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Identity, Expression and Age Information using Active Appearance Model Features

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Rapid advancement in the fields of Image Processing, Computer Vision and Pattern Recognition due to the growing need in real world applications, involves the requirement of information such as Identity, Gender, Mood, Age *etc.*, from a face image. Obtaining all this information from a face image is an intriguing and exigent task. Aging changes both shape as well as texture and it is an irreversible, uncontrollable and personalized. The way of aging in male is different from female and hence the accuracy of age estimation process can be improved if it is preceded by gender classification. This work takes care of this by using gender information for categorizing age range of the given face image. Gender classified appearance parameters are fed into male or female age estimator. Age estimation is then performed using Neural networks which classifies age range of the given face image. Experimental results on FG-NET age database demonstrate the effectiveness of the framework and validates that performance is better than existing approaches. This paper also discuss about face recognition and expression recognition using Active Appearance Models (AAM). An attempt has been made in obtaining identity and mood information from a given face image.

Keywords : Active Appearance Models, Face Recognition, Gender Classification, Age Estimation, Expression Recognition.

1. INTRODUCTION

The human face conveys important information such as identity, expression, race (or ethnic group), gender and age of the individual. All these information obtained from a given face image has applications such as access control, surveillance, face recognition, age synthesis, electronic customer relationship management and thus has attracted the attention of many researchers. Face appearance of a person changes with the process of growing older. These changes increases the difficulty of computer based face recognition task. There are two stages of aging: (1) Early growth and development occurs from birth to adulthood where there are greater change in carniofacial growth (shape changes), (2) Adult aging from adult to old age is because of skin aging (texture changes). These changes in appearance vary from person to person and it is contributed by various factors like ancestry, health, lifestyle, race, gender, working environment, climate, decrease or increase in weight, emotional stress, smoking, drug use, diet, and emotional stress [1,2].

Males and Females may also age differently as they have varying type of face aging pattern [1,3]. This is due to the difference in makeup, hair style, accessories in female or mustache and beard in case of males. In adulthood, female faces appear younger than male faces. Figure 1 shows the face images of male and female with age labeled at the top. From the above facts it is clear that the performance of the age estimator may be improved by using gender information [4]. Thus, a method where age estimation is preceded by gender classification as shown in block diagram 2 is proposed. The concept of using gender information for age estimation was first tried out by Hayashi *et al.*, [5]. They considered wrinkles appearing on the face, shape and size to model age and gender. Later Iga *et al.*, [6], used geometric arrangement, texture, Hair, Mustache and lu-

Figure 7. Sample Images of a Person with Age Labeled at the Top.

face images instead of appearance parameter is 65.42 (%). Table 5 shows the results of gender classification performed on appearance parameters from AAM. This clearly shows that gender classification using appearance parameters increases the performance. The proposed method is tested by providing annotated face image from both training and test set, followed by feature extraction and classification as shown in Figure 2. Table 5 shows the results of gender classification, age estimation and gender classification followed by age estimation. Age estimation is performed using neural networks for both cases.

Table 5
Results of Gender Classification Followed by Age Estimation is Compared with Age Estimation. AEUGI- Age Estimation using Gender Information.

Methods	Accuracy (%)
Gender classification	92.523
Age estimation	72.274
AEUGI	77.259

The quality of images available in the FG-NET database is not that good and it affects the performance of the algorithm. Results clearly show that age estimation performed after gender classification increases the performance. Thus, it is evident that incorporating gender information increases the performance of age estimation process.

5. CONCLUSIONS

Active Appearance model feature extractor gives good results in case of face recognition, age estimation using gender information and expression recognition. The affect of two different types of shape landmark points using Muct and Cohn-kanade face database illustrates the importance of these points for AAM feature extraction. It is easily observable from the results that the use of AAM steadily increases the performance of gender classification. Experimental results from FG-NET database verify that incorporating gender information for age estimation increases the age estimation performances. The expression recognition also gives a good performance using AAM feature extractor. An attempt in obtaining both identity and mood information can be further improved by considering the appropriate shape landmark points for particular purpose.

REFERENCES

1. Yun Fu, Guodong Guo and Thomas S. Huang. Age Synthesis and Estimation *via* Faces: A Survey. *IEEE Transactions on Pattern Analysis And Machine Intelligence*, 32(11), November 2010.
2. E. Patterson, K. Ricanek, M. Albert and E. Boone. Automatic Representation of Adult Aging in Facial Images. *Proc. 6th IASTED Int. Conf. on Visualization, Imaging, and Image Processing*, pages 171-176, August 2006.
3. G. Guo, Y. Fu, T. S. Huang and C. Dyer. Locally Adjusted Robust Regression for Human Age Estimation. *Proc. IEEE Workshop Applications of Computer Vision*, 2008.
4. N. S. Lakshmiprabha, J. Bhattacharya and S. Majumder. Age Estimation Using Gender Information. *International Conference on Information Processing, Springer Verlag*, CCIS 157, pages 211-216, 2011.
5. J. Hayashi, M. Yasumoto, H. Ito and H. Koshimizu. A Method for Estimating and Modeling Age and Gender Using Facial Image Processing. *Proc. 7th Int. Conf. on Virtual Systems and Multimedia*, pages 439-448, 2001.
6. R. Iga, K. Izumi, H. Hayashi, G. Fukano and T. Ohtani. A Gender and Age Estimation System from Face Images. *Proc. SICE Ann. Conf.*, pages 756-761, 2003.
7. Guodong Guo, Charles R. Dyer, Yun Fu and Thomas S. Huang. Is Gender Recognition Affected by Age?. *IEEE Int. workshop on Human Computer Interaction (HCI' 09)*, 2009.

8. T. F. Cootes, G. J. Edwards and C. J. Taylor. Active Appearance Models. *Proc. European Conf. on Computer Vision, Springers*, 2: 484-498, 1998.
9. S. Milborrow and J. Morkel and F. Nicolls. The MUCT Landmarked Face Database. *Journal of Pattern Recognition Association of South Africa*, 2010.
10. P. Lucey, J. F. Cohn, T. Kanade, J. Saragih, Z. Ambadar and I. Matthews. The Extended Cohn-Kanade Dataset (CK+): A Complete Dataset for Action Unit and Emotion-Specified Expression. *In the Proceedings of IEEE workshop on CVPR for Human Communicative Behavior Analysis*, San Francisco, USA, 2010.
11. T. F. Cootes, G. J. Edwards and C. J. Taylor. Active Appearance Models. *IEEE Transactions on Pattern Analysis And Machine Intelligence*, 23(6): 681-685, 2001.
12. T. F. Cootes, C. J. Taylor, D. H. Cooper, and J. Graham. Active Shape Models-Their Training and Application. *Computer Vision and Image Understanding*, 61(1): 38-59, 1995.
13. N. Jamil, S. Iqbal, N. Iqbal. Face Recognition Using Neural Networks. *IEEE Proc. of INMIC technology for the 21st century*, pages 277-281, 2001.
14. Z. Sun, X. Yuan, G. Bebis and S. J. Louis. Neural-Network-Based Gender Classification Using Genetic Search for Eigen-Feature Selection. *Proc. Inter. Joint Conf. on Neural Networks*, pages 2433-2438, 2002.
15. The FG-NET Aging Database, `http://www.fgnet.rsunit.com/`.

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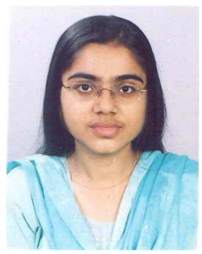

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