# Human Age Estimation Using Ranking SVM

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**Abstract.** This paper proposes a human age estimation method using Ranking SVM method. Given a face image, most previous methods estimate the human age directly. However, the face images from the same age vary so much that it's really a difficult problem to estimate the human age accurately. In this work, we adopt an alternative way to estimate the human age. First, the rank relationship of the ages is learned from various face images. Then, the human age is estimated based on the rank relationship and the age information of a reference set. There are two advantages of the proposed method. (i) The rank relationship rather than the absolute human age is learned so that the absolute age estimation problem can be simplified. (ii) The human age is determined based on the rank relationship and the known human age of the reference set so that the face image variations from the same age group can be considered. Experimental results on MORPH and Multi-PIE databases validate the superiority of the rank based human age estimation over some state-of-the-art methods.

**Keywords:** age estimation, Ranking SVM, rank relationship

## 1 Introduction

Recently, there has been growing interest in human age estimation due to its potential applications such as human-computer interaction and electronic customer relationship management (ECRM). The task of human age estimation is to estimate a person's exact age or age-group based on face images.

There has been a number of human estimation methods proposed in recent years. Guo et al. [1] used SVM to learn the relationship between feature and age, which treated the age estimation as a multi-class classification problem. In [2], researcher adopted SVR to estimate human age and used SVM for local adjustment. In [3], Guo et al. investigated the gender classification and age estimation problem, indicating that the gender information is helpful for age estimation. There were also works using manifold learning based methods to solve the age estimation problem [4–6]. Guo et al. [7] defined a framework for automatic age estimation in which different manifold learning methods were used for gender classification and age estimation respectively. Geng et al. [8] proposed AGES for age estimation, and each aging pattern was composed of images from the same person. However, AGES achieved good result on the supposition that test image was similar with one of the training subjects and it was difficult to correctly predict the testing instance without corresponding training data.

Observing that the ranking age relationship is more easily to be determined, some researchers proposed to use ranking model for age estimation which is supposed to be more effective to estimate the age accurately. So far, several ranking methods have been proposed. Yang et al. [9] employed Ranking Boost with Haar features to estimate the human age. However, they only considered the ranking information among images from the same person, and the relationship from different persons were ignored. Chang et al. [10] proposed Ordinal Hyperplanes Ranker for age estimation which aggregated K-1 binary classifiers. In age estimation phase, there were K-1 age estimation operators which was somewhat computationally expensive in real applications. All the previous ranking models just used the pairs composed of images from different ages, which could only reflect the order information indicating who is younger or older. The consistent information from the pairs was ignored. For a robust algorithm, it should not only calculate the image's age correctly, but also ensure images with the same ages getting consistent age estimation values.

In this paper, we propose a Ranking SVM [11] based human age estimation approach. The framework of our algorithm is shown in Figure 1. In the training phase, the ranking information of images is exploited by applying a Ranking SVM method. In the testing phase, with a reference set including true age information prepared in advance, the ranking relationship between the test image and images in the reference set is determined by the learned Ranking SVM model. The age of the test image is finally obtained based on the ranking relationship and the true age of the images in the reference set. Different from the previous methods, not only the pairs composed of different age images (defined as Ordinal Pairs), but also those from the same age (defined as Consistent Pairs) are considered in the rank learning phase. Moreover, the adaptive regularized coefficient is also used in the Ranking SVM to improve the age estimation accuracy. To our best knowledge, the Ranking SVM has not been explored before in age estimation problem.

## 2 Proposed Method

### 2.1 Feature Extraction and Data Organization

In this paper, Gabor feature with five scales and eight orientations in [12] is employed, then 3000 dimensions selected by Adaboost learning for face recognition are used for face representation [13]. Since the feature extraction is beyond the scope of this paper, we simply use the feature representation for face recognition. The assumption is that the features used for face recognition are also suitable for age estimation.

The organization of pairs for the Ranking SVM is an important step. Previous methods constructed data only using ordinal pairs, however, the consistent pairs

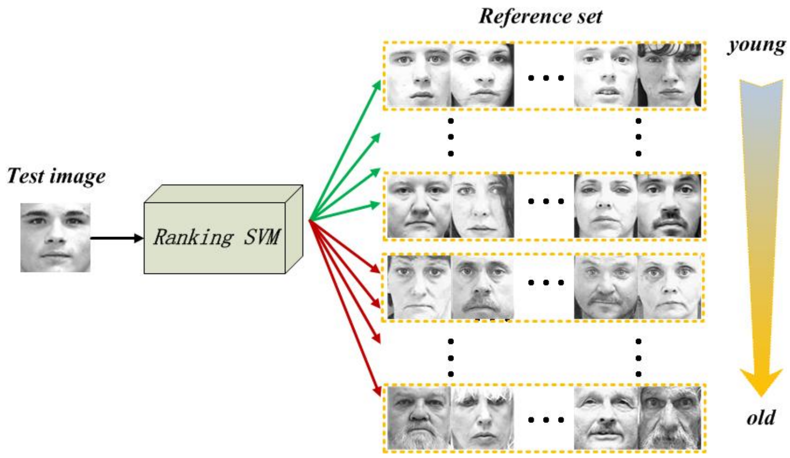



**Fig. 1.** After getting the ranking value, the image is compared to the reference set which is organized with the same age in each row. The age grows gradually row by row along the direction of the arrow located right.

which contain consistent information were ignored. In our experiments, we build pairwise instances $(x_i, x_j)$ in both types for ranking:

$$O = \{(x_i, x_j)|age(x_i) > age(x_j)\} \tag{1}$$

$$I = \{(x_i, x_j)|age(x_i) = age(x_j)\} \tag{2}$$

where $age(.)$ is a function obtaining images' true age. For set $O$, the age of $x_i$ is larger than $x_j$; for set $I$, their ages equal to each other.

### 2.2 Ranking SVM

Herbrich et al. [11] proposed Ranking SVM to classify the order of pairs of objects. Suppose that there are numbers of objects with various grades, the purpose of Ranking SVM is to obtain the weight vector $w$ corresponding to the function $f(x) =< w, x >$ and project images with $w$ to get the ranking value. Specific to the age estimation problem, we hope to calculate a weight vector $w$ which can project older person with higher ranking value than the younger one. Traditional Ranking SVM only used the ordinal pairs which could not ensure getting consistent ranking values in the same grade. Parikh et al. [14] proposed a novel form of Ranking SVM to predict the relative strength of each attribute in test images, which utilized both ordinal and consistent pairs. Experimentally, we find that although Ranking SVM without consistent pairs can get correct order, the gap inside each grade is also significant which can be ameliorated by the ranking model utilizing both pairs. Inspired by this work, in our Ranking SVM, we consider couple constraints, one ensuring the order among different age correct, another guaranteeing the values calculated in the same age consistent. The formula we utilize in our paper is defined as follows:

$$min\{\frac{1}{2}\|w^T\|_2^2 + (\sum C_{ij}^o \xi_{ij}^2 + \sum C_{ij}^s \gamma_{ij}^2)\} \tag{3}$$

$$s.t. \quad w^T(x_i - x_j) \geq 1 - \xi_{ij}; \quad \forall (i,j) \in O \tag{4}$$

$$|w^T(x_i - x_j)| \leq \gamma_{ij}; \quad \forall (i,j) \in I \tag{5}$$

where $C_{ij}^o$ and $C_{ij}^s$ are the adaptive regulative coefficients of ordinal and consistent pairs, $\xi_{ij}$ and $\gamma_{ij}$ denote the corresponding slack variables respectively. We solve the above problem using Newton's method mentioned in [15]. In the Ranking SVM, the adaptive regulative coefficient should differ according to the cost of misclassification. For example, when the difference of the true ages in the pair are small, the cost of misclassification will also be small, so we set a small regulative coefficient, and vice versa. In this paper, We defined $C_{ij}^o$ as

$$C_{ij}^o = \frac{age(x_i) - age(x_j)}{max(age) - min(age)} \tag{6}$$

where $max(age)$ and $min(age)$ are the training data's maximum and minimum age. The $C_{ij}^s$ value is stationary for all the consistent pairs.

### 2.3 Age Estimation

The research in [16] has shown that human's age processing follows the common development trend: when puberty, craniofacial structure grows rapidly; when adulthood, the skin texture changes great. However, different people have different rates of aging process. In the previous works, most methods ignored the personalized information. For example, when applying SVM [1], all the images of 20 years old have the same certain label 20 supposing that the 20 years old persons have the same aging process. In our algorithm, we construct a reference set in which each age group has a number of persons with different ranking values which contain two properties: the difference among the values reflects the personalized property, meanwhile, most of the values located in some range reflect the common trend. In prediction phase, when the number of images in one age group, whose ranking value is smaller than the test image, is larger than a predefined threshold, we think the age of the test image is larger. The proposed algorithm is summarized as follows:

1. Images are organized into two models: ordinal pairs set $O$ and consistent pairs set $I$.
2. Ranking SVM is employed to get the ranking function $f(x)$
3. A reference set is constructed according to their true ages. The ranking values of images in the set are calculated by $f(x)$.

4. For a test image $x$, the ranking value is firstly calculated by $f(x)$ and then compared with the reference set to obtain the estimation age. If the value is larger than some proportion of the images from one age in the set, we define $x$'s age is larger than that age. Experimentally, the proportion is set to 0.5. Inspired by [10], the final age is calculated as

$$age(x) = 1 + \sum_{k=1}^{K} G(\sum_{j}^{J} G(f(x) > f(x_j)) > \frac{J}{2}) \tag{7}$$

where $K$ is the number of age grades and $J$ is the number of images in each age $k$ in the set. Function $G(.)$ is 1 if the inner condition is true and 0 otherwise.

To summarize, the proposed algorithm employs Ranking SVM as classifier which reflects the nature of age relationship. Both ordinal and consistent pairs are used in our experiment to improve the accuracy and consistence simultaneously. We also set adaptive regularized coefficients according to the age's gap in each ordinal pair.

## 3 Experiments

### 3.1 Databases

We performed age estimation experiments on two databases: MORPH Album 2 [17] and Multi-PIE [18]. MORPH Album 2 contains about 55,000 face images with several races and its age ranges from 16 to 77 years old. We randomly select a subset about 8000 images in our experiment. For training set, each age contains over 20 images. The reference set is constructed with the same strategy, and the rest are used for testing. The Multi-PIE database consists 4 sessions about more than 755,000 images, which come from 337 different persons with 15 different poses and 20 illuminations. In our experiment, we use session 1 containing 249 persons. To reduce the influence from pose and illumination changes, we employ frontal images with illumination 6-8.

### 3.2 Experimental Results

The images are cropped and resized to $128 \times 128$. In our experiments, we compare the proposed method with standard age estimation SVM [1], SVR [2], Sparse [19] and Partial Least Squares (PLS) [20, 21]. In SVM and SVR learning, the non-linear RBF kernel which has shown its effectiveness in previous age estimation algorithm is used for estimation and the associated parameters such as $C$ and $\gamma$ are selected by five-fold cross validation. The number of hidden variables in PLS is 30. Experimentally, we define the image is older than some age if the estimation value is larger than a certain percentage of the images from that age in the reference set. Figure 2 shows the mean age error (MAE) with different

**Table 1.** MAEs of the compared age estimation methods on the MORPH and Multi-PIE databases.

| Train | Test | MAE(year) | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | SVM | SVR | PLS | SPARSE | RSWARC | RSWCP | Ours |
| MORPH | MORPH | 11.87 | 8.63 | 5.41 | 7.60 | 5.25 | 5.37 | 5.12 |
| MORPH | Multi-PIE | 14.42 | 10.61 | 8.68 | 8.31 | 6.95 | 7.02 | 6.92 |

percentage configuration and indicates that the algorithm gets the best result under the percentages of 50%. To demonstrate the importance of the consistent pairs and the adaptive regularized coefficient, we also compare our method with Ranking SVM Without Consistent Pairs (RSWCP) and Ranking SVM Without Adaptive Regularized Coefficient (RSWARC). The performance of age estima-

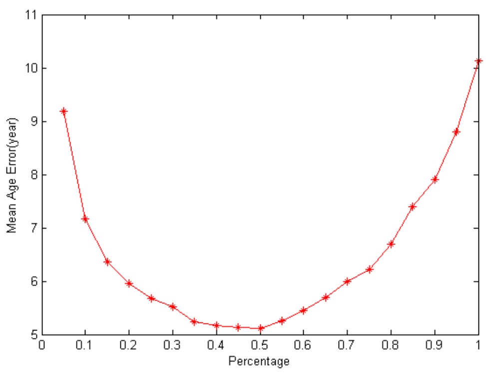
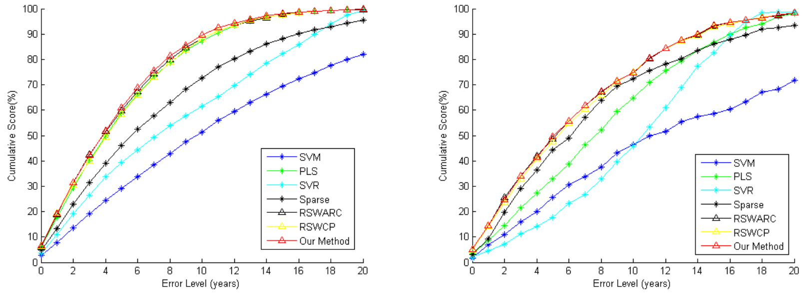



**Fig. 2.** The MAE under different percentage when comparing with reference set.

tion are evaluated by the mean absolute error (MAE) and cumulative score (CS) [1, 2] in our experiments.

Table 1 shows the MAE results of different methods derived on the MORPH and Multi-PIE database. The experimental results on the MORPH demonstrate that our Ranking SVM method ($MAE = 5.12$) using ranking relationship between images instead of absolute age value achieves the best result. For all the algorithms, SVM ($MAE = 11.87$) gives the worst result, indicating that treating age just as category labels is not optimal. Compared with RSWARC ($MAE = 5.25$), RSWCP ($MAE = 5.37$) is worse which indicates that the consistent pairs is useful to improve the performance of age estimation. Figure 3 shows the CS curves for different error levels. Almost in all the error levels, the Ranking SVM has the highest accuracy which validates its effectiveness for age estimation problem.




(a) (b)

**Fig. 3.** CS curves of the error levels from 0-20 of different age estimation algorithms on (a) MORPH and (b) Multi-PIE databases.

To examine the generalization of our algorithm, we further design a cross-database experiment. Images from MORPH are also used for training data and reference set and the facial images from Multi-PIE are used for testing. Table 1 and Figure 3 show the MAE and CS results. We can find that for cross-database age estimation, the performance of other methods decline more remarkably compared to the proposed method whose MAE is still small. For example, although the PLS has an MAE of 5.41 years on the MORPH database, which is similar to our proposed method, its performance ($MAE = 8.68$) years is much worse than ours ($MAE = 6.97$) on Multi-PIE database, indicating that the proposed method has good generalization performance and is practical in real application.

## 4 Conclusion

In this paper, we propose Ranking SVM based algorithm for age estimation in which the age estimation problem is divided into two steps. The first ranking step uses Ranking SVM to get the ranking value and the final age is estimated by being compared with the reference set. Ordinal and consistent pairs are employed to make the result correct and consistent. The adaptive regularized coefficients are introduced to Ranking SVM learning to further improve the performance. Experimental results show that the proposed Ranking SVM algorithm outperforms some existing methods.

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