Facial Age Estimation with Age Difference

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Abstract - *Human Face recognition remains a significant problem in now a day in computer vision and pattern recognition. Estimating the correct age or age group is a most difficult problem in recent algorithms. To overcome this problem we need a better algorithms. In earlier days there were no better algorithms to detect any age labels or groups. So further we are implementing the better concept to provide accurate age group and age gender which contains the weakly labeled data through the deep convolutional neural network (CNN). This is being calculated using entropy loss and cross entropy loss is to be applied on single image to exhibit a singular peak value. Using the combination of these entropy losses we can derive the neural network to predict the age group. The images taken are being attached with dates more the one thousand or more taken into the system database. In this database each image or a picture is attached with the timestamp and people identity. Finally, at the end the estimation of the age will be calculated and also the age gender is also calculated which is advantage for the proposed method. This can estimate the age difference correctly and performance will be improved in the system.*

Keywords – Age estimation, age difference, convolution neural network

1.Introduction

Now a days, age estimation has been a major concept in recent world. The main concept is to identify the age group and age gender using the algorithm convolution neural network. Our project tell how the age is estimated based on the face image being provided by the user or a system. This is being much better way when it comes with others algorithms the implementation of CNN gives the better experience and provide accurate result. Age estimation is used in many ways, where as it is being provided with the image, in order to find the age based on the facial parts like shape of the nose, chin, jaws etc., When it comes to gender we have a unique features or shapes and many. This is how the age estimator works and Is being implemented.In many of the online platforms,users are simply asked to enter their birthday,which could be easily

Manipulated.This is not a big secret.The companies should find those users under 13 years old and their accounts should be deleted.

2. Existing System

In the existing system, they proposed the deep learning techniques for age estimation based on the convolution neural network (CNN). The age extraction feature has been newly introduced. It will make use of feature maps obtained in multiple layers for our predicted work instead of using the feature obtained at the top layer. They trained the model of CNN for a different classes age estimation task. The standard structure is used to predict the age of a human face given by a testing facial image.

Disadvantages:

1. There is no concept of automation in estimation of age.
2. There is insufficient label data to analysis all the age pattern.

3. l It Faces some challenges including detecting tiny,partial & non-frontal faces.

3.Proposed System

In our proposed system, we proposed an approach to estimate the age difference information.

We find the age difference information with three kinds of loss functions, i.e. entropy loss, cross entropy loss and K-L divergence distance. These loss functions can not only force the probability distribution of age classes to have one single peak value but it also makes the probability distribution to be located within the correct range. The proposed approach will be an important component, which is able to find the human faces with arbitrary poses, arbitrary age, and arbitrary ethnicity.

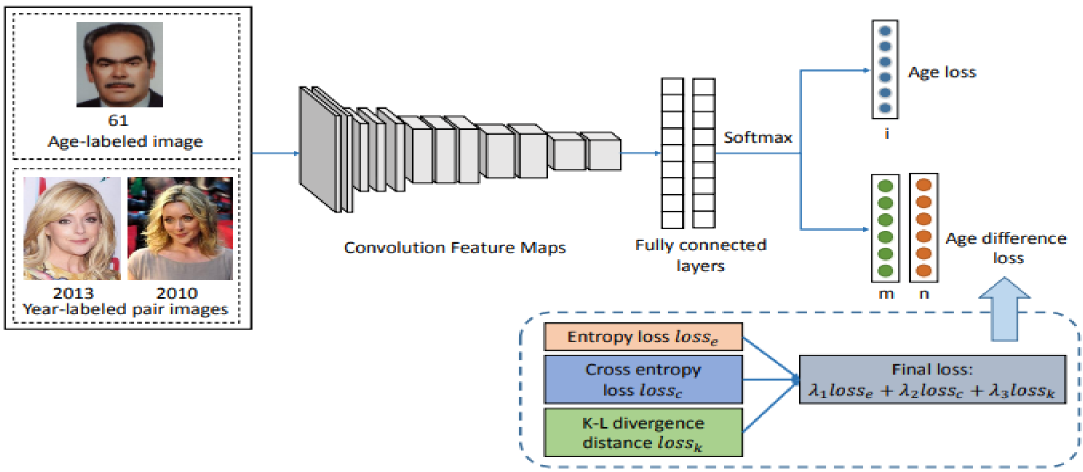
We also given a data set containing more than 200,000 face images attached with their taken dates. Each image is labeled with both the time stamp and people identity.

Advantages:

1. Convolution neural networks have been successfully done for many tasks related to facial estimation, face detection, face alignment, and also demographic estimation.
2. We used deep networks to represent the image, which will reach peaks of the power of the image.

4. Approach

In this section, we describe the details of age difference dataset construction and age estimation based on the age difference.



A. Age Difference Data Collection

Training the deep age difference estimator requires face images with year labels. There are numerous resources of

such images on the websites such as Filckr.com where a huge number of human photos are available with taken and uploaded dates. To build our dataset, we crawled millions of photos by the query names from LFW dataset.

With the face images labeled with their taken dates, we aim to explore the age information from the difference of ages. In this work, we take advantage of age difference information to improve the age estimator.

(a) Original image (b) Face detection (c) Face landmark (d) Face alignment

Entropy Loss Formulation:

Loss: If the age difference between a pair

of face images n and m is K years, assuming the image n is

K years younger than the image m, then the age of image n

should be no more than c− K years old and the age of image

m should be older than K years old. According to this, we

can infer that the probability values from c− K to c elements of image n should be zero and the same for image m from 0 to K elements.

Entropy Loss: Since the output of the network is the probability distribution across a possible age range, each entry indicates the probability of the age class. Given an age probability vector, the array should have a single peak, rather than be uniformly distributed. We choose the entropy loss to satisfy this requirement. Because the entropy loss will be 0 only if one entry is 1 and all others are 0. If the probabilities are uniform values, the loss will be largest.

$$loss_e = -\sum_{k=1}^{c} Q_{nk} \log(Q_{nk}).$$

Before deriving the backward function, the gradient of with respect to f_{nk} is

$$\frac{\partial Q_{nk}}{\partial f_{np}} = Q_{nk}(\delta(k=p) - Q_{np}).$$

Cross Entropy Loss: If the age difference between a pair of face images n and m is K years, assuming the image n is K years younger than the image m, then the age of image n should be no more than c− K years old and the age of image m should be older than K years old. According to this, we can infer that the probability values from c− K to c elements of image n should be zero and the same for image m from 0 to k elements.

$$loss_c = -\sum_{i=1}^{2} b_i \log(Q_n^i) = -\log(Q_n^1). \tag{8}$$

Here $Q_n^1 = \sum_{k=0}^{c-K} Q_{nk}$.

For the back propagation, the gradient of $loss_c$ with respect to f_{nk} is

$$\begin{aligned}\frac{\partial loss_c}{\partial f_{np}} &= \frac{\partial loss_c}{\partial Q_n^1} \cdot \frac{\partial Q_n^1}{\partial f_{np}} \\ &= -\frac{1}{\sum_{k=1}^{c-K} Q_{nk}} \left(\sum_{k=1}^{c-K} Q_{nk}(\delta(k=p) - Q_{np}) \right) \\ &= Q_{np} - \frac{Q_{nk}\delta(k=1,\cdots,c-K)}{\sum_{k=1}^{c-K} Q_{nk}},\end{aligned} \tag{9}$$

Translation K-L Divergence Loss: Given a pair of images with age difference K of the same person, the age probability distributions should be approximate after a translation of all entries with K steps. In this step, we design a translation Kullback-Leibler (K-L) divergence loss function to quantify the dissimilarity between the distributions of image n and the translated distribution of image m.

We expect $Q_{nk} = Q^1_{mk}$, $Q^1_{mk} = Q_m(k+K)$, $0 \le k \le c - K$ and the K-L divergences distance between these two probabilities is defined as

$$KL(Q_n, Q'_m) = \sum_{k=1}^{c} Q_{nk} \log \frac{Q_{nk}}{Q_{m(k+K)}}. \tag{10}$$

Since K-L distance is asymmetric, we make it as symmetric as

$$loss_k = \sum_k Q_{nk} \log(\frac{Q_{nk}}{Q_{m(k+K)}}) + Q_{m(k+K)} \log(\frac{Q_{m(k+K)}}{Q_{nk}}), \tag{11}$$

and for the image m the K-L divergence loss is

$$loss_k = \sum_k Q_{n(k-K)} \log(\frac{Q_{n(k-K)}}{Q_{mk}}) + Q_{mk} \log(\frac{Q_{mk}}{Q_{n(k-K)}}). \tag{12}$$

Here the $Q_{n(k-K)}$ is the translated probability distribution of image n.

The gradient for backward for the image n is

$$\begin{aligned}&\frac{\partial loss_k}{\partial f_{np}} = \frac{\partial loss_k}{\partial Q_{nk}} \cdot \frac{\partial Q_{nk}}{\partial f_{np}} \\ &= \sum_k Q_{nk}(\delta(k=p) - Q_{np}) \log(\frac{Q_{nk}}{Q_{m(k+K)}}) + \\ &Q_{nk}(\delta(k=p) - Q_{np}) - \frac{Q_{m(k+K)}}{Q_{nk}} Q_{nk}(\delta(k=p) - Q_{np}) \\ &= Q_{np} \log(\frac{Q_{np}}{Q_{m(k+K)}}) - Q_{np} \sum_k Q_{nk} \log(\frac{Q_{nk}}{Q_{m(k+K)}}) + \\ &Q_{np} - Q_{m(p+K)}.\end{aligned} \tag{13}$$

Finally, the overall loss of the whole age difference estimation network is

$$\min \psi = \min(\lambda_1 loss_e + \lambda_2 loss_c + \lambda_3 loss_k) \tag{14}$$

where λ_1, λ_2 and λ_3 are terms of trade-off between the errors. We set $\lambda_1 = 0.3$.

Testing on Year-label Datasets: Since the year-label dataset does not have the ground truth age label, we only test the age difference estimator on it. In the same way of age-labeled data, nearly 30,000 images from 700 subjects are randomly selected as the testing set. These images are combined into 122,986 pairs. Meanwhile, more than 123,000 images from 12,300 subjects are set as training data and combined into 522,452 pairs. The MAE of the age difference is 1.74 while the average age difference of the year labeled dataset is 7 years. To evaluate the effectiveness of age difference information, we compare the results between with and without the year labeled dataset. In the first two rows, we show the MAE performance. With the assistance of age difference information, the MAE on the age-labeled datasets is decreased from 3.13 to 2.78, which is the state-of-the-art result as far as we know. Figure 11 shows the comparison results of CS curve. The comparison demonstrates that the age difference information can improve the age estimator.

5. Conclusion

In this paper, we proposed a new age estimation method based on neural networks and open computer vision.these results showed that the proposed age estimation methods outperforms previous methods by producing a better estimation result. By introducing new proposed age estimation method, we find the problem of age groups without age label and propose an approach to estimate the age of face. Images of faces are to be taken at different years of the same subjects, we find the information from the difference of age via deep convolutional neural networks. Firstly, we introduced a deep estimator based on datasets. An entropy loss function is placed at the peak of CNNs.

In the future work, we plan to introduce more physical and biological features of people,such as appearance, hair style, height,pose and gait.

6.References

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