The Effect of FaceAgeing in Face Recogntion

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Abstract- **Age progression still has many challenges and affects face recognition tasks. Over the past decade, many researchers have been working on face processing system in order to tackle these challenges of face recognition gap especially in the presence of variation in the age of an individual. In this paper, we propose a new preprocessing method that can improve a face for recognition. Here we align the faces into one template and remove a background which can hold some objects that affect the recognition. In particular, in the stage of recognition, we use a convolutional neural network based architecture along with the pre-trained VGG-Face model to extract features. These features are passed into a Cosine similarity classifier classification. A thorough experimental examination of face identification is achieved on the most widely used age database which is FGNET ageing with a huge age gap and different ethnicity and gender. Our experimental results on the FGNET face database illustrate that the proposed approach has the ability to outperform the present state of the art methods.**

Keywords— Age progression, Face recognition, Cosine similarity

I. INTRODUCTION

Currently, one of the most important topics n computer vision is the face analysis and related applications for face recognition or verification. Due to the range of application scenarios, for example, finding missing children after years, face recognition in age-invariant has been receiving a growing attention. In fact, the recognition process has many challenges and depends on some factors: illumination, expressions of face, ageing, variations of lighting, pose and so on [1]. However, recognition under ageing of a person still is one of the most problems, because some people might appear older or younger than other people, despite the fact, their ages are the same. In addition, the progression of age during the life cannot model by using an easy progression. For instance, people who are in a healthy case could reach longevity will likely look fairly different from other people who could be suffered from incidents or illness in their lives [2].

Consequently, when people grow up, the appearance of their faces can be very different and it makes the recognition process more difficult not only for machines but even at the human. In the most well-known face database which is FGNET [3], there is a huge gap and variation in ages as shown in figure 1. The faces of the same person do not like same at different ages, even in the same age group. The child at age 2 years looks a little different at age 5, but it has a significant gap at age 43, which is impassable to identify the person.

Fig. 1. Some samples faces form the FGNET face database in four different ages.

In recent years, most age related works have been introduced on face recognition to handle age-invariant difficulties and challenges [4][5]. For instance, the gradient orientation pyramid was introduced by Ling et al [6] as a feature and for the recognition step, they applied a Support Vector Machines SVMs. However, Li [7] used Local Binary Pattern (LBP) [8] and Scale Invariant Feature Transform SIFT [9] for features extraction and Random Subspace Linear Discriminant Analysis (RS-LDA) [10] method for face recognition propose. Therefore, there is numerous discriminative algorithms endeavour to design a suitable feature and an effective classification system.

The rest of the paper is organised as follows. First, in Section 2, we outline some of the relevant literature related to the topics of discussion of this paper. Then, in Section 3, we discuss the main methodology we have adopted in our work. Section 4 of this paper has been dedicated to outlining our experiments and results. Finally, in Section 5 we conclude the paper.

II. RELATED WORK

In the face recognition cross ageing, the early approaches try to produce faces of different ages in order to simulate the recognition process [5].

Xu et al [11], proposed a neural networks model named coupled autoencoders to deal with age-invariant face identification problem. Their experiments applied to three public databases and FGNET [3] one of them and their results showed that the proposed method has an effect on recognition.

In 2018, Zhou et al [2], introduced a model called Identity-Inference, which depend on an age subspace learnt from appearance-age labels. In the first step, they used Probabilistic Linear Discriminant Analysis (PLDA). After that, the ageing subspace learnt with the apparent age labels and an identity subspace located by an Expectation Maximization (EM) algorithm [12]. In the experiments, they used FGNET [3] and the results illustrated that their technique can reach high performance comparing with the state-of-the-art.

Wen et al [13], proposed a novel approach to learn age invariant features from a face based on convolutional neural networks and which called a deep face recognition framework. Their experiments conducted on FGNET [3] and other ageing databases and reported a significant performance.

Gong et al [4], introduced a new method to solve a problem in the representation and classification in face recognition in age invariant. They extracted information from an image by using maximum entropy feature descriptor and a new system called identity factor analysis for the matching process. They conducted their experiments on FGNET face database [3] and they got results.

III. Proposed Method

In this section, we introduce the proposed method which includes three main steps. In the first stage, the pre-processing process is applied to all input images. Secondly, the resulted images pass into Convolutional Neural Networks model for extracting features. Then, the extracted features are fitted to a classifier for classification.

A. *The pre-processing stage*

In this step, all coloured images will change into a grayscale colour. The reason for that because some images are not in the RGB colour space and we need to make sure all of them deal with the same system of colour. The resulted images I_o are in grayscale and we change them into RGB system by using equation 1.

$$I_n=\text{cat}(3,I_o,I_oI_o) \quad (1)$$

where I_n is an new image.

Also, all backgrounds are removed from the faces and alignment operation is applied to set all faces in the same position, as in figure 2.

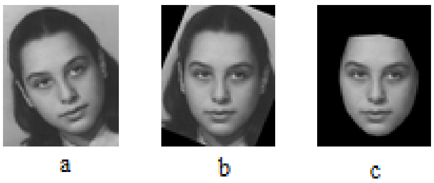

Fig. 2. a) the original image. B) aligned image. c) the cropped image.

B. *The feature extraction*

To extract the features from the cropped images, we use one of a most popular example of machine learning in the recent times model which is the VGG-Face model [14]. This model developed by Oxford Visual Geometry Group [14]. The model was trained on a huge dataset containing 2.6 million face images of more than 2.6K individuals. The architecture of VGG-Face contains 38 layers starting from the input layer up to the output layer. Figure 3 shows the basic architecture of this mode. However, in order to decide the best layer within the VGGF model to utilise for facial feature extractions, we usually carry out a number of trial and error experiments. In the particular case, we tested the layers 34 through to 37. Our experiments suggested to us that the layer 34 provides the best performance

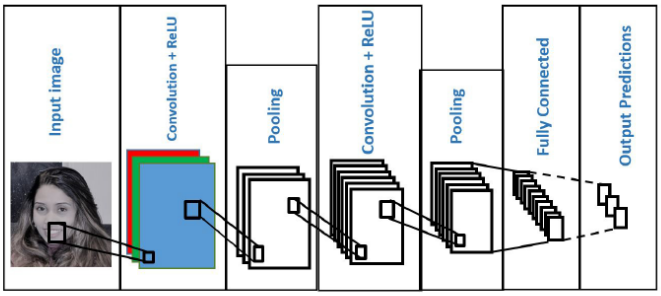

Fig. 3. Illustration of the basic architecture of VGG-Face model.

C. *Classification stage*

In the classification stage, there are many approaches to classify images. In this work, all extracted features from the images are used for purpose of classification. In our experiments, we have utilised the Cosine similarity CS [15]. It uses an inner product space to measure the cosine angle between those two vectors. Euclidean dot product formula as in equation 2 can be used to derive the cosine similarity.

$$a\,.\,b = ||\ a\,||\,||\,b\,||\ cos\ \theta, \quad (2)$$

where a *and* b are two vectors and θ is an angle between them.

By using a magnitude or length, which is as the Euclidean norm or Euclidean length of vector $x = [x_1, x_2, x_3, \dots, x_n]$ as in equation 3 the similarity is computed as in equation 4.

$$\|\mathrm{x}\|=\sqrt{x_1^2 + x_2^2 + x_3^2 + \cdots + x_n^2} \quad (3)$$

$$\begin{aligned} similaity = \cos\theta &= \frac{A\,.\,B}{\|\ A\ \|\ \|\ B\ \|} \\ &= \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\ \sqrt{\sum_{i=1}^{n} B_i^2}}, \end{aligned} \quad (4)$$

where A *and* B are two vectors.

For classification in all the experiments, we use the cosine similarity to minimize a distance between the test image $test_{im}$ and training images $training_i^n$ by using equation 5.

$$minimum = min\ (dist(test_{im}, training_i^n\ )) \quad (5)$$

, where i is an image number and n is the total images in the training set and,

$$dist(test_{im}, training^n) = \frac{\sum_{j=1}^{m} training_j^i \, test_{im}}{\sqrt{\sum_{j=1}^{m} training_j^{i^2}} \sqrt{\sum_{j=1}^{m} test_{im}^2}}, \qquad (6)$$

where m is a length of vector.

IV. Experiments and Results

Here we have conducted experiments on a challenging face ageing database [3]. This database includes 1002 face images from 82 different individuals of different ages. All subjects have significant variations in the age range as mentioned in figure 4.

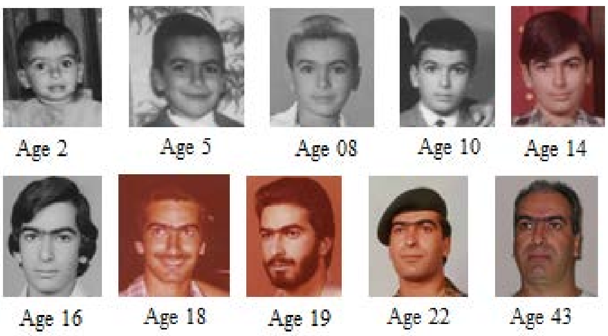

Fig.4. The sample of FGNET database (same subject with different ages).

In the experiments, we follow the training and test sets approach as in [7]. We use a leave one image out (LOIO) cross validation strategy. We repeat that strategy and report the result in each iteration and finally, we take the average. The results of this experiment are summed in table 1 and as we can see our approach reached 89.3% which is the best result comparing with the-state-of-art.

Table 1. The comparison between our method and other methods.

Method	Face recognition rate
3D ageing model (2010) [5]	37.4 %
Discriminative ageing model (2011) [7]	47.5 %
Hidden factor analysis model (2013) [16]	69 %
Feature-ageing model (2015) [17]	71.3 %
Maximum entropy model (2015) [4]	76.2 %
AG-IIM with feature fusion by CCA (2018) [2]	88.23 %
Our method	89.3 %

V. CONCLUSIONS

In this paper, we have applied a machine learning approach for face recognition in the age variation. The pre-processing step has been conducted in order to improve the ageing face images. Depend on the VGG-Face model the features extracted from the faces and we utilised Cosine similarity for classification. Our extensive experimental results on more complex face database FGNET validate that our approach gave the high recognition rate comparing with other methods.

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