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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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 [12], psychology [15], neuroscience [21] and sociology [46]) because its difficulty and its applications. Some of these applications are automatic detection of facial expressions [10], face detection [41], face recognition [72], face verification [70] and automatic estimation of age [27], gender [3] and ethnicity [40].

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 [68], 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.

1.1 Goals

This work aims to study the differences (if any) of automatic age estimation from real age labels and apparent age labels. Given that do not exist any face image dataset with this two label annotations, a database with such requisites has been created. In order to do so, a web-based application was developed using the *Facebook API* to facilitate a collaborative and competitive collection of face images.

As a consequence of this work, the first database in the literature containing real age and apparent age annotations for the face images was created and analysed. This database will allow researchers to tackle a different and new sub-problem of age estimation, *Apparent Age Estimation*.

In *Real Age Estimation* other external factors such as time evolution, habits and surgeries have to be taken into account. However *Apparent Age Estimation* is based purely in the perception field.

1.2 Age Challenge

Given the innovative of the database, the HuPBA (Human Pose and Behaviour Analysis) research group [16] together with the company ChaLearn [8] are going to prepare an international challenge competition later this year and present the results in a workshop in the ICCV conference 2015 edition within the ChaLearn Looking at People series [9] [17] [18] [19].

The challenge pretends to establish a State of the Art techniques for Apparent Age Estimation and compare the methods and the results with the Real Age Estimation State of the Art.

2 State of the art

Age estimation has historically been one of the most challenging problems within the field of facial analysis [22][36]. 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 ageing process are uncontrollable and person specific [24][27][63].

The age estimation problem has generally three stages or blocks, the first one is the face detection and alignment, the second one is the age representation in the images and the third one the estimation itself with the computed data. There are many different techniques for both stages. [22]

2.1 Face Detection and Alignment

See whether to write this section or not

2.2 Age Representation

Age Representation is a very important step in the age estimation process. A good age representation will contain enough variation of the data to express the full complexity of the problem. There are many ways in the literature to represent ageing factors from an image, the most important are described below.

2.2.1 Anthropomorphic Models

The first known work on age estimation from facial images was done by Y. Kwon and N. Lobo [48]. Their approach is based in cranio-facial development theory using geometrical ratios between different face regions to classify images into one of three age groups (babies, young adults and senior adults). They used frontal images in a very strict set up to be able to locate all face components. N. Ramanathan et al. [64, 65] used a similar approach in this case using 8 ratios rather than the 6 used by Y. Kwon et al.

The problem of this model 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. It is also a problem that the methods require of frontal images since it limits the future applications.

2.2.2 Active Appearance Models

Active Appearance Models (AAM) is a statistical shape model proposed by T.F Cootes et al. [11]. This model contains the shape and grey-level appearance of the object of interest which can generalize to almost any valid example. This technique has been used to find the shape of faces by many researchers. A. Lanitis et al. [52, 53, 51] were the first in extend the AAM model for age estimation by defining an ageing function $age = f(b)$, where $\mathbf{f}$ is an ageing function and $\mathbf{b}$ is a vector containing the parameters learned by the AAM.

A. Lanitis et al. [51] also tried different classifiers such as Quadratic Functions, Shortest Distance Classifier, Supervised Neural Network and Unsupervised Neural Network. Among all of them they reported that Quadratic Functions where the ones performing best.

This model captures shape and texture information and in general performs better than the *Anthropomorphic Models*. This method can deal with any range of ages rather than just with young ages like the previous model. However, as suggested by X. Geng et al. [28], the ageing functions is empirically determined, so there is no evidence suggesting that the relation between face and age is described just by a quadratic function.

2.2.3 Ageing Pattern Subspace

X. Geng et al. [27, 28] were the ones that explored this model initially which is called AGing pattErn Subspace (AGES). They define an *ageing pattern* as a sequence of personal face images sorted in time order. Given a grey-scale face image $\mathbf{I}$, where $\mathbf{I}(x, y)$ determines the intensity of the pixel (x, y), then an ageing pattern can be represented as a three-dimensional matrix $\mathbf{P}$, where $\mathbf{P}(x, y, t)$ is the intensity of the pixel (x, y) in the face image at the time t. The images vector is filled with the available face images leaving empty the missing faces in the t axis. Now, the images in the age pattern vector can be precessed and transformed into meaningful feature vectors.

In order to extract the features X. Geng use AAM as used in [52] since they capture the shape and texture of the face images. By representing ageing patterns in this way, the concepts of identity and time are naturally integrated into the data without any pre-assumptions.

The principal drawback of the AGES method is that assumes that there are images of the same individual at different ages, which is not true in all the age databases, like in the Yamaha Gender and Age (YGA) database [23], and it is difficult to collect such a databases.

2.2.4 Age Manifold

The manifold learning methods are applied to find a sufficient embedding space and model the low-dimensional manifold data with a multiple linear regression function. Y. Fu et al. [23, 24] were the first in proposing a manifold embedding approach for the age estimation problem.

The objective of this method is to find the low-dimensional representation in the embedded subspace capturing the intrinsic data distribution and geometric structure as well as its representation. G. Guo et al. [30] [31] shows that the Orthogonal Locality Preserving Projections (OLPP) [7] is a good an effective algorithm to connect the manifold learning with subspace learning. In a posterior work [33], G. Guo et al. introduces a new approach, using kernel partial least square (KPLS) regression which reduces feature dimensionality and learn the ageing function in a single step.

Then T. Wu et al. [73] proposed to model the facial shapes as points on a Grassmann manifold. Age estimation is then considered as regression and classification problems on this manifold. Then, they proposed a method for combining this shape-based approach with other texture-based algorithms.

The main drawback of the age manifold representation is the number of training instances required to learn the embedded manifold with statistical sufficiency.

2.2.5 Appearance Models

Appearance Models focus on wrinkles, face texture and pattern analysis. From the beginning, researchers have tried to capture wrinkles and distinguish them from facial lines. Y. Kwon et al. [48] proposed a wrinkle detector based on snakelets [45] placed into key wrinkle areas of the face. Hayashi et al. [37] [38] [42] combined both shape and texture to estimate age and gender. In Hayashi's proposed approach, the skin is extracted based on a shape model and then a histogram equalization is applied to emphasize wrinkles.

Other researchers have used the texture descriptor Local Binary Patterns (LBP) [2] in the age estimation problem, such as [29] [75] obtaining good classification results with Nearest Neighbour and SVM classification algorithms. The Gabor [55] filter texture descriptor has also been used in the age estimation task [26], probing to be more discriminative than LBP.

G. Guo et al. [35] proposed to use Biological Inspired Features (BIF) [67] for age estimation via faces. The BIF descriptor tries to mimic how the visual cortex works, with a hierarchy of increasingly sophisticated representations.

To Finish

G. Guo et al. proposed different approaches to the age estimation problem such as [32], where they propose probabilistic fusion approach, or [35] 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. [36] uses the BIF features in an hybrid classification framework improving the previous results. G. Guo et al. [34], 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. [24], K. Luu et al. [56, 57] reduced dimensionality by using facial landmarks and Active Shape Models (ASM) [56] and an improved version, Contourlet Appearance Model (CAM) [57], where they prove the efficiency of using facial landmarks.

2.2.6 Other

To Finish

There are some other variations of the age estimation problem which require different approaches.

Later N. Ramanathan et al. [63] approached the age estimation problem by estimating the age difference between two face images of the same individual based on a Bayesian age-difference classifier.

Other different variations of the problem has been addressed, A. Lanitis et al. [50] performed a first approach to age estimation using Head and Mouse tracking movements, Y. Makihara et al. [58] used a gait-based database to estimate the age, B. Xia et al. [74] proposed an age estimation method based on 3D face images.

2.3 Age Estimation Algorithm

Given an age representation, the next step is to determine the individual's age out of the ageing features. Age labels can be seen as a discrete set of classes or as a continuous label space, hence classification and regression methods can be used.

2.3.1 Classification Methods

Finish

2.3.2 Regression Methods

Finish

2.3.3 Hybrid Methods

Finish

2.4 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

Publication	Year	Database (#subjects, #images)	Age Image Representation	Method	Accuracy	MAE
A. Lanitis et al. [53]	2002	Private (60, 500)	Active Appearance Models	Quadratic Aging Function	71%	3.94 ± 3.8
A. Lanitis et al. [51]	2004	Private (40, 400)	Active Appearance Models	Quadratic Aging Function	N/A	3.82 ± 5.58
X. Geng et al. [28]	2006	FG-NET (82, 1.002)	AGES	Regression	N/A	6.77
Add More Methods						

Table 2.1: Age Estimation Methods

identify the individual, such as a government employee, but want to know his or her age.

2.4.1 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.

2.4.2 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 [39] 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 [43], such as age, hight, weigh, gender, ethnicity and eye colour, are used in combination with classic biometric traits.

2.4.3 Age-based Indexing Face Databases

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.

2.4.4 Human-Computer Interaction and e-Commerce

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 [5] indexes the search results so the links that appear first appeal more to the user, Amazon [54] uses a recommender system to suggest products to the potential buyers according to their previous purchases, Netflix [47] 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 [44] is an example of the use of age estimation for recommend products.

2.5 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 2.2 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* [53] 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 [51], [53], [59], research in the field has experienced a renewed interest from 2006 on, since the availability of large databases like

Database	#Faces	#Subj.	Range	Type of age	Controlled Env.	Balanced age Distr.	Other annotation
FG-NET [53, 49]	1,002	82	0 - 69	Real Age	No	No	68 Facial Landmarks
GROUPS [25]	28,231	28,231	0 - 66+	Age group	No	No	-
PAL [59]	580	580	19 - 93	Age group	No	No	-
FRGC [61]	44,278	568	18 - 70	Real Age	Partially	No	-
MORPH2 [66]	55,134	13,618	16 - 77	Real Age	Yes	No	-
YGA [23]	8,000	1,600	0 - 93	Real Age	No	No	-
FERET[62]	14,126	1,199	-	Real Age	Partially	No	-
Iranian face [4]	3,600	616	2 - 85	Real Age	No	No	Kind of skin and cosmetic points [1]
PIE [69]	41,638	68	-	Real Age	Yes	No	-
WIT-BD [71]	26,222	5,500	3 - 85	Age group	No	No	-
Caucasian Face Database [6]	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 [20]	306,600	300	15 - 64	Age Group	Yes	No	-
Ni's Web-Collected Database [60]	219,892	-	1 - 80	Real Age	No	No	-
OUI-Adience [14]	26.580	2.284	0 - 60+	Age Group	No	No	Gender

Table 2.2: Age-based Databases

MORPH-Album 2 [66], which contains 55 times more age-annotated images than the *FG-NET* database.

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

3 Data Collection

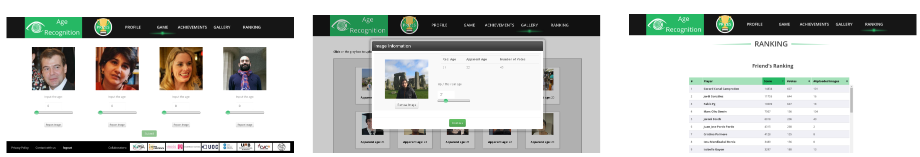
As described in Section 2.5 there are many age-based databases of facial images. However, all existing datasets are based on real age estimation.

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.

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:

[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. [13]

- 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.
- A system of **achievements** was implemented, including the four types of achievements shown in the Table 3.1.

Achievement	**Description**
Share it!	Invite your friends to play and you will get stars.
Precision	The better your guesses, the higher your rank.
Vote!	Vote on more images to get more stars.
Add Pictures!	Upload more images to get more stars.

Table 3.1: List of achievements with its description

- 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

When the users access the web for first time they have to register using their Facebook account and accept the terms and conditions for the application usage (further explanation of the legal terms in the Subsection 3.1.3). After registration the *How to play* panel will be displayed giving a short description of all the parts of the application.

As it is shown in the Figure 3.1, at the top of the site, there is a control menu that allows the users to move through all the site with just one click. A description of the different panels is written below:

- **Profile**: In this section the users can keep track of their statistics (Number of uploaded images, number of votes, points obtained and global ranking position).

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

- **Game**: This is the main section (Figure 3.1a), four images are shown at the same time and the users are asked to guess the age of all of them. They can report the images if any of them is considered offensive, bad quality, more than one person appear in the image, etc.
- **Achievements**: In this panel the users can keep track of their achievements and shows the next goals.
- **Gallery**: In this section (Figure 3.1b) the players are able to see the images they have uploaded and see how many people have voted on them and get an estimation of the people opinion. They are also able to upload new images in this panel, while uploading they are asked to crop (if necessary) and specify the real age of the person in the image.
- **Ranking**: The last panel (Figure 3.1c) allows users to compare their scores with their Facebook friends in the *Friends Ranking* and to all the players in the *Global Ranking*.

3.1.3 Troubleshooting

When creating a public image database there are at least two things to keep in mind: image quality and image license.

To have good quality images the users are asked to upload images of a single person, preferable a portrait. In order to facilitate these requisites, the option of cropping the image is given in the uploading step. Also a minimum image size is setted to avoid tiny images to be uploaded.

When users first register in the website they are asked to read and accept the terms and conditions which stablish that the uploaded images rights must be hold by the user or the images have a license that allows the use of them and their redistribution free of charge. The users are also warned that the images will be used for research purposes and will be publicly available for this use.

3.2 HuPBA Age Dataset

This section will describe and analyse the collected database called HuPBA Age Dataset.

The Table 3.2 shows the main characteristics of the database. The web application gather more than 1500 images and almost 15000 votes, which means almost 10 votes pes image in average.

<table>
<tr><th colspan="2">Features</th><th>Count</th></tr>
<tr><td colspan="2">Images</td><td>1506</td></tr>
<tr><td rowspan="2">Users</td><td>female</td><td>44</td></tr>
<tr><td>male</td><td>110</td></tr>
<tr><td rowspan="2">Votes</td><td>female</td><td>1753</td></tr>
<tr><td>male</td><td>13144</td></tr>
</table>

Table 3.2: HuPBA Age Database Characteristics

The distribution of the different age labels among the ages (Figure 3.2) is not uniform as ideally should be, but instead contains more instances of people form ages in between 20 and 30 than the rest of ages. There is also a very low incidence individuals under 15 years old and over 70 years old. It can also be observed that both real and apparent age have a very similar distribution.

Show statistic analysis of the database

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

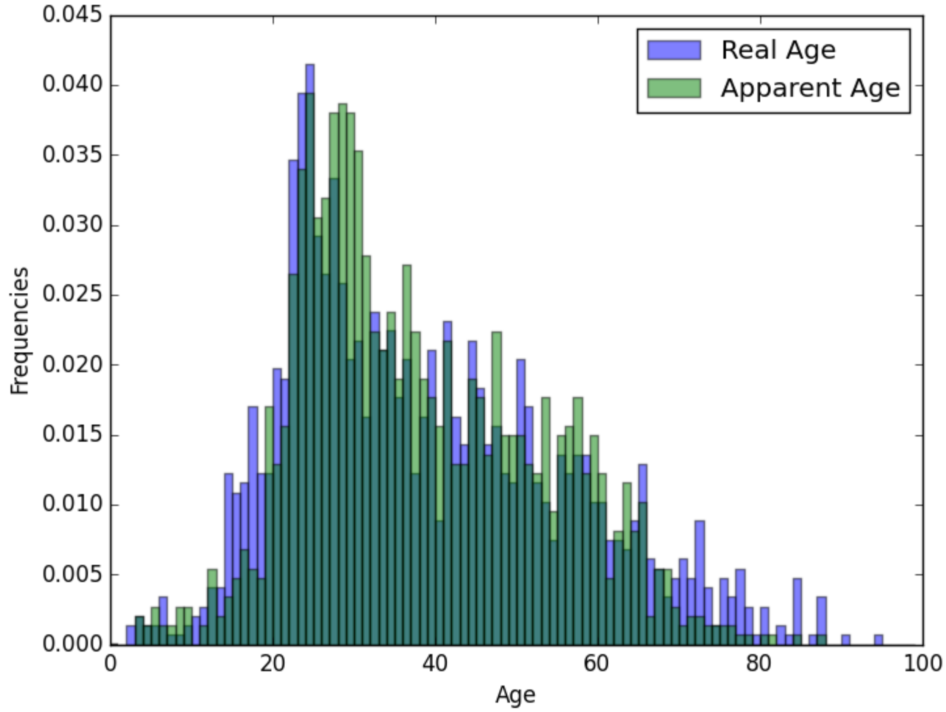


Figure 3.2: Labels Distribution

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.

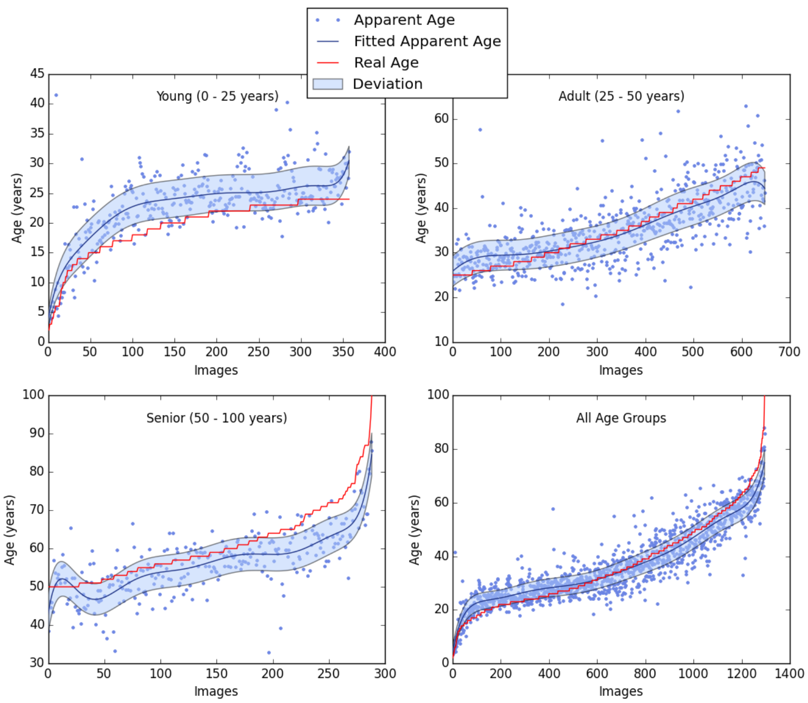


Figure 3.3: Labels Distribution

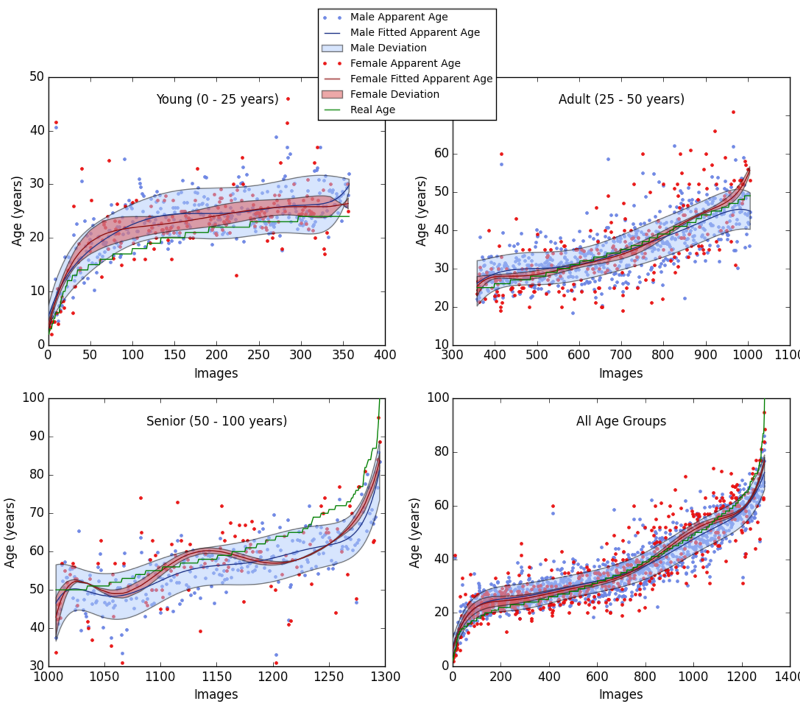


Figure 3.4: Gallery Panel

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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