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A novel adaptive crossover bacterial foraging optimization algorithm for linear discriminant analysis based face recognition

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ABSTRACT

This paper presents a modified bacterial foraging optimization algorithm called adaptive crossover bacterial foraging optimization algorithm (ACBFOA), which incorporates adaptive chemotaxis and also inherits the crossover mechanism of genetic algorithm. First part of the research work aims at improvising evaluation of the optimal objective function values. The idea of using adaptive chemotaxis is to make it computationally efficient and crossover technique is to search nearby locations by offspring bacteria. Four different benchmark functions are considered for performance evaluation. The purpose of this research work is also to investigate a face recognition algorithm with improved recognition rate. In this connection, we propose a new algorithm called ACBFO-Fisher. The proposed ACBFOA is used for finding optimal principal components for dimension reduction in linear discriminant analysis (LDA) based face recognition. Three well-known face databases, FERET, YALE and UMIST, are considered for validation. A comparison with the results of earlier methods is presented to reveal the effectiveness of the proposed ACBFO-Fisher algorithm.

1. Introduction

Face recognition has attracted much attention due to its potential value for human identification/verification applications. Improvising face recognition techniques is a theoretical challenge. In the real world, face images vary according to poses, illumination, and different expressions. Therefore, extracting features, which clearly distinguish the genuine and imposter face images, are of prime concern.

In existing face recognition techniques [1–13], usually the top order 'm' principal components are used for dimension reduction. The rest 'n–m' lower order principal components are eliminated. Allowing for top order 'm' principal components may be true from image processing (image compression) point of view. However, from pattern classification (pattern recognition) point of view, this approach may not be accurate. There might be some useful information on lower order principal components, which are also very useful for discriminating different classes from the sample space. Therefore, it is hard to decide a value for 'm'. This warrants us to develop an appropriate search strategy to select the optimal principal components. Hence, we need to develop an efficient search technique to select the best principal components from all principal components given by principal component analysis (PCA) [1,2]. In a nutshell, face recognition (FR) involves finding optimal features achieving the best results using a minimum distance classifier. Such a problem is usually formulated as an optimization problem solved by an iterative procedure in order to properly explore the search space (sample space) of the candidate solutions precisely needed for the problem. The optimization process used by traditional FR methods is highly influenced by the selection of optimal features. Recently, evolutionary algorithms (EAs) have demonstrated its ability to deal with complex real world problems in pattern recognition and computer vision. Research in this direction is mainly motivated by the global optimization nature of evolutionary approaches, which allows them to perform a robust search in complex and ill-defined search spaces. The first attempt to solve FR problem using EAs is found in [14]. The authors in [14] proposed evolutionary pursuits (EP) that implements characteristics of the genetic algorithm (GA) for probing the space of promising solutions to find the optimal basis vectors. They have claimed that EP has improved face recognition performance compared to the PCA and the Fisher's Linear Discriminant (FLD). In this paper, we propose a new algorithm called ACBFO-Fisher with improved recognition rate. Note that both GA and ACBFO are evolutionary algorithms.

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Further, it is seen that the genetic algorithm (GA) is used to develop GA-Fisher algorithm for FR systems [15]. The GA employs crossover and mutation techniques for the optimal search process. The disadvantages with the GA are that the offspring never ends at the same location as their parents. As a result, the search process is arbitrary. Further, mutation carried out in GA only results in a phenotypically change, never undergo a physical dispersal. This provoked us to use bacteria foraging optimization (BFO) technique to introduce a new BFO-Fisher algorithm in [16]. However, it is seen that the step size for foraging is fixed in BFO, which lead to more computation. Moreover, it is hard to decide a fixed step size to improve objective function values. This has motivated us to make the step size adaptive with the fitness function values to improve search results. In addition, the crossover feature of a genetic algorithm is also supplemented to add more nutrition.

This idea is explored here to propose a new algorithm coined as ACBFO. We also introduce an efficient face recognition algorithm called ACBFO-Fisher using the ACBFO algorithm with improved performance. In this paper, ACBFO-Fisher is used for dimension reduction in linear discriminant analysis (LDA) [3,4]. To back up our statements, some experimental results are presented. Three different well-known face databases, FERET, Yale and UMIST, are used for experiments. Results are also compared with GA-Fisher, BFO-Fisher, ABFO approach, and CBFO approach. Finally, we believe that the proposed method has more scope for FR, provides stability and better recognition rate in most of the cases.

The organization of the paper is as follows: Section 1 is the introduction. Section 2 discusses the related work. Section 3 describes the development of adaptive crossover bacterial foraging optimization algorithm called as ACBFOA. The proposed ACBFOA is validated by using important benchmark functions. Section 4 introduces ACBFO-Fisher algorithm and selection of the best principal components. Experimental results and discussions are presented in Section 5. Concluding remarks are given in Section 6.

2. Related work

Until now, many face representation schemes have been introduced based upon holistic features and local appearance features [1]. The holistic features include – principal component analysis (PCA) [2], linear discriminant analysis (LDA) [3–5] and independent component analysis (ICA) [6,7]. The basic idea of PCA is to construct a subspace that represents an input image with lower dimensional feature vectors, which are known as Eigenfaces. LDA seeks a linear transformation by maximizing the ratio of between-class variance and within-class variance. LDA based features used by face recognition (FR) systems are known as Fisherfaces [5,8]. ICA is a generalization to PCA, which is sensitive to the high-order relationship between image pixels. Many algorithms are developed using LDA [3–10]. It is observed that for FR, LDA outperformed PCA [9,10]. In general, Fisherfaces outperforms Eigenfaces [8]. On the other hand, the local appearance features include – Gabor features [11] and local binary patterns (LBPs) [12]. These are two different types of representative features used in FR. Gabor wavelets [11] capture the local structure corresponding to specific spatial frequency (scale), spatial locality, and selective orientation, which are demonstrated to be discriminating and robust to illumination and expression changes. LBP operator [12], which describes the neighboring changes around the central point, is a simple yet effective way of representing faces. It is invariant to any monotonic gray scale transformation and is, therefore, robust to illumination changes to some extent.

The PCA algorithm finds an optimal linear transformation that maps the original n-dimensional data space into an m-dimensional feature space ($m < n$), with reduced dimensionality. Suppose N sample training images are given as $[x_1, x_2, \ldots, x_N]$. Then, each face image is modeled as n-dimensional vector formed via lexicographic ordering of a 2D pixel array. The total scatter matrix can be represented as:

$$S = \sum_{k=1}^{N} (x_k - \bar{x})(x_k - \bar{x})^T \quad (1)$$

where $\bar{x}$ denotes the mean of the N sample vectors in the training set and can be represented as:

$$\bar{x} = \frac{1}{N} \sum_{k=1}^{N} x_k \quad (2)$$

The eigenvectors $e_1, e_2, \ldots, e_m$ of S associated with the first m largest eigenvectors $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_m$ are from the linear transformation matrix: $E = [e_1, e_2, \ldots, e_m]$. The m eigenvectors $e_1, e_2, \ldots, e_m$ constitute an m-dimensional feature space. PCA based features used by the face recognition (FR) system are known as Eigenfaces [2,13]. Given a face image x for testing, the PCA analysis expands the face in terms of m eigenfaces. The linear transformation W^T produces an m-dimensional feature vector $a = (a_1, a_2, \ldots, a_m)^T$, that is

$$a = W^T (x - \bar{x}) \quad (3)$$

Each of the transform coefficients $a_i = e_i^T (x - \bar{x})$, $i = 1, 2, \ldots, m$ describes the contribution of each eigenface to the face image. The transform coefficients serve as features for face recognition. The feature vector is then compared to the feature vector of each face image in the database to recognize the unknown test face. The face image can be approximated as:

$$x \approx \bar{x} + Wa = \bar{x} + \sum_{i=1}^{m} a_i e_i \quad (4)$$

which is a linear combination of m eigenfaces.

LDA gives optimal discriminant feature vectors, which maximizes the Fisher index. Note that the ratio between the between-class scatter matrix and within-class scatter matrix is called Fisher Index. However, LDA-based approach has some limitations and show poor results due to “small sample size (sss)” problem. The ‘sss’ problem occurs when sample size is less than the number of pixels in an image. It makes within-class scatter matrix singular. As a result, its inverse does not exist. To overcome this problem, the within-class scatter matrix should be made nonsingular. This can be achieved by using a method called Fisherfaces [8]. Interestingly, Fisherfaces use PCA for dimension reduction to overcome ‘sss’ problem in LDA. Some of the alternatives of LDA are also reported in [5].

The Evolutionary Pursuit [14], which employed genetic algorithm (GA) search method using a fitness function to select optimal principal components for dimension reduction, is used in Eigenface based FR. In the GA-Fisher algorithm [15], GA is employed for finding the optimal principal components for dimension reduction with a provision for making the within-class scatter matrix nonsingular. Authors in [15] proposed a Fisherface based FR. Recently, we proposed [16] a Fisherface based FR algorithm using bacterial foraging optimization [17] as the search technique. BFO-PCA is used for finding the optimal principal components for dimension reduction in LDA [16]. The proposed algorithm is known as BFO-Fisher [16]. From [16], it is seen that the bacterial foraging optimization strategy can be employed in place of GA, as a better search option.

From the literature, we find that most researchers intend to introduce new kinds of the nature inspired algorithms. In bacteria foraging algorithm, the energy intake per unit time is maximized. A