



Face Aging Effect Using Sparse Representation

Sonal Ajmire, Karuna Bagde, Prabhakar Ramteke

Student M.E CSIT, Dept. of I.T, HVPM, Sant Gadge Baba Amravati University, Amravati, India

Assistant Professor, Dept. of CSE, HVPM, Sant Gadge Baba Amravati University, Amravati, India

Head of Department, Dept. of CSE, HVPM, Sant Gadge Baba Amravati University, Amravati, India

ABSTRACT: Aging as the name suggests is the process of becoming older. In the world of photography, the face aging simulation has received rising investigations nowadays, whereas it still remains a challenge to generate convincing and natural age-progressed face images. Here, we present a novel approach to such an issue using sparse representation. In contrast to the majority of tasks in the literature that integrally handle the facial texture, the proposed aging approach separately models the person specific facial properties that tend to be stable in a relatively long period and the age-specific clues that gradually change over time. It then transforms the age component to a target age group via sparse reconstruction, yielding aging effects, which is finally combined with the identity component to achieve the aged face. Thus, the simulator gives the face of the person with aging effects. It recognizes the face of the person with or without spectacles.

KEYWORDS: Aging, sparse representation, facial texture.

I. INTRODUCTION

The human face conveys rich information such as age, gender, emotion, ethnicity, attitude and so on [1]. In the past years, great efforts have been made to make the face analysis easy. The machine based analysis requires the machine learning. As we grow old, the features of face changes in some manner. The wrinkles and dark circles may grow. Thus the face looks old. The changes in the captured image can be due to more or less exposure to light or due to pose changes. This also involves the age invariant face recognition [2] [3] [4], age estimation [5] [6] [7] etc. Particularly, face aging simulation has been given increasing attention in these years, since the solution to this complex issue benefits many attractive applications [8], [9].

II. RELATED WORK

Face aging simulation has experienced a gradual transition from computer graphics to computer vision. According to the studies in [10], [11], and [12], human face age progression can be generally summarized as two stages, *i.e.*, child growth and adult aging. The skeletal growth plays a dominant role from infancy to grown-up, while the texture details (*e.g.* wrinkles) distinguish seniors from young adults. Inspired by these observations, some approaches based on crania development theory and skin wrinkle analysis have been investigated in recent years, and the previous work roughly develops in three directions: i. Coordinate Transformation Based ii. Texture Transplanting Based iii. Aging Function Based. Parsimony has a rich history as a guiding principle for inference. One of its most celebrated instantiations, the principle of minimum description length in model selection, stipulates that within a hierarchy of model classes, the model that yields the most compact representation should be preferred for decision-making tasks such as classification.



International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijirce.com

Vol. 5, Issue 6, June 2017

III. PROPOSED ALGORITHM

A. Design Considerations:

- Use labelled training samples from k distinct object classes to correctly determine the class to which a new test sample belongs.
- Arrange the given n_i training samples from the i^{th} class as columns of matrix $A_i^{1/4} \dots 1/2v_i$ and so on.
- Identify w grayscale image.
- Keeping track of previously used samples.
- Define new matrix A for entire training set as concatenation of n training samples of all k objects.

B. Description of the Proposed Algorithm:

Aim of the proposed algorithm is to easily recognize the face and give aging effects to the face.

Step 1: Taking Training Samples:

Taking sufficient training samples of the i^{th} object class, $A_i^{1/4} \dots 1/2v_i; 1; v_i; 2; \dots; v_i; n_i \dots 2 \text{ IRm}_{ni}$, any new (test) sample $y \in \text{IRm}$ from the same class will approximately lie in the linear span of the training samples associated with object $i: y \approx \sum_{j=1}^{n_i} \alpha_j v_j; 1; 2; \dots; n_i; \delta \mathbb{P}$ for some scalars, $\alpha_j \in \mathbb{R}, j = 1; 2; \dots; n_i$.

Step 2: Selection Criteria:

Since the membership i of the test sample is initially unknown, we define a new matrix A for the entire training set as the concatenation of the n training samples of all k object classes:

$$A = \begin{bmatrix} A_1 & A_2 & \dots & A_k \\ v_{1;1} & v_{1;2} & \dots & v_{1;n_1} \\ v_{2;1} & v_{2;2} & \dots & v_{2;n_2} \\ \vdots & \vdots & \ddots & \vdots \\ v_{k;1} & v_{k;2} & \dots & v_{k;n_k} \end{bmatrix} \in \mathbb{R}^{(n_1+n_2+\dots+n_k) \times m}$$

Then, the linear representation of y can be rewritten in terms of all training samples as $y \approx Ax_0 \in \mathbb{R}^m; \delta \mathbb{P}$

where $x_0 \in \mathbb{R}^n; x_{0;1} = \alpha_1; x_{0;2} = \alpha_2; \dots; x_{0;n_i} = \alpha_{n_i}; x_{0;1} = 0; \dots; x_{0;n_i} = 0; \dots; x_{0;n_i} = 0; \dots; x_{0;n_i} = 0 \in \mathbb{R}^n$ is a coefficient vector whose entries are zero except those associated with the i^{th} class.

Step 3: Giving aging effects

After defining new matrix we will get the aging effects in the persons face.

IV. PSEUDO CODE

Step 1: Input: a matrix of training samples $A = [A_1; A_2; \dots; A_k] \in \mathbb{R}^{m \times (n_1+n_2+\dots+n_k)}$ for k classes, a test sample $y \in \mathbb{R}^m$, (and an optional error tolerance $\epsilon > 0$.)

Step 2: Normalize the columns of A to have unit ℓ_2 -norm.

Step 3: Solve the ℓ_1 -minimization problem: $\hat{x} = \arg \min_{\|x\|_1} \|Ax - y\|_2$ subject to $\|x\|_1 \leq \epsilon$ (Or alternatively, solve $\hat{x} = \arg \min_{\|x\|_1} \|x\|_1$ subject to $kAx - y\|_2 \leq \epsilon$.)

Step 4: Compute the residuals $r_i = \|y - A_i \hat{x}_i\|_2$ for $i = 1; \dots; k$.

Step 5: Output: $\hat{y} = \arg \min_i r_i$.

Step 6: End.

International Journal of Innovative Research in Computer and Communication Engineering

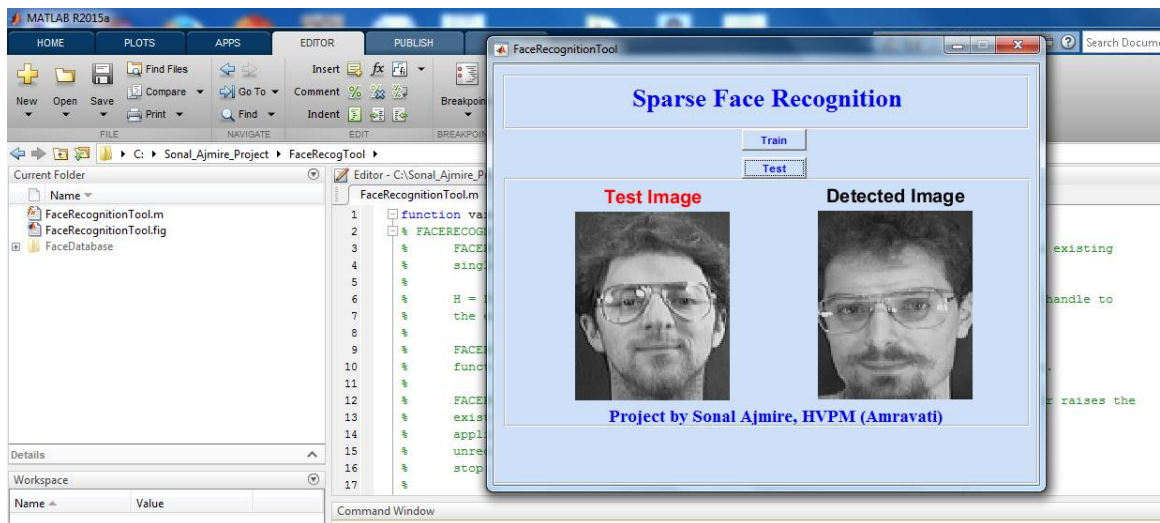
(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 6, June 2017

V. SIMULATION RESULTS

The performance evaluation of our method can be done by calculating the elapsed time for training and testing the image. Firstly, training of the data is done to read all the images from the training data. After that the test image is given and the image that is similar to the test image is found from the training data. The screenshot 1 below shows the screenshot of the test image and the detected image.



Screenshot 1: Test image and detected image

VI. CONCLUSION AND FUTURE WORK

Our experimental study proves that our method of sparse representation gives the expected result in minimum time that is in seconds. Some sample images are taken to show the time required. Table 1 shows the time that is required by the system for training and testing the images. Thus multiple images can be taken and their training and testing time can be calculated. This method is efficient as it shows the expected result in less time. We have proposed a system that takes the images and give an image that is similar. These images include the aging effect as well as different expressions on the face.

In future, we plan to introduce a more efficient system for showing the images. It may include increasing the efficiency of resizing techniques.



International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 6, June 2017

REFERENCES

1. Hongyu Yang, Di Huang, Yunhong Wang, Heng Wang and Yuanyan Tang "Face Aging Effect Simulation Using Hidden Factor Analysis Joint Sparse Representation" , *IEEE TRANSACTIONS ON IMAGE PROCESSING*, VOL. 25, NO. 6, JUNE 2016, pp. 2493-2507.
2. U. Park, Y. Tong, and A. K. Jain, "Age-invariant face recognition," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 32, no. 5, pp. 947-954, May 2010.
3. H. Yang, D. Huang, and Y. Wang, "Age invariant face recognition based on texture embedded discriminative graph model," in *Proc. IEEE/IAPR Int. Joint Conf. Biometrics*, Clearwater, FL, USA, Sep./Oct. 2014, pp. 1-8.
4. D. Gong, Z. Li, D. Lin, J. Liu, and X. Tang, "Hidden factor analysis for age invariant face recognition," in *Proc. IEEE Int. Conf. Comput. Vis.*, Dec. 2013, pp. 2872-2879.
5. M. Yang, L. Zhang, J. Yang, and D. Zhang, "Metaface learning for sparse representation based face recognition," in *Proc. 17th IEEE Int. Conf. Image Process.*, Sep. 2010, pp. 1601-1604.
6. G. Guo, Y. Fu, T. S. Huang, and C. R. Dyer, "A probabilistic fusion approach to human age prediction," in *Proc. IEEE Comput. Vis. Pattern Recognit.*, Jun. 2008, pp. 1-6.
7. G. Guo, Y. Fu, C. R. Dyer, and T. S. Huang, "Image-based human age estimation by manifold learning and locally adjusted robust regression," *IEEE Trans. Image Process.*, vol. 17, no. 7, pp. 1178-1188, Jul. 2008.
8. Y. Fu, G. Guo, and T. S. Huang, "Age synthesis and estimation via faces: A survey," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 32, no. 11, pp. 1955-1976, Nov. 2010.
9. N. Ramanathan, R. Chellappa, and S. Biswas, "Computational methods for modeling facial aging: A survey," *J. Vis. Lang. Comput.*, vol. 20, no. 3, pp. 131-144, 2009.
10. Y. H. Kwon and N. da Vitoria Lobo, "Age classification from facial images," *Comput. Vis. Image Understand.*, vol. 74, no. 1, pp. 1-21, 1999.
11. J. T. Todd, L. S. Mark, R. E. Shaw, and J. B. Pittenger, "The perception of human growth," *Sci. Amer.*, vol. 242, no. 2, pp. 132-144, 1980.
12. A. M. Albert, K. Ricanek, Jr., and E. Patterson, "A review of the literature on the aging adult skull and face: Implications for forensic science research and applications," *Forensic Sci. Int.*, vol. 172, no. 1, pp. 1-9, Oct. 2007.

BIOGRAPHY

Sonal Ajmire is a student in the Information Technology Department, College of Hanuman Vyayam Prasarak Mandal, Sant Gadge Baba Amravati, University. She received Bachelor of Engineering (BE) degree in 2015 from Sant Gadge Baba Amravati University, Amravati, India. She is pursuing Master of Engineering from HVPM Amravati.

Karuna Bagde is Assistant Professor in Computer Science and Engineering Department, College of Hanuman Vyayam Prasarak Mandal, Sant Gadge Baba Amravati University. She received Mater of Engineering (ME) in CSE and Master of Philosophy (M.Phil) in CS from India.

Prabhakar Ramteke is Professor in Computer Science and Engineering Department, College of Hanuman Vyayam Prasarak Mandal, Sant Gadge Baba Amravati University. He received Master of Engineering (ME) in Computer Science and Engineering and Doctorate of Philosophy (Ph.D) from India.