A RANKING APPROACH FOR HUMAN AGE ESTIMATION BASED ON FACE IMAGES

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***Abstract*—In our daily life, it is much easier to distinguish which person is elder between two persons than how old a person is. When inferring a person's age, we may compare his or her face with many people whose ages are known, resulting in a series of comparative results, and then we conjecture the age based on the comparisons. This process involves numerous pairwise preferences information obtained by a series of queries, where each query compares the target person's face to those faces in a database. In this paper, we propose a ranking-based framework consisting of a set of binary queries. Each query collects a binary-classification-based comparison result. All the query results are then fused to predict the age. Experimental results show that our approach performs better than traditional multi-class-based and regression-based approaches for age estimation.**

***Keywords*-Age estimation; ranking; binary classification; face recognition.**

I. Introduction

Inference of human ages has become an important topic in recent studies. To build an age estimator, many approaches formulate the training problem as a regression problem or a multi-class classification problem. Given a set of training examples $\{(x_i, y_i)|i = 1, \ldots, n\}$, where x_i is the i-th training person (face image) and y_i is the age of this person (in most cases is an integer), the regression approach basically learns a function f that can fit the mapping from x_i to y_i with appropriate regularization, and the multi-class approach simply treats y_i as discrete labels and learns a classifier for inferring the age.

For age estimation problem, multi-class approaches could overlook some essentially useful information because they assume that the labels are independent or have no inherent relationship to each other. However, the labels (i.e., ages) of this problem indeed have a strong interrelationship since they form a well-ordered set. For example, if a face image is 10 years old, this face is also near to the label of 9 or 11 years old, but a multi-class approach cannot reflect this property because their labels are basically irrelevant to each other.

By contrast, the regression approaches take advantage of the ordering information for estimation, and are expected to have better performance than classification to this problem. Typical nonlinear regression approaches such as Gaussian Process (GP) or Support Vector Regression (SVR) have been used to solve the age estimation problem. However, human face may be aging in different forms, shape and texture variations during different ages [1]. This property makes the random process formed by the aging patterns non-stationary in general, and so the kernel functions used to measure the pair-wise similarities between ages could be shift- or time-varying. Nevertheless, learning non-stationary kernels for a regression problem is usually difficult because it will easily cause over-fitting in the learning process.

Intuitively speaking, human aging processes show diversity in different age ranges. This means that the difference between ages, say, 52 and 51 years old, is not necessarily equivalent to that between, say, 22 and 21 years old, due to the fact that facial aging process is a non-stationary procedure. Hence, the reliable information we can use would be the *relative order* among the age labels, instead of their exact values.

The above observations inspire us to propose a ranking-based approach for age estimation. Note that the labels considered in age estimation are usually dense enough when we need to estimate an integer by the relative order. In our approach, the age labels are only treated as a well-ordered set regardless their exact values. This approach learns the rank of ages by using preferences from binary decisions via a series of queries. Each query reduces the age estimation problem to an easier one of distinguishing which object is ranked higher. According to this kind of preferences, the rank of each object can be inferred.

The rest of this paper is organized as follows. First, we review the relative works in Section 2. The framework of ranking-based age estimation is introduced in Section 3. Experimental results are presented in Section 4. Section 5 gives conclusions.

II. Related Work

Previous researches in human age estimation via face images can be roughly divided into two categories, the multi-

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class-based approach and the regression-based approach. The first type regards each age as a class label and various learning methods have been employed for the classifier training. For example, Yang and Ai [2] employed a real AdaBoost algorithm to train a strong classifier by composing a sequence of Local Binary Pattern histogram features. Geng et al. [3] introduced aging pattern subspace that describes the long term aging process of a person and estimates the age by minimizing the reconstruction error.

The second type regards each age as a positive real value. Fu and Huang [4] applied manifold learning and quadratic regression to age estimation, and claimed that their proposed framework is more suitable compared with linear and cubic regressions. Ni et al. [5] presented a multi-instance regression method in order to adopt the face images with noisy labels that are collected from Web image resources. Guo et al. [6] investigated biologically inspired features which compose of a pyramid of Gabor filters at all positions in face images, and used either Support Vector Machine (SVM) or SVR with Radial Basis Function (RBF) kernel in their framework.

Besides simplex multi-class classification and regression, Guo et al. [7] combined SVR and SVM for learning and predicting human age. Robust regression is employed to approximate the data at first, and then classification is used for local adjustment.

Using the same kernel in different age ranges may not be suitable for the time-varying relationship in age estimation problem. In this paper, we propose a ranking-based approach which makes use of relatively more reliable information for training an age predictor instead of learning non-stationary kernel.

III. Age Ranking Framework

Since our approach employs only the relative order of labels, we treat the age labels y_i as the rank order, $y_i \in \{1, \ldots, K\}$, where K is the number of labels that is typically set as 80 in our approach.

Instead of exhaustive pairwise comparisons to all the images in the database, the query is designed to compare with the face images of age k in our approach. Consider that, for a given age k, we can separate the dataset into two subsets

$$\begin{aligned} X_k^+ &= \{(x_i, y_i) | y_i > k\} \\ X_k^- &= \{(x_i, y_i) | y_i \leqslant k\} \end{aligned} \tag{1}$$

We then employ these two sets to conduct a query: "Is the face elder than age k?"

Note that, the above query exactly forms a binary classification problem that identifies which class is preferred. Each of the binary-classification problems actually has more data available for training (the datasets X_k^+ and X_k^-) than the data only in age k. Conceptually, our approach transfers the age estimation problem into a series of simpler and easier-to-solve sub-problems. Each sub-problem is only associated with two classes, i.e., binary classification. After a series of such classifications, abundant preference information is obtained and used for age estimation.

Recently, many algorithms for ordinal ranking have been proposed. Li and Lin [8] proposed a reduction from ordinal ranking to binary classification which is close to our assumption. Therefore, this method is adopted in our approach. First, the training examples are divided into two subsets, X_k^+ and X_k^-, by equation (1) for $k = 1, \ldots, K$. For all k, these two subsets would be jointly learned by a threshold model binary classifier f as

$$f(x_i, k) = g(\phi(x_i)) - \theta_k, \tag{2}$$

where θ_k is an ordered threshold, i.e., $\theta_1 \leqslant \theta_2 \leqslant \ldots \leqslant \theta_K$. $g(\phi(x_i))$ is a linear function defined as follows:

$$g(\phi(x_i)) = w^T \phi(x_i), \tag{3}$$

where w is a vector for linear combination and $\phi(\cdot)$ is an implicit mapping with a corresponding Mercer's kernel K^*, i.e., $\phi(x_i^T)\phi(x_i) = K^*(x_i, x_j)$, for all i,j. In our implementation, RBF kernels are used in the experiments.

This threshold model classifier gives us preference information for each query. Then, a ranking rule r constructed from f is used to collect all the preferences information and predict the age of x_i:

$$r(x_i) \equiv 1 + \sum_{k=1}^{K-1} [\![f(x_i, k) > 0]\!]. \tag{4}$$

where $[\![\cdot]\!]$ is 1 if the inner condition is true, and 0 otherwise.

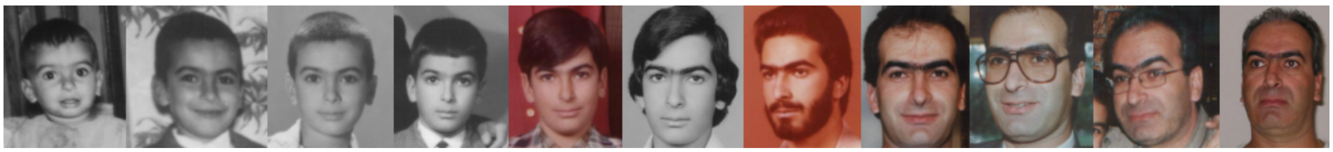
IV. Experimental Results

The age estimation experiments are performed on two databases. The first is the MORPH [9] Album 2 database containing 55608 face images with about three aging images per person ranging from 16 to 77. In order to reduce the variation between ethnic groups, we select 5492 Caucasian descent face images.

The second is the FG-NET aging database [10] containing 1002 color or gray face images of 82 individuals with large variations of pose, expression and lighting. Each subject has more than ten aging images ranging from 0 to 69. Each face image has 68 labeled landmark points characterizing its shape information.

Age range distributions and example face images in MORPH and FG-NET databases are shown in Table 1 and Figure 1, respectively. Note that the distributions of two databases are quite different. We use Active Appearance Models(AAMs) [11] feature extraction method in the experiment because of its advantage in extracting both the shape and intensity features of human images. AAMs has been also adopted in many methods as a primitive or a baseline

(a)



(b)

Figure 1. Example images in (a) MORPH Album 2 database and (b) FG-NET aging database.

Age Range	MORPH (%)	FG-NET (%)
0-9	0	37.03
10-19	8.94	33.83
20-29	26.04	14.37
30-39	32.16	7.88
40-49	24.58	4.59
50-59	7.37	1.50
60-69	0.82	0.80
70-77	0.09	0

Table I
AGE RANGE DISTRIBUTIONS IN MORPH AND FG-NET DATABASE

MORPH	Rank	SVR	SVM	kNN	BP	BT
MAE	**6.49**	6.99	7.55	9.39	10.03	11.97
std	0.17	0.07	0.08	0.28	1.00	0.24

Table II
MEAN ABSOLUTE ERROR IN MORPH DATABASE

FG-NET	Rank	SVR	SVM	kNN	BP	BT
MAE	**5.79**	6.05	6.72	8.34	10.25	15.73
std	0.61	0.50	0.83	0.69	1.71	1.10

Table III
MEAN ABSOLUTE ERROR IN FG-NET DATABASE

feature extraction method [3], [7]. For both databases, AAMs extracts the number of features that preserves 95 percent of the variability.

SVM and SVR are probably the most popular methods for classification and regression, respectively. Many age estimation approaches [6], [7], [12] suggested SVM and SVR in their frameworks. In the experiments, the methods that we compare include SVR, SVM, k-Nearest Neighbors (kNN), Back Propagation neural network (BP), and Binary decision Tree (BT). The parametric configurations of the above methods are as follows. In SVR and SVM learning, RBF kernel function is used and related parameters, C and γ, are selected using 5-fold cross validation. LIBSVM [13] is used for SVR and SVM evaluation. The k in kNN is 30. BP has a single layer with 100 neurons and the number of output neurons is the same as that of the classes. We use 80% of images for training and select the parameters via cross validation. The rest of images (20%) are used for testing over 30 trails of random splits for the final results.

Two popular measures are used to evaluate the performance of age estimation, Mean Absolute Error (MAE) and Cumulative Score. $MAE = \sum_{i=1}^{N} |\overline{l_i} - l_i|/N$, where $\overline{l_i}$ is the predicted age, l_i is the ground truth, and N is the number of testing images. Cumulative score is defined as $CumulativeScore(L) = (N_{e<L}/N) \times 100\%$, where $N_{e<L}$ is the number of testing images with absolute error less than the error level L.

Tables 2 and 3 show the experimental results by using MAE and standard derivation. We find that SVR has better performance than the multi-class classification methods such as SVM, kNN, BP and BT. This is because regression has the advantage of employing the relationship among labels. Our proposed ordinal ranking age estimation framework performs better than regression and achieves the lowest MAEs of 6.49 and 5.79 years in MORPH and FG-NET databases, respectively. Figure 2 and 3 show the results of cumulative score at different error levels, which are increasing with error level. When the cumulative score is fixed, the smaller error level is the better. It can be seen that the proposed ranking-based framework has the highest accuracy compare to other algorithms at different error levels. According to the experimental results, ordinal ranking consistently outperforms all the other comparative algorithms in both databases.

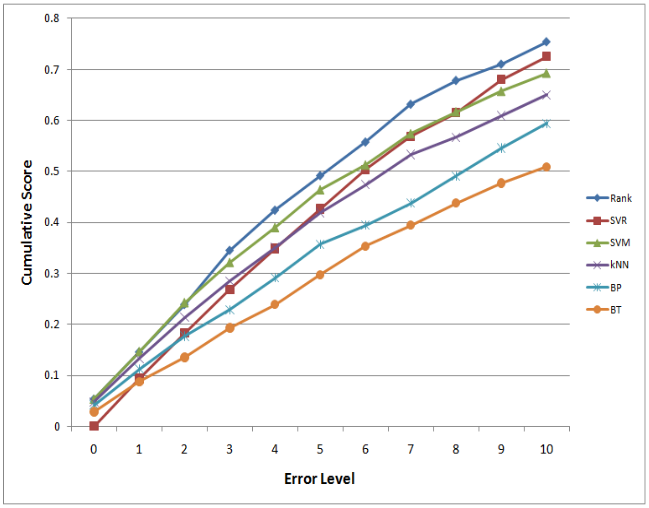


Figure 2. Cumulative score of MORPH database

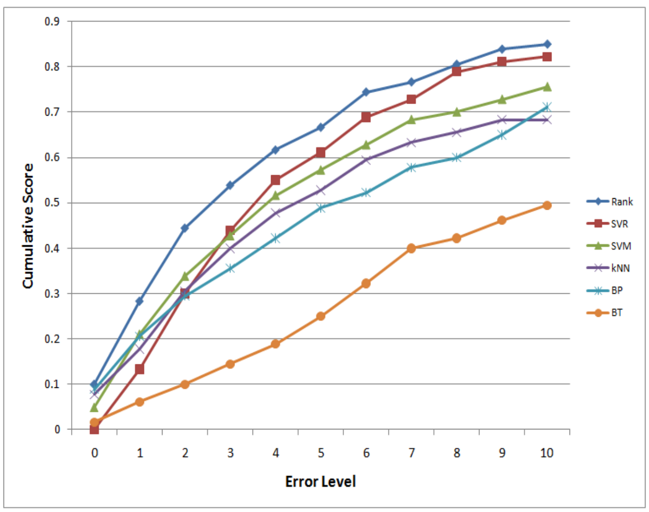


Figure 3. Cumulative score of FG-NET database

V. Conclusion

Due to the aging process is non-stationary, this paper proposes a novel ranking-based framework focusing on the use of relative-order information that shall be more reliable for age estimation. Our approach reduces the inference problem to a set of proper and simpler binary questions, and combines the binary decisions for age prediction. According to the experimental results, the proposed method outperforms traditional methods that solve this problem by treating it as either a multi-class or a regression problem.

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