# Estimating Age Value from Super-Resolution Reconstruction Facial Images

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***Abstract*—Automatic age estimation based on facial images is important but challenging in face recognition research. A Super-Resolution Reconstruction algorithm was proposed to implement the age estimation of facial images, which cut the facial image into small pieces. Then after building high resolution images by using the Super-Resolution Reconstruction algorithm, the RBF neural network was used to train and test these high resolution images. At last, the classifier ensemble with genetic algorithm was used to estimate age information. Finally, experimental results demonstrate that it is an effective method.**

***Index Terms*—age estimation, super-resolution reconstruction, facial image**

## I. Introduction

Facial image analysis has long been an extensively interesting topic in both human computer interaction and cognitive studies. The human face, as information sources for human computer interaction and important visual cues, conveys a significant amount of nonverbal information to facilitate the real-world human-to-human communication, and signification nonverbal information for the communication and interaction between human and machine. As a result, in the vast potential applications of multimedia communication, human computer interaction and security, many intelligent systems are expected to have the capability to accurately recognize and interpret human faces in real time. Analyzing facial attributes, such as identity, age, gender, expression, and ethnic origin, play a crucial role in real facial image analysis applications. In such applications, various attributes can be estimated from a captured face image to infer the further system reactions. For example, if the user's age is estimated by a computer, an age specific human computer interaction system may be developed for secure network/ system access control.

Throughout the years, computer-based automatic human age estimation has become an active research topic in computer vision and pattern recognition due to its potential applications. The applications include security control, image/video retrieval, advertisement survey and surveillance monitoring. In particular, age recognition algorithms can deny young kids access to adult web sites; prevent vending machines from selling alcohol to underage people; and determine the age of people who spend more time viewing a particular advertisement.

Apart from a large body of research on aging synthesis and rendering, however, automatic image-based age estimation is an important technique involved in many real-world applications, it is still a challenging problem to estimate human ages from face images. Since different individuals age quite differently, the aging process is determined by not only the person's gene, but also many external factors, such as health, living style, living location, and weather conditions. Males and females may also age differently due to the different extent in using makeup. Based on different application protocols, automatic image-based age estimation is not a standard classification problem and can be regarded as a multiclass classification or a regression problem. And it is very hard to collect a large size face aging image database, especially the chronometrical image series for a single person. In addition, the age progression displayed on the faces is uncontrollable and personalized. Due to the prolific and diversified information of human faces, such special characteristics of aging variation cannot be captured accurately.

How to extract general discriminative aging features while reducing the negative influence of individual differences still remains an open problem. Based on cranio-facial development theory and skin wrinkle analysis, Won and Da Vitoria Lobo presented a theory and practical computations for visual age classification from three age-groups: babies, young adults, and senior adults [2]. Hayashi et al. Researched about an age and gender estimation based on wrinkle texture and color of facial images and proposed an image processing algorithm for wrinkle modeling, but the accuracy of this method is not high [3, 4]. In the same year, A. Lanitis et al. used age function to predict how an individual might look like in the future or how he/she used to look in the past[5]. In 2004, A. Lanitis et al proposed special age estimation method and special appearance estimation method [6]. Jun-Yan Wang proposed age function synthesization to estimate age in [7] [8]. Lan Hu and Li-Min Xia researched age estimation based on boosting RBF neural network [9] and artificial immune recognition


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system [10]. Zhi-Hua Zhou et al. proposed the AGES (aging pattern sub-space) method for automatic age estimation [11-13]. Qing Yu and Ji-Xiang Du proposed a method based on improved NMF to estimate ages for FG-NET database [14]. Based on winner-take-all (WTA) rule, Ji-Xiang Du et al. proposed an independent component analysis method to realize the age estimation task on FG-NET database [15]. Chen proposed a subspace learning method for facial age estimation via pairwise age ranking [24], and Tan used an ordinary preserving manifold analysis algorithm to estimate the human age [25].

According to previous work above, researchers commonly use age function, neural network and subspace projection to resolve age estimation problem. The most existing image-based age estimation methods can be categorized three main categories, such as anthropometric model, aging pattern subspace, and age regression. In references [1-4], the cranio-facial development theory and facial skin wrinkle analysis are used to create the anthropometric model. The changes of face shape and texture patterns related to growth are measured to categorize a face into several age groups. These methods are suitable for coarse age estimation or modeling ages just for young people. However, they are not designed for continuous or refined age classification. The aging pattern subspace method used in reference [11-13] can handle incomplete data, such as missing ages in the training sequence, models a sequence of individual aging face images by learning a subspace representation. The age of a test face is determined by the projection in the subspace that can best reconstruct the face image. For the regression methods, facial features are extracted by the active appearance models (AAMs) that incorporate the shape and appearance information together. An input face image is then represented by a set of fitted model parameters. The regression coefficients are estimated from the training data with an assumption of the regression function such as a quadratic model [5-8] or neural network [9, 10, 14, 15].

In this paper, due to not paying attention to subspace projection but more concerning about the special facial part which play crucial roles in age estimation, we propose a new age estimation method based on super-resolution reconstruction algorithm[16-19]. To our knowledge, no previous work has studied this issue, and we believe that this study can provide a general guide to age estimation on large databases or crossing databases.

We first introduce super-resolution reconstruction algorithm for our study. Designing experiments framework in detail is introduced in Section 3 and Section 4, and age estimation on the FG-NET database is presented in Section 5. Finally we give some conclusions.

## II. SUPER-RESOLUTION RECONSTRUCTION ALGORITHM

The purpose of image super-resolution (SR) is to recover a high resolution (HR) image from one or more low resolution (LR) images. Image super-resolution method can be applied in many applications, such as low resolution video processing and remote sensing analysis.

The simplest method for super-resolving the low-resolution image is the interpolation algorithm. Generally, the bilinear interpolation and bicubic interpolation are effective to recover a high resolution image from a low-resolution nature image. Interpolation methods are the most convenient and have low computational complexity. However, the precision of reconstruction is low and the recovery of high-frequency information is poor if the magnification factor is large.

The learning based super-resolution methods are regarded as the most popular and promising methods, which acquire prior knowledge by learning. In 2002, Freeman et al. proposed the first learning-based super-resolution algorithm [16]. In this method, the Markov Random Field was used to model the relation between LR and HR images. Experimental results show the effectiveness of their algorithm in nature images with larger magnification. Motivated by this algorithm, Yang et al. [17, 18] proposed the single image SR method based on dictionary learning techniques. Their SR method adaptively chooses the most relevant reconstruction neighbors based on sparse coding. This method can avoid over-fitting and is robust to noise, and the visual effects of the reconstructed images are outperforming other methods, such as bicubic interpolation. It is shown that the LR images can be well recovered by using small databases of HR and LR atom pairs rather than using large databases composed of HR and LR raw image pairs. With the same motivation, Chen et al. proposed a novel super-resolution reconstruction algorithm based on the subspace learning technology [19].

In this paper, we will recover the super-resolution face image from a given low-resolution image using the single image SR method proposed in [18]. This method will rely on patches from example images and does not require any learning on the high-resolution patches. And, it only requires a much smaller database.

Construction of overcomplete dictionaries is the most important step to image super-resolution construction. Dictionary learning which is searching optimal basis of sparse representation is not only satisfies sparse representation constraint, but also generate a more sparse and accurate representation. The problem of satisfying the qualification above can be formulated as:

$$\arg\min_{D,\alpha} \sum_i \| x_i - D\alpha_i \|_2^2 + \lambda \|\alpha_i\|_0 \qquad (1)$$

where $x_i$ is each training sample, $\alpha_i$ is a sparse representation of $x_i$ in the dictionary $D$ and $\lambda$ is a regularization parameter. K-SVD algorithm [17] finds the sparse representation first and then update only one column $d_k$ in the dictionary $D$ and the coefficients that correspond to it, denoted as $x_T^k$ . Returning to the objective function (1), the penalty term can be rewritten as:

$$\sum_i \|x_i - D\alpha_i\|_2^2 = \|X - D\alpha\|_F^2$$
$$= \left\| X - \sum_{j=1}^{K} d_j \alpha_T^j \right\|_F^2 \quad (2)$$
$$= \left\| (X - \sum_{j \neq k} d_j \alpha_T^j) - d_k \alpha_T^k \right\|_F^2$$
$$= \|E_k - d_k \alpha_T^k\|_F^2$$

Here, it would be tempting to suggest the use of the SVD to find alternative $d_k$ and $\alpha_T^k$. The SVD finds the closest rank-1 matrix (in Frobenius norm) that approximates $E_k$, and this will effectively minimize the error as defined in (2). So we decompose it to $E_k = U\Delta V^T$ with SVD. We define the solution for $\tilde{d}_k$ as the first column of $U$, and the coefficient vector $\tilde{\alpha}_T^k$ as the first column of $V$ multiplied by $\Delta(1,1)$.

We only need one dictionary to apply in image denoise, deblocking and inpainting but there is need to use two overcomplete dictionaries of different scales at the same time in image reconstruction with super-resolution. For meeting the isomorphism between low resolution dictionary and high resolution dictionary in sparse representation, we propose the problem as:

$$\min_{D,W,\alpha} \sum_i \|x_i - D\alpha_i\|_2^2 + \lambda\|y_i - W\alpha_i\|_2^2 + \lambda\|\alpha_i\|_0 \quad (3)$$

where $D$ is the low resolution dictionary and $W$ is the high resolution dictionary corresponded with $D$, $\alpha_i$ is the sparse representation both meeting $x_i$ and $y_i$ in these two dictionaries respectively. For using K-SVD to solve the problem, (2) can be rewritten as:

$$\min_{P,\alpha} \sum_i \|z_i - P\alpha_i\|_2^2 + \lambda\|\alpha_i\|_0 \quad (4)$$

where $z_i = \begin{pmatrix} x_i \\ \lambda_0 y_i \end{pmatrix}$, $P = \begin{pmatrix} D \\ \lambda_0 W \end{pmatrix}$.

Given the optimal solution $\alpha$ to (4) with BP algorithm, the high resolution patch can be reconstructed as $y_i = W\alpha_i$ [18].

## III. Building High Resolution Image with Super-Resolution Reconstruction Algorithm

The method of super-resolution reconstruction have been widely applied in the facial image processing field, including face recognition, face reconstruction and aging simulation of human faces in recent years. However, this method has not been applied in age estimation up to this time. So estimating age with super-resolution reconstruction algorithm is proposed in our paper for the first time.

Suppose one facial image is $m \times m$ pixels. After dividing the image into $n$ local blocks for same size, where each local block is $(m/\sqrt{n}) \times (m/\sqrt{n})$ pixels, we get $n$ local blocks of low resolution. Using super-resolution reconstruction algorithm, we reconstruct these $n$ local blocks for $k$ times and build $n$ high resolution images, where each image is $((m/\sqrt{n}) \times k) \times ((m/\sqrt{n}) \times k)$ .The procedure of high-resolution image formation is shown on Figure 1.

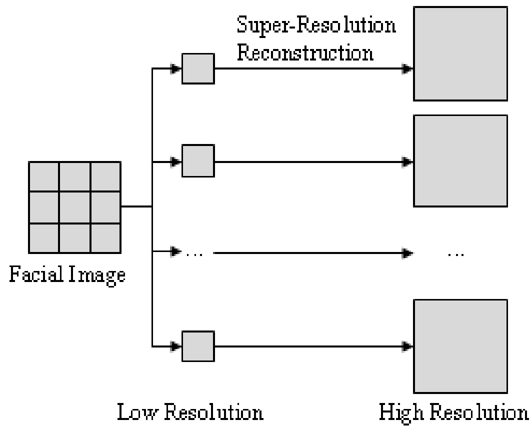



Figure 1 Procedure of high-resolution image formation

Suppose there are $g$ facial images, according the method discussed above these images can generate $n$ matrixes as training samples. Each matrix is defined as $V_i$ which is composed with local high resolution images defined as $V_{i1}, V_{i2}, \cdots, V_{ig}$. After then we use PCA (Principal Component Analysis, PCA) to extract local facial feature from each $V_i$ and reduce the dimensions of matrixes.

PCA can simplify the data model by dimensional reduction and maintain most information of the original data at the same time. The biggest advantage of PCA is no parameter limit, which means the result is only limited to the original data. As has been facial images were divided, the extracted feature is local feature not global feature. It avoids bringing unnecessary noise by using the traditional PCA method to extract global facial feature.

Therefore, the method discussed above takes advantage of PCA greatly and avoids the shortcoming of PCA and can get the most discriminative local features.

## IV. Integration of Local Classifiers

Using a combination of many different predictors to resolve a special problem, ensemble learning can improve the generalization ability of the learning system greatly. Recently, ensemble learning has become one of the four main research areas in machine learning.

Then after reducing the dimension with PCA and extracting the feature, we can get $n$ features of small dimension. For the convenient integration of local classifiers, we propose that we make an early estimation for these $n$ features by using radial basis function which called RBF for short and after then we can get $n$ sets of early predicted age. In age estimation, we judge whether our method has better performance than prior methods and whether our method improve the accuracy of age estimation as soon as computing difference between true and predicted age. For describing conveniently, the early predicted age is called local classifier which is called LC for short. Reference [20] pointed out that a combination of many different classifiers can improve predictions if there is a great difference between each classifier. Due to using different facial feature, there is a big difference between these classifiers. According ensemble learning theory, using a method to integrate these classifiers can reduce the error effectively. So we propose that we use the weighted summation to integrate local classifiers because of its best performance in much integration of classifier methods [21]. In our experiment we integrate local classifiers in score level that means we sum weights for early predicted age and get final predicted age.

After summing weights for $n$ local classifiers, we get unified classifier which is called UC for short:

$$UC = \sum_{i=1}^{n} w_i \cdot LC_i \ , \ \sum_{i=1}^{n} w_i = 1 \tag{5}$$

where $w_i$ is the weight value for the $i$ th local classifier. Construction of unified classifier is shown on Figure 2.

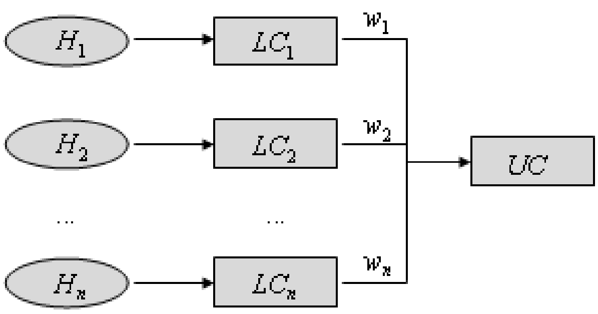



Figure 2. Construction of unified classifier

## V. Experiments

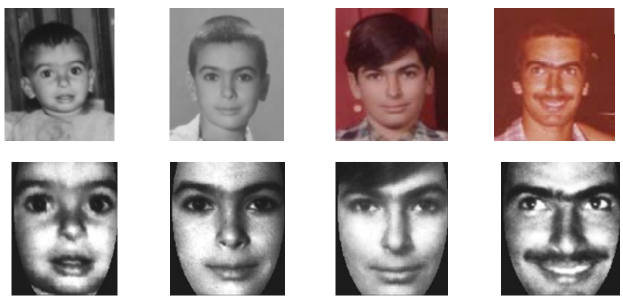
In this section, we report experimental results obtained on one publicly available age databases by comparing super-resolution reconstruction algorithm with a number of related age estimation methods and we set some parameters in the experimental such as the number of local block and image size.

### A. Experimental Setting

To our knowledge, that one database that is publicly available to date is FG-NET. We have conducted facial age estimation experiments on this database. In the FG-NET database, there are totally 1002 facial images from 82 persons with 6-18 images per person labeled with the ground-truth ages. The ages vary over a wide range from 0 to 69.But there are only 91 images of person whose ages ranged from 36 to 69 years. So we selected 911 facial images of person whose ages ranged from 0 to 35 years in our experiment (Fig 3).

Figure 3: Part of samples from FENET database. The first row and second one represent two persons with varying ages.

The facial part of each image was manually cropped into 150×130 pixels and aligned according to the eyes' positions shown in Figure 4. In our experiments, each color facial image was transformed into a gray-scale one by using the function rgb2gray in Matlab R2008a.For facilitating the calculation, we compress each facial image into 96×96 pixels and divide each facial image into 9 small local block based on spatial location of facial image. Each of the local block is 32×32 pixels. We designed the experiment, including original size, two times, three times and four times to demonstrate that our method is effective. The image of super-resolution reconstruction between different times is shown in Figure 4.



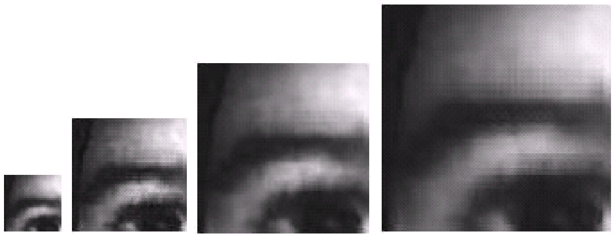


Figure 4. The normalized images and the Super-Resolution reconstruction images

For fair comparison with the traditional PCA method and improved NMF method, we also reduce dimensions to 84%, 88%, 90%, 92% energy in our experiments. Then after building high resolution images, the RBF neural network was used to train and test these high resolution images [22, 23] and we compute the weight with genetic algorithms.

According to [11], we use two performance measures in our comparative study. The first one is the mean absolute error (MAE). Suppose there are $N$ facial images and the true and predicted ages of the $i$ th image are denoted by $RAge_i$ and $EAge_i$ , respectively. The MAE is calculated as:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|RAge_i - EAge_i| \qquad (6)$$

Where $|RAge_i - EAge_i|$ denotes the absolute value of a scalar value. Another popular measure is the cumulative score. Of the $N$ facial images, suppose $N_{e\le l}$ images have absolute prediction error no more than $l$ years. Then the cumulative score is calculated as:

$$CumScore(l) = N_{e\le l} / N \times 100\% \qquad (7)$$

We only consider cumulative scores at error levels from 0 to 10 because age estimation with an absolute error larger than 10 is unacceptable for many practical applications.

The methods compared are tested under the leave-one-person-out (LOPO) mode for the FG-NET database as in our experiment. In other words, for each fold, all the images of one person are set aside as the test set and those of the others are used as the training set to simulate the situation in practical applications. Using LOPO mode, our experiment has more convincing.

*B.. Experiment Result*

In the preliminary work, we have proved that we lost some useful feature information of face on 84% energy and had interference of noise information on more than 90% energy when we reduced the dimension by using PCA method. We made an experiment of image reconstruction, which can test the validity of the Algorithm on 88% energy because it has the better performance of the preliminary work.

TABLE 1.

MEAN ABSOLUTE ERROR ON 88% ENERGY

| Different times | MAE |
|---|---|
| Original size | 5.8467 |
| Enlarge two times | 5.6635 |
| Enlarge three times | 5.7209 |
| Enlarge four times | 6.0060 |

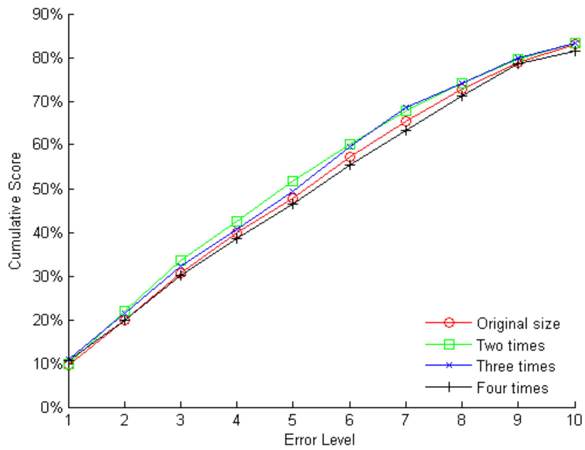



Figure 5. Estimate results on 88% energy

On 88% energy, Table 1 summarizes the results based on the MAE measure. We can see that the MAE of enlarging two times and three times even outperforms the result of the original size for age estimation, showing that the algorithm is very effective for this experiment. We also report in Figure 5 the results for different times in terms of the cumulative scores at different error levels from 1 to 10, showing that enlarging two times is the best at almost all levels. The result of enlarging four times in Table 1 and Figure 4 shows that there is a limit to the super-resolution reconstruction algorithm which is limited to its limitations and the selection of training images. The results should be better if we get clearer facial images.

For the experiment of comparing different methods, we get the data of enlarging two times because of its best performance in the previous experiment and the weight results was shown in Figure 6. Due to using different facial features, the difference between each weight is greater. The weight result shows that we can make sure which facial part is more significant to age estimation and it is very helpful for the future work of age estimation.

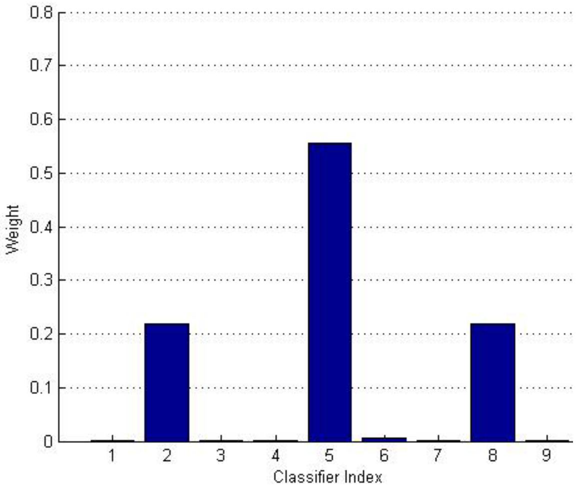
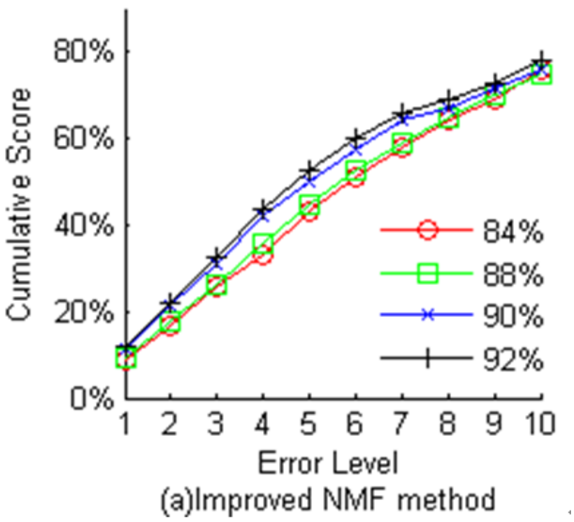
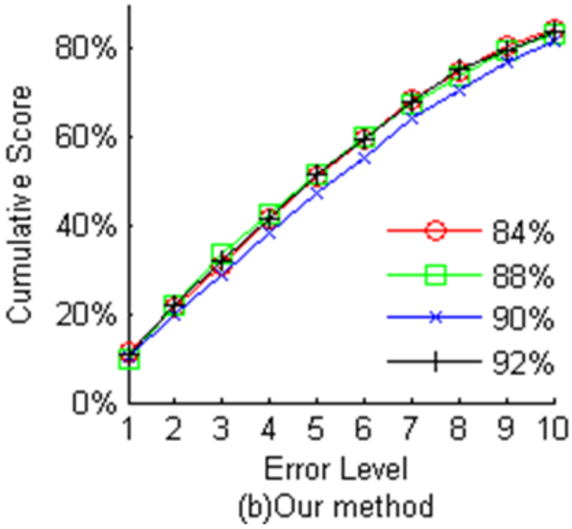



Figure 6. Weight of classifiers on 88% energy

For comparing the result easily, we conduct experiments using other age estimation methods, including traditional PCA method which has the same energy as our method and improved NMF method which has same subspace dimension. The results in cumulative scores are recorded in Figure 7 and Table 2, respectively. We can see that super-resolution reconstruction algorithm get the best performance on 88% energy in Figure 6 and Table 2. Comparing our method with the other two methods, the result of our method is better than PCA at all error levels and has greatly improved than improved NMF at error levels from 2 to 10 in 84% and 88% energy. Although our result has slightly increased than improved NMF at levels from 7 to 10 on 90% and 92% energy, our best result on 88% energy has better performance than improved NMF on 92% energy at error levels from 3 to 7 and these error levels which we can accept are very significant to practical application.



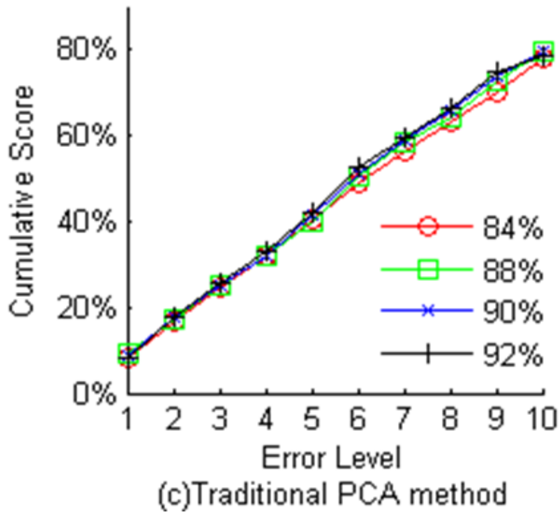




Figure 7 Estimation results using PCA, Super-Resolution Reconstruction and improved NMF respectively

Figure 7 also shows that PCA method and improved NMF method are limited to the value of energy but our method is not. We can see that our method has strong stability because of little difference of results on four energy levels from Table 2. Besides, the wasting time of our method in training and testing samples is much less than improved NMF method and that means our method ensure its feasibility in practical application.

TABLE 2.

RESULTS USING PCA, SUPER-RESOLUTION RECONSTRUCTION AND IMPROVED NMF

| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| PCA | 84% | 0.08308 | 0.16847 | 0.24371 | 0.32038 | 0.40756 | 0.49112 | 0.56459 | 0.63472 | 0.70174 | 0.78322 |
| | 88% | 0.09168 | 0.17205 | 0.25007 | 0.32233 | 0.39962 | 0.50708 | 0.58402 | 0.64251 | 0.72564 | 0.79896 |
| | 90% | 0.08485 | 0.17598 | 0.25116 | 0.32225 | 0.41475 | 0.51165 | 0.59168 | 0.65722 | 0.73687 | 0.79859 |
| | 92% | 0.08455 | 0.17653 | 0.25626 | 0.32932 | 0.41881 | 0.52577 | 0.59609 | 0.66485 | 0.74762 | 0.78808 |
| SR | 84% | 0.11307 | 0.21362 | 0.31168 | 0.41428 | 0.50848 | 0.59749 | 0.68691 | 0.75169 | 0.80736 | 0.84306 |
| | 88% | 0.09947 | 0.21870 | 0.33645 | 0.42412 | 0.51774 | 0.60092 | 0.67632 | 0.73976 | 0.79596 | 0.83266 |
| | 90% | 0.10490 | 0.20023 | 0.28817 | 0.38204 | 0.47470 | 0.55280 | 0.64471 | 0.70846 | 0.77259 | 0.82038 |
| | 92% | 0.10966 | 0.22119 | 0.32257 | 0.41382 | 0.51547 | 0.59797 | 0.67779 | 0.75263 | 0.79893 | 0.84168 |
| INMF | 84% | 0.08792 | 0.16792 | 0.25547 | 0.32929 | 0.43115 | 0.51316 | 0.57931 | 0.64126 | 0.6904 | 0.7591 |
| | 88% | 0.09099 | 0.17807 | 0.26091 | 0.35655 | 0.44792 | 0.52835 | 0.58805 | 0.65002 | 0.70404 | 0.7472 |
| | 90% | 0.11465 | 0.21695 | 0.31090 | 0.41981 | 0.4987 | 0.57574 | 0.6408 | 0.67011 | 0.71761 | 0.7577 |
| | 92% | 0.11869 | 0.22124 | 0.32393 | 0.43478 | 0.5250 | 0.59873 | 0.6573 | 0.6897 | 0.7270 | 0.7786 |

In addition, since the experimental settings are identical, we directly compare the results obtained by super-resolution reconstruction algorithm with those reported in other reference obtained by some methods, which include WAS [5], AAS [6], HumanA [11], HumanB [11], AGES [12], KAGES [13], and Improved NMF [14].Table 3 summarizes the results based on the MAE measure and we can see that super-resolution reconstruction algorithm even outperforms other state-of-the-art methods for age estimation. According to the above, experimental results demonstrate that it is an effective method.

TABLE 3.

MEAN ABSOLUTE ERROR IN AGE ESTIMATION

| Reference | Method | MAE |
|---|---|---|
| [5] | WAS | 8.06 |
| [6] | AAS | 14.83 |
| [11] | HumanA | 8.13 |
| [11] | HumanB | 6.23 |
| [12] | AGES | 6.77 |
| [13] | KAGES | 6.18 |
| [14] | Improved NMF | 7.26 |
| | Our Method | 5.66 |

## VI. Conclusion

A facial image contains different age information in different parts of the face. Due to the different feature information of the face, we have proposed a novel formulation of the age estimation problem based on a super-resolution reconstruction algorithm. We demonstrate experimentally that super-resolution reconstruction is capable of enhancing features that bring beneficial influence on the age estimation and it performs better than that based on PCA, improved NMF and the former performs the best. However, the selection of useful facial parts and performance of the algorithm is two crucial factors that have a direct relationship with the final result, which are what we aim to study in the future work. On the other hand, the capability of the feature extraction method is not good enough for practical application. Therefore, we anticipate combining super-resolution reconstruction algorithm and more effective feature extraction method to solve age estimation problem in the future research.

## VII. Acknowledgment

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