Optimal Filter design for Face Classification using Bacteria Foraging Algorithm

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Abstract :- Robust face recognition and classification has been an area of interest for researchers in many disciplines of science and engineering. In this paper, we present a new technique for designing optimal filters for face classification using the bacteria foraging algorithm. The simulation results show that the optimal filter is able to classify the face images correctly into the target and anti-target image sets. This technique will have wide applications in biometric systems for face classification.

Key-words:- Face classification, Optimal filter, Bacteria foraging algorithm.

1 Introduction

Biometric based personal recognition and authentication is the process of verifying the identity of a person based on his or her physiological features like, face, fingerprint and iris or behavioural characteristics such as speech or signature [1, 2]. The characteristics desirable for these biometric data are uniqueness, distinctiveness, easily obtainable, time-invariant (no significant changes over a period of time), easily transmittable, distinguishable by humans without much special training and be able to be acquired as non-intrusively as possible [3]. Applications of biometrics range from access control, transaction authentication, voice mail, to forensic work, where the task is to determine whether a biometric sample belongs to a given suspect.

The need for a robust and cost effective biometric system for security applications has been highlighted by security agencies the world over. Recent advancements in digital and optical technologies, biometric sensors, and matching algorithms have led to the deployment of biometric recognition systems in a variety of security applications [4-18]. Current biometric systems make use of fingerprints, hand geometries, facial thermograms, palm prints, and voice, as well as the iris, retina, pupil, face, signature, and gait in order to establish a person's identity [5].

Face recognition is used to identify one or more persons from still images or a video image sequence of a scene by comparing input images with faces stored in a database. In a face recognition system, face features are extracted or coded offline from the original images and stored in the face feature database. In the identification stage, the same features are extracted from the input face, and the features of the input image are compared with the features of each model image in the database [7]. In most systems, searching is the most computationally expensive operation due to the large number of images available in the database. Efficient search algorithms and fast screening algorithms are prerequisites of identification systems [8].

Only a few of these algorithms can achieve a completely reliable performance because of the inherent problems due to the wide variations in the appearance of a particular face with changes in pose, lighting, facial makeup and facial expression [9]. Therefore the variations between the images of the same face are often larger than image variations due to change in same face class. One possible way of overcoming this limitation is to work in three dimensions instead of two dimensions [10]. But three dimensions is costly and more difficult to manipulate and is also ineffective in authenticating people in most contexts. A novel face recognition approach is proposed, using an asymmetric protocol, enrolment in three dimensions but identification performed from two dimensions images [10]. Few other widely used face recognition approaches are linear discriminant analysis [11], principle component analysis [12] and partial Hausdorff distance [13].

Foraging theory is based on the assumption that animals search for and obtain nutrients in a way that maximizes their energy intake E per unit time T spent foraging. They try to maximize a function like $\frac{E}{T}$ [19]. Maximization of such a function provides nutrient sources to survive and additional time for other important activities (e.g., fighting, fleeing, mating, reproducing, sleeping, or shelter building).

In this paper we use a modified version of the BFA to design optimal filters for face classification. The paper is organized as follows. In section 2 we present a brief outline of the BFA. Section 3 describes the proposed technique. Simulation setup and results are given in section 4. The paper is concluded in section 5.

2 The Bacteria Foraging Algorithm

Let $J(\theta), \theta \in R^p$ be the function who's minimum is to be evaluated, where we do not have measurements or an analytical description of the gradient $\nabla J(\theta)$. The bacterial foraging can be used to solve this non-gradient optimization problem. Then the θ is the position of a bacterium over the optimization area and the combined effects of attractants and repellents from the environment can be considered as $J(\theta)$. The magnitude of $J(\theta)$ in the range $J(\theta)<0$, $J(\theta)=0$, and $J(\theta)>0$ representing that the bacterium at location θ is in nutrient-rich, neutral, and noxious environments, respectively. The chemotaxis is a foraging behavior that implements a type of optimization where bacteria try to climb up the nutrient concentration (find lower and lower values of $J(\theta)$), avoid noxious substances, and search for ways out of neutral media (avoid being at positions θ where $J(\theta)=0$). It implements a type of biased random walk.
The chemotactic actions of E. coli can be summarized as:

(A1) If in neutral medium, alternately tumbles and runs i.e. it searches.
(A2) If swimming up a nutrient gradient (or out of noxious substances), swim longer (climbs up nutrient gradient or down noxious gradient) i.e. it seeks increasingly favorable environments.
(A3) If swimming down a nutrient gradient (or up noxious substance gradient), then searches and avoids unfavorable environments.

In this way, it can climb up nutrient hills and at the same time avoid noxious substances. Let j be the index for the chemotactic step. Let k be the index for the reproduction step. Let l be the index of the elimination-dispersal event. Let

$$P(j,k,l)=\{\theta^i(j,k,l)|i=1,2,\ldots,S\} \quad (1)$$

represent the position of each member in the population of the S bacteria at the j^{th} chemotactic step, k^{th} reproduction step, and l^{th} elimination-dispersal event. Let $J(i,j,k,l)$ denote the cost at the location of the i^{th} bacterium $\theta^i(j,k,l) \in R^p$. For actual bacterial populations, S can be very large (e.g., $S=10^9$), but p = 3. Let N_c be the length of the lifetime of the bacteria as measured by the number of chemotactic steps they take during their life. Let $C(i)>0, i=1,2,\ldots,S$ denote a basic chemotactic step size that we will use to define the lengths of steps during runs. A tumble, a unit length random direction, is represented using $\varphi(j)$. It is used to define the direction of movement after a tumble. Let

$$\theta^i(j+1,k,l)=\theta^i(j,k,l)+C(i)\varphi(j) \quad (2)$$

where, $C(i)>0$ is the step size taken in the random direction specified by the tumble. If at $\theta^i(j+1,k,l)$ the cost $J(i,j+1,k,l)$ is better (lower) than at $\theta^i(j,k,l)$, then another chemotactic step of size $C(i)$ in this same direction will be taken and repeated up to a maximum number of steps N_s. This represents that the cell will tend to keep moving if it is headed in the direction of increasingly favourable environments. The other steps in the algorithm are swarming, reproduction and elimination [20].

3 The Proposed Technique

The main goal of the algorithm is to optimize the cost function, i.e. the correlation function, so that the filter function will give high correlation peaks for targets images and low value for ant-targets images. The correlation function used as cost function for the optimization is defined as,

$$J=\frac{\sum_{targets}\text{correlation}(M,TI)}{\sum_{anti-targets}\text{correlation}(M,AT)} \quad (3)$$

where M-optimal filter, TI-targets, AT-anti-targets. The steps of the BFA are as follows.

Step 1–Initialization.

Step 2–Iterative Algorithm for Optimization: This section models the bacterial population chemotaxis, swarming, reproduction, elimination and dispersal.

The algorithm works as follows. First, the input images are converted into grey-scale images. By using the 'Prewitt' edge operator, the images are converted into edge images. An adaptive threshold filter is used to remove the unwanted areas of the image and to complement the binary image. The cost function used for optimization is the first order correlation coefficient between optimal filter to the target images over all anti target images. For each bacterium the correlation function is evaluated through the tumbling stage. The swarming effect is also added to this to give the net effect of social foraging of bacteria. For all bacteria over all chemotactic steps the iteration is carried out. The healthiest bacteria (which have the highest fitness value) are allowed to regenerate. The newly generated bacteria's are placed near to their parents. Now we will have half of the old one and other half are new one, in order to keep the total number of bacteria constant. According to a random probability, a bacterium will be eliminated and newly created one will dispersed over the image field. This will reduce the probability of the optimization getting stuck in local optima.

4 Simulation Results

Computer simulations have been done to corroborate the proposed technique. The set of target and anti-target images are shown in Fig. 1. Figure 2 shows the variation of the average fitness of the entire bacteria population after each bacterium has taken j chemotactic steps. It is evident from the figure that the chemotactic steps progressively improve the fitness level of the filter, thereby its classification capability. After the final filter is obtained using BFA, it is used for classification of the target and anti-target images. The results of the classification are depicted in Fig. 3. It can be seen from the plot that there is a clear demarcation between the correlation peak value of the target images and the anti-target images. Thus, the optimal filter designed using BFA can successfully classify face images.

5 Conclusion

In this paper, a new technique has been proposed which uses BFA to design an optimal filter for face classification. An optimal filter was designed using this technique for eight target images and eight anti-target images. The filter was able to classify all the images correctly. This technique will have wide applications in biometric systems for face classification.

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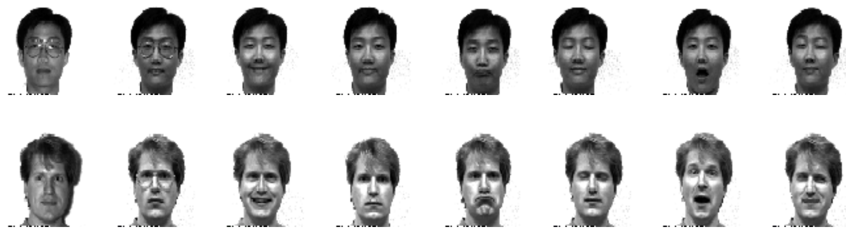

Fig. 1 First row: Target images. Second row: Anti target images.

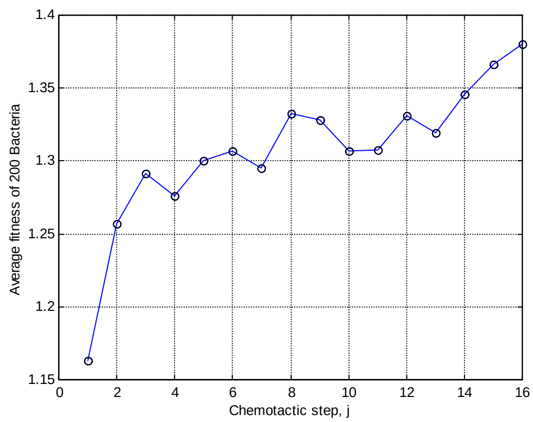

Fig. 2 Variation of the average fitness of the entire bacteria population after each bacterium has taken *j* chemotactic steps.

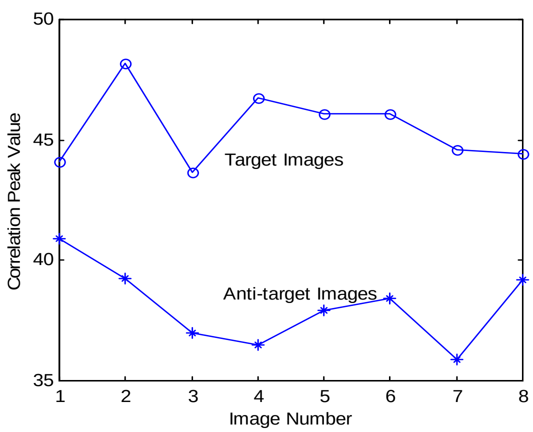

Fig.3 Classification of Target and Anti-target images.