Face Recognition: A Combined Parallel BB-BC & PCA Approach to Feature Selection

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Abstract—This paper proposes a soft computing based integrated approach to optimal features selection and dimensionality reduction of images. Principal Component Analysis (PCA) is the standard and popular method applied for features reduction of images for face recognition applications. The proposed approach combines Parallel Big Bang–Big Crunch (PBB-BC) and PCA. The approach applies PCA for evaluation of Principal components of a given image and PBB-BC is used for optimal number of feature selections from amongst those evaluated by PCA. We implemented our approach in MATLAB and validated it on ORL dataset. We compared the performance of proposed PBB-BC-PCA with Eigenfaces/PCA, Fisherfaces and PCA-MA approaches. The performance of the proposed integrated approach was much better than the other three; clearly establishing the supremacy of proposed approach over the other two.

Keywords—Image recognition, dimensionality reduction, Principal Component Analysis (PCA), Parallel Big Bang–Big Crunch, Fisher faces, Memetic Algorithm (MA)

I. INTRODUCTION

Face recognition is the process of identifying an unknown face from the given set of image in a database. In a face recognition system each image in the database is compared with an unknown face. If the unknown face matches with any image in the database then the unknown image is said to be recognized. The major drawback of this face recognition approach is that if the images have larger dimension then it will be impractical to compare the image element by element. The large dimensions of a images will increase the computational and space complexities. Hence, it is highly desirable to reduce the dimensionality of the data set while retaining the significant features of a given image data set. Literature is rich with dimensionality reduction approaches. The Principle component Analysis (PCA) [1], Fisherfaces approach [2][3], Independent Component Analysis (ICA) [4][5], Linear Discriminant Analysis (LDA) [6][7] and Kernel Principal Component Analysis (KPCA) [8][9][10] are mostly used techniques in dimensionality reduction. Fisherfaces approach is also referred as Fisher’s Linear Discriminant method (FLD). It is a classification approach originally developed by R.A. Fisher in 1936 [2][3]. FLD is very popular technique for dimensionality reduction while preserving the class discriminatory information. This approach tries to differentiate between the classes rather than data. The KPCA is a nonlinear extension of PCA technique. An integrated approach using PCA and memetic algorithm (MA) was proposed in [11]. This paper presents a Combined Parallel Big Bang – Big Crunch (PBBBC) and PCA approach to optimal feature selection in image recognition applications. The approach combines PCA and PBBBC [12][13] optimization approaches to reduce the dimensions of the image database. We implemented our approach in MATLAB. We were able to achieve a significant dimensionality reduction through this new approach. Section-II of this paper reviews PCA algorithm. Section-III present PBBBC approach, section-IV of the paper proposes the new integrated approach; section-V presents simulation results and discussion on the dimensionality reduction and time complexity issues. Section-VI concludes the paper.

II. PCA ALGORITHM

PCA was developed by Karl Pearson in 1901 [1]. It is very popular technique for dimensionality reduction of images. PCA transforms a large number of correlated variables into a smaller number of uncorrelated variables. These uncorrelated variables are called principal components (PCs) [14]. The PCA Algorithm can be implemented as given below:

Let there be an image database consisting of M images each of N pixels (for an image size of 60×60,
N consists of 3600 pixels). This database is represented by $A = N \times M$ matrix:
Let the $i^{th}$ row of this matrix $A$ be represented by a vector $A_i = x_{1i}, x_{2i}, ..., x_{M}$.

**Step 1:** Calculate the Mean of $A_i$ as given below:

$$\mu_i = \frac{1}{M} \sum_{j=1}^{M} A_{ij} \quad (1)$$

**Step 2:** Evaluate the $N \times M$ matrix $\Phi$ as follows:

$$\Phi_{ij} = A_{ij} - \mu_i \quad (2)$$

**Step 3:** Compute its covariance matrix:

$$C = \Phi \times \Phi^T \quad (3)$$

**Step 4:** Compute eigenvalues of $C$: $\lambda_1 > \lambda_2 > ... > \lambda_M$

**Step 5:** Compute the eigenvectors of $C$: $u_1, u_2, ..., u_M$

**Step 6:** Arrange the eigenvectors in descending order and select “$k$” eigenvalues from it.

In face recognition process, each training image ($r$) is transformed into its eigenface components (projected into “face space”) by a simple operation as given below:

$$W_k = u_k^T (r - \mu) \quad [14].$$

Thus the complexity of database with $M$ images is reduced to $k$ images, where $k < M$.

The primary disadvantage of the PCA is that the principal components are usually a combination of all available variables. Hence it is very difficult to distinguish which variable is important and which is not statistically significant [15]. PCA technique is also referred to as eigenface method of face recognition [13].

III. PARALLEL BIG BANG-BIG CRUNCH OPTIMIZATION ALGORITHM

The Big Bang Big Crunch (BB-BC) optimization technique [12] is very useful algorithm to find optimal solutions to the complex problems involving functions with nonlinear behavior. It is applied on the problems where traditional mathematical programming methods prove to be of little use. The optimization algorithm is based upon Big Bang - Big Crunch theory of the evolution of the universe. The algorithm functions in two phases. In the first phase called Big Bang phase, energy dissipation produces disorder and randomness; whereas, in the second phase called Big Crunch phase, randomly distributed particles are drawn into an order. Inspired by this theory, an optimization algorithm was proposed, which was called the Big Bang-Big Crunch optimization algorithm [13].

Parallel BB-BC algorithm a multi-population algorithm, was first proposed by Shakti et. al. [13]. The pseudocode for Parallel BB-BC is given in figure 1.

IV. THE PROPOSED OPTIMAL FEATURES SELECTION APPROACH

The proposed optimal feature selection approach is the extension of PCA. In this approach, we first create a $A = N \times M$ matrix (database) of all the images as explained in PCA approach. We then apply PCA to the database and compute eigenvectors. The corresponding values of the eigenvectors are arranged in the descending order and the significant features are retained. Thus the $N \times M$ matrix will be reduced to $N \times k$ matrix where $k < M$. We then apply PBBBC algorithm to reduce the database further to $N \times J$ where $J < k$. We find that these two steps reduce the database size from $N \times M$ matrix to $N \times J$ where $J$ is far smaller than $M$ which is the original number of images.

For face recognition, all the training images are projected on the selected/reduced $J$ features and the set of “$J$” weights is calculated [14]. When a new unknown face is encountered, it will again be projected on the selected “$J$” features and the new weights for this image are calculated. The difference between the weights of the unknown face and image weights of the training set is evaluated. The smallest of the differences less than a given threshold identifies that the unknown face belongs to that particular image in the database.

V. SIMULATIONS, RESULTS AND DISCUSSION

We implemented the proposed approach that combines PCA and PBB-BC algorithms using MATLAB. For training and testing purpose we used the ORL database (available at http://www.cam-orl.co.uk/facedatabase.html). This database contains 400 greyscale images. Each image is of 92x112 resolutions. The database consists of images of 40 different persons. Each person has 10 images. In all there are total of 400 images in the database. For the sake of brevity we have resized the images into 60x60 resolutions. The database size is 3 MB. Further we used images of only 10 persons out of the given 40 persons. For training purposes we used two cases. In case 1 we used 3 images of each person. Rest of the 7 images/person were used for
Figure 1. Pseudocode for the Parallel BB-BC Algorithm

```
Begin
/* Big Bang Phase */
Generate N populations each of size NC candidates randomly;
/* End of Big Bang Phase */
While not TC /* TC is a termination criterion */
/* Big Crunch Phase */
For i = 1: N
  Compute the fitness value (center of mass using Equation 1) of all the candidate solutions of i^{th} population;
  \[ x_c = \frac{1}{\sum_{i=1}^{NC} f_i} \sum_{i=1}^{NC} f_i \]
  (5)
  Best fit individual can be chosen as the center of mass instead of using Eq. 1;
  Sort the population from best to worst based on fitness (cost) value;
  Select local best candidates l_{best}(i) for i^{th} population;
End
From amongst "N" l_{best} candidates select the globally best g_{best} candidate;
For i =1: N
  With a given probability replace a gene of l_{best}(i) with the corresponding gene of global best g_{best} candidate
End
/* End of Big Crunch Phase */
/* Big Bang Phase */
Calculate new candidates around the center of mass by adding or subtracting a normal random number whose value decreases as the iterations elapse using Equation 2;
\[ x^{new} = x_c + l(rand) / k \]
(6)
/* End of Big Bang Phase */
End
```

testing purpose. Hence, our training dataset consisted of 30 images and test dataset had 70 test images. In case 2 we used 5 images of each person for training. Rests of the 5 images/person were used for testing purpose.
The parameters as given in table 1 were set for PBBBC algorithm.

<table>
<thead>
<tr>
<th>Table 1. Parameters used in PBB-BC</th>
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<tbody>
<tr>
<td><strong>Parameter</strong></td>
</tr>
<tr>
<td>Number of Populations</td>
</tr>
<tr>
<td>Population Size</td>
</tr>
<tr>
<td>Number of iterations</td>
</tr>
<tr>
<td>Combination Probability</td>
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</table>

DIMENSIONALITY REDUCTION/ FEATURE SELECTION:

we selected top 30% of all eigenvectors based upon their eigenvalues for simulation purposes. Hence, we used PCA to drop 70% features. After feature reduction by PCA, The PBBBC was applied to select the optimal feature subset from this reduced features set. We used PBB-BC algorithm to choose 6 optimal feature sets consisting of 3 features to 8 features as given in Table 2.
The proposed work was tested on different number of features. For case 1 we conducted 10 trials for each set of features and recorded the average recognition rate. Table 2 shows the recognition rate with different feature sets. The same has been shown in figure 2 also. We observe as the number of features were increased from 3 to 8, the recognition rate also increased and became constant after it reached to
98.5714%. For case 2 when the number of training images/person was increased to 5, we observed that PBB-BC algorithm produced 100% recognition rate with a set of 5 features only whereas both PCA-MA algorithm and fisherface approach could reach the 100% recognition rate with a minimal set of 6 feature. PCA of course produced 100% recognition rate with 13 features. This is presented in Table 3. We compared the performance of our proposed PBBBC approach to PCA, PCA-MA and fisherfaces approaches. The performances of the 4 algorithms have been presented in figure 2. It clearly shows that the proposed approach gives the better results as compared to PCA-Memetic Approach, Eigenface method and Fisherfaces approach.

![Figure 2. Comparision of PCA-PBB-BC, PCA-MA and Eigenfaces Approaches](image)

<table>
<thead>
<tr>
<th>Approach</th>
<th>No. of features selected</th>
<th>Recognition Rate (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Eigenface/PCA</td>
<td>13</td>
<td>100</td>
</tr>
<tr>
<td>Fisherface</td>
<td>6</td>
<td>100</td>
</tr>
<tr>
<td>PCA+MA[11]</td>
<td>6</td>
<td>100</td>
</tr>
<tr>
<td>PCA+ PBB-BC</td>
<td>5</td>
<td>100</td>
</tr>
</tbody>
</table>

VI CONCLUSIONS

In this paper we have proposed an integrated PBBBC and PCA approach to feature selection and dimensionality reduction. PCA was followed by Parallel BB-BC Algorithm. The approach used PCA for dimensionality reduction and Parallel BB-BC was utilized for optimal feature selection. Parallel BB-BC approach has been explained and compared with MA, Fishерfaces and Eigenface (PCA) approaches. The approach was implemented in MATLAB and was tested on ORL data base, the simulation results clearly indicates that Parallel BB-BC out performs PCA-MA, Fisherfaces and Eigenface approaches on account of feature selection. The results have shown that the performance of the Fisherfaces approach is better than Eigenfaces approach but falling behind the PCA-MA and PCA-PBBBC approaches. In case 1 when 30% of the images were used for training and 70% of the images (for a given person) were used for testing; PBBBC gave the highest recognition rate out of the 3 approaches. In case 2 when 5 images were used for training and 5 for testing; we found that PBBBC was able to select 5 optimal features to produce 100% recognition rate whereas PCA-MA and Fisherface approach produced 100% recognition rate with 6 and Eigenface (PCA) approach produced the same rate with 13 features. Thus, simulation proves that proposed PCA-PBB-BC is a highly suitable approach for dimensionality reduction and optimal feature selection.

REFERENCES


