ISSN: 2277-3754
ISO 9001:2008 Certified
International Journal of Engineering and Innovative Technology (IJEIT)
Volume 4, Issue 7, January 2015

Human Age Estimation Framework using Bio-Inspired Features for Facial Image

Santhosh Kumar G, Dr. Suresh H. N.
Research scholor, BIT, under VTU, Belgaum India
Professor, Bangalore Institute of Technology, Dept.of Elecronics and Instrumentation Engg.
Bangalore–04, Karnataka

***Abstract*— Human age estimation using biometric features has wide range of real-world application in law enforcement, security control, and human computer interaction. However, despite advances in automatic age estimation, it remains a challenging problem. Age estimation is challenging due to age progression, extracting these features accurately are very important for better performance. One of the most successful works is based on biologically inspired features (BIF). In this paper we extend BIF by automatic initialization and extracting fine details of facial features using active appearance model (AAM) and analyzing a more complete facial area by including the forehead details. Besides, we combine regression-based and classification-based models and test them experimentally on standard datasets showing the superiority of our proposed algorithm.**

Index Terms—**Automatic age estimation, Facial feature extraction, Active appearance model.**

I. INTRODUCTION

Including identity, emotional expression, gender, pose, beards etc. Human face is robust because it changes in a short period. With the progress of aging, human faces shows remarkable changes such as face size getting larger, face skin becomes darker and wrinkly. The main goal of age estimation is to compute a person's exact age or age-group based on face attributes derived from a facial image. One of the main challenges of facial age estimation is the lack of sufficient training data. A suitable training data should include multiple face images of the same person covering a wide range of ages. Since the aging progress is uncontrollable, the collection of such a training dataset usually requires great efforts in searching past images and we cannot obtain future images. Consequently, the available training dataset just contain few face images of each person and images at higher age are especially rare. Age estimation from facial image is an active area of research in several disciplines such as image processing, pattern recognition and computer vision. The estimation of age from the appearance of the human being depends on the ability of the person on his past and personal experience, it also vary from person to person, Hence developing automatic facial age estimation system that are even better and more accurate than the human ability of age estimation has become an attractive yet challenging topic in recent years. It is a challenge for human-based age estimation and, even more challenger for computer-based age estimation. Having computer-based age estimation, open the door for wide, range of useful applications like an electronic consumer relationship management and demographic data collection, Add agency can find out what kind of scroll advertisements can attract the passenger and entertainment scenarios. In this paper, we extend our previous work [6] based on the biologically-inspired features (BIF) that showed promising results for the age estimation problem as well as the gender recognition problem

II. LITERATURE SURVEY

Previous work on aging can be broken down into two major categories: (1) age progression which aims at simulating the aging effects on human faces [1] (i.e. simulate how the face would look like at a certain age), and (2) age estimation which aims to label a face image automatically with the exact age (year) or the age group (year range of the individual face). Two main modules are existed in the current age estimation frameworks: age representation and age estimation techniques. For the age representation, the anthropometric model describes the growth of a person's head from infancy to adulthood where, face anthropometry is the science of measuring sizes and proportions on human faces. This method is limited because human head shape does not change too much in adult period. The Aging Pattern Subspace (AGES) method builds an aging subspace for all images belonging to one individual rather than treating them as separate images then, project test images on learnt subspace to estimate ages. Appearance models [8] take into account global and local feature, which is capable of capturing different facial wrinkles. Given an aging feature representation, the next step is to estimate ages. The age estimation can be viewed as classification-based or regression-based . Yun Fu, Guodong Guo have proposed the four concepts about human age in there paper entitled with "Age synthesis and estimation via faces: A survey" they have proposed the definition of Actual Age, Apparent Age, Perceived Age & Estimated Age, in this paper they have carried out a brief survey of the different technique for the synthesis of facial image and age estimation. The paper discus about the existing technique & popular algorithm for the age estimation. Xin Geng, Zhi-Hua have described the age estimation based on facial aging pattern, they have used the AGES method for the age estimation of

ISSN: 2277-3754
ISO 9001:2008 Certified
International Journal of Engineering and Innovative Technology (IJEIT)
Volume 4, Issue 7, January 2015

human being, AGES stands for the aging pattern sub space is the sequence of personal face images sorted in time order this gives the better result as compared to other method but it requires the 'generic training dataset' which contain face images under all possible pose and illumination, which is not available always in reality. In age estimation from facial image the extraction of the feature is important task, the different author has proposed different method for the feature extraction from facial image.

III. IMPLEMENTATION

The proposed algorithm for age estimation is divided into five steps. First the facial landmarks for the face image are detected automatically using AAM[8] (as opposed to the case of BIF[6] where this step was manually performed). The image is cropped to just the area covering a fixed number of points generated from the AAM step (several numbers of points was tested experimentally). Then, the cropped face is filtered by a set of Gabor functions by exploring imaginary and magnitude parts at different orientations and scales. The filtered outputs undergo a feature dimensionality reduction step by just keeping the maximum (MAX) and standard deviations (STD) of the Gabor filtered outputs.

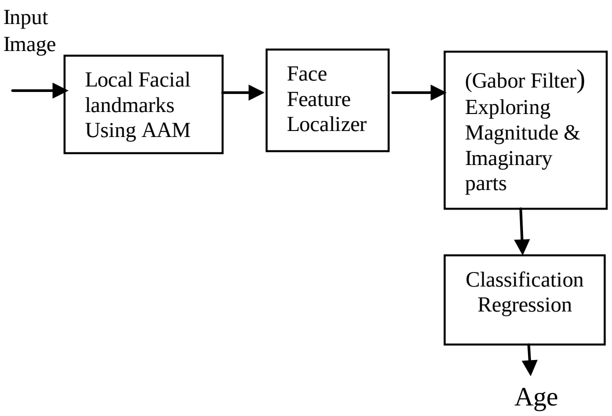

Fig 1: Age Estimation Frame work

Finally, both a classification-based and regression-based models were used in the training phase to produce the final age model estimator. The complete algorithm block diagram is illustrated in Fig1.

A. *Face feature localizer*

In this step, we aim at accurately localizing the facial region to extract features only from the relevant parts of them input image and texture across target object using active appearance model. In our previous work we explored the use of Active Appearance Models for the automatic localization of facial landmark points; which has two main stages, namely training and fitting. In the training stage, manually located landmark points for hundreds of images were collected in such a way that each landmark represents a distinguishable point presented on every example image.

Fig 2: 75 and 20 points samples from FG-NET.

In this work, we use different set of points (75 and 20) which were provided. Then, we build two separate statistical appearance models (1) 75 points model and (2) 20 points model by AAM based on the annotated images. In fitting stage, we detect the whole face and eye region in the input image using 75 and 20 points models respectively. Second, we initialize the shape points and align images by fitting to automatically obtain the detected shape features. Finally the input image is cropped to the area covered by the AAM fitted landmark points. The difference between using 20 and 75 landmark points is illustrated in Fig. 2

B. Extended Gabor-like features

The Gabor filter is a linear filter whose impulse response is defined by a harmonic function multiplied by a Gaussian function. This filter is used to detect line endings and edge borders over multiple scales and with different orientations. We follow a similar approach as in but with the addition of different forms of Gabor functions, namely the imaginary and magnitude parts. The cropped image output from the feature detection localizer block using Active Appearance Model (AAM) is filtered by a family of Gabor functions with different forms with 8 orientations and 16 scales. The following Gabor function for a particular scale (sigma) and orientation (theta) describe the R – Real part:

$$R = \exp\left(-\frac{x^2+\gamma^2 y^2}{2\sigma^2}\right)\times\cos\left(\frac{2\pi}{\lambda}X\right) \tag{1}$$

While, the following Gabor function describes the I Imaginary part:

$$I = \exp\left(-\frac{x^2+\gamma^2 y^2}{2\sigma^2}\right)\times\sin\left(\frac{2\pi}{\lambda}X\right) \tag{2}$$

Where X = x cosθ+ y sinθ and Y = -x sinθ +y cosθ and θ varies between 0 and π . The parameters λ (wavelength), σ(effective width), and γ(aspect ratio) =0.3 are based on the work in . The Starting filter size is(3x3) rather than (5x5) which enables revealing facial characteristics in more detailed manner. We generate a third part using R – Real and I – Imaginary parts, which is the M – Magnitude part. It is described by the following equation:

$$M = \sqrt{R^2 + I^2} \tag{3}$$

Gabor features are redundant with high dimensionality which will lead to difficulties in training.

ISSN: 2277-3754
ISO 9001:2008 Certified
International Journal of Engineering and Innovative Technology (IJEIT)
Volume 4, Issue 7, January 2015

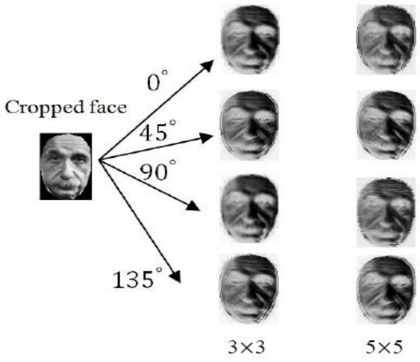

Fig 3: Gabor filtered results at band 1 (two scales with filer sizes 3 ×3 and 5× 5) at four orientations. Note that in the case of 3x3 filter forehead features start to be more visible. We use two operators to summarize the outputs of Gabor functions as in [1], namely the maximum operator "MAX" and the standard deviation operator "STD". The three sets of Gabor- like parts are shown in Fig. 3 with the "MAX" and "STD" operators applied on them.

C. Classification or Regression

Age estimation can be treated as a classification problem, when each age is considered as a class label. Alternatively, age estimation can be treated as a regression problem where each age is considered as a regression value. In our experiments, we use both SVR and SVM methods for age estimation on the FG-NET [4] and MORPH [14] standard databases. The RBF SVR can address the three limitations of the traditional quadratic regression model: (1) the simple quadratic function may not model properly the complex aging process, especially for a large span of years, e.g., 0-70. ; (2) The least square estimation is sensitive to outliers that come from incorrect labels in collecting a large image database; and (3) the least square estimate criterion only minimizes the empirical risk which may not generalize well for unseen examples.

IV. COMPARISON OF ALGORITHMS

Algorithm	MAE
K-nearest neighbour	8.24
Support Vector Machine	7.25
Local feature of face image & regression	6.85
Aging Pattern Subspace	6.77
Nonlinear Aging Pattern Subspace	6.18
Ranking with uncertain labels	5.33
Metric learning & Gaussian Process Regression	5.08
Manifold learning & locally adjusted robust regression	5.07
Regression Patch Kernel	4.95
Active Appearance Model	4.37
Enhanced bio-inspired features	3.17

Table 1: MAE (years) Comparison

V. CONCLUSION

In this paper, we presented a human age estimator based on the bio-inspired features-based method [6]. We have combined BIF h the Active Appearance Model (AAM) for initialization. Besides, we have experimented with the extraction of finer facial features as opposed and shown experimentally the superiority of the proposed contributions. Evaluated on the FG-NET [4] and MORPH [14] benchmark databases, our algorithm achieved high accuracy in estimating human ages compared to published methods. We also tested the proposed algorithm on MORPH database to show its generalization capabilities. As far as the future work is concerned, we aim at exploring other more powerful modeling technique that can statistically model the relation between the number of variables.

ACKNOWLEDGMENT

The authors would like to thanks all the People who have helped us in this research work for the development of the facial image database using Bio-inspired features.

REFERENCES

[1] J. Suo, S. Zhu, S. Shan and X. Chen, "A Compositional and Dynamic Model for Face Aging" IEEE Transactions on Pattern Analysis and Machine Intelligence, 2009.

[2] X. Geng., Z.-H.Zhou., and K. Smith-Miles. "Automatic age estimation based on facial aging patterns". IEEE Trans. on PAMI, 29(12):2234–2240, 2007.

[3] A.Lanitis,C. Draganova, and C. Christodoulou."Comparing different classifiers for automatic age estimation". IEEE Trans. on SMC-B, 34(1):621–628, 2004.

[4] fg-net aging database. In http://www.fgnet.rsunit.com

[5] Y. Kwon and N. Lobo."Age classification from facial images". Computer Vision and Image Understanding, 74(1):1–21, 1999.

[6] Mu, G.W., Guo, G.D., Fu, Y., Huang, T.S. "Human age estimation using bio-inspired features", CVPR09 (112-119).

[7] T. F. Cootes, C. J. Taylor, D. H. Cooper and J. Graham."Active Shape Models | their Training and Application". CVIU 61, 38{59 (1995).

[8] Y. Fu, Y. Xu, and T. S. Huang, "Estimating human ages by manifold analysis of face pictures and regression on aging features," in Proc. IEEE Conf. Multimedia Expo., 2007, pp. 1383–1386.

[9] A. Lanitis, C. Taylor, and T. Cootes, "Toward automatic simulation of aging effects on face images," IEEE Trans. Pattern Anal. Mach. Intell., vol. 24, no. 4, pp. 442–455, Apr. 2002.

ISSN: 2277-3754
ISO 9001:2008 Certified
International Journal of Engineering and Innovative Technology (IJEIT)
Volume 4, Issue 7, January 2015

[10] Y. Wei "Research on Facial Expression Recognition and Synthesis", Master Thesis, 2009.

[11] GG. Guo, Y. Fu, T. Huang, and C. Dyer. Locally adjusted robust regression for human age estimation. In *IEEE WACV*, 2008.

[12] S. Yan, H. Wang, T. S. Huang, and X. Tang."Ranking with uncertain labels". In IEEE conf. on Multimedia and Expo, pages 96–99, 2007.

[13] S. Yan, H. Wang, X. Tang, and T. Huang."Learning auto-structured regress or from uncertain nonnegative labels". In IEEE conf. on ICCV, 2007.

[14] K. Ricanek and T. Tesafaye, "MORPH: A longitudinal image database of normal adult age-progression," in Proc. the 7th Int'l Conf. Automatic Face and Gesture Recognition, Southampton, UK, 2006, pp. 341–345.

[15] BIOID database <http://www.bioid.com/>.

[16] J. Mutch and D. Lowe. Object class recognition and localization using sparse features with limited receptive fields. In CVPR pages 11–18, 2006.

[17] V. N. Vapnik, Statistical Learning Theory, John Wiley, 1998.

AUTHOR'S PROFILE

Prof. Santhosh Kumar G received his BE (ECE) from EWIT, Visveswaraya Technical University, Karnataka, India in the year 2007 and completed his M.Tech (VLSI & Embedded system design) from Dr. AIT, Visveswaraya Technical University, Karnataka, India in the year 2010 and since then he is actively involved in teaching and research and has six years of experience in teaching. At present he is working as Assistant Professor in East West Institute of Technology, Bangalore Affiliated to Visveswaraya Technical University. He has good exposure in the field of Network Analysis, signal processing, Image Processing, Analog and Digital circuits. He has published more 5 research papers in the refereed international journals and presented contributed research papers in refereed international and national conferences.

Dr. H.N. Suresh received his BE (E&C) from P.E.S College of Engineering, Mysore University, Karnataka, India, in the year 1989 and completed his M.Tech (Bio Medical Instrumentation) from SJCE Mysore affiliated to University of Mysore., in the year of 1996 and since then he is actively involved in teaching and research and has Twenty six years of experience in teaching. He obtained his PhD (ECE) from Anna university of Technology. He worked at various capacities in affiliated University Engineering Colleges. For Visveswaraya Technical University and Bangalore University he worked as a Chairman for Board of Examiners, and member of Board of Studies etc. At present he is working as Professor and Research and PG co-coordinator in Bangalore Institute of Technology, Bangalore, Affiliated to Visveswaraya Technical University. He has good exposure in the field of signal processing, Wavelet Transforms, Neural Networks, Pattern recognition, Bio Medical Signal Processing, Networking and Adaptive Neural network systems. He has published more 45 research papers in the refereed international journals and presented contributed research papers in refereed international and national conferences. He is a member of IEEE, Bio Medical Society of India, ISTE, IMAPS & Fellow member of IETE