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DOI:

[10.1007/s11554-019-00903-9](https://doi.org/10.1007/s11554-019-00903-9)

Document Version

Accepted author manuscript

[Link to publication record in Manchester Research Explorer](#)

Citation for published version (APA):

Tian, Q., Zhang, W., Mao, J., & Yin, H. (2019). Real-Time Human Cross-Race Aging-Related Face Appearance Detection with Deep Convolution Architecture. *Journal of Real-Time Image Processing*. <https://doi.org/10.1007/s11554-019-00903-9>

Published in:

Journal of Real-Time Image Processing

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Real-Time Human Cross-Race Aging-Related Face Appearance Detection With Deep Convolution Architecture

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Received: 6 May, 2019 / Accepted: date

Abstract Human age estimation (AE) is an emerging research topic in computer vision and machine learning and has attracted increasing amount of research due its wide potential applications. In the process of human aging, facial appearances change from glabrous to crinkly similarly across all races, from European, Hispanic and African to Asian. To specially explore the relationships between aging and facial appearances across races, this paper is devoted to determining the correspondence between facial aging and facial appearances. Specifically, we first extract appearance vector features from facial images with their spatial structure preserved. Then, we propose to select the aging-related features shared by different races to explore their aging-related common facial regions, while removing redundant features. Thirdly, we improve the proposed model by incorporating potential cross-race relationships in an automated learning manner. Additionally, we extend our model with deep convolution architecture. Finally, we evaluate the proposed methodologies on a large face aging database with real-time efficiency.

1 Background

Facial age estimation (AE) or aging research is an interesting research topic and has attracted increased attention in computer vision and pattern recognition because of its useful applications such as security monitoring ([28]), consumer recommendation ([18]), identity recognition ([26], [3]) and information forensics ([6], [53]).

To estimate facial appearance age, various methods have been presented. They generally fall in three groups, namely,

classification-based (e.g. [1, 8, 10, 19, 36, 43]), regression-based (e.g. [5, 7, 9, 20–22, 27, 39, 40, 42, 46, 48, 49]), and hybrid approaches (e.g. [11, 12, 17]). When we treat each age as an individual class, AE can be formulated as classification learning. To this end, [19] first extracted the Active Appearance Models from face images and then directly used the nearest neighbor or neural networks to classify facial ages. [43] developed a Gaussian mixture model to roughly classify human faces into several age bands. Additionally, [8] generated conditional probability neural network by taking into account the distributions of the aging sequence to estimate human age. To preserve the similarity of adjacent ages, [1] encoded the age labels as soft probability distributions. More recently, [36] adopted the extreme learning machines for age classification. Motivated by the wide success of deep learning (DL) [45, 52], the DL-based models have also been used to classify human age ([31], [50], [47], [24]).

In accordance with the continuity of human aging, the AE problem should be treated as regression rather than classification. Along this line, [20] regressed human facial ages using a quadratic fitting function. [37] constructed a statistically linear model for age regression. [7] adopted a multi-linear regressor to fit ages. Impressed by the promising performance of ξ -SVR, [27] employed it for human age regression. Furthermore, [49] modelled a SDP function for robust age estimation. Later, [48] further speeded up and optimized their regressor, instead of relying on the EM algorithm. Besides, [9] constructed the called AGES regressor to recover missing age patterns outside the gallery. Although the aforementioned methods can achieve the goal of age regression to certain extent, the ordinal characteristic of aging sequence is not utilized ([5, 42]). To alleviate this issue, [5] constructed an ordinal model (OHRank) to regress human ages. In addition, [21, 23] constructed an ordinal distance space to train more discriminative age regressor. Then, [22] intro-

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duced age-related feature selection to generalize the ability of the regressor.

However, the methods reviewed above treat AE separately from other facial attributes, which hinders performance of AE, as some research (e.g. [13], [14]) showed that facial appearances are changing gradually with increasing wrinkles in the process of human aging and that different race people are aging similarly in facial appearance. To this end, in this paper we concentrate on exploring facial aging-related appearance features across races. Specially, we explore which regions of human facial appearance are more relevant to their aging, and incorporate jointly the feature selection and facial appearance structure preservation to improve the accuracy of AE. Additionally, we extend the model with deep convolution architecture to improve its discriminating capacity with real-time efficiency. To the best of our knowledge, little research has been dedicated to this problem.

The rest of this paper is organized as follows. Section 2 presents our proposed method. Section 3 reports validation results and provides an analysis. Finally, Section 4 concludes this work.

2 The proposed method

Related literature ([13], [14]) shows that facial appearances change gradually with increasing wrinkles in the process of human aging, and that different races age similarly in facial appearance. Herein we explore aging-related facial appearance regions and thus adopt these features to benefit AE, removing aging-irrelevant facial features, in order to improve the discriminative and generalization ability of the AE estimators.

2.1 Objective function

To find out facial appearance features related to aging, without loss of generality, we take the ridge regression (RR) [15] as the base model for facial age regression. Besides, assume that we are given N n_1 -by- n_2 facial images with centralized vector-form feature representations and age labels $\{x_i, y_i\}_{i=1}^N \in \mathbb{R}^d \times \mathbb{R}$ (i.e., $n_1 \times n_2 = d$). Then, we can train an RR regressor on these images by minimizing the following function:

$$\min_w \frac{1}{N} \sum_{i=1}^N \|w^T x_i - y_i\|_2^2 + \lambda \|w\|_2^2, \quad (1)$$

where $w \in \mathbb{R}^d$ is the regression vector and λ stands for the nonnegative hyper-parameter. While $x \in \mathbb{R}^d$ is a vector representation reshaped from the i th image matrix, the spatial structure of the original image is not specifically preserved in the vectorization transformation that the spatial relationships of the image, such as the neighbor-similarity, are not

considered. To alleviate such drawbacks, we need to incorporate the omitted spatial information for the RR-based image regression. Motivated by our previous work [41], the spatial smooth subspace learning (SSSL) [4] can be used desirably to compensate such missed image spatial information. In SSSL [4], the spatial information in the images is made for use by spatially smoothing the projection vector w as

$$\Gamma = \|\Delta w\|^2 = w^T \Delta^T \Delta w = w^T \Upsilon w, \quad (2)$$

with

$$\Delta = D_1 \otimes I_2 + D_2 \otimes I_1, \quad (3)$$

where $\otimes$ denotes the Kronecker operator, $\{I_j\}_{j=1}^2$ are n_j -order identity matrices, and the smoothing operator $D_j \in \mathbb{R}^{d \times d}$ is a block-diagonal matrix with diagonal elements $\{-1, -2, \dots, -2, -1\}$ and sub-diagonal elements of all ones. Replacing the second term of (1) by (2) yields the SSSL regularized RR (shortened as RR-SSSL)

$$\min_w \frac{1}{N} \sum_{i=1}^N \|w^T x_i - y_i\|_2^2 + \frac{\lambda}{2} w^T \Upsilon w. \quad (4)$$

While the spatial structure information of facial images is incorporated in Eq.(4), the resulting RR regressor in real applications tends to over-fitting since $d = n_1 \times n_2$ is usually much higher than image numbers N , particularly in the scenario of AE. Moreover, the features of facial appearance suffer from serious redundancy. Therefore, it is desirable to perform feature selections for the RR-SSSL regressor. In addition, research ([13], [14]) shows that people of different races are aging similarly in facial appearance. Motivated by the above findings, we propose to perform similar features selection across races on RR-SSSL via group-lasso algorithm ([29]), termed as RR-SSSL-GL, with remodelled objective function as

$$\min_{W=[w_1, \dots, w_R]} \sum_{r=1}^R \frac{1}{N_r} \sum_{i=1}^{N_r} \|w_r^T x_{ri} - y_{ri}\|_2^2 + \frac{\lambda_1}{2} \text{tr}(W^T \Upsilon W) + \frac{\lambda_2}{2} \|W\|_{2,1}, \quad (5)$$

where R denotes the number of human races, x_{ri} and y_{ri} respectively denote the i th instance and its label of N_r samples from the r th race, $\text{tr}(\cdot)$ stands for the trace operator, and $W = [w_1, \dots, w_R] \in \mathbb{R}^{d \times R}$ is the entire projection matrix for the races. The last $l_{2/1}$ -term in (5) helps select these facial features that are most relevant to aging and shared by all races.

Besides the joint feature selection characterized by $l_{2/1}$ -term in (5), there possibly exist potential correlations between the races in the process of learning their joint projection matrix W , which are expected to be incorporated in the objective function. Motivated by the work of [51] and [25],

we propose to model these potential correlations among the projection vectors w_i ($i = 1, \dots, R$) of W in an automated learning manner. To be specific, we introduce the covariance matrix (denoted as Ω) of W to model the possible relationships within and between w_i , $i = 1, \dots, R$. Along this line, (5) can be remodelled as

$$\begin{aligned} \min_{\{W=[w_1, \dots, w_R], \Omega\}} & \sum_{r=1}^R \frac{1}{N_r} \sum_{i=1}^{N_r} \|w_r^T x_{ri} - y_{ri}\|_2^2 + \frac{\lambda_1}{2} \text{tr}(W^T \Upsilon W) \\ & + \frac{\lambda_2}{2} \|W\|_{2,1} + \frac{\lambda_3}{2} \text{tr}(W \Omega^{-1} W^T), \\ \text{s.t. } & \Omega \succeq 0, \\ & \text{tr}(\Omega) = 1, \end{aligned} \quad (6)$$

where $\Omega \succeq 0$ guarantees the positive semi-definiteness of Ω and $\text{tr}(\Omega) = 1$ controls its complexity, λ_1 , λ_2 and λ_3 are non-negative trade-off parameters. The model of (6) is termed as RR-SSSL-GL-O for short. An illustration of this methodology is shown in Figure 1.

2.2 Optimization

Since (6) is jointly convex with respect to W and Ω , we take an alternating strategy to optimize it. That is, we fix one variable and optimize with regard to another.

When Ω is fixed, then (6) can be equivalently rewritten as

$$\begin{aligned} \min_{W=[w_1, \dots, w_R]} & \sum_{r=1}^R \frac{1}{N_r} \sum_{i=1}^{N_r} \|w_r^T x_{ri} - y_{ri}\|_2^2 + \frac{\lambda_1}{2} \text{tr}(W^T \Upsilon W) \\ & + \frac{\lambda_2}{2} \|W\|_{2,1} + \frac{\lambda_3}{2} \text{tr}(W \Omega^{-1} W^T), \end{aligned} \quad (7)$$

which is convex but not generally smooth because of the non-smooth third term. To solve (7), we adopt an accelerated proximal gradient (APG) algorithm [2]. Specifically, (7) can be grouped into two parts, i.e., smooth part $f(W) := \sum_{r=1}^R \frac{1}{N_r} \sum_{i=1}^{N_r} \|w_r^T x_{ri} - y_{ri}\|_2^2 + \frac{\lambda_1}{2} \text{tr}(W^T \Upsilon W) + \frac{\lambda_3}{2} \text{tr}(W \Omega^{-1} W^T)$, and non-smooth term $g(W) := \frac{\lambda_2}{2} \|W\|_{2,1}$. Then, we define the generalized gradient update rule as follows

$$\begin{aligned} Q(W, W^t) &= f(W^t) + \langle W - W^t, \nabla f(W^t) \rangle \\ &+ \frac{l}{2} \|W - W^t\|_F^2 + g(W), \end{aligned} \quad (8)$$

where $\|\cdot\|$ denotes the Frobenius norm operator, $\nabla f(W^t)$ is the gradient of $f(W)$ with regard to W at the t th iteration, l is the step size obtained through the line search techniques [44], and $\langle \cdot, \cdot \rangle$ is the matrix inner-product operator. Then,

W^{t+1} at the $(t+1)$ th step can be updated as

$$\begin{aligned} W^{t+1} &= \arg \min_W \frac{1}{2} \|W - (W^t - \frac{1}{l} \nabla f(W^t))\|_F^2 + \frac{1}{l} g(W) \\ &= \arg \min_{W=[w_1^T, \dots, w_d^T]^T} \frac{1}{2} \sum_{j=1}^d \|W_{j:} - (W^t - \frac{1}{l} \nabla f(W^t))_{j:}\|_F^2 \\ &\quad + \frac{\lambda_2}{2l} \|W_{j:}\|_2, \end{aligned} \quad (9)$$

where $W_{j:}$ indicates the j th row of W . From (9), it can be seen that the entire W can be solved in a divide-and-conquer manner and enjoys the following analytical solution [2]

$$W_{j:}^{t+1} = \begin{cases} \left(1 - \frac{\lambda_2}{2l\|(W^t - \frac{1}{l} \nabla f(W^t))_{j:}\|_2}\right), & \text{if } \|(W^t - \frac{1}{l} \nabla f(W^t))_{j:}\|_2 > \frac{\lambda_2}{2l} \\ 0, & \text{otherwise.} \end{cases} \quad (10)$$

Through iteratively performing (10) until $Q(W, W^t)$ converges to $f(W) + g(W)$, the final solution W^* is obtained.

When W is fixed, then (6) equivalently becomes

$$\begin{aligned} \min_{\Omega} & \text{tr}(W \Omega^{-1} W^T) \\ \text{s.t. } & \Omega \succeq 0, \\ & \text{tr}(\Omega) = 1. \end{aligned} \quad (11)$$

Interestingly, (11) also has analytical solution

$$\Omega = \frac{(W^T W)^{\frac{1}{2}}}{\text{tr}((W^T W)^{\frac{1}{2}})}. \quad (12)$$

For initialization, we set Ω to $\frac{1}{R} I_R$ with I_R being an R -order identity matrix. We optimize (6) with regard to W and Ω in an alternating manner until convergence. The complete algorithm are summarized in Algorithm 1. It is worth noting that since the methods RR, RR-SSSL, RR-SSSL-GL presented above are covered by RR-SSSL-GL-O, so they also can be solved via the same algorithm, or directly with the analytical solutions for RR and RR-SSSL (due to space limit, we omit the details).

2.3 Time complexity analysis

The time complexity of Algorithm 1 is mainly in computing the gradient of $f(W)$ and optimizing for (9). More specifically, the time complexity for calculating the gradient of $f(W)$ is $\mathcal{O}(dN)$, and the time complexity for solving (9) is $\mathcal{O}(dR)$. Therefore, the total time complexity of Algorithm 1 is $\mathcal{O}(d(N+R)I_{iter})$.

Fig. 1 Methodology illustration of the proposed RR-SSSL-GL-O method on face image.

Fig. 2 Architecture of our RR-SSSL-GL-O model extended with deep convolution networks. 'Conv' denotes the convolution layers, 'ReLU' is the activation function, 'Pooling' denotes the max-pooling layers, and 'FC' indicates the fully-connected layers.

Algorithm 1 RR-SSSL-GL-O

Require:

Training set $\{x_i, y_i\}_{i=1}^N \in \mathbb{R}^d \times \mathbb{R}$ from R races;
 Trade-off parameters $\lambda_1, \lambda_2, \lambda_3$;
 Number of maximal iterations I_{iter} ;
 Initialization: $\Omega = \frac{1}{R}I_R, W^0 = \mathbf{0}, i=0$;

Ensure:

The projection matrix W and correlation matrix Ω ;

```

1: While  $i < I_{iter}$ 
2:    $t = 0$ ;
3:   Calculate  $W^{t+1}$  through (10);
4:   While  $f(W^{t+1}) + g(W^{t+1}) > Q(W, W^{t+1})$ 
5:      $t = t + 1$ ;
6:     Calculate  $W^{t+1}$  through (10);
7:   End While
8:   Calculate  $\Omega$  through (12);
9:    $i = i + 1$ ;
10: End While.
```

2.4 Extension with deep architecture

Motivated by the wide success of deep convolution learning in the field of image processing, we further extend our model with deep architecture. Along this line, we refer to the VG-

G network [38] and modify it to cater for our requirements. Specially, we modify the last fully-connected layer with d neurons and take its output to replace the hand-crafted features for the proposed RR-SSSL-GL-O model. In this way, the architecture of our model is deepened with deep feature representations that are learnt automatically from training data. The complete architecture of our deep model is illustrated in Figure 2.

3 Experiments

To evaluate the efficiency of the proposed methodology in discovering aging-related facial appearances for AE across races, we have conducted experiments on the largest publicly available human aging face dataset, namely Morph (Album II) [35], in which each image is annotated with corresponding age and race information. In addition, The Morph dataset contains over 55,000 unique images of more than 13,000 individuals, spanning from 2003 to late 2007. The ages range from 16 to 77 with a median age of 33. The faces were drawn from *European, Hispanic, African, Asian,*

and *Other* races. Examples of the Morph faces are shown in Figure 3. The distributions of face samples are summarized in Table 1. It can be seen that samples distributions are not balanced in terms of ages and races. We cropped

Fig. 3 Face image examples of *Asian* (a), *African* (b), *Hispanic* (c), *Other* (d) and *European* (e) from the Morph database.

the face regions from the face images according to eyes locations, normalized them to 50×50 pixels and then pulled them into 2500-dimensional vectors as representation features. We tuned the trade-off parameters through a five-fold cross-validation in range $[0, 10^{-5}, 10^{-3}, 10^{-1}, 10^1, 10^3, 10^5]$. The results reported are the averages over ten runs with random data partitions. In the experiments, the methods to be compared are summarized below

- RR: The method formulated in (1).
- RR-SSSL: The method formulated in (4).
- RR-GL: The method formulated in (6) with removing Ω and setting $\lambda_1 = 0$ and $\lambda_3 = 0$.
- RR-SSSL-GL: The method formulated in (5).
- RR-SSSL-GL-O: The method formulated in (6).

- Deep-RR-SSSL-GL-O: The extended counterpart of RR-SSSL-GL-O with deep convolution architecture shown in Figure 2. In the experiment, the model was pretrained on the AgeDB [30] dataset and then fine-tuned on Morph with certain percentage of training samples. The model parameters were optimized through stochastic gradient descent (SGD) [16] with batch-size of 64, initial learning rate of 0.001 (which was decayed by 0.1 per 15 epochs), momentum of 0.9, weight decay of 0.0005, and last fully connected layers with dropout ratio of 0.5.

3.1 Performance comparison

Experimental comparisons were performed on pixel features extracted from the Morph database. The results are shown in Figure 4. We have the following findings. Firstly, with increasing percentage of training samples, the MAEs of all methods are reduced. It validates that increasing training percentage produces better discriminative ability of the AE estimators. Secondly, the MAEs of AE yielded by RR, RR-SSSL, RR-SSSL-GL, and RR-SSSL-GL-O reduce successively, demonstrating the rationality and effectiveness of preserving spatial structure (SSSL), selecting jointly discriminative features (GL) and incorporating joint correlation relationships between the races. Thirdly, the MAEs by RR and RR-SSSL (*both them are not incorporated with joint feature selection*) are significantly higher than the other methods with joint feature selection, indicating the benefit of removing redundant features to reduce the dimensionality of data. Fourthly, the MAEs on different races are not at the same level. Generally, the *Hispanic* race has the lowest MAEs, while the *Other* race has the highest MAEs. From Table 1, we can see that the *Other* race possesses very few samples, which may seriously limit the AE generalization performance. By contrast, although the number of samples in *Hispanic* race is fairly limited (especially compared with *African* and *European*), the lowest MAEs on *Hispanic* demonstrate its best discriminative characteristic in facial aging. Last but not least, the MAEs yielded by the Deep-RR-SSSL-GL-O are significantly the lowest. It demonstrates that extending the model architecture with deep layers of convolution networks can significantly improve its predicting accuracy on facial age.

3.2 Aging-related facial appearance exploration

To explore which regions the degree of facial appearance are changing relating to human aging, we reshape the learned projection vectors w_i ($i = 1, \dots, R$) corresponding to the races (with 30 percentage of samples for training) and visualize them in Figure 5. We can observe the following rules. Firstly, compared with the baseline method RR, although the face

Table 1 Races and ages distributions of the Morph database.

Race	European	Other	Hispanic	African	Asian	Total
Total	10559	63	1769	42589	154	55134
Age	<20	20-29	30-39	40-49	50+	Total
Total	7469	16325	15357	12050	3933	55134

Fig. 4 Age estimation performance comparison with 10 percent (a), 30 percent (b), and 50 percent (c) of samples for training while the rest for testing on the Morph database.

spatial structure information is preserved via SSSL technology in *RR-SSSL*, the learned aging-related facial appearances are still not obvious. The benefit of SSSL is destroyed

by the high-dimensional facial appearance representations (with 2500-dimensional pixel-features but relatively small number of training samples). Secondly, from *RR-GL* to *RR-*

Fig. 5 2D-visualization of the learned projection vectors regarding the face images of *European, Other, Hispanic, African* and *Asian* races (from the first column to the last column) by RR-SSSL-GL-O, RR-SSSL-GL, RR-GL, RR-SSSL, and RR (from the first row to the last row).

SSSL-GL and to RR-SSSL-GL-O, the facial appearance regions learned related to human aging are gradually becoming refined with clear contours. It demonstrates that incorporating more reasonable prior knowledge helps discover better facial aging-related appearance regions. Thirdly, the amplitudes of learned features regarding to different facial regions are almost the same. Generally, the regions around eyes, cheekbone and mouth are with high amplitudes, showing their great relevance to facial aging. Last but not least, the facial feature contours with respect to the *Asian* and *Other* races are more clear to distinguish than the other races. As previously analyzed, the *Asian* and *Other* races possess fewer face samples than the other three races. It means that compared to the other races, the *Asian* and *Other* races suffer from smaller facial appearance variances in head pose, illumination, and facial expressions, etc, which hinder discovering the contours of facial aging-related appearances.

3.3 Correlations between the races in facial aging

To further explore the correlation relationships among the races, we visualize the learned covariance matrix Ω among the projection vectors regarding the races in Figure 6. We can see that the degrees of correlations between the races are not the same, meaning that correlation relationships of the races are not the same and should be learned naturally from data instead of defining arbitrarily.

3.4 Real-time verification

In order to evaluate the real-time performance of the compared methods, we conducted experiments on the Morph dataset on Matlab R2017b computing station with i7-CPU and 48GB RAM memory. Specially, we randomly selected 10% instances as training set and took the rest as testing set. For statistical reliability, we repeated five times and report the averaged time cost for training and testing stage in Table 2.

From the reported results, we can see that nearly all the models can be trained with real-time cost (in an off-line manner), especially for testing, all the methods can make decisions less than 1 millisecond. They illustrate the real-time efficiency of all the compared methods.

4 Conclusion

In this work, we mainly explored the relations between human aging and relevant facial appearances shared by different races. We first extracted appearance vector features from facial images with spatial structure preservation. Then, we proposed to select aging-related features shared by different races in a joint manner to explore their aging-related common facial regions, while removing the redundant features. Thirdly, we improved the proposed model by incorporating the potential cross-race relationships in automated learning manner. In addition, we further extended our model with deep convolution networks for more discriminative fea-

Fig. 6 Visualization of the learned covariance matrix Ω among the races on the Morph database.

Table 2 Averaged real-time performance of the compared methods (in seconds per image). The Deep-RR-SSSL-GL-O model was trained in an off-line manner, so we do not count its training time cost.

Method	RR	RR-SSSL	RR-GL	RR-SSSL-GL	RR-SSSL-GL-O	Deep-RR-SSSL-GL-O
Training time	0.0011	0.0013	0.3399	0.5984	1.9183	/
Testing time	0.0003	0.0003	0.0004	0.0005	0.0004	0.0754

ture representations. Finally, we evaluated the performance superiority and real-time efficiency of the proposed methodologies on large-scale face data set. In future, we will perform deep research with distributed data scenarios with privacy preservation [32–34].

Acknowledgments

This work was supported partially by the National Natural Science Foundation of China under grant 61702273, the Natural Science Foundation of Jiangsu Province under grant BK20170956, the Natural Science Foundation of the Jiangsu Higher Education Institutions of China under grant 17KJB520022, the Fundamental Research Funds for the Central Universities No. NJ2019010, the Project Funded by the Priority Academic Program Development of Jiangsu Higher Education Institutions, the Priority Academic Program Development of Jiangsu Higher Education Institutions (PAPD) fund, and the Startup Foundation for Talents of Nanjing University of Information Science and Technology.

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