Bacteria Foraging Fusion For Face Recognition Across Age Progression

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Abstract

The phenomenon of "aging" in humans leads to significant variations in facial features. Various factors such as bone growth, ethnicity and dietary habits influence the facial aging pattern. This increases the difficulty in performing automated face recognition. In this paper, we propose an algorithm that improves the performance of face recognition by applying the bacteria foraging fusion algorithm. The proposed algorithm mitigates the effect of facial changes caused due to aging by combining the LBP features of global and local facial regions at match score level, by means of the bacteria foraging fusion algorithm. Experimental results are presented using the FG-Net and IIIT-Delhi face aging databases. The IIITDelhi database, which has been collected by the authors, consists of over 2600 age-separated labeled face images of 102 individuals. To account for real life and natural conditions, images include changes in the face due to illumination, pose, and presence of accessories such as eyeglasses. The results demonstrate that the proposed approach outperforms traditional fusion schemes, existing algorithms and a commercial system.

1. Introduction

Human face plays a vital role in establishing the identity of a person and describing other useful information such as age, ethnicity, gender, and expression. Humans have a remarkable capability of recognizing faces with good accuracy. However, it is challenging for them to process large amount of data; therefore, there is a need to automate this process. Several face recognition algorithms and systems have been proposed in the literature and constant efforts are being made to improve the performance of these systems in terms of both accuracy and time. Even after decades of research, there are several challenges that affect the performance of face recognition algorithms including pose, expression, and illumination. Figure 1 shows images of a person with different pose, illumination, and facial expressions. However, in designing an efficient face recognition system, it is also important to consider the role played by facial aging. Figure 2 shows face images of an individual with age variations (the first and last image have age difference of around 50 years). This example clearly illustrates that over a period of time, facial aging causes high intra-class variations and therefore, traditional face recognition algorithms may not be able to handle these variations.

Figure 1. Face images with differences in illuminations, pose, and facial expressions.

Figure 2. Face images of an individual illustrating the variations due to aging. The images have been downloaded from the internet.

The problem of *aging* has been explored not only by psychophysicists and researchers working in human perception, which has helped in understanding the craniofacial growth, but also by computer vision researchers in developing algorithms to mitigate the effect of facial aging [12, 17]. The changes produced by aging are not uniform across different ages as well as subjects and it is affected by different factors. Specifically, during formative years, the variations in the shape of a face are more prominent while in the later stages of adulthood, texture variations such as wrinkles and pigmentation are more visible. Further, factors including biological developments such as bone growth, facial muscle elasticity, ethnicity, gender, and environment are also important. Research in developing algorithms to address facial aging can be broadly divided into three categories: age estimation, computational models for predicting the face at a certain age, and face recognition across age progression. Since the main objective of this research is to recognize faces across age progression, we present the literature review of computational models for age progression and face recognition. *Computational Models for Age Progression*: A computational model for estimating facial appearances across different ages should incorporate the factors that influence the process of aging, for example gender, ethnicity, diet, and age group. Burt and Perrett [3] identified seven age groups spanning the age of 20 to 54 years. They characterized the shape of each input face image by finding out a set of fiducial features and generated the composite image for each age group by averaging shape and skin color from face images of the same age group. Tiddeman et al. [21] extended the idea proposed by Burt and Perrett and used wavelet based methods for defining facial textures and creating 'composite faces'. They used edge strength and Markov Random Fields to retain edges (wrinkles) and improve texture characterization respectively. Ramanathan and Chellappa worked on facial aging effects specially for individuals of age 0-18 years [15]. They used the fact that primary reason for facial growth in formative years is craniofacial growth. They combined cardioidal strain transformation along with age-based anthropometric data to develop a facial aging model. In another paper, they introduced shape and texture variation model for estimating the facial aging in adults [16]. The shape variation model was developed by physical models that characterize the functionalities of different facial muscles such as linear, sheet, and sphincter muscles. The texture variation model was used to characterize facial wrinkles in predesignated facial regions such as the forehead and nasolabial region. Suo et al. [20] proposed to use the multi-resolution face models built upon 'And'-'Or' graphs. The 'And' nodes were used in finding the fine representation of faces whereas the 'Or' nodes were used in finding different possible configurations. Since it used multiple resolutions, the global and local appearance variations such as color, skin pigments, and wrinkles were modeled at different resolutions.

Face Recognition Across Age Progression: The methods of face recognition across age progression can be categorized as generative and non-generative [7, 17]. Generative methods involve inducing the changes in the input facial images to incorporate aging variations. Non-generative methods do not involve any change in the input data but age-invariant signatures are computed from the input faces and employed to perform identity verification. Ling et al. [8] proposed a non-generative method in which they showed that the image gradient orientations are age-invariant and remain similar across ages. They designed a face operator to extract the image gradient orientations and used Support Vector Machine (SVM) classifier to verify faces across ages. Singh et al. [19] proposed a mutual information-based transformation algorithm to minimize the difference between two age separated images. Park et al. [13] developed a 3D facial aging model which was then applied to solve the problem of age-invariant face recognition. Their approach is based on the fact that exact craniofacial aging can be developed only in 3D. The advantage of using a 3D model is that it reduces the variations due to lighting and pose. Mahalingam and Kambhamettu [9] used graph based face matching. They extracted the feature points using local feature analysis (LFA) and the face descriptor was developed by applying LBP to each feature point. They developed an age model for each subject and face was matched using a 2-step approach involving maximum a posteriori (MAP) and graph matching approaches. Guo et al. [6] studied the relationship between face recognition accuracies and age intervals. They performed their experiments on MORPH-II, a very large face recognition database. They found out that when the age gap between the gallery and probe image is more than 15 years, the performance declines much more as compared to within 15 years. They also observed that the use of soft biometric features can help in improving face recognition across age progression. Li et al. [7] proposed discriminative model, referred as DM, for achieving age-invariant recognition. They developed an approach involving the use of scale invariant feature transform (SIFT), multi-scale local binary pattern as local descriptors, and multi-feature discriminant analysis. The proposed scheme outperformed the commercial system 'FaceVacs' by a significant difference.

Research Contribution: It is our assertion that facial regions such as periocular, binocular and mouth are effected differently due to aging. Therefore, assigning specific weights to the information extracted from these regions may help in designing effective algorithms for face recognition which are robust to changes due to age progression. Further, the algorithms specifically tailored to mitigate the effect of facial aging by proper training may be able to identify faces more efficiently. In this paper, we propose a bacteria foraging algorithm for recognizing faces with age variations. The proposed algorithm, via training, computes the weights pertaining to the facial regions as well as the full face, and assimilates the weighted match scores. In this paper, the IIIT-Delhi face aging database is presented and utilized to evaluate the performance of the proposed algorithm. The results of the proposed approach have been compared with VeriLook [1] (referred as COTS: Commercial Off The Shelf) and other fusion approaches.

2. Bacteria Foraging Fusion Algorithm

The proposed algorithm relies on the observation that not all regions of the face contribute uniformly to face recognition over time. Therefore, the weights of these individual features have to be optimized particularly for face recognition across age variations. Figure 3 illustrates the steps involved in the proposed algorithm.

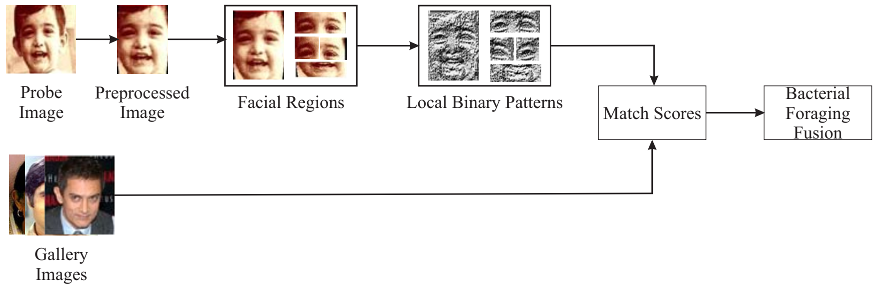


Figure 3. Illustrating the steps involved in the proposed bacterial foraging based fusion algorithm for face recognition.

2.1. Preprocessing and Feature Extraction

The preprocessing, feature extraction and matching steps are described below.

- The first step towards associating an identity with an image is detecting the face from within a given image. The Viola Jones face detection algorithm [23] is applied to detect faces from the input image. After face detection, the eye coordinates of each image are manually selected and the faces are aligned with the inter-eye distance of about 90 pixels and the size of detected images are 128×128 pixels.
- As mentioned earlier, different regions of the face are effected differently by the aging process. In order to incorporate different weights to each facial region, the facial regions, namely right and left periocular regions, binocular region, and the mouth region are extracted from the face image using eye coordinates.
- Local Binary Pattern (LBP) descriptor [11] is calculated for the face, right and left periocular regions, binocular region, and the mouth region. The LBP descriptors of two images/regions are compared using the chi-square distance. In the proposed algorithm, total of five match scores are computed, $\{s_1, s_2, ..., s_5\}$.

2.2. Bacteria Foraging based Fusion

Various nature-inspired optimization algorithms, such as the Genetic optimization and Particle Swarm Optimization algorithms, have been used in biometrics [5]. In this paper, the bacterial foraging based fusion algorithm is proposed to learn the weights to be employed for the weighted sum rule fusion [4, 10, 14]. It is our assertion that bacterial foraging fusion should better optimize the weights compared to traditional weighted sum rule (where weights are generally chosen based on the accuracy on the training data) and genetic search based optimization (where random mutation and/or crossover operations are used to find optimal weights). Since traditional weighted sum rule and genetic algorithm based fusion are sensitive to the increasing problem complexity and dimensionality, i.e., as the number of constituents for fusion increases, both these techniques may result in local optimization, especially, in the case of biometrics. On the other hand, bacterial foraging approaches, intuitively, are appropriate for modeling optimization process. As mentioned by Muller et al. [10], *"Bacteria are single-cell organisms, one of the simplest form of life developed on earth. Despite their simplicity, they acquire information about their environment, orient themselves in the environment, and use this information efficiently to survive. This reaction of the organism to its environment has been subject to intensive research in the past decades. It is also interesting for scientists in the field of optimization to study the bacterial behavior. Like bacteria, optimization algorithms may be viewed as entities that gather information about a function landscape and then use this information to move to an optimum. At the same time, the simplicity and robustness of the process of bacterial chemotaxis suggests a starting point for constructing an optimization algorithm".* Inspired from this observation, we also believe that weight optimization in weighted sum rule fusion can be modeled using the bacterial foraging process. Further, as mentioned earlier, an efficient training based weight optimization for different facial features may help in mitigating facial aging effect. The proposed algorithm for optimizing weights in sum rule is explained as follows:

What to optimize: The weighted sum rule is defined as:

$$f(\overline{w}, \overline{s}) = \sum_{i=1}^{N} w_i s_i \quad (1)$$

where $\overline{w}$ represents weights and $\overline{s}$ represents the biometric scores pertaining to $i = 1, ..., N$ matchers or classifiers. Since $\overline{s}$ is computed by the matchers, the variable that needs to be optimized is $\overline{w}$. Therefore, the weighted sum rule can be represented as:

$$f(\overline{w}) = \sum_{i=1}^{N} w_i s_i \quad (2)$$

and $\overline{w}$ needs to be optimized such that the recognition performance (i.e. identification accuracy) is maximized. Thus, the fitness function is the identification accuracy. An additional constraint can be imposed such that $\sum w_i = 1$.

How to optimize: Using the 1-D bacterial foraging optimization [4, 10, 14], the weights of the facial regions are optimized using the following technique. Each weight vector containing the weights of the facial regions is considered as one bacteria.

1. **Step 1 - Chemotaxis**: This step simulates the movement (swim and tumble) of *Ecoli bacterium*. Let $B^i(j,k,l)$ be the i^{th} bacterium at the j^{th} chemotactic, k^{th} reproductive and l^{th} elimination dispersal step, and $C(i)$ be the size of step taken in a random direction. The movement of B^i in each chemotactic step can be written as,

$$B^i(j+1,k,l) = B^i(j,k,l)+C(i)\frac{\triangle i}{\sqrt{\triangle^T(i)\triangle(i)}}+\lambda(i) \tag{3}$$

   $\triangle i$ refers to a vector having elements in the range [-1, 1] and in a random direction. The regularization parameter $\lambda(i)$ adds a very small value in chemotactic step in order to avoid local optima and diversify the movement.

2. **Step 2 - Swarming**: In ecological system, *E.coli* bacterium forms intricate patterns known as swarms through cell-to-cell signaling. Swarming helps the bacteria to aggregate into groups and find the optimal solution as a concentric pattern with high density. In biometrics, this step can be viewed as a fitness function. Here, the fitness function is rank-1 identification accuracy by the combination of bacteria (i.e., different accuracies are computed corresponding to different weight values, and these accuracies are used as the fitness function). Instead of identification accuracy, one can also use the total identification error as the fitness function; the only difference would be that in the first case, the fitness function has to maximize the value and in later, it has to minimize.

3. **Step 3 - Reproduction**: This step is based on the concept that the least healthy bacterium dies and healthier ones split into two bacteria. Based on the fitness function (or health status), all the bacteria are sorted in the reverse order. From this sorted list, only the first half of the population is chosen and the remaining are discarded. The surviving bacterium splits into two (identical) and therefore, the size of total population remains the same. In this step, we apply a regularization approach and randomly generate offspring bacteria that are added into the reproduction. Every 50 iterations, during elimination and reproduction, ten random offspring bacteria are added into the overall pool within the maximum allowed population limit. This regularization ensures a high degree of diversity and the solution does not converge to a local minimum.

4. **Step 4 - Elimination and Dispersal**: In this step, each bacterium with value of fitness fuction less than a threshold t, is removed and a new bacterium is randomly added at a random location. This step removes suboptimal solutions from the search space and avoids moving towards the local optima.

In bacteria foraging optimization, weights $\overline{w}$, of the sum rule fusion are used as the input function to be optimized with rank-1 accuracy as the fitness function. After a fixed number of generations, the bacteria converged to an optimum value. Hence, the algorithm was terminated when the number of generations of bacteria reached the optimum value. At the end of convergence, optimal weights are obtained which are used in weighted sum rule during testing. The values of parameters chosen in the algorithm have been calculated by conducting various cross validation trials and finding the best parameter.

3. Performance Evaluation

The performance of the above mentioned algorithms are evaluated on two face aging databases. The details of the databases, experimental protocol, fusion schemes for comparison, and experimental results are presented in this section.

3.1. Face Aging Databases

- *FG-Net facial aging database* [2]: It contains 1002 age-separated face images of 82 subjects. The age range of the subjects in the database is 0-69 years. On an average, there are 12 images per subject in the database.

- *IIITDelhi face aging database*: Motivated by the large number and variety of images of celebrities available on the internet, the authors have collected age separated face images of various individuals on the lines of Labeled Faces in the Wild (LFW) protocol. The database contains 2618 images of 102 Indian celebrities. There are 49 female and 53 male celebrities in this database and the age span of celebrities is between 4 and 88 years. Some sample images from the IIIT-Delhi face aging database are shown in Figure 2.

3.2. Experimental Protocol

The IIITDelhi and FG-Net databases are both divided into two partitions, training and testing, that approximately contain 30% of the subjects for training and 70% for testing. From the IIITDelhi database, images of 70 subjects have been randomly chosen for testing while the remaining 32 subjects are used for training. Similarly, 58 subjects (70%) from the FG-Net database have been randomly chosen for testing while images of the remaining 24 subjects (30%) are used for training. Two experiments are performed on both the databases. In the first experiment, the probe set consists of one among the latest (oldest) face images of every subject, while the remaining images are in the gallery. In the second experiment, the probe set contains one earliest (youngest) face image of every subject and the remaining images are used as the gallery.

3.3. Comparison with Existing Algorithms

The performance of the proposed fusion algorithm is compared with the following existing fusion algorithms:

- Sum Rule [18]: The most basic form of fusion, sum rule, is applied to various combinations of facial regions. The LBP scores from each facial region are normalized and then sum rule is applied with various combinations of facial regions.
  - Binocular, left and right periocular
  - Face and binocular
  - Face, binocular, left and right periocular
  - Face, left and right periocular
  - Left and right periocular
  - Face, binocular and mouth
  - Mouth, left and right periocular
  - Face and mouth
  - Face, mouth, binocular, left and right periocular
- Weighted Sum Rule [18]: In weighted sum rule, different weights are assigned to each facial region while combining the scores. These weights are calculated by using the accuracy achieved by each facial region as training set. The weight of region X can be computed as:

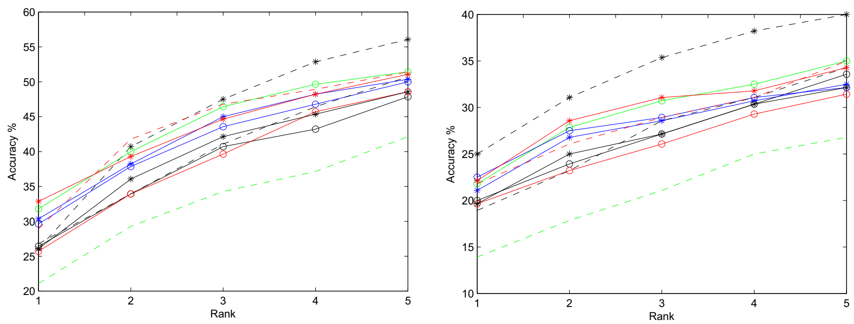
$$Weight(X) = \frac{Individual Accuracy of X}{\Sigma Individual Accuracy of All Regions} \quad (4)$$

- SVM [22]: The scores pertaining to each facial region is provided to the SVM fusion algorithm and the probability estimate vector returned by the learned SVM is used as the metric for face identification.
- GA-based Score Fusion: In the proposed fusion algorithm, the weights are learnt through genetic search (instead of bacterial foraging).

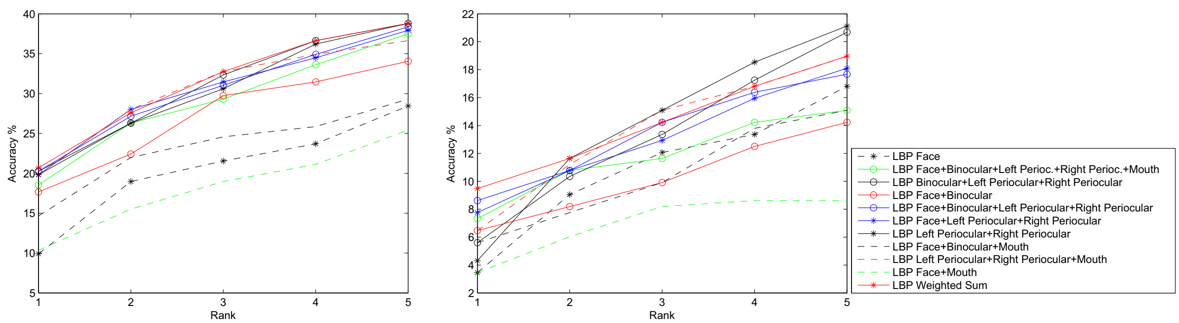
3.4. Results and Analysis

The performance of the proposed and existing algorithms are computed for identification with four times random cross validation. The Cumulative Match Characteristic (CMC) curves shown in Figures 4 and 5 and Table 1 summarize the results obtained using the two protocols: the oldest or the youngest image is used as probe.

- The results show that it is more difficult to recognize a person if the youngest image is used as probe compared to using the oldest image as probe.
- It can be seen that the combination of face, mouth, binocular, left and right periocular regions yields the best rank 1 accuracy in the case of LBP score fusion.
- The weighted sum rule does not offer much advantage as compared to the sum rule. The rank-1 accuracy improved only by 0.3-2.2% for all the cases on both the databases.
- In the case of SVM-based fusion, experiments are performed to determine the parameters (including kernel choice and its parameterization) that yield the best accuracy. A linear kernel with $c = 1$ and $\gamma = 5$ yields the best accuracy; however, in all the cases, rank-1 accuracy by SVM fusion is not more than 10%.
- The proposed bacteria foraging fusion algorithm yields the maximum accuracy when the match scores of all the facial regions are combined. In case of the "oldest image" as probe, a rank-1 accuracy of 54.3% is achieved on the IIITDelhi database and 64.5% on the FG-Net database. Similar results are observed on using the "youngest image" as probe as well.
- The results also suggest that the combination of both holistic and local regions provides complementary information and boosts the performance considerably. Therefore, in face aging, local regions such as binocular, mouth and periocular regions play an important role in establishing the identity of the probe image.
- The performance is also compared with a recently developed DM-based face recognition algorithm ([7]) for facial aging. In all the experiments, we observe that the proposed algorithm yields higher identification accuracy compared to the DM approach. We believe that the DM algorithm requires more training samples and it is computationally more demanding compared to the proposed algorithm.
- Apart from comparing the proposed approach with a recent algorithm mentioned in the literature, the results were also compared with COTS. It can be seen that the proposed approach outperforms COTS in all the experiments.
- We have also performed experiments with other facial feature extraction and matching algorithms, such as Principal Component Analysis, Scale Invariant Feature Transform, and Sparse representation. In our experiments, LBP outperforms other matchers. However, due to space constraints, we are not providing the details of these results.

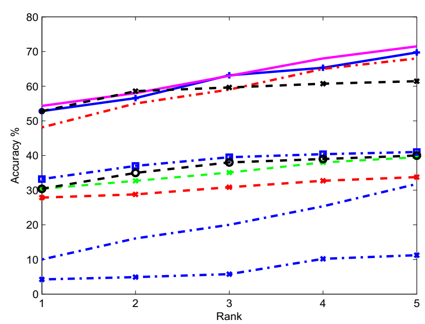


(a)

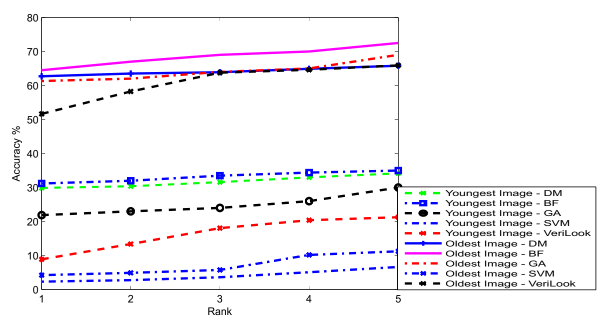


(b)

Figure 4. CMC curves showing the results of sum rule and weighted sum rule fusion algorithms on the (a) IIITDelhi and (b) FG-Net databases. The first column shows the results when the "oldest image" is used as the probe whereas the second column shows the results with the "youngest image" as the probe. Rank-1 accuracy of these algorithms have been shown in Table 1.



(a)



(b)

Figure 5. CMC curves comparing the performance of different fusion algorithms on the (a) IIITDelhi and (b) FG-Net databases. Rank-1 accuracy of these algorithms have been shown in Table 1.

4. Conclusion and Future Work

The contribution of this research is two fold: designing a bacteria foraging fusion algorithm to mitigate the effect of facial aging and preparing age separated (and annotated) face aging database of 102 subjects. The experimental results on the IIITDelhi and FG-Net databases suggest that the proposed algorithm optimizes the weights more efficiently compared to traditional weighted sum rule, SVM fusion, genetic algorithm based fusion approach as well as existing discriminative model based (facial aging) algorithms. An important issue for further research is how aging affects the face shape and texture in different regions for different subjects. This may lead to a user-tailored "anti-aging" scheme where a prior knowledge on the subject is used to differently select the face areas and compute the related weights.

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Algorithm	Facial Region(s)	Oldest Image as Probe		Youngest Image as Probe	
		IIITDelhi	FG-Net	IIITDelhi	FG-Net
Unimodal	Face	26.1%	10.0%	25.0%	3.4%
Sum Rule	Face, Mouth	21.1%	10.3%	13.9%	3.4%
Sum Rule	Face, Binocular	25.7%	17.6%	19.6%	6.5%
Sum Rule	Periocular	26.1%	19.8%	19.6%	4.3%
Sum Rule	Binocular, Periocular	26.4%	20.2%	20.0%	5.6%
Sum Rule	Face, Periocular	30.4%	19.8%	21.1%	7.7%
Sum Rule	Face, Binocular, Mouth	26.8%	14.6%	18.9%	5.6%
Sum Rule	Mouth, Periocular	29.0%	19.8%	21.8%	6.5%
Sum Rule	Face, Binocular, Periocular	29.6%	20.2%	22.5%	8.6%
Sum Rule	Face, Mouth, Binocular, Periocular	31.8%	18.5%	21.8%	7.3%
Weighted Sum	Face, Mouth, Binocular, Periocular	32.8%	20.7%	22.1%	9.5%
SVM Fusion	Face, Mouth, Binocular, Periocular	8.6%	4.2%	10.0%	2.3%
GA based Fusion	Face, Mouth, Binocular, Periocular	48.1%	61.3%	30.4%	21.9%
Bacteria Foraging	*Face, Mouth, Binocular, Periocular*	*54.3%*	*64.5%*	*33.3%*	*31.2%*
DM [7]	Overlapping Patches	52.8%	62.7%	30.4%	29.9%
VeriLook (COTS)	Face	52.7%	51.6%	27.8%	8.9%

Table 1. Rank-1 accuracy obtained by using the proposed and existing algorithms on the IIITDelhi and FG-Net databases.

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