
GP	—Good flexibility [Espejo et al. 2010] —The ability of tree-based representation of GP to represent random nonlinear forms [Zhang and Zuo 2007]	—Large number of parameters [Espejo et al. 2010] —High training time [Bozorgtabar et al. 2011]
AIS	—Suitable for pattern recognition and optimization due to its simplicity —Can handle the S3 problem [Luh 2011]	—Slow convergence [Fu-gang 2010] —High-dimensional networks cannot be easily visualized [Krzysztof et al. 2009]
ACO	Can find the optimal facial features without any prior knowledge [Kanan et al. 2007]	—Convergence is guaranteed —Complex implementation
PSO	—Low computational cost and high convergence rate —Simple to implement and uses few parameters	—Convergence toward local optima [Wang and Xiao 2005] —The difficulty to control diversity
ABC	—High flexibility and uses few control parameters —Can handle multidimensional and multimodal FR systems [Yan and Li 2011]	—Low accuracy [Yan and Li 2011] —Slow convergence [Karaboga et al. 2012]
BFO	Can achieve good RR using few features [Jakhar et al. 2011]	High computational cost [Jakhar et al. 2011]
FFNN	High accuracy [Prasad et al. 2011]	High computational cost
SOMs	—Can be used in dimensionality reduction tasks [Patole et al. 2010] —Can deal with scale invariance, rotation, and distortion of images	—High computational cost —SOM-based clusters might not be stable [Zhang and Zuo 2007]
HNN	—Fast and simple —Insensitive to little variations in the image [Chand 2010]	Binary data constraints
SNNs	—SNN overcomes limitations on traditional neural networks pertaining to computational cost	Consumes more computation time
RBFNN	—Simple and generalizable [Zhang and Zuo 2007] —Good approximation capabilities [Maglogiannis et al. 2008]	High computational cost [Maglogiannis et al. 2008]

voting rule (MVR) and Sum Rule. It has been shown that the classification performance of bio-inspired-based FR algorithms deteriorates considerably when a small training set is used. Furthermore, if the number of samples is large, the null space of the within-class matrix is reduced, which in turn results in low classification rates. To address this problem, Zhao et al. [2007] proposed an ensemble-based evolutionary feature extraction algorithm that incorporates bagging along with GA to enhance the recognition performance in case of large-scale datasets. In their proposed work, some

Table IX. Summary of Bio-Inspired Ensemble-Based FR Systems

Author	Ensemble Method	Methodology	Database	RR
Zhao et al. [2007]	Bagging	Some classes are randomly chosen and GA runs on the replicate to get a classifier. The ensemble classifier is created by combining the base classifiers with a majority voting.	Yale	100%
			ORL	97%
Mallipeddi and Lee [2012]	Bagging	Different combinations of feature vectors are obtained using DE to maximize the distances of the classes in the subset. The results were fused by means of majority voting.	Yale B	80.3%
			ORL	66.2%
Sedai and Rhee [2007]	Adaboost	GA is applied to divide the strongest features into different subsets of features.	FERET	96.4%
Choi et al. [2009]	Random Projection	A set of randomly localized features of the face were built together with some internal random networks. The ensemble classifier is formed by fusing these several networks via the sum rule.	AR	89.9%

classes are randomly chosen from the training subset and the samples of these classes form a bootstrap replicate, whereas all the other samples have been utilized for testing. Then, the base learner is called on the replicate to get a classifier. After doing this for the set number of iterations, the overall classifier is created by combining the base classifiers with a majority voting scheme. The effectiveness of the proposed approach has been tested using Yale and ORL face databases. Most recently, Mallipeddi and Lee [2012] proposed an ensemble-based FR using discriminant PCA features and the differential evolution algorithm. Bagging is used to sample classes from the initial set of classes. Different combinations of feature vectors are obtained using differential evolution, which has been used to maximize the distances of the classes in the subset. Each group of the obtained PCA features was utilized for FR and the results were fused by means of a majority voting strategy. In their experiments, they have observed that maximizing the number of bagging samples can improve the accuracy but at the expense of computational load. Choi et al. [2009] proposed a random network ensemble-based FR system mainly for images that have large variations with few training images. A set of randomly localized features of the face image were built together with some internal random networks to minimize the correlation within the network. The ensemble classifier is formed by fusing these several networks via a summation schema. Sedai and Rhee [2007] proposed a bio-inspired FR system based on GA and Adaboost. First, feature vectors are extracted based on Gabor filters. Second, GA is applied to divide the strongest features into different subsets of features. The classification models of the searched feature subsets are combined using Adaboost. The results showed that applying GA along with Adaboost for feature decomposition enhanced the classification performance of the FR system. The summary of bio-inspired ensemble-based FR systems is shown in Table IX.

9. FACE RECOGNITION CHALLENGES

Recent surveys in FR approaches have revealed many unsolved challenges such as pose, illumination, and occlusion. Pose variation was identified as one of the prominent challenges in the domain of FR and it has received considerable interest in the area of FR. Many promising techniques have been presented to tackle the challenge of recognizing faces in different random poses. Among these, bio-inspired methods have contributed their role as well [Kato et al. 2011; Salan and Iftekharuddin. 2012; Wi and Kiong 2012; Pisharady and Saerbeck 2012]. Pisharady and Saerbeck [2012] proposed a pose-invariant FR system based on biologically inspired C2 standard model features. An RR of 98.25% was reported on the FEI dataset [Thomaz and Giraldi 2010], whereas an RR of 95.40% was reported on the MIT-CBCL dataset. In another work, Wi and Kiong [2012] proposed a 3D pose-invariant FR model based on a biological visual system. Gabor wavelets were applied to represent simple receptive fields on the cell of the primary visual cortex. Complex and simple hierarchical structures were used to attain translation and scale invariance. During the acquisition step, images might become blurred and noisy because of the linear motion of camera. Consequently, the classification performance of 2D FR systems degrades considerably due to the noise and variations. During preprocessing of the image, the illumination problem is handled using normalization methods like gamma correction and histogram equalization. Bozorgtabar et al. [2012] proposed an FR approach that is insensitive to large variation in illumination using Fuzzy LDA (FLDA) and FFNN. At the preprocessing step, histogram truncation is used, and then the homomorphic filter is applied for normalization. First, the FLDA algorithm is used to extract some useful features of the face image. Second, the FFNN technique is applied for classification based on the previously extracted features. Experiments were performed on the ORL database, where an RR of 95.5% was reported. Li et al. [2004] built several eigen-spaces according to the direction of the illumination where the coefficients of each facial feature in the corresponding eigenspace were selected. After that, a single-layered back-propagation ANN was trained based on the selected coefficients. At the testing stage, the input image that has a random illumination orientation was fed into the different channels of ANNs with various illumination orientations. In their experiments, they concluded that the RR of their proposed approach outperforms the traditional method with a single ANN. Motivated by the sophisticated function of the human retina, which allows the eyes to recognize objects under varying illumination conditions, Vu and Caplier [2011] proposed a method of illumination normalization by mimicking the performance of its two layers: the photoreceptors and the outer plexiform layer. In their proposed system, they simulated the performance of the retina by combining two adaptive nonlinear functions, a Difference of Gaussian filter and a truncation. Experiments was performed on the Extended Yale B, FERET, and AR databases, where the good recognition rates obtained in all tests prove the robustness of their approach. Different algorithms have been proposed for pose-invariant and illumination-invariant FR so far, but there is limited proposed work in which the same framework can deal with both problems simultaneously. Kato et al. [2011] proposed a robust approach for angle-aware FR that was modified to handle the effect of lighting variations as well. They built an approach with efficient utilization of memory to keep images with various angles and illumination data by means of multilayer perceptron (MLP). Experimental results show the effectiveness of their proposed method. Face images are often prone to occlusion in unconstrained environments. The presence of partial occlusions in face images can dramatically affect the performance of FR systems. Several approaches have been proposed toward occlusion-invariant FR. Along this line, Kurita et al. [2003] proposed an ANN-based technique to recognize partially occluded faces. In the reconstruction phase, an auto-associative network was utilized to find the image that had the best match with the occluded face. After that, the texture from the closest match was taken to the occluded parts of the input image. Tan et al. [2005b] proposed an SOM-based FR method to handle the S3 problem. A multiple SOM algorithm was applied for each class in order to train a single SOMs so as to recognize occluded and expression invariant images.

10. CONCLUSIONS AND FUTURE TRENDS

In this survey, an up-to-date and comprehensive overview of bio-inspired approaches pertaining to the FR literature is provided. Bio-inspired approaches for FR are systematically classified and summarized (see Figure 3). Methodologies involving chromosome encoding, performance analysis, and the pros and cons of each algorithm are presented. Recognizing faces under unconstrained scenarios still has many open problems to be solved, and approaching these problems with a bio-inspired approach apart from purely principled approaches could enhance modern FR systems. The main drawbacks of evolutionary approaches are premature convergence, low accuracy, and slow convergence [Chen and Mahfouf 2009]. To avoid premature convergence, one possible solution is hybridization with local search heuristics where the exploration ability of evolutionary algorithms ensures the fast convergence of the solutions, while the exploitation ability of local search algorithms makes the search jump out of local optima [Isaacs et al. 2007; Martnez-estudillo et al. 2005]. AIS can be integrated to other evolutionary algorithms to tackle the premature convergence problem [Krzysztof et al. 2009]. The major limitation of the GP algorithm is that it requres a longer training time, which becomes worse when using large data [Espejo et al. 2010]. To cope with such a problem, incremental learning has been applied in Chien et al. [2002] and Kishore et al. [2000], where the evolutionary process begins with few instances of the training data and gradually adds more subsets during the evolutionary process. Interestingly, a more efficient approach to decrease the training time is to parallelize GP. Generally, ANN-based algorithms have been reported to achieve good recognition rates; however, they are computationally expensive and time consuming. Furthermore, ANN-based algorithms may not be suitable for a single image per subject problem because more than one image is required to train the system. Many attempts have been reported in parallelizing the ANNs to accelerate the required training time [Schuessler and Loyola 2011; Crdenas et al. 2010]. The performances of several bio-inspired algorithms in terms of recognition rates have been summarized in Figure 4. Purely principled FR algorithms are reliable, efficient, convenient, and secure; however, there remain some challenges that can be effectively handled by bio-inspired algorithms. In Figure 5, we compare the performance of bio-inspired techniques against some of the popular conventional methods. Bio-inspired approaches exhibit some special characteristics that enable them to outperform traditional FR methods. First, they are efficiently adaptive, which enables the development of real-time FR models that have the ability of automatic online learning. Second, bio-inspired algorithms offer different mechanisms to deal with uncertainty. Furthermore, bio-inspired methods have the capability of providing a robust platform to effectively recognize faces that can be noisy, partially occluded, or inaccurately located [Zhang and Zuo 2007]. Finally, bio-inspired approaches have a massively parallel architecture that can be exploited to speed up the computation. Finally, we end this article by providing some intuitive future directions on how bio-inspired algorithms can contribute significantly to address the challenges faced by present FR systems:

I. Large-scale and unconstrained FR is a challenging task that requires speed, accuracy, and scalability. To that end, bio-inspired approaches can contribute in addressing the big data challenge where a number of bio-inspired approaches have already been proposed and proven to be successful in this field [Cox and Pinto 2011; Pinto et al. 2011]. Interestingly, evolutionary algorithms and ANNs are promising approaches owing to their inherent parallelization that allows them to be applied on large-scale and highly complex systems [Zhang and Zuo 2007]. Membrane

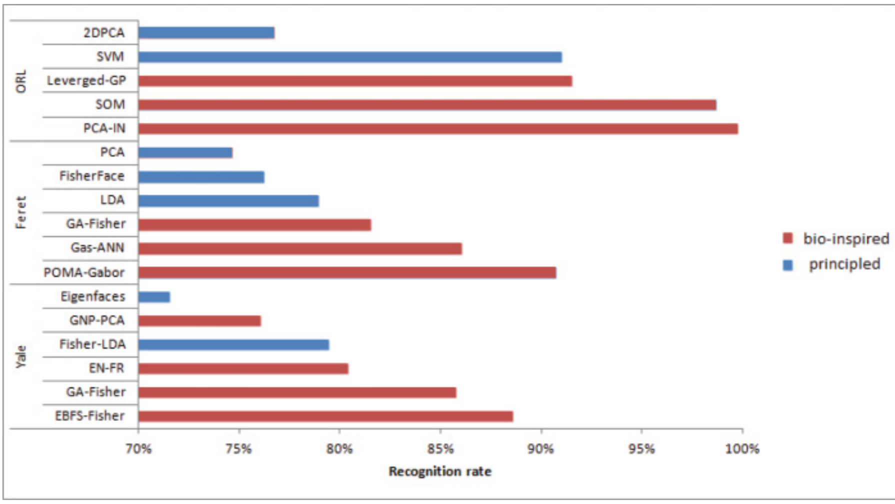

Fig. 5. A comparison of bio-inspired versus purely principled FR algorithms.

computing (MC) has emerged as a new field of natural computing that is mainly based on the assumption that the flow of metabolites within the compartmental architecture and functioning of biological cells can be interpreted as a flow of information for computations [Paun 2005]. Owing to its inherent large-scale parallelism, MC can be exploited to address the big data challenge in FR. Furthermore, bio-inspired FR approaches can be implemented under the framework of MC to fully exploit the advantages of both algorithms, where promising results have been recently reported by combining membrane computing and evolutionary computing [Zhang et al. 2014].

II. The imbalanced learning problem is often encountered in typical FR systems where the acquisition of face images is limited. Technically speaking, this problem occurs when the dataset exhibits an uneven distribution of samples per subject [He and Garcia 2009]. Thus, this could pose an implicit bias to the learning process [Freund and Schapire 1999]. Bio-inspired algorithms might be exploited to handle the problem of imbalanced data. Along this line, Milar et al. [2011] presented an evolutionary-based technique to address the imbalanced data problem in classification rules.

III. A number of efficient bio-inspired approaches could be efficiently applied to the FR problem such as cuckoo search (CS), bat, and EP algorithms. For instance, the FR problem can be formalized using CS, where the extracted features of the face can be represented by the host nest and each cuckoo's egg is considered as the new solution. For each host nest, the quality of the egg is either one or zero, which represents whether the feature is selected or not. For the bat algorithm, the bat's position is represented by binary vectors wherein the bits 1 and 0 correspond to the presence or the absence of the features, respectively. In EP, each chromosome encodes the features of the face where mutation only can be used to generate new offspring and the new generation can be selected using a probabilistic scheme according to the fitness of individuals.

IV. The interdisciplinary collaboration between cognitive neuroscience and computer vision could facilitate the development of fully automated FR systems that may surpass human performance [Bruce et al. 1998; Sinha et al. 2006; Gilad-Gutnick et al. 2012]. Interestingly, biologically inspired FR systems can significantly enhance the recognition rate and robustness of the conventional FR approaches, especially when viewing conditions are challenging or complexities such as occlusions are encountered. Since humans naturally possess remarkable visual intelligence pertaining to recognizing faces, it is worth looking at some interesting findings about the human perception of faces to develop practical automatic FR systems. Among these findings, it has been demonstrated that the ability of humans to tolerate degradations increases with familiarity in the sense that they can recognize familiar faces as a function of available spatial resolution, even in very low-resolution images [Chellappa et al. 2010]. Along this line, Chiachia et al. proposed a novel person-specific face representation for recognition based on three ideas related to human face perception, namely, the particularities, the familiarity, and the invariant aspects [Chiachia et al. 2011, 2014]. Consideration of these important studies pertaining to the brain's strategies of face recognition while designing FR models could provide clues and inspiration for the development of more robust FR systems.

V. Performance analysis of biometric systems with the aid of recent developments in statistical data analysis could bring in some new insights to better understand how various factors such as occlusion, image quality, and subject characteristics affect face recognition algorithms. Based on statistical data analysis techniques, Lee et al. [2013] recently introduced some key sensitivity analysis methods to analyze the performance of biometric systems. The authors used a video-based automated system for the problem of iris recognition as a case study to illustrate the idea. Such exploratory studies in cross-disciplinary areas such as statistical data analysis could add new dimensions to the biometrics domain including face recognition.

LIST OF ACRONYMS

FR. face recognition
AIS. artificial immune system
ANNs. artificial neural networks
GA. genetic algorithm
GP. genetic programming
DE. differential evolution
PCA. principal component analysis
RR. recognition rate
GNP. genetic network programming
S3. small sample size
MA. memetic algorithm
PSO. particle swarm optimization
CLPSO. comprehensive learning particle swarm optimizer
SI. swarm intelligence
ACO. ant colony optimization
ABC. artificial bee colony
BFO. bacterial foraging optimization
BP. back propagation
DPSO. discrete particle swarm optimization
BPSO. binary particle swarm optimization
AIPSO. adaptive inertia particle swarm optimization
EBFS. E-coli bacterial foraging strategy
DCT. discrete cosine transforms
BPN. back propagation neural-network
SOMs. self-organizing maps

RBF. radial basis function
SNNs. spiking neural networks
SRM. spike response model
RoBM. robust Boltzmann machine
ESNN. echo state neural network
RBFNN. radial basis function neural network
ROLS. regularized orthogonal least square
LSTM. long short-term memory
HNN. Hopfield neural network
FFNN. feed forward neural network
NBBTSVM. no-balance binary tree support vector machine
MVR. majority voting rule
ME. mixture of experts
ENN. Elman neural network
SVM. support vector machine
MC. membrane computing
CS. cuckoo search
EP. evolutionary programming
EAs. evolutionary algorithms
ES. evolution strategy
DWT. discrete wavelet transform
DCT. discrete cosine transform
FRGC. face recognition grand challenge
FERET. facial recognition technology
ORL. Olivetti research laboratory
CMU PIE. carnegie mellon university pose, illumination, and expression
MIT-CBCL. massachusetts institute of technology - center for biological and computational learning
CAS-PEAL. academy of sciences pose, expression, accessories, and lighting
UMIST. university of manchester institute of science and technology
XM2VTS. extended multi modal verification for teleservices and security applications
BU-3DFE. binghamton university - 3D facial expression
UMB-DB. university of milano bicocca database

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