Effects of pose and image resolution on automatic face recognition

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Abstract: The popularity of face recognition systems has increased due to their use in widespread applications. Driven by the enormous number of potential application domains, several algorithms have been proposed for face recognition. Face pose and image resolutions are among the two important factors that influence the performance of face recognition algorithms. In this study, the authors present a comparative study of three baseline face recognition algorithms to analyse the effects of two aforementioned factors. The algorithms studied include (a) the adaptive boosting (AdaBoost) with linear discriminant analysis as weak learner, (b) the principal component analysis (PCA)-based approach, and (c) the local binary pattern (LBP)-based approach. They perform an empirical study using the images with systematic pose variation and resolution from multi-pose, illumination, and expression database to explore the recognition accuracy. This evaluation is useful for practical applications because most engineers start development of a face recognition application using these baseline algorithms. Simulation results revealed that the PCA is more accurate in classifying the pose variation, whereas the AdaBoost is more robust in identifying low-resolution images. The LBP does not classify face images of size 20 \times 20 pixels and below and has lower recognition accuracy than PCA and AdaBoost.

Nomenclature

\begin{itemize}
\item $k_f(z)$ face classifier
\item $\hat{e}_t$ pseudo-loss
\item $Y_{i+1}$ mislabel distribution
\item $L(R_t, \hat{D}_t, A_t)$ LDA-based feature extractor
\item 3D MM 3D morphable model
\item $\chi^2$ (chi-square) dissimilarity matrix
\item $f(x, y)$ labelled image
\end{itemize}

1 Introduction

Face recognition, frequently performed unconsciously by humans has achieved a great deal of attention from the academic and industrial communities during the past two decades \cite{1}. Face recognition aims at identifying or verifying a person’s identity by matching an input face image against the known faces in a database. Two basic face recognition categories are: (a) face identification and (b) face verification \cite{2}. In face identification, a probe (test) image of an unknown individual is identified by comparing the image with an image gallery (training) of the known individuals. The identification scenario is also known as one-to-many (1:N) matching. In face verification a query face image is compared with only the image of a claimed identity. Alternatively, verification is the process of determining a person’s claimed identity. Face verification scenario is also known as one-to-one (1:1) matching. Fig. 1 shows the general procedure of a face recognition system. Initially, facial features are calculated and stored for the gallery (training) images. Later, these features are compared with the features of the probe (test) image and a similarity metric called score is computed for a given comparison.

In many real-world applications, human faces are captured in unconstrained environments. The performance of the face recognition algorithms drops rapidly due to various factors such as facial expressions, background clutter, surgery, and hairstyle \cite{3}. Moreover, occlusion, non-uniform illuminations (shadows, underexposure, and overexposure), pose, and ageing significantly degrade the face recognition accuracy \cite{4}. Owing to the aforementioned factors, face recognition has remained a challenging problem in pattern recognition. Owing to the rapid increase in assassinations and violence in recent times, face recognition systems demand even more attention in terms of accuracy and robustness when used in various domains such as forensic applications, access control, and security in public places. In such applications, the robustness of the system plays an important role \cite{5}. Many databases of facial images [two-dimensional (2D)/3D], for example, \cite{6–9} have been developed to test the accuracy of face recognition algorithms. Each database is designed to test a specific facial aspect such as pose, illumination, low resolution (LR), expression, and occlusion. Face pose and image resolution are the two important factors that seriously challenge most of the developed face recognition algorithms. We investigate three well-known baseline face recognition algorithms using face images under different poses, from completely frontal up to $\pm 45^\circ$ view, and LR face images. We perform experiments for a very challenging task such as when there is only one gallery image available and four different pose images are used as probe. We find that the principal component analysis (PCA)-based algorithm is more accurate in classifying the pose than the adaptive boosting (AdaBoost) and local binary pattern (LBP)-based algorithms. The AdaBoost-based algorithm is more robust in recognising the LR face images such as 20 $\times$ 20, 10 $\times$ 10, and 5 $\times$ 5 pixels. The LBP-based face recognition algorithm has lower recognition accuracy than the PCA and AdaBoost and fails to recognise small face sizes of 20 $\times$ 20 pixels and below. Main contributions of this work are as highlighted as under:

- We carry out an empirical study by systematically varying face pose and image resolution and test the AdaBoost, the PCA, and the LBP-based face recognition algorithms.
We cover a large range of variation in pose and image resolution in our experiments in order to explore which of the face recognition algorithm is suitable for a given scenario.

We also present a comparison of the recognition rates of these face recognition algorithms for challenging situations such as when only one training sample is available in the gallery (training) and for four different poses (+45°, +35°, 0°, and −35°) as probe (test).

The rest of this paper is organised as follows. Section 2 briefly reviews recent advances in face recognition and highlights some well-known face recognition algorithms. Section 3 concisely outlines the three baseline face recognition algorithms that are compared in this paper. Simulation results and brief discussion are presented in Section 4. Section 5 concludes this paper and highlights some directions for possible future work.

2 Related work

During the past two decades many strategies, for example, [2, 4, 5] have been employed to improve the accuracy and robustness of the current face recognition algorithms. In [10], the proposed scheme utilised piecewise affine transformation. From a nine layer deep neural network, face was successfully derived with more than 120 million parameters using locally connected layers. Algorithm achieved 97.35% accuracy on labelled faces in wild (LFWs) dataset [11]. Sun et al. [12] proposed a deep learning-based scheme, known as Deep hidden IDentity features in which features were extracted from the
last hidden layer of convolutional networks (ConvNets). ConvNets were learned as classifiers to recognise about 10,000 faces in the training set. Moreover, deep ConvNets formed dense identity-related features in the top layers with only a small number of hidden neurons. An accuracy of 97.45% was reported on LFW database.

In [13], the proposed algorithm formulated on Markov random fields (MRFs) utilised the energy of the recognised match between a pair of images. Dynamic block size, shape adaptation, label pruning, and error pre-whitening measures were introduced to handle the pose variation. Experiments conducted on pose, illumination, and expression (PIE) database reported an average of 90% accuracy. In [14], Xiaoyang and Triggs solved face recognition problem by combining normalised illumination with local texture-based face representations. Published results showed an average accuracy of 89% on Face Recognition Grand Challenge (FRGC)-v2 [15] and Yale database [16]. In [17], Yang and Zhou presented the numerical implementation of a sparsity-based framework with no discussion on image resolution. Experiments were conducted to compare the performance against several L-1-minimisation solvers. Promising results were obtained in terms of accuracy up to 82% on PIE database [18]. In [19], researchers proposed learning coupled mapping technique to increase the accuracy of LR face image recognition. Experiments were conducted on Face Evaluation and Recognition Test (FERET) [20] database and an average recognition accuracy of 90% was observed with no discussion on face pose. In [21], an exponential entropy-based normalised scheme was proposed and integrated with the MRF-based deformation model. Experiments conducted on FERET and FRGC databases revealed an average accuracy of 89.9 and 71.77%, respectively. In [22], Volker and Thomas presented a robust 3D morphable model (MM) by simulating the image information in 3D space using graphics, shape, and texture for efficient pose recognition. Experiments conducted on Carnegie Mellon University (CMU)-PIE and FERET database reported an accuracy of 92.3 and 95.9%, respectively. Despite the improvements in recognition rates, face recognition is still a challenging domain. Variations in face pose and image resolution degrade the performance of most of face recognition algorithms. Currently, after 20 years of research, the researchers have started obtaining the useful technological solutions to recognise individuals in diverse applications [23, 24]. In our paper, we present a useful comparison of the recognition rates of three well-known baseline face recognition algorithms for challenging situations such as when only one training sample is available in the gallery and four different pose images (+45°, +35°, 0°, and –35°) are used as probe. Moreover, we also investigate the effect of image resolution on the recognition accuracy by using a range of image sizes starting from 231 × 251 to 5 × 5 pixels. In Section 3, we present a brief overview of the three face recognition algorithms being compared in this paper.

3 Face recognition algorithms

3.1 AdaBoost with linear discriminant analysis (LDA) as a weak learner-based face recognition algorithm

The iterative algorithm AdaBoost [23, 25] is combined with the LDA as a weak learner for feature selection, whereas the classic nearest centre classifier [24] based on normalised Euclidian distance is used for classification. For the AdaBoost with the LDA-based face recognition algorithm, we formulate the recognition task of facial samples as:

Let a training set, \( \mathcal{Z} = \{ (z_i, y_i) \}_{i=1}^{n} \) consisting of a number of samples \( z_i \) and their corresponding class labels \( y_i \), a total of \( N = \sum_{i=1}^{n} L_i \) samples are available in the set. Let \( Z \) be the sample space: \( z_i \in Z \), and \( F = \{1, \ldots, C\} \) be the label set: \( y_i = (1) \in F \). Now taking as input such as set \( Z \), the objective of learning is to estimate a function or classifier \( h(z) = h(Z) \), that is, \( h \) will correctly classify unseen samples \( (z, y) \). The AdaBoost algorithm operates by repeatedly applying a given weak learner to a weighted version of the training set in a series of several rounds \( T = 1, \ldots, T \), and finally linearly combines weak classifiers \( \{ h_i(z) \}_{i=1}^{T} \) constructed in each round into a single and accurate (referred to as strong classifier) classifier \( h_T(z) \). Equation (1) shows the final strong classifier

\[
h_T(z) = \arg\max_{y \in F} \sum_{t=1}^{T} \left( \log \frac{1}{P(y_t(z))} \right) h_t(z, y)
\]

The integration of AdaBoost with the LDA leads to an ensemble-based learning method that takes advantage of boosting techniques [26]. Final classifier obtained is an ensemble of several LDA solutions and is more accurate. Fig. 2 shows the pseudocode of AdaBoost-LDA-based face recognition algorithm.

3.2 PCA-based face recognition algorithm

In the PCA-based algorithm, first of all the face images are centred and decomposed into small sets of featured images, which are actually the principal components called eigenfaces of the initial training set. Subsequently, all of the centred images are projected into face space by multiplying them with the eigenfaces basis. For classification, the euclidean distances between the projected probe image and the projections of all the centred training images are calculated. The test image of a person is supposed to have minimum distance from the training image(s) of that person in the training database. In the PCA-based face recognition algorithm as the image is projected onto the face space, there are three possible options:

i. If the input image is near the face space and near a face class, then the individual is correctly recognised.

ii. If the input image is near the face space, but not near a known face class, then it is an unknown person.

iii. If the input image is distant from the face space and the known face classes, then it is not a face image.

One of the very distinguishing features of the PCA-based recognition algorithm is its ability to learn and recognise new face images in unsupervised manner [27].

3.3 LBP-based face recognition algorithm

In the LBP [28], description of a pixel is created by thresholding the values of the 3 × 3 neighbourhood pixels against the value of the central pixel and the result is interpreted in binary form as shown in Fig. 3a. For the task of recognition, face is divided into small regions from which the LBP histograms are extracted and concatenated to form a single feature histogram. Classification is performed using a nearest neighbour classifier with the chi square \((\chi^2)\) as a dissimilarity measure defined in (2) and illustrated in Fig. 3b

\[
\chi^2(x, y) = \sum_{i=1}^{D} \left( x_i - y_i \right)^2 / (x_i + y_i)
\]

where \( D \) is the dimensionality of the spatially enhanced histograms. A histogram of the labelled image \( f(x, y) \) is defined as

\[
H_{ij} = \sum f(x, y) = i, \quad i = 0, 1, 2, \ldots, n - 1
\]

where \( n \) is the number of different labels produced by the LBP operator. Finally, a spatially enhanced histogram is constructed using the set of all local histograms as described in (4)

\[
H_{ij} = \sum f(x, y) = i, \quad i = 0, 1, 2, \ldots, n - 1, \quad j = 0, 1, 2, \ldots, m - 1
\]

Equation (4) contains an effective description of the face such as information about the facial patterns on a pixel level. Finally, histograms are concatenated to build a global description of the face.
4 Simulation results

We mainly focus on the effects of pose and image resolution on the three face recognition algorithms. Experiments are performed in two phases. In first phase, the pose is studied, whereas in second phase, the effect of image resolution is investigated. MATLAB 2011a is used as a simulation tool on Intel core i-7 machine having 3.4 GHz processor with 8 GB of random access memory.

4.1 Pose analysis

Face recognition algorithms are tested on datasets containing images in gallery (training) and probe (test). The number of images in gallery, probe set, pose variations in the images set, and number of images per person are the key parameters to assess the robustness of face recognition algorithms. To examine the pose, we use images from multi-PIE database [29]. Multi-PIE database contains a huge collection of images captured under diverse conditions.
Currently, multi-PIE database has 750,000 facial images of 337 subjects collected in four different poses in a span of 5 months. In multi-PIE database, subjects are imaged under 15 different view angles and 19 diverse illuminations conditions. We use this database because it has images with systematic pose variation suitable for our experiments to quantify the effect of pose on the three face recognition algorithms.

Our earlier study [18, 23] reveals that as we increase the samples in gallery, recognition accuracy increases. For this paper, we consider a very challenging task where only one training image (frontal mug-shot) is available in gallery as shown in Fig. 4a. Fig. 4b shows the four different facial pose images taken from multi-PIE database used as probe. These four poses are chosen because these are the general cases in practice such as searching images of licenced drivers, missing peoples, immigrants, and person verification at entry ports [28]. In initial experiments, the size of all the facial images is cropped to 231 × 251 pixels.

To start with face recognition experiments, ten subjects, both males and females are chosen. Initially, one image per person is used in gallery (in Fig. 4a), whereas four images under different poses (+45°, +30°, 0°, –35°) as shown in Fig. 4b are used as probe. Table 1 shows the recognition results of ten different subjects.

Table 2 shows the classification results of 980 different subjects. From Tables 1 and 2, some of the observations are in order:

- The LBP is not robust to pose. Only the frontal facial images are correctly classified across the entire range from 231 × 251 to 30 × 30 pixels.
- The PCA-based algorithm is more accurate in classifying four different poses (see Fig. 4b) across different face image sizes ranging from 231 × 251 to 30 × 30 pixels followed by AdaBoost and then LBP.
- The PCA-based face recognition algorithm correctly classifies +45° pose. While AdaBoost and LBP have same recognition accuracy (30%) on this pose.
- For pose 3 (frontal), both the PCA and AdaBoost have 100% accuracy, whereas LBP has 90% accuracy for frontal facial images. Accuracy of the LBP was low, because some of the subjects were slightly illuminated (wearing eye side glasses) that lowered the recognition accuracy of the LBP-based algorithm. This is also shown in Table 1, where frontal pose for subject 10 (female shown in Figs. 4a–b) is not recognised by the LBP-based face recognition algorithm.
- The PCA-based face recognition algorithm is clear winner in classifying poses, followed by AdaBoost and LBP.

**Fig. 3** LBP-based face recognition algorithm

- LBP operator thresholds every pixel against its neighbourhood and infers the result in binary
- LBP descriptors are created by splitting facial image into a grid and computing LBP histograms for each grid. The histograms are merged into a single feature vector that contains complete description of the face

**Fig. 4** Ten subjects from multi-PIE database used in

- a Gallery (training)
- b Probe (test)
In the next phase of our experiments, we analyse the effects of image resolution to test the recognition performance of each algorithm. We perform detailed experiments by varying facial image sizes such as 231 × 251, 200 × 200, 180 × 200, 140 × 160, 120 × 140, 100 × 100, 80 × 80, 50 × 50, 40 × 40, and 30 × 30 pixels. The obtained results are summarised in Table 2. The face recognition accuracy rapidly changed for the PCA and the LBP-based face recognition algorithms on face image sizes of 20 × 20, 10 × 10, and 5 × 5 pixels. Fig. 5 shows the LR face images of sizes 30 × 30, 20 × 20, 10 × 10, and 5 × 5 pixels. Figs. 6a–c show the recognition performance on four poses of three algorithms for face sizes of 20 × 20 and 10 × 10 pixels. The recognition performance of extremely small face sample size such as 5 × 5 pixels is shown in Fig. 6d. Clearly, from Figs. 6a–c, one notable feature is that AdaBoost-based recognition algorithms have 100% accuracy for frontal facial image of size of 10 × 10 and for a challenging face sample size of 5 × 5 pixels. In normal circumstances, even a human eye struggles to recognise a small size as 5 × 5 pixels. Therefore, an interesting finding of our work is that the AdaBoost-based face recognition algorithm surpasses the PCA and the LBP-based face recognition algorithm on LR images. From Figs. 6a–c, key observations are highlighted below:

### Table 1: Recognition results of the PCA, AdaBoost, and LBP varying the face pose in the test images

<table>
<thead>
<tr>
<th>Subject</th>
<th>Image quality</th>
<th>Face recognition algorithm</th>
<th>Recognition accuracy, %</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>good</td>
<td>PCA</td>
<td>✓ ✓ ✓ ✓</td>
</tr>
<tr>
<td></td>
<td></td>
<td>AdaBoost + LDA</td>
<td>× ✓ ✓ ✓</td>
</tr>
<tr>
<td></td>
<td></td>
<td>LBP</td>
<td>× ✓ ✓ ✓</td>
</tr>
<tr>
<td>2</td>
<td>good</td>
<td>PCA</td>
<td>✓ ✓ ✓ ✓</td>
</tr>
<tr>
<td></td>
<td></td>
<td>AdaBoost + LDA</td>
<td>× ✓ ✓ ✓</td>
</tr>
<tr>
<td></td>
<td></td>
<td>LBP</td>
<td>× ✓ ✓ ✓</td>
</tr>
<tr>
<td>3</td>
<td>slightly illuminated</td>
<td>PCA</td>
<td>✓ ✓ ✓ ✓</td>
</tr>
<tr>
<td></td>
<td></td>
<td>AdaBoost + LDA</td>
<td>× ✓ ✓ ✓</td>
</tr>
<tr>
<td></td>
<td></td>
<td>LBP</td>
<td>× ✓ ✓ ✓</td>
</tr>
<tr>
<td>4</td>
<td>slightly illuminated</td>
<td>PCA</td>
<td>✓ ✓ ✓ ✓</td>
</tr>
<tr>
<td></td>
<td></td>
<td>AdaBoost + LDA</td>
<td>× ✓ ✓ ✓</td>
</tr>
<tr>
<td></td>
<td></td>
<td>LBP</td>
<td>× ✓ ✓ ✓</td>
</tr>
<tr>
<td>5</td>
<td>slightly illuminated</td>
<td>PCA</td>
<td>✓ ✓ ✓ ✓</td>
</tr>
<tr>
<td></td>
<td></td>
<td>AdaBoost + LDA</td>
<td>× ✓ ✓ ✓</td>
</tr>
<tr>
<td></td>
<td></td>
<td>LBP</td>
<td>× ✓ ✓ ✓</td>
</tr>
<tr>
<td>6</td>
<td>good</td>
<td>PCA</td>
<td>✓ ✓ ✓ ✓</td>
</tr>
<tr>
<td></td>
<td></td>
<td>AdaBoost + LDA</td>
<td>× ✓ ✓ ✓</td>
</tr>
<tr>
<td></td>
<td></td>
<td>LBP</td>
<td>× ✓ ✓ ✓</td>
</tr>
<tr>
<td>7</td>
<td>good</td>
<td>PCA</td>
<td>✓ ✓ ✓ ✓</td>
</tr>
<tr>
<td></td>
<td></td>
<td>AdaBoost + LDA</td>
<td>× ✓ ✓ ✓</td>
</tr>
<tr>
<td></td>
<td></td>
<td>LBP</td>
<td>× ✓ ✓ ✓</td>
</tr>
<tr>
<td>8</td>
<td>good</td>
<td>PCA</td>
<td>✓ ✓ ✓ ✓</td>
</tr>
<tr>
<td></td>
<td></td>
<td>AdaBoost + LDA</td>
<td>× ✓ ✓ ✓</td>
</tr>
<tr>
<td></td>
<td></td>
<td>LBP</td>
<td>× ✓ ✓ ✓</td>
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<tr>
<td>9</td>
<td>good</td>
<td>PCA</td>
<td>✓ ✓ ✓ ✓</td>
</tr>
<tr>
<td></td>
<td></td>
<td>AdaBoost + LDA</td>
<td>× ✓ ✓ ✓</td>
</tr>
<tr>
<td></td>
<td></td>
<td>LBP</td>
<td>× ✓ ✓ ✓</td>
</tr>
<tr>
<td>10</td>
<td>slightly illuminated</td>
<td>PCA</td>
<td>✓ ✓ ✓ ✓</td>
</tr>
<tr>
<td></td>
<td></td>
<td>AdaBoost + LDA</td>
<td>× ✓ ✓ ✓</td>
</tr>
<tr>
<td></td>
<td></td>
<td>LBP</td>
<td>× ✓ ✓ ✓</td>
</tr>
</tbody>
</table>

### Table 2: Classification accuracy of the PCA, AdaBoost, and LBP algorithms

<table>
<thead>
<tr>
<th>Subjects</th>
<th>Face recognition algorithm</th>
<th>Recognition accuracy, %</th>
</tr>
</thead>
<tbody>
<tr>
<td>980</td>
<td>PCA</td>
<td>100 100 100 100</td>
</tr>
<tr>
<td></td>
<td>AdaBoost + LDA</td>
<td>30 60 100 40</td>
</tr>
<tr>
<td></td>
<td>LBP</td>
<td>30 34 90 35</td>
</tr>
</tbody>
</table>

### 4.2 Images resolution analysis

In the next phase of our experiments, we analyse the effects of image resolution to test the recognition performance of each algorithm. We perform detailed experiments by varying facial image sizes such as 231 × 251, 200 × 200, 180 × 200, 140 × 160, 120 × 140, 100 × 100, 80 × 80, 50 × 50, 40 × 40, and 30 × 30 pixels. The obtained results are summarised in Table 2. The face recognition accuracy rapidly changed for the PCA and the LBP-based face recognition algorithms on face image sizes of 20 × 20, 10 × 10, and 5 × 5 pixels. Fig. 5 shows the LR face images of sizes 30 × 30, 20 × 20, 10 × 10, and 5 × 5 pixels. Figs. 6a–b show the recognition performance on four poses of three algorithms for face sizes of 20 × 20 and 10 × 10 pixels. The recognition performance of extremely small face sample size such as 5 × 5 pixels is shown in Fig. 6c. Clearly, from Figs. 6b–c, one notable feature is that AdaBoost-based recognition algorithms have 100% accuracy for frontal facial image of size of 10 × 10 and for a challenging face sample size of 5 × 5 pixels. In normal circumstances, even a human eye struggles to recognise a small size as 5 × 5 pixels. Therefore, an interesting finding of our work is that the AdaBoost-based face recognition algorithm surpasses the PCA and the LBP-based face recognition algorithm on LR images. From Figs. 6a–c, key observations are highlighted below:
The LBP-based face recognition algorithm struggles on LR images. The LBP face recognition algorithm does not recognise any face pose of sample size of 20 × 20 pixels and below. Alternatively, the LBP-based face recognition algorithm requires a face sample size of at least 20 × 20 pixels.†

- For a small face size 20 × 20 and 10 × 10 pixels, AdaBoost and PCA have 100% classification for pose 3 (frontal).
- The AdaBoost-based face recognition algorithm correctly classifies pose 3 (frontal) of extremely small face size 5 × 5 pixels, while the PCA-based algorithm has extremely LR rate (8%) on this size.
- The AdaBoost-based face recognition algorithm is extremely robust to LR. In fact LR does not affect recognition accuracy of AdaBoost algorithm from 231 × 251 to 5 × 5 pixels across entire ranges of face sample sizes.
- The AdaBoost-based algorithm is clear winner in classifying LR images. This particular finding motivated us to develop a useful computer vision application [18].

4.3 Discussion on performance of the compared algorithms

Although Section 4.1 reveals that the PCA-based recognition algorithm is robust in pose classification. However, recently proposed face recognition algorithm such as locally linear regression [1] and continuous pose normalisation [2] handle pose variation very well with the following concerns:

- Algorithm presented in [1] requires substantial pre-processing, for example, size and sampling of the face patches, fixing of eye position, and aspects of the face to be at least 60 × 60 pixels. Similarly, Liu et al. [2] requires 3D transformations, facial textures, and face symmetry.
- Recently, 3D MM [4, 21, 22] are proposed to handle pose variations. However, they also require face images to be decomposed into geometric and photometric parts. Aforementioned algorithms are computationally expensive and inflexible to be used in real time. Moreover, these schemes only consider standard sized facial images such as 60 × 60 pixels and above.
- We believe that the comparison presented in this paper provides an insight on which baseline algorithm is more suitable and improvable for situations such as occluded face(s) of robber(s), disguise, and low-quality/resolution images from a crime scene.

4.4 Challenges for face recognition algorithms

Although we demonstrated the performance of baseline face recognition algorithms on multi-PIE database. However, recently...
developed database, for example, LFW database [11] indicates that images of same person may look extremely different under various factors. As shown in Fig. 7 (images taken from the LFW database), the outlook of a person dramatically changes due to variation in face pose, expressions, illuminations, and occlusions. Therefore, the aforementioned concerns seriously challenge the state-of-the-art face recognition algorithms. On the LFW database, there are three challenging evaluation settings: (i) image unrestricted training, (ii) image restricted training, and (iii) unsupervised setting. Continuous efforts are in progress to develop a robust face recogniser to handle the aforementioned issues. For reader’s interest, below we briefly discuss the recently proposed techniques (2013–2015) and evaluations on the LFW database (More latest results on LFW database can be found at: http://www.vis-www.cs.umass.edu/lfw/results.html).

Recently, Junlin et al. [30] presented a discriminative deep metric learning (DDML). The proposed method learnt a Mahalanobis distance metric to maximise inter-class variations, while minimising the intra-class variations. For classification, the DDML trained a deep neural network and calculated minimum distance between face pairs and feature space. For image restricted setting, an accuracy of 90.68% was reported on the LFW database. Ngoc [31] evaluated their developed algorithm on the LFW database by exploring the relationships between patterns of oriented difference, gradient operations, and face image structures. For image restricted setting, an accuracy of 86.19% was reported. In [32], the proposed framework transformed the original pose-invariant face recognition problem into a partial frontal face recognition problem. A robust patch-based face representation scheme was introduced to represent the synthesised partial frontal faces. For every patch, a transformation dictionary was learnt under the multitask learning scheme that transformed the features of different poses into a discriminative subspace. Consequently, face matching was performed at patch level. Experiments conducted under unrestricted setting reported an accuracy of 92.955%. Zhen et al. [33] presented a robust face recognition scheme utilising multiple metric learning on the LFW database. During implementation, they divided face image into several spatial blocks. Later each block was represented by sum-pooling the non-negative sparse codes of position free patches. Finally, face region descriptors of all blocks were integrated using authors developed scheme, which they referred pairwise-constrained multiple metric learning. An accuracy of 89.35% was reported under image restricted protocol.

We observe that the unsupervised setting is the most difficult since there are no training examples available. On the contrary, image restricted/unrestricted settings allow researchers to utilise available image pair information in the training set. We plan to evaluate and improve the three baseline algorithms using the LFW database on the two most challenging settings such as image restricted and unsupervised environment as these scenarios are more realistic in practice.

4.5 Computational complexity

We evaluate the computational complexity in terms of the time consumed to recognise a probe face. Owing to space limitation, we show the execution time of six different image ranges in Table 3. The PCA is clear winner in terms of time complexity.

Table 3 Time cost comparison

<table>
<thead>
<tr>
<th>Image size, pixels</th>
<th>Face recognition algorithm</th>
<th>Execution time, s</th>
</tr>
</thead>
<tbody>
<tr>
<td>231 × 251</td>
<td>PCA</td>
<td>0.53040</td>
</tr>
<tr>
<td></td>
<td>AdaBoost + LDA</td>
<td>5.69411</td>
</tr>
<tr>
<td></td>
<td>LBP</td>
<td>0.95161</td>
</tr>
<tr>
<td>120 × 140</td>
<td>PCA</td>
<td>0.29400</td>
</tr>
<tr>
<td></td>
<td>AdaBoost + LDA</td>
<td>2.29114</td>
</tr>
<tr>
<td></td>
<td>LBP</td>
<td>0.50191</td>
</tr>
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<td>30 × 30</td>
<td>PCA</td>
<td>0.22891</td>
</tr>
<tr>
<td></td>
<td>AdaBoost + LDA</td>
<td>0.99841</td>
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<tr>
<td></td>
<td>LBP</td>
<td>0.88921</td>
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<tr>
<td>20 × 20</td>
<td>PCA</td>
<td>0.21841</td>
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<td>AdaBoost + LDA</td>
<td>0.95161</td>
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<td></td>
<td>LBP</td>
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</tr>
<tr>
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<td>PCA</td>
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<td>5 × 5</td>
<td>PCA</td>
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<tr>
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<td>LBP</td>
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Fig. 7 Sample images from the LFW database: Images of same individual look entirely different due to variation in
a Pose
b Expression
c Illumination
d Occlusion
followed by the LBP and AdaBoost. Time cost comparison reveals that the three implemented algorithms are near real time.

5 Conclusions and future work

We briefly reviewed recent advances in face recognition and presented comparative study of three baseline face recognition algorithms. Face recognition algorithms studied in this paper are: PCA, AdaBoost with LDA as a weak learner, and the LBP. The main goal of the study was to explore the robustness of each of these face recognition algorithms with respect to variation in pose and image resolution. Images from multi-PiE database were used for evaluation. For experimental setup, one frontal mug-shot was used in gallery while four different pose images are used as probe. For face size of $231 \times 251$ down to $30 \times 30$ pixels, the LBP-based algorithm surpassed the PCA and the LBP. The AdaBoost-based algorithm exhibited 100% classification accuracy for size of $10 \times 10$ and $5 \times 5$ pixels. A major finding of the research was that LR images of the multi-PiE database do not affect the classification accuracy of AdaBoost-based face recognition algorithm.

A general trend in the research in face recognition is to focus on one aspect such as pose, LR, occlusion, or illumination and optimise the algorithm. This is a useful tactic, as in most cases, the complete scenario of the system is known. The final goal of researchers in face recognition domain is to develop an automated and robust face recognition system that can emulate the human vision system. To reach this objective, mutual, synchronised, and constant efforts are required among the researchers, neuroscientists, and psychophysicists.

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7 References