Master in Artificial Intelligence (UPC-UB-URV)

Master of Science Thesis

Automatic Age Estimation in Still Images

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Acknowledgements

To write some time in the future...

Abstract

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3.1 Historical context

One of the earliest works in age estimation was done by A. Lanitis et al. [24, 25, 26] where the age is modelled by a quadratic aging function. They propose two different aging estimation methods: weighted appearance specific method [25, 26] -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 [24] -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. [33, 34] 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 [33] and estimating the age of young faces using the facial growth geometry [34]. 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 on 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 problem 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. [28, 29] reduced dimensionality by using facial landmarks and Active Shape Models (ASM) [28] and an improved version, Contourlet Appearance Model (CAM) [29], where they prove the efficiency of using facial landmarks. Then T. Wu et al. [39] 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. [23] performed a first approach to age estimation using Head and Mouse tracking movements, Y. Makihara et al. [30] used a gait-based database to estimate the age, B. Xia et al. [40] proposed an age estimation method based on 3D face images.

There are also some surveys in age estimation by N. Ramanathan et al. [35] and Y. Fu et al. [8].

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

3.2 Applications

There are many real-world application related to age estimation.

Age estimation has always been a topic of interest because of its applications, however its a difficult task and it was not until few years ago that the community started getting useful results. The main applications for age estimation methods are the following:

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3.2.1 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 technology 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.

3.2.2 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, hight, weigh, gender, ethnicity and eye colour, are used in combination with classic biometric traits.

3.2.3 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.

3.2.4 Human-computer interaction

With the growth of e-commerce, companies want to offer a more personalized experience to the customers. 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 [27] uses a recommender system to suggest products to the potential buyers according to their previous purchases, Netflix [21] 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.

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3.3 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 3.1 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.

[1] Surgical points, fracture or laceration on face.

Database	#Faces	#Subj.	Range	Type of age	Controlled Env.	Balanced age Distr.	Other annotation
FG-NET [22]	1.002	82	0 - 69	Real Age	No	No	68 Landmarks
Morph2 [36]	55.134	-	16 - 77	Real Age	Yes	No	-
YGA [9]	8.000	1.600	0 - 93	Real Age	No	No	-
FERET [32]	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[1]
PIE [37]	41.638	68	-	Real Age	Yes	No	-
Images of Gropus [11]	28.231	-	0 - 66+	Age group	No	No	-
WIT-BD [38]	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 [31]	219.892	-	1 - 80	Real Age	No	No	-
OUI-Adience [6]	26.580	2.284	0 - 60+	Age Group	No	No	Gender

Table 3.1: Age-based Databases

Publication	Year	Database (#subjects, #images)	Age Image Representation	Method	Accuracy	MAE
A. Lanitis et al. [26]	2002	Private (60, 500)	Active Appearance Models	Quadratic Aging Function	71%	3.94 ± 3.8
A. Lanitis et al. [24]	2004	Private (40, 400)	Active Appearance Models	Quadratic Aging Function	N/A	3.82 ± 5.58
X. Geng et al. [12]	2006	FG-NET (82, 1.002)	AGES	Regression	N/A	6.77

Table 3.2: Age Estimation Methods

4 Data Collection

4.1 Web Application

4.2 HuPBA Age Dataset

5 Data Collection

5.1 Web Application

5.2 HuPBA Age Database

6 Experimental Results

7 Conclusions and Future work

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