



Master of Science Thesis

# Automatic Age Estimation in Still Images

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Barcelona, 24th April 2015



# Acknowledgements

To write some time in the future...

# Abstract

# Resum (Catalan)

# Resumen (Spanish)

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# 1 Introduction

## 2 State of the art

### 2.1 Historical context

One of the earliest works in age estimation was done by A. Lanitis et al. [25, 26, 27] where the age is modelled by a quadratic aging function. They propose two different aging estimation methods: weighted appearance specific method [26, 27] -where the aging factor of a new individual is computed by the weighted sum of the aging functions of other individual- and appearance and age specific method [25] -where the new individual is first classified into a cluster with similar aging factor patterns, then is classified into different age ranges and an age-specific classifier is applied to estimate the final age-.

There are some drawbacks to this "aging function" approach pointed out by X. Geng et al. [12]. The formula of the aging function is empirically determined, there is no evidence suggesting that the relation between face and age is described just by a quadratic function. The new aging function for the unseen images is simply a linear combination of the already known aging functions. X. Geng et al. claimed to solve these problems in their new proposed method AGing pattErn Subspace (AGES) [12]. Where each face image is represented by a point in the aging pattern subspace.

Later N. Ramanathan et al. [34, 35] approached the age estimation problem in two different scenarios, estimating the age difference between two face images of the same individual based on a Bayesian age-difference classifier [34] and estimating the age of young faces using the facial growth geometry [35]. The problem of the last approach is that only can be applied to face images of young people in a growing age since afterwards the facial geometry does not change as much.

Y. Fu et al. were the first to approach the problem through manifold analysis methods [10, 9]. Each face image is assigned to its low-dimensional representation via manifold embedding. Following this approach G. Guo and Y. Fu et al. [13] proposed a new method based on a study of different dimensionality reduction and manifold embedding and add a robust regression step to the previous framework. In a posterior work [15], G. Guo et al. introduces a new approach, using kernel partial least square (KPLS) regression which reduces feature dimensionality and learn the aging function in a single step.

G. Guo et al. also proposed different approaches to the age estimation prob-

lem such as [14], where they propose probabilistic fusion approach, or [17] where they introduce the Biological Inspired Features (BIF) for the age estimation problem and propose some changes adding a novel "STD" operator. H. Han et al. [18] uses the BIF features in an hybrid classification framework improving the previous results. G. Guo et al. [16], in a recent paper (2014), used the BIF features, and focus to investigate a proposed single-step framework for joint estimation of age, gender and ethnicity. Both the CCA (Canonical Correlation Analysis) and PLS (Partial Least Square) based methods were explored under the joint estimation framework.

Under the same idea as Y. Fu et al. [10], K. Luu et al. [29, 30] reduced dimensionality by using facial landmarks and Active Shape Models (ASM) [29] and an improved version, Contourlet Appearance Model (CAM) [30], where they prove the efficiency of using facial landmarks. Then T. Wu et al. [40] proposed to use facial landmarks and project them into a Grassmann manifold to model the age patterns.

Other different variations of the problem has been addressed, A. Lanitis et al. [24] performed a first approach to age estimation using Head and Mouse tracking movements, Y. Makihara et al. [31] used a gait-based database to estimate the age, B. Xia et al. [41] proposed an age estimation method based on 3D face images.

There are also some surveys in age estimation by N. Ramanathan et al. [36] and Y. Fu et al. [8].

More recently studies have obtained a very high accuracy in face validation using deep learning [1].

## 2.2 Applications

There are many real-world application related to age estimation. Automatic age estimation is useful in situations where we do not need to specifically identify the individual, such as a government employee, but want to know his or her age.

### 2.2.1 Security control and surveillance monitoring

In the last years security control and surveillance monitoring have gotten more relevant with the growth of internet content and the spread of technol-

ogy that allows access to that content to under-age teenagers. Automatic age estimation systems can be used to prevent minors to buy alcohol in a grocery store, enter a bar or purchase tobacco from vending machines.

### 2.2.2 Biometrics

There are two types of biometric systems based on the number of traits used for recognition, unimodal biometric systems which consist on a single recognition trait and multimodal biometric systems, which combines evidences obtained from multiple sources [19] such as fingerprints, iris, face, etc. The multimodal system is more robust, more reliable and secure against spoof attacks. However, the data acquisition is much more troublesome than the unimodal. In order to overcome this inconveniences, soft-biometrics [20], such as age, height, weight, gender, ethnicity and eye colour, are used in combination with classic biometric traits.

### 2.2.3 Age-based indexing face images

With the rise of interest for big data new and more efficient ways to retrieve data have to be developed. In large face image datasets, age can be used for index such a databases so the queries to the dataset are simpler and faster. This is specially important in law enforcement where large image databases of suspects have to be filtered in order to find the most accurate suspects.

### 2.2.4 Human-computer interaction

With the growth of e-commerce, companies want to offer a more personalized experience to their customers. Personalizing the offer or the product itself increase the user's satisfaction and the companies sells. Some examples of such a policies are the following: Google [4] indexes the search results so the links that appear first appeal more to the user, Amazon [28] uses a recommender system to suggest products to the potential buyers according to their previous purchases, Netflix [22] held a competition in 2009 to create a film recommender system and gave a price of US \$1,000,000. Age estimation system could have an important role in the sector since age is a discriminative feature for different client profiles. Visada [21] is an example of the use of age estimation for recommend products.

## 2.3 Age-based Databases

There are many databases of faces in the literature, however, not so many capture the age of the individuals. This fact is due to the complexity of crawling such an information (if existent) from the usual fonts such as *Flickr* or *Facebook* and due to privacy issues. Moreover, the difficulty is even higher if the database contains chronological image series of individuals. The Table 2.1 shows the most relevant databases used in the literature. The *FG-NET* is a baseline database used to compare with other age estimation methods since its one of the oldest and more studied one.

Database	#Faces	#Subj.	Range	Type of age	Controlled Env.	Balanced age Distr.	Other annotation
FG-NET [23]	1.002	82	0 - 69	Real Age	No	No	68 Landmarks
Morph2 [37]	55.134	-	16 - 77	Real Age	Yes	No	-
YGA [9]	8.000	1.600	0 - 93	Real Age	No	No	-
FERET [33]	14.126	1.199	-	Real Age	Partially	No	-
Iranian face [3]	3.600	616	2 - 85	Real Age	No	No	Kind of skin and cosmetic points <sup>1</sup>
PIE [38]	41.638	68	-	Real Age	Yes	No	-
Images of Gropus [11]	28.231	-	0 - 66+	Age group	No	No	-
WIT-BD [39]	26.222	5.500	3 - 85	Age group	No	No	-
Caucasian Face Database [5]	147	-	20 - 62	Real Age	Yes	No	Shape represented in 208 key points
LHI [2]	8.000	8.000	9 - 89	Real Age	Yes	Yes	-
HOIP [7]	306.600	300	15 - 64	Age Group	Yes	No	-
Gallagher's Web-Collected Database [11]	28.231	-	0 - 66+	Age Group	No	No	-
Ni's Web-Collected Database [32]	219.892	-	1 - 80	Real Age	No	No	-
OUI-Adience [6]	26.580	2.284	0 - 60+	Age Group	No	No	Gender

Table 2.1: Age-based Databases

Publication	Year	Database (#subjects, #images)	Age Image Representation	Method	Accuracy	MAE
A. Lanitis et al. [27]	2002	Private (60, 500)	Active Appearance Models	Quadratic Aging Function	71%	$3.94 \pm 3.8$
A. Lanitis et al. [25]	2004	Private (40, 400)	Active Appearance Models	Quadratic Aging Function	N/A	$3.82 \pm 5.58$
X. Geng et al. [12]	2006	FG-NET (82, 1.002)	AGES	Regression	N/A	6.77

**Table 2.2:** Age Estimation Methods

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<sup>1</sup>Surgical points, fracture or laceration on face.



## 3 Data Collection

### 3.1 Web Application

### 3.2 HuPBA Age Dataset

# 4 Method

## 4.1 Biological Inspired Method

### 4.1.1 Background

### 4.1.2 System overview

## 4.2 Deep Learning Method

### 4.2.1 Background

### 4.2.2 System overview

## 5 Experimental Results

## 6 Conclusions and Future work

# References

- [1] DeepFace: Closing the Gap to Human-Level Performance in Face Verification. In *Conference on Computer Vision and Pattern Recognition (CVPR)*.
- [2] LHI image database. Available at <http://www.lotushill.org/LHIFrameEn.html>, 2010.
- [3] A. Bastanfard, M.A. Nik, and M.M. Dehshibi. Iranian face database with age, pose and expression. In *Machine Vision, 2007. ICMV 2007. International Conference on*, pages 50–55, Dec 2007.
- [4] Sergey Brin and Lawrence Page. The anatomy of a large-scale hypertextual web search engine. *Comput. Netw. ISDN Syst.*, 30(1-7):107–117, April 1998.
- [5] D Michael Burt and David I Perrett. Perception of age in adult caucasian male faces: Computer graphic manipulation of shape and colour information. *Proceedings of the Royal Society of London. Series B: Biological Sciences*, 259(1355):137–143, 1995.
- [6] E. Eidinger, R. Enbar, and T. Hassner. Age and gender estimation of unfiltered faces. *Information Forensics and Security, IEEE Transactions on*, 9(12):2170–2179, Dec 2014.
- [7] Softopia Japan Foundation. Human and Object Interaction Processing (HOIP) Face Database. Available at <http://www.hoip.jp/>, 2014.
- [8] Yun Fu, Guodong Guo, and T.S. Huang. Age synthesis and estimation via faces: A survey. *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, 32(11):1955–1976, Nov 2010.
- [9] Yun Fu and T.S. Huang. Human age estimation with regression on discriminative aging manifold. *Multimedia, IEEE Transactions on*, 10(4):578–584, June 2008.
- [10] Yun Fu, Ye Xu, and T.S. Huang. Estimating human age by manifold analysis of face pictures and regression on aging features. In *Multimedia and Expo, 2007 IEEE International Conference on*, pages 1383–1386, July 2007.
- [11] A. Gallagher and T. Chen. Understanding images of groups of people. In *Proc. CVPR*, 2009.

- [12] Xin Geng, Zhi-Hua Zhou, Yu Zhang, Gang Li, and Honghua Dai. Learning from facial aging patterns for automatic age estimation. In *Proceedings of the 14th Annual ACM International Conference on Multimedia*, MULTIMEDIA '06, pages 307–316, New York, NY, USA, 2006. ACM.
- [13] Guodong Guo, Yun Fu, C.R. Dyer, and T.S. Huang. Image-based human age estimation by manifold learning and locally adjusted robust regression. *Image Processing, IEEE Transactions on*, 17(7):1178–1188, July 2008.
- [14] Guodong Guo, Yun Fu, C.R. Dyer, and T.S. Huang. A probabilistic fusion approach to human age prediction. In *Computer Vision and Pattern Recognition Workshops, 2008. CVPRW '08. IEEE Computer Society Conference on*, pages 1–6, June 2008.
- [15] Guodong Guo and Guowang Mu. Simultaneous dimensionality reduction and human age estimation via kernel partial least squares regression. In *Computer Vision and Pattern Recognition (CVPR), 2011 IEEE Conference on*, pages 657–664, June 2011.
- [16] Guodong Guo and Guowang Mu. A framework for joint estimation of age, gender and ethnicity on a large database. *Image and Vision Computing*, 32(10):761 – 770, 2014. Best of Automatic Face and Gesture Recognition 2013.
- [17] Guodong Guo, Guowang Mu, Yun Fu, and Thomas S. Huang. Human age estimation using bio-inspired features. In *CVPR*, pages 112–119. IEEE, 2009.
- [18] Hu Han, Charles Otto, and Anil K. Jain. Age estimation from face images: Human vs. machine performance. In *ICB'13*, pages 1–8, 2013.
- [19] Lin Hong, Anil K. Jain, and Sharath Pankanti. Can multibiometrics improve performance. Technical Report MSU-CSE-99-39, Department of Computer Science, Michigan State University, East Lansing, Michigan, December 1999.
- [20] Anil K. Jain, Sarat C. Dass, and Karthik Nandakumar. Soft biometric traits for personal recognition systems. In David Zhang and Anil K. Jain, editors, *ICBA*, volume 3072 of *Lecture Notes in Computer Science*, pages 731–738. Springer, 2004.

- [21] Praveen Srinivasan JB Duler. Visada, Personalized Beauty Discovery from a Selfie. <http://visada.me/>, 2015. [Online; accessed 08-March-2015].
- [22] Yehuda Koren, Robert Bell, and Chris Volinsky. Matrix factorization techniques for recommender systems. *Computer*, 42(8):30–37, August 2009.
- [23] A. Lanitis. FG-NET Aging Data Base, November 2007. Available at [http://www.eecs.qmul.ac.uk/~yf300/FG\\_NET\\_data/index.html](http://www.eecs.qmul.ac.uk/~yf300/FG_NET_data/index.html).
- [24] A. Lanitis. Age estimation based on head movements: A feasibility study. In *Communications, Control and Signal Processing (ISCCSP), 2010 4th International Symposium on*, pages 1–6, March 2010.
- [25] A. Lanitis, C. Draganova, and C. Christodoulou. Comparing different classifiers for automatic age estimation. *Trans. Sys. Man Cyber. Part B*, 34(1):621–628, February 2004.
- [26] A. Lanitis, C.J. Taylor, and T.F. Cootes. Modeling the process of ageing in face images. In *Computer Vision, 1999. The Proceedings of the Seventh IEEE International Conference on*, volume 1, pages 131–136 vol.1, 1999.
- [27] A. Lanitis, C.J. Taylor, and T.F. Cootes. Toward automatic simulation of aging effects on face images. *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, 24(4):442–455, Apr 2002.
- [28] Greg Linden, Brent Smith, and Jeremy York. Amazon.com recommendations: Item-to-item collaborative filtering. *IEEE Internet Computing*, 7(1):76–80, January 2003.
- [29] Khoa Luu, Karl Ricanek, Tien D. Bui, and Ching Y. Suen. Age estimation using active appearance models and support vector machine regression. In *Proceedings of the 3rd IEEE International Conference on Biometrics: Theory, Applications and Systems*, BTAS’09, pages 314–318, Piscataway, NJ, USA, 2009. IEEE Press.
- [30] Khoa Luu, Keshav Seshadri, Marios Savvides, Tien D. Bui, and Ching Y. Suen. Contourlet appearance model for facial age estimation. In Anil K. Jain, Arun Ross, Salil Prabhakar, and Jaihie Kim, editors, *IJCB*, pages 1–8. IEEE, 2011.

- [31] Y. Makihara, M. Okumura, H. Iwama, and Y. Yagi. Gait-based age estimation using a whole-generation gait database. In *Biometrics (IJCB), 2011 International Joint Conference on*, pages 1–6, Oct 2011.
- [32] Bingbing Ni, Zheng Song, and Shuicheng Yan. Web image mining towards universal age estimator. In *Proceedings of the 17th ACM International Conference on Multimedia*, MM '09, pages 85–94, New York, NY, USA, 2009. ACM.
- [33] P.Jonathon Phillips, Harry Wechsler, Jeffery Huang, and Patrick J. Rauss. The {FERET} database and evaluation procedure for face-recognition algorithms. *Image and Vision Computing*, 16(5):295 – 306, 1998.
- [34] N. Ramanathan and R. Chellappa. Face verification across age progression. *Image Processing, IEEE Transactions on*, 15(11):3349–3361, Nov 2006.
- [35] N. Ramanathan and R. Chellappa. Modeling age progression in young faces. In *Computer Vision and Pattern Recognition, 2006 IEEE Computer Society Conference on*, volume 1, pages 387–394, June 2006.
- [36] N. Ramanathan, R. Chellappa, and S. Biswas. Computational methods for modeling facial aging: A survey. *Journal of Visual Languages and Computing*, 20(3):131 – 144, 2009.
- [37] K. Ricanek and T. Tesafaye. Morph: a longitudinal image database of normal adult age-progression. In *Automatic Face and Gesture Recognition, 2006. FGR 2006. 7th International Conference on*, pages 341–345, April 2006.
- [38] T. Sim, S. Baker, and M. Bsat. The cmu pose, illumination, and expression (pie) database. In *Automatic Face and Gesture Recognition, 2002. Proceedings. Fifth IEEE International Conference on*, pages 46–51, May 2002.
- [39] Kazuya Ueki, Teruhide Hayashida, and Tetsunori Kobayashi. Subspace-based age-group classification using facial images under various lighting conditions. In *Proceedings of the 7th International Conference on Automatic Face and Gesture Recognition*, FGR '06, pages 43–48, Washington, DC, USA, 2006. IEEE Computer Society.



- [40] Tao Wu, Pavan K. Turaga, and Rama Chellappa. Age estimation and face verification across aging using landmarks. *IEEE Transactions on Information Forensics and Security*, 7(6):1780–1788, 2012.
- [41] Baiqiang Xia, Boulbaba Ben Amor, Mohamed Daoudi, and Hassen Drira. Can 3D Shape of the Face Reveal your Age? In *International Conference on Computer Vision Theory and Applications*, Lisbonne, Portugal, January 2014.