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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List of Algorithms

1 Introduction

Computer Vision is a field in Artificial Intelligence that has being going on since 1960 with digital image processing by computers was possible. Since the beginning of artificial vision, facial analysis has been a major interest in the research community (not just in Computer Vision but in other scientific areas such as biology [7], psychology [10], neuroscience [12] and sociology [30]) because its difficulty and its applications. Some of these applications are automatic detection of facial expressions [6], face detection [27], face recognition [53], face verification [51] and automatic estimation of age [17], gender [2] and ethnicity [26].

Age estimation is a field within the facial analysis area in Computer Vision that tackles the problem of automatically predicting the age of people from visual data (still images, video data, depth maps, etc.). One of the main issues that the age estimation problem has is that there are many factors that influence human perception of age, some factors affect the aging of a person [49], such as smoking, drinking alcohol, doing sports, alimentation, etc. and others affect the face appealing such as scars, plastic surgery, make-up, facial hair, etc.

Some definitions should be established beforehand regarding the concept of human age:

- *Real age*: The actual age (number of years passed since the person was born).
- *Apparent age*: Perceived age from humans from the visual appearance.
- *Estimated age*: The predicted age by a machine from the visual appearance.

This work aims to create and analyse the first database in the literature containing real age and apparent age annotations for the face images. In order to do so, a web-based application has been developed using *Facebook API* to facilitate a collaborative and competitive collection of images.

Analysis of the two annotations (real and apparent) with two different baselines.

Most of the related work in the literature are based on estimating real age. However, in this work, apparent age will also be studied

Challenge

Given the innovative of the database, ChaLearn is going to prepare a challenge for the ICCV conference, challenging the participants to upload better solutions to the problem than the ones presented here.

2 State of the art

2.1 Historical context

Talk about soft computing

Age estimation has historically been one of the most challenging problems within the field of facial analysis [13][24]. Despite the multiple applications in many different areas of age estimation there are relatively few publications compared to other topics in facial analysis. This difficulty is due to many factors:

- Depending on the application scenario, the age estimation problem can be taken as a multiclass classification problem or a regression problem.
- Large database are difficult to collect, especially series of chronological image from the same individuals.
- The factors the affect the aging process are uncontrollable and person specific [15][17][45].

Talk about close related fields (age synthesis, face validation, etc)

The age estimation problem has generally two stages or blocks, the first one is the age representation in the images and the second one the estimation itself with the computed data. There are many different techniques for both stages. [13]

2.1.1 Age Representation

Age Representation: List of techniques

2.1.2 Age Estimation Algorithm

2.1.2.1 Classification Methods

2.1.2.2 Regression Methods

2.1.2.3 Hybrid Methods

2.1.3 Related areas

Age Estimation Algorithm: Classificaiton, Regression and Hybrid

One of the earliest works in age estimation was done by A. Lanitis et al. [34, 35, 36] where the age is modelled by a quadratic aging function. They propose two different aging estimation methods: weighted appearance specific method [35, 36] -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 [34] -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. [18]. 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) [18]. Where each face image is represented by a point in the aging pattern subspace.

Later N. Ramanathan et al. [45, 46] 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 [45] and estimating the age of young faces using the facial growth geometry [46]. 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 [15, 14]. Each face image is assigned to its low-dimensional representation via manifold embedding. Following this approach G. Guo and Y. Fu et al. [19] 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 [21], 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 [20], where they propose probabilistic fusion approach, or [23] 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. [24] uses the BIF features in an hybrid classification framework improving the previous results. G. Guo et al. [22], 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. [15], K. Luu et al. [38, 39] reduced dimensionality by using facial landmarks and Active Shape Models (ASM) [38] and an improved version, Contourlet Appearance Model (CAM) [39], where they prove the efficiency of using facial landmarks. Then T. Wu et al. [54] 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. [33] performed a first approach to age estimation using Head and Mouse tracking movements, Y. Makihara et al. [40] used a gait-based database to estimate the age, B. Xia et al. [55] proposed an age estimation method based on 3D face images.

There are also some surveys in age estimation by N. Ramanathan et al. [47] and Y. Fu et al. [13].

More recently studies have obtained a very high accuracy in face validation using deep learning [51].

2.2 Applications

There are many real-world application related to age estimation. Automatic age estimation is useful in situations where there is no 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 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.

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 [25] 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 [28], such as age, hight, weigh, 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 [37] uses a recommender system to suggest products to the potential buyers according to their previous purchases, Netflix [31] 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 [29] is an example of the use of age estimation for recommend products.

2.3 Age-based Datasets

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 with the number of samples, the number of subjects, the age range, the type of age annotations and additional information if any. The *FG-NET* [36] is one of the first and most consolidated age database, it is used to compare with other age estimation methods.

After an initial interest in automatic age estimation from images dated back to the early 2000s [34], [36], [41], research in the field has experienced a renewed interest from 2006 on, since the availability of large databases like *MORPH-Album 2* [48], which contains 55 times more age-annotated images than the *FG-NET* database.

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

Database	#Faces	#Subj.	Range	Type of age	Controlled Env.	Balanced age Distr.	Other annotation
FG-NET [36, 32]	1,002	82	0 - 69	Real Age	No	No	68 Facial Landmarks
GROUPS [16]	28,231	28,231	0 - 66+	Age group	No	No	-
PAL [41]	580	580	19 - 93	Age group	No	No	-
FRGC [43]	44,278	568	18 - 70	Real Age	Partially	No	-
MORPH2 [48]	55,134	13,618	16 - 77	Real Age	Yes	No	-
YGA [14]	8,000	1,600	0 - 93	Real Age	No	No	-
FERET[44]	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 [50]	41,638	68	-	Real Age	Yes	No	-
WIT-BD [52]	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 [1]	8,000	8,000	9 - 89	Real Age	Yes	Yes	-
HOIP [11]	306,600	300	15 - 64	Age Group	Yes	No	-
Ni's Web-Collected Database [42]	219,892	-	1 - 80	Real Age	No	No	-
OUI-Adience [9]	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. [36]	2002	Private (60, 500)	Active Appearance Models	Quadratic Aging Function	71%	3.94 ± 3.8
A. Lanitis et al. [34]	2004	Private (40, 400)	Active Appearance Models	Quadratic Aging Function	N/A	3.82 ± 5.58
X. Geng et al. [18]	2006	FG-NET (82, 1.002)	AGES	Regression	N/A	6.77

Table 2.2: Age Estimation Methods

3 Data Collection

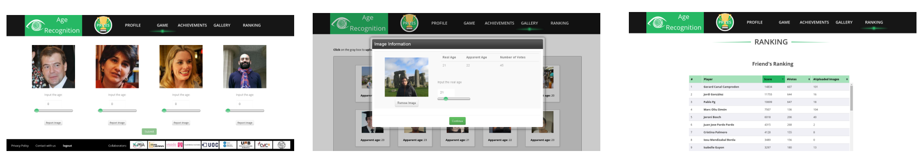
As described in Section 2.3 there are many age-based databases of facial images. However, all existing datasets are based on real age estimation.

The idea of this work is to compare the performance between predicting real or apparent age labels. In order to do so, a web-based application has been developed using *Facebook's API* to collect a database with these annotations.

3.1 Web Application

The aim of the web-based application was to speed up the collection and labelling processes and reach more people with broader backgrounds to create an age database as diverse as possible. These processes were implemented in a gamified [1] fashion so the experience of the users with the application was satisfactory and engaging.

The application uses the API of Facebook to create a ranking with the user's Facebook friends and add a factor of competitiveness to the game, and also to collect information about the labellers such as gender, age and nationality.



(a) Game Panel **(b)** Gallery Panel **(c)** Ranking Panel

Figure 3.1: Age Recognition Application. (a) User can see the images of the rest of participants and vote for the apparent age. (b) User can upload images and see their uploads in the gallery, they also can see what is the average age the other users think the people of their uploaded images look like. (c) User can see the points they achieves by uploading and voting photos and the ranking among their friends and all the participants in the application.

[1]Gamification is the use of game thinking and game mechanics in non-game contexts to engage users in solving problems and increase users' self contributions. [8]

3.1.1 Gamification Strategy

The web-application is basically a platform to label and upload images, which is not funny or motivating. However, using gamification techniques the labeller engagement can be increased. The gamification strategies used were mainly three:

- The users or players get **points** for uploading and voting (labelling) images. The closer the vote is to the apparent age (average current voted age) the more points the player gets. This strategy is pretended to persuade the users to wrongly label the images.
- Two **ranking** tables are shown to the users, one with the ranking positions of the users' Facebook friends and another showing the global classification. This strategy was created with the purpose of increase engagement between users, making them compete with each other.
- Thanks to one of the Challenge sponsors, California Naturel [2], a bunch of cosmetic lots were offer as a **prize** for the ones who lid the global ranking. The aim of the prize was to push participation further.

3.1.2 Application Structure

The web application

We ask the users to upload images of a single person and we give them tools to crop the image if necessary, we also ask them to give the real age (or as close as possible) of the person in uploaded image, allowing more analysis and comparisons with real age and apparent age.

3.1.3 Troubleshooting

The application was developed using Django's framework

3.2 HuPBA Age Dataset

Few weeks after release the application we have alread collected near 1000 images and near 10000 votes. These numbers will continue growing in order

[2] `http://www.californianaturel.com/`

to generate the future competition. Some of the properties of the database which is being collected with the web application are listed below:

- Thousands of faces labeled by many users.
- Images with background.
- Non-controlled environments.
- Non-labeled faces neither landmarks, making the estima- tion problem even harder.
- One of the first datasets in the literature including estimated age labeled by many users to define the ground truth with the objective of estimating the age.
- The evaluation metric will be pondered by the mean and the variance of the labeling by the participants.
- The dataset also provides for each image the real age although not used for recognition (just for analysis purposes).

In the same way for all the labelers we have their nationality, age, and gender, which will allow analyzing demographic and other interesting studies among the correlation of labelers. In relation to the properties of existing datasets shown in Table I, ours include labels of the real age of the individuals and the apparent age given by the collected votes, both age distributions are shown in the Figure 2. The images of our database has been taken under very different conditions, which makes it more challenging for recognition purposes.

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

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