AGE ESTIMATION BASED ON FACIAL SHAPE TRANSFORMATION AND CCNNs

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Abstract

The human face is a fundamental part that is used in direct communication and classification; therefore, the Facial Ageing process has been of a good interest to many researchers due to the fact that the face appearance changes as person age resulting in difficulties to identify certain individuals. The ability to synthesize the effects of ageing in individual face has many uses from helping the search for missing people to improving recognition algorithms and aiding surgical planning.

In this paper, we aim to extract some facial features and use it for estimating the age of individual using different techniques. The CCNNs have been trained with a set of face features in order to estimate the age of the person in the corresponding face image. We also proposed a facial aging technique that comprises of a shape transformation model aimed to differentiate one's appearance across ages. In addition, we have asked a number of volunteers to estimate the age of people in the typical sample of face images so we could compare the performance of our age estimator against the performance of humans. Our results indicate that machines can estimate the age of a person almost as reliably as humans.

Keywords - Facial Aging, CCNNs, Shape transformation, Facial recognition.

1. INTRODUCTION

Facial Ageing is a very important issue, as ageing in general, is part of our daily life process. Facial ageing is used in security, finding missing people and other applications. It is also a form of Facial recognition that helps identifying suspects. The biggest advantage of using the face in many applications is that wherever a person may be, the face is also there. Moreover, the face carries a significant number of features that identify individuals such as gender, emotional state, ethnic origin, age etc [1].

During this work, we are going to address the problem of facial appearance changes that arise as a result of aging. The effects of facial ageing generally introduce visible changes in facial shape and texture such as the visibility of wrinkles and the general appearance. As a result, one of the vital aspects of studying the difficulty of facial aging is the assimilation of a face dataset that captures the subtle appearance variations introduced as a result of aging. Face images which are collected for this purpose should be devoid of other sources of variations such as pose variations, illumination variations, differing facial expressions etc. Furthermore, the resolution of face images plays a critical role in effectively modelling the subtle changes in the facial shape and the facial texture across different ages.

In this context, many researchers have been working in the area of automatic interpretation of face images [1-3] as well as systems which have the capability of identifying faces [4], recognizing emotions [5], gender [6], and head orientation [7] have been developed. This is despite the fact that the age of a person plays an important role during interaction; currently few researchers have been involved in designing automatic age estimation systems based on actual face images.

Furthermore, the factors which have an influence on facial ageing can be divided into two causes either internal or external. The internal causes are which occur within the human body as a result of biological changes such as a minor change in the shape of the skull when people age and the jaw shrinks[8-10], and the illness which causes slow but constant deterioration of organs and cells resulting in the production of wrinkles. On the other hand, the external causes are related to the surrounding environment such as Photoaging [8, 11], which is the damage to the skin caused by the sun radiations or ultraviolet rays. As well as smoking, drugs and stress; which can weaken the overall health of the skin [12].

In this paper, our aim is to extract some facial features and use it for estimating the age of an individual by using a Cascade Correlation Neural Networks (CCNNs) which have been trained using a set of facial features and their corresponding ages so that when they are given an unknown set of features they produce the output which is an estimate of the age of the person in the face image used. We also proposed a facial aging technique that comprises of a shape transformation model that is aimed at characterizing one's appearance across different ages of their lives. In addition to this we have asked a number of volunteers to guess and give an estimate regarding ages of the people in the typical sample of face images from our test that we set in order to compare the performance of our age estimator against the estimation of humans.

In the following section, we are presented an overview of the appropriate work. While a brief description of shape transformation process, age estimator using CCNN, as well as age estimation by humans are introduced in the methodology section. The results we have obtained are talked about in the experimental results section and the concluded remarks based on the proposed work are presented in the last section.

2. RELATED WORK

Despite the general topic of face image processing had received considerable interest [1-3], only a small number of researchers carried out research work in the modelling and/or simulating aging effects on face images area. Many research groups such as [13-17] proposed geometric transformation functions that best reflected facial shape transformations across ages and further studied other aspects of facial aging such as facial wrinkle configurations, facial aging in 3D etc. whilst [18] provides a concise account of many such contributions. It was based on this idea that a number of researcher [19, 20] spent time to investigate the use of coordinate transformations in order to impose age-related changes on human faces. The investigation and experimental evaluation for this work have proved that, the age which was shown of the transformed facial outline can be modified in accordance to the transformation features that had been used. Burt and Perrett [21] spent time investigating the aging process using caricature algorithms and some facial features for different age groups. They had to calculate the differences in shape and colour between the features for the different age groups in order to be able to simulate age effects on untested facial images.

Furthermore, the issues they faced such as prediction of person appearance across different age, automatic age estimation from facial images, and facial identification across age progression etc, have been of interest in the recent years. [22-30] propose different methods to address the aforementioned problems.

3. METHODOLOGY

This section presents a brief description of shape transformation process, age estimator using CCNNs, as well as age estimation by humans.

3.1 Shape Transformation

For this work we have used a facial technique based on the method proposed by Burt and Perrett [21]. To be able to train the models, we have used a database that contains 1200 pairs of facial images, we chose 30 image pairs from different age groups(20−30 years, 30- 40 years, 40-50 years, and 50- 60 years). Examples of the typical images that used in our experiments are shown in Fig.1.

Fig.1. Typical images used in our experiments for two people at different ages.

For each image pair, 40 facial features which are shown in Fig.2 were marked as well as the shape transformations detected on each person across ages. Furthermore, the image pairs from each age group were classified into three distinguishable categories i.e. (a) gaining-weight (b) losing-weight and (c) shape-variation. Fig.2 illustrates a couple of age separated face images; also it shows the shape variations observed on each person across ages.

It is due to the difficulties of getting appropriate images for our experimental work, that the numbers of images for each individual are not constant. To accompany the needs we had for this work, the database was divided into training and testing datasets which were used for all experiments, as well as for the age estimation algorithms presented in the following section. The distribution of the images in each dataset was done so that each person does not have images in both sets.

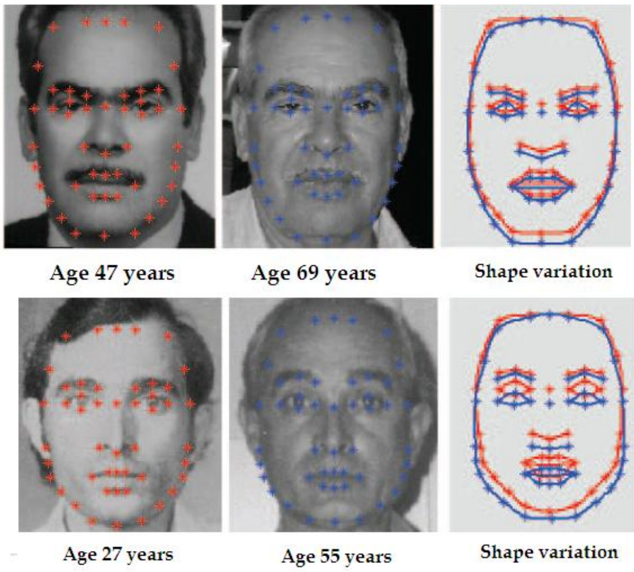

Fig.2. A pair of age separated facial images and the shape variation across ages.

Let U_i and V_i, i= 1… n, related to the facial features selected on the i^{th} individual belonging to age groups t_1 and t_2 respectively. And let the i individuals that correspond to the category weight-gaining across age transformation. Hence, the average facial shape transformations for individuals undergoing similar age transformations and weight-gaining can be calculated as:

$$\Delta S_{t1}^{t2} = \frac{1}{N} \sum_{i=1}^{N} [Vi - Ui] \qquad (1)$$

Using a test image of person X whose facial shape configuration at t_1 is U_x, the transformed shape at age t_2 was calculated by $V_x = U_x + \Delta S_{t1}^{t2}$ and the shape variation was done by implementing shape warping functions.

3.2 Age Estimation Using CCNNs

In this section, we investigated the use of CCNN in order to estimate the age of a person when given a set of face features. Based on the training set, each type of network is evaluated so that it is easier to establish the optimal architecture and optimal features. In each case, the generalization capability of the neural network is assessed as a function of the initial features of the respective network.

We know that In a CCNN, the number of input nodes is achieved by the input features, whilst the number of output nodes is achieved by the amount of different output classes. The training of a CCNN starts with no hidden nodes. The direct input-output connections are trained by using the whole training set; this is done with the aid of the back propagation learning algorithm. Then hidden nodes gradually get added and every new node is connected to every input node and to every pre-existing hidden node. The aim of this adjustment is to maximize S, the sum overall output units o of the magnitude of the correlation1 between V, the candidate unit's value, and E_o, the residual output error observed at unit o. S can be defined as:

$$S = \sum_o \left| \sum_p \left(V_p - \overline{V}\right)\left(E_{p,o} - \overline{E_o}\right) \right| \qquad (2)$$

Where o is the network output at which the error is measured and p is the training pattern. The quantities $\overline{V}$ and $\overline{E_o}$ are the values of V and E_o averaged over all patterns.

However, for our purpose, numerical representations of features are used to construct the input variables for the training and testing stages of the machine learning system. The face features were calculated and normalized to be in between the range of 0.1 and 0.9. The output layer is a single node representing the corresponding age of each face scaled in the interval [0-1]. In accordance to our experiments, the optimal network architecture and features were shown as follows: one hidden layer with 7 hidden nodes gave the best results for age estimation. The processing time for training the network is in the order of minutes.

3.3 Age Estimation by Humans

We know that humans are not accurate in estimating the age of people based on facial features. The humans' accuracy of age estimation depends on different aspects, such as the ethnic origin of a person shown in an image, the overall situation under which the face is observed, as well as the actual abilities of the observer to understand and analyze facial information in detail [25]. This experiment aimed to get an indication of the accuracy in age estimation by humans; this was done in order to compare between the machine performance and the human performance.

As part of this work, it was decided to conduct experiment using a total of 15 volunteers, we presented them with facial images, and they gave an age estimation of the people shown on the images. It should be pointed out that the volunteers were not familiar with any of the people in the facial images we used to get there age estimation from. In addition for the human's estimation we used the whole facial image which included the hair line for them to take in to consideration whilst they observed the images. In contrast the hairline was removed from the images which were age estimated by the machines which means that they could only make an estimation of the age from the internal facial area that was presented to them.

4. EXPERIMENTAL WORK

We carried out a facial shape transformation experiments on a database of 30 age-separated images. We assumed that the eldest images correspond to the gallery image [G : g1, g2, . . . , g80] and the latest counterpart correspond to the probe image [P : p1, p2, . . . , p80]. The objective is to study face identification rates with and without applying the facial aging technique. Therefore, we created seven aged images for each of the gallery images and selected the aged image which makes a best match with the corresponding probe image.

In this experiment we introduced three categories of shape variations, weight-gaining type, weight-losing type and weight-variation. The Euclidean distance between the projections was computed in order to measure the similarity between faces. Fig.3 illustrated the obtained results.

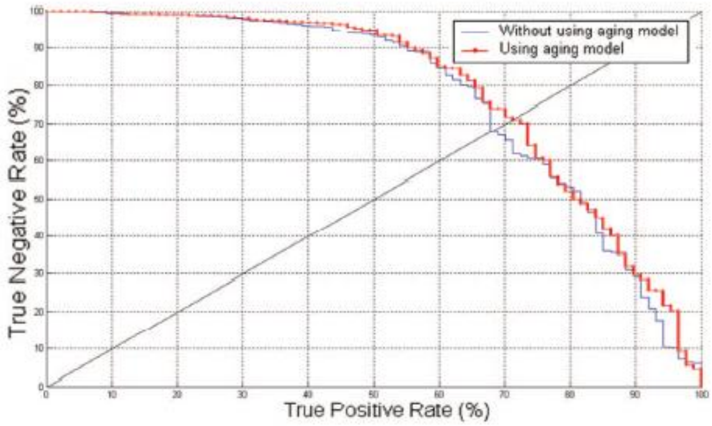

Fig.3. The 2 ROC plots illustrate the facial verification performance for the two cases, 'with and without age transformations.

For CCNNs experiments, we used 80 images divided into two sets of 40 images in each set. Each set contains images for 10 people at ages ranging from 2 to 70 years. During the experimental work, we trained a facial model using images from the training set, and we coded the images of the training and testing set into the corresponding facial features. The resulting representation was used for training as well as for testing our aging classifier. This process was repeated by interchanging the training and testing datasets, so that we could obtain results on a larger number of test cases.

Moreover, a random subset of 40 images was used for testing the accuracy of humans in the task of age estimation. Those images were presented to 15 observers who were asked to estimate the age of the subjects shown in the images. The overall results obtained are shown in Table 1.

Table 1. Results of our experiments (all numbers show the absolute Error in years)

<table>
<tr><th rowspan="2">METHOD</th><th rowspan="2">SHAPE TRANSFORMATION</th><th rowspan="2">CCNN</th><th colspan="3">HUMAN OBSERVERS</th></tr>
<tr><th>MALE</th><th>FEMALE</th><th>ALL</th></tr>
<tr><td>AGE SPECIFIC</td><td>4.21</td><td>3.82</td><td rowspan="3">2.62</td><td rowspan="3">3.45</td><td rowspan="3">2.94</td></tr>
<tr><td>APPEARANCE SPECIFIC</td><td>3.93</td><td>3.15</td></tr>
<tr><td>AGE AND APPEARANCE SPECIFIC</td><td>3.75</td><td>3.25</td></tr>
</table>

5. CONCLUSIONS

The presented facial aging system is based on real data that was collected on facial aging for different growth patterns that are observed across ages. In this paper, we introduced an experimental evaluation into the problem of automatic age estimation, where the shape transformation of face and the performance of CCNN classifiers were evaluated. In addition, the used technique accounts subjective characteristics such as weight gaining or weight losing.

According to our experimental results, shape transformation of facial can be used for achieving a good age estimation results. However, the best results were obtained when a CCNNs classifier is used. In order to train age classifiers, it was essential to have available information about the exact age of each subject in the database. The results of automatic age estimation obtained compare favourably with the results achieved by humans on age estimation based on facial images. In particular, shape transformation of face, CCNNs classifier, and human observers achieved an age estimation errors of 3.75, 3.25, and 2.94 years respectively when tested on a similar database.

The achieved results prove that it is possible to develop an efficient machine learning system in the short-term that include automatic age estimation in their functionality.

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