An Overview of Research Activities in Facial Age Estimation Using the FG-NET Aging Database

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Abstract. The FG-NET aging database was released in 2004 in an attempt to support research activities related to facial aging. Since then a number of researchers used the database for carrying out research in various disciplines related to facial aging. Based on the analysis of published work where the FG-NET aging database was used, conclusions related to the type of research carried out in relation to the impact of the dataset in shaping up the research topic of facial aging, are presented. In particular we focus our attention on the topic of age estimation that proved to be the most popular among users of the FG-NET aging database. Through the review of key papers in age estimation and the presentation of benchmark results the main approaches/directions in facial aging are outlined and future trends, requirements and research directions are drafted.

Keywords: Facial age estimation, Aging databases, FG-NET Aging Database

1 Introduction

The availability of public databases can play a crucial role in the development of a research field as it enables researchers to get engaged in research activities quickly and at the same time it promotes the idea of comparative evaluation. Especially in cases where the data collection process demands a lengthy procedure, the availability of public datasets can have a substantial impact on a field. In the research area of soft biometrics a typical example where the generation of suitable databases is, by nature, a lengthy process involves face aging datasets displaying age-separated face images of the same individual. Due to the non-availability of face aging databases, up to 2004 only a small number of researchers considered the problem of facial aging, mainly based on small in-house face datasets containing age-separated face images [37] [34] [21] [26] [25]. Back in 2004 two face aging datasets were made publicly available: The MORPH [36] and the FG-NET Aging Dataset (FG-NET-AD) [22] . When MORPH was first released it contained a large number of images but only about three instances of the same person. On the other hand the FG-NET-AD contained a small number of images and subjects, but included about 12 age-separated images per subject. Despite the fact that none of the two datasets was ideal, both datasets played an instrumental role in initiating research activities in the area of facial aging. The availability of public aging databases promoted the topic of facial age estimation among the most extensively researched topics in soft biometrics.

Detailed coverage of the topics of facial aging can be found in related survey papers [35], [11] and books [9]. In [32] a technical report on the performance of age estimation algorithms is presented with emphasis given on the analysis of the results obtained rather than the adopted methodologies. Unlike the aforementioned survey papers, in this paper we concentrate our attention on the use of the FG-NET-AD. As part of this effort an analysis related to research publications reporting work where the FG-NET-AD was utilized is presented. In particular an analysis related to thematic areas of published papers over the years, an overview of the most representative papers reported in the literature and a collection of benchmark results are presented. The analysis of research outcomes related to the FG-NET-AD can be used for formulating trends and directions adopted in facial aging analysis and most importantly for shaping future directions in this area. In particular we focus our attention on research related to facial age estimation that attracted the interest of the majority of researchers working in facial aging.

The remainder of the paper is structured as follows. In section 2 information about the FG-NET-AD and statistics related to the dataset usage are presented. An overview of key papers in facial age estimation that report experimental results using the FG-NET-AD and a summary of comparative results are presented in sections 3 and 4. In Section 5 a discussion related to future research directions and needs for additional aging datasets are described, followed by concluding comments.

2 Database Description

2.1 FG-NET project

The FG-NET-AD was generated as part of the Project FG-NET (Face and Gesture Recognition Network) [10]. FG-NET was funded by the European Union as part of the 5th Framework Programme, Information Society Technologies in the category of initiative Support Measures Networks of Excellence and Working Groups. The project consortium was comprised of the University of Manchester (UK) (project coordinator), Technological University of Munich (Germany), INRIA (France), Aalborg University (Denmark), Cyprus College (Cyprus) and IDIAP (Switzerland). One of the major aims of the project was to encourage research technology development in the area of face and gesture recognition by specifying and supplying image sets to support activities in face and gesture recognition. Within this context, among other datasets, the FG-NET-AD was generated.

2.2 Database Contents

The FG-NET-AD contains 1002 images from 82 different subjects with ages ranging between newborns to 69 years old subjects. However, ages between zero to 40 years are the most populated in the database. With the exception of images showing individuals at more recent ages, for which digital images were available, in most cases FG-NET-AD images were collected by scanning photographs of subjects found in personal collections. As a consequence the quality of images depends on the photographic skills of the photographer, the quality of the imaging equipment used, the quality of photographic paper and printing and the condition of photographs. As a result face images in the FG-NET-AD display considerable variability in resolution, quality, illumination, viewpoint and expression. Occlusions in the form of spectacles, facial hair and hats are also present in a number of images. Each image in the dataset was annotated with 68 landmark points located at key positions and also a semantic description of each image was recorded. In particular information about the age, gender, expression, pose, image quality and appearance of occlusions (i.e. moustaches, beards, hats or spectacles) were recorded.

2.3 Analysis of Database Usage

So far the FG-NET-AD has been distributed to more than 4000 researchers, supporting in that way wide-spread aging-related research activities. In this section we present key facts related to the FG-NET-AD usage, based on a survey of the literature referencing the FG-NET-AD in articles listed at Google Scholar. Within this context the Google Scholar engine was used to search and identify the academic literature from 2005 until early 2014 that references the FG-NET-AD. A total number of 358 publications originated from 167 different institutions from 37 countries from all six continents were located. The distribution of the publications over the past 10 years is shown in Figure 1. Between 2005 to 2011 a steady increase in articles referencing the FG-NET-AD is observed, reflecting the gradual but steadily increasing interest of the research community in topics related to facial aging. The decrease from 2012 till 2014 is mainly attributed to scientific publications of the corresponding years, not indexed yet by the Google Scholar Engine.

Published papers describing research work using the FG-NET-AD were classified into the main research thematic areas of age estimation, face recognition, age progression/modeling, feature extraction/location, gender classification, biometrics, face modeling, face detection and pose estimation. Publications that were found to cover work extending across more than one thematic area were placed in all appropriate thematic areas. A significant number of other diverse thematic areas such as race classification, makeup detection, sketch matching, psychology related and perception related papers have been found in smaller numbers and have been grouped under the Other category. The distribution of papers into the main thematic areas over the years is shown in Figure 2. It is worth pointing out that although the primary scope of the dataset was to support

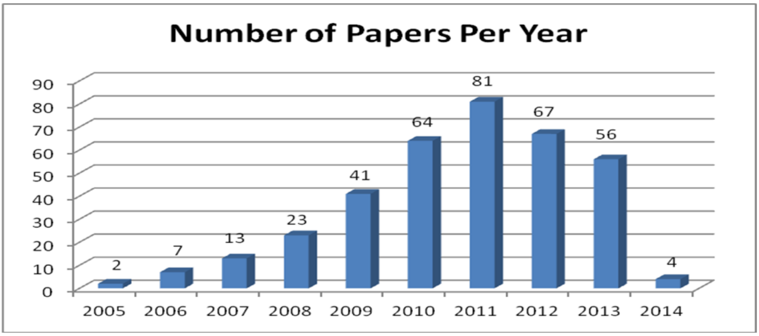

Fig. 1. Number of papers where images from the FG-NET-AD were used, per year

research in age progression, according to the findings in Figure 2, the highest share of papers are related with facial age estimation indicating the increased interest of the research community into soft biometrics.

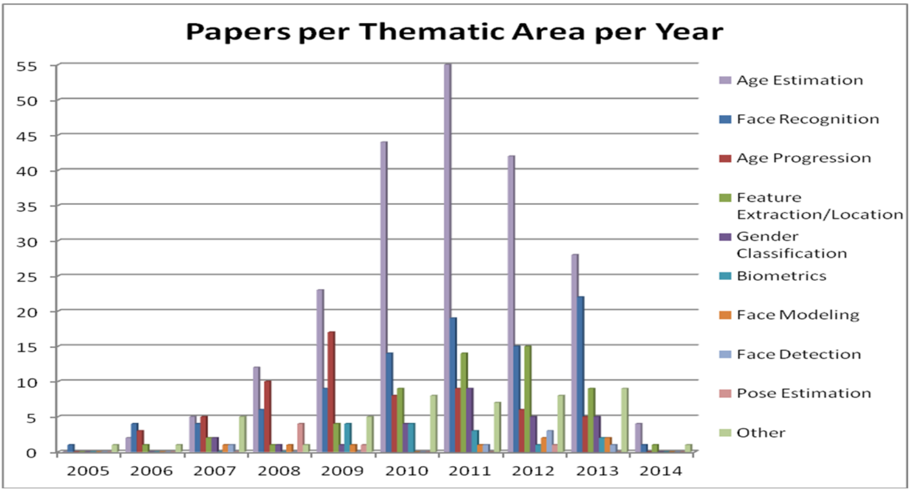

Fig. 2. Number of papers in different thematic areas per year

3 Research on Age Estimation Using the FG-NET-AD

According to the data presented in Figure 2, the topic of age estimation dominates research efforts in facial aging. The main reasons for this trend are:

i) Potential applications: Machine-based age estimation methods could figure in a wide range of applications involving man-machine interfaces such as ageadaptive interfaces and the enforcement of age-based access restrictions both to physical and electronic sites.

ii) Humans are not perfect in the task of age estimation; hence automated age estimates could complement/aid the task of human operators.

iii) The problem of age estimation, bears similarities with other standard face interpretation/pattern recognition tasks (i.e. face recognition, expression recognition etc.) hence the overall problem domain is more accessible to researchers.

iv) Accurate age estimates are usually required for other facial aging related applications (i.e. age invariant face recognition and age progression) hence the starting point in dealing with facial aging is usually the task of age estimation.

v) For age estimation there are concrete ways to test the performance of different algorithms allowing in that way the efficient comparative evaluation of different algorithms.

The output of an age estimation algorithm can be an estimate of the exact age of a person or the age group of a person. For exact age estimation the performance of an age estimation algorithm is usually based on the mean average error (MAE) between real and estimated ages over a test set and plots of Cumulative Score (CS) that shows the number of test cases which have an absolute error smaller than a given threshold. In the case of age-group age estimation errors usually refer to the percentage of correct classifications.

Researchers who carried out research in facial age estimation investigated the use of both standard pattern recognition/regression approaches and techniques adapted to the facial aging problem. In general most researchers conclude that the aging variability encountered in face images requires the use of dedicated techniques. The main trends of research activities are focused on determining suitable feature vectors that better reflect aging information in conjunction with efforts in customizing classification algorithms to take into account certain characteristics of the problem of age classification such as the problem of data sparseness i.e. the fact that for a given individual it is impossible to have training samples covering all the ages in the range of interest. A number of researchers deal with this problem by capitalizing on the observation that samples belonging to neighboring age groups display aging-related similarity even though they belong to different subjects.

Geng et al [13] generate aging patterns for each person in a dataset consisting of face images showing each subject at different ages. In this case the problem of data sparseness is addressed by filling in missing samples using the Expectation Maximization algorithm. Given a previously unseen face, the face is substituted at different positions in a pattern and the position that minimizes the reconstruction error indicates the age of the subject. Experimental results prove that this method outperformed previous approaches reported in the literature and also performed better than widely used classification methods.

A common trend in age estimation is the use or regression based on face subspace representations. Along this line Guo et al [16] propose a discriminative subspace learning based on manifold criterion for low-dimensional representations of the aging manifold. Regression is applied on the aging manifold patterns in order to learn the relationship between coded face representations and age. A key aspect of the work described in [16] is the use of a global SVR for obtaining a rough age estimate, followed by refined age estimation using a local SVR trained using only ages within a small interval around the initial age estimate. Luu et al [30] project faces in an AAM [7] subspace and then adopt a two-stage hierarchical age estimation approach. The first stage involves the initial classification of faces into young and old followed by the use of an SVM regressor trained using images from the chosen age range, in order to get the final age estimate.

Instead of projecting faces in low dimensional subspaces, a number of researchers experimented with the use of different types of Biologically Inspired (bio-inspired) features derived from the facial area. For example Mu et al [31] propose a model that contains alternating layers called Simple and Complex cell units that resemble object recognition models of the human visual system. Features for the simple layer (S) are extracted based on Gabor filters with different scales, standard deviations and orientations. The C layer involves the use of a standard deviation function for pooling S-layer features at different bands, scales and orientations. The dimensionality of the feature vector is reduced using Principal Component Analysis and a support vector regressor is used for obtaining age estimates. The overall framework of using bio-inspired features [31], has been studied extensively both in the area of age estimation and age invariant face recognition [40]. In a more recent approach, El Dib et al [8] extract bio-inspired facial features at a fine level and information from the forehead is also utilized resulting in an error rate of 3.17 years. The trend of dealing with facial features at different levels was also adopted by Suo et al [38] who propose an age estimation algorithm based on a hierarchical face model. The model represents human faces at three levels that include the global appearance, facial components and skin zones. An age estimator is trained from the feature vectors and their corresponding age labels. Han et al [18] adopt a hierarchical approach where bio-inspired features are extracted from individual facial components. Facial components are then classified into one of four age groups and then within an age group an SVM regressor is trained to predict the age. It was found that the best performance was attained from a fusion of the best performing features, i.e. holistic bio-inspired features, shape and eye region bio-inspired features. Han et al [18] also ran an experiment involving human-based age estimation of images from the FG-NET-AD, using crowd-sourcing and the results were compared to the proposed automated method. For the FG-NET-AD, the human age estimation experiment generated a MAE of 4.7. Hong et al [19] introduce the so called biologically inspired active appearance model where instead of using pixel intensities, shape-free faces are represented by bio-inspired features [31] during the process of AAM training. A regression-based age estimator is then used for estimating the age of samples based on the coded representations of faces.

As part of the efforts of using features related to the aging process Zhou et al [51] describe an age classification method based on the Radon transform. Difference of Gaussians filtering is applied on the face image to extract perceptual features, which are processed using the Radon transform. An entropy-based SVM classification algorithm is then used to select features. The algorithm is tested regarding the accuracy of classifying a face as over twenty or under twenty years old. Choi et al [5] propose an age estimation method based on extracting features directly related to aging. Within this context authors propose the extraction of wrinkles using a set of region specific Gabor filters, each of which is designed based on the regional direction of wrinkles. Li et al [27] also attempt to provide a generalized framework for selecting Gabor features that preserve both global and local aging information and at the same time minimize the redundancy between features. The method was tested both on age group classification and exact age estimation.

In order to deal with the problem of data sparseness a number of researchers focused their attention on assigning age labels to different ages in a way that optimizes the training process. A method based on the relative ranking of age labels is proposed in [1]. The proposed ordinary hyperplane ranking algorithm is based on using relative ranking information and a cost-sensitive property to optimize the age estimation process. Within this context the age estimation problem is decomposed into a number of binary decisions that classify a given face into a class of faces with age greater or smaller than a given age. The combination of the results of all individual classifiers yields the final age estimation result. Chao et al [2] propose the label-sensitive concept in an attempt to take advantage of correlations that exist between different classes in age estimation. As part of this effort the learning process of samples belonging to a certain age, takes also into account weighted samples belonging to neighboring ages. The proposed formulation is used in conjunction with a customized age-oriented local regression algorithm that performs the age classification task in a hierarchical fashion. The problem of class similarity between adjacent ages is also addressed in [12] where the concept of using label distributions is introduced. Along these lines during the training process samples belonging to a certain age category contribute to the training process of the class they belong to and also to the training of adjacent classes. The proposed label distribution method was used in conjunction with the proposed IIS-LLD and CPNN label distribution learning algorithms.

The use of Neural Network-based techniques for age estimation was also investigated. Zheng et al [50] use a back propagation neural network, where the inputs are geometrical features and local binary patterns, in order to classify faces into juveniles and adults. Yin and Geng [47] use a Conditional Probability Neural Network where the inputs are a facial descriptor and an age estimate and the output is the probability that the face descriptor is extracted from a face showing the given age. Based on this methodology the training process for a certain age takes into account faces showing the exact age and also samples with other ages enlarging in that way the training set. As a result the learning process is more efficient.

The majority of age estimation methods reported in the literature are based on texture-based features. In contrast Thukral et al [39] use face shape landmarks information in a hierarchical approach where the test image is first classified into an age group using several classifiers fused using the majority rule. Then the Relevance Vector Machine regression model of that age group is used to estimate the age. Wu et al [41] rely on facial shapes represented by point-coordinates on a Grassmann manifold. Based on this framework, the so called aging signature is extracted for each sample, by considering the tangent vectors of the deformation needed to deform a given face shape to the average face shape. A regressor-based age estimator that relates aging signatures to age is used during the age estimation process. This framework was also tested in the task of face verification.

4 Age Estimation FG-NET-AD Benchmark Results

In Table 1 we present a summary of age estimation results reported in the literature, in relation to experiments using images from the FG-NET-AD. The summary of the results presented can act as a benchmark for new age estimation experiments involving the FG-NET-AD. Most researchers reporting results using the FG-NET-AD adopted the Leave One Person Out (LOPO) approach where for each of the 82 subjects in the database, an age estimator is trained using images of the remaining 81 subjects and the results are averaged over the 82 trials. Given the small number of images available in the FG-NET-AD this is the optimum and recommended approach. The current benchmark for age estimation is the work of El Dib et al [8] where a mean average error of 3.17 is recorded when the LOPO approach is used. It is worth quoting that within three years of the publication of the first standardized age estimation results based on the LOPO method [13] reported MAE were almost halved [8], indicating in this way the benefits of standardised comparative evaluation. In the case of human-age estimation the recorded benchmark is 4.7 when all images from the FG-NET-AD were processed through crowd-sourcing by 10 volunteers [18]. Geng et al [12] also report a human age estimation MAE of 6.23 derived based on the observations of 29 volunteers using a sub-sample of 51 FG-NET-AD images. Clearly a number of reported algorithms match and even better the indicative performance of humans as recorded in [18] and [12].

In general two main trends seem to form the current directions in age estimation: The first is the use of bio-inspired features [31], [8], [19] and the second is the exploitation of age label distributions and ranking [2], [1], [12]. In addition efforts in investigating feature extraction from facial areas that contain increased age related information [18] also show promise.

5 Discussion

The availability of two publicly available aging databases (MORPH and FG-NET-AD) played an important role in initiating an increased interest in research related to facial aging among the computer vision community. According to the analysis of published work, the topic of facial age estimation has been the most popular among researchers active in the area of facial aging. The increased interest in this area resulted in the development of robust age estimation algorithms

Table 1. A summary of Age Estimation Results using Images from the FG-NET-AD

Reference	**Method**	**Train-Test Images**	**Result (MAE)**
Ni2009 [33]	Multi-Instance Regression	600 train 402 test	9.49
Zhou2005 [52]	Regression using Boosting	800 train 202 test	5.81
Xiao2009 [42]	Regression with distance metric	300 train 702 test	5.04
Luu2009 [30]	2 stage SVR in AAM subspace	802 train 200 test	4.37
Han2013 [18]	**Human age estimation**	Entire FG-NET-AD	**4.7**
Geng2013 [12]	**Human age estimation**	51 images	**6.23**
Geng2007 [13]	Aging Pattern Subspace	LOPO	6.22
Thukral2012 [39]	Fused classifiers using shape	LOPO	6.2
Gunay2013[15]	Radon Features	LOPO	6.18
Wu2012 [41]	Grassmann manifold	LOPO	5.89
Yan2007 [45]	Regressor with uncertain labels	LOPO	5.78
Yan2007 [44]	Ranking with uncertain labels	LOPO	5.33
Yan2009 [43]	Submanifold Embedding	LOPO	5.21
Ylioinas2013[48]	Binary Pattern Density Estimate	LOPO	5.09
Guo2008 [16]	Manifold Learning and Regressor	LOPO	5.07
Kilinc2013[20]	Geometric and Gabor Binary Pattern	LOPO	5.05
Guo2008 [17]	Probabilistic Fusion Approach	LOPO	4.97
Liang2014[28]	Multi-feature ordinal ranking	LOPO	4.97
Yan2008 [46]	Regression from patch kernel	LOPO	4.95
Zhang2013 [49]	Hierarchical Model	LOPO	4.89
Li2012 [27]	Ordinal Discriminative Features	LOPO	4.82
Mu2009 [31]	Bio-inspired features (BIF)	LOPO	4.77
Yin2012 [47]	Probability Neural Network	LOPO	4.76
Geng2013 [12]	Learning Label Distribution	LOPO	4.76
Chen2013 [3]	Cumulative Attribute SVR	LOPO	4.67
Han2013 [18]	Component and holistic BIF	LOPO	4.6
Chen2013[4]	Pairwise Age Ranking	LOPO	4.56
Chang2011 [1]	Ordinal hyperplanes ranker	LOPO	4.48
Chao2013 [2]	Label-sensitive regression	LOPO	4.38
Hong2013 [19]	Bio-Inspired AAM	LOPO	4.18
El Dib2010 [8]	**Enhanced Bio-Inspired features**	LOPO	**3.17**

capable of providing age estimates that can be used in most applications requiring user age information. It is anticipated that future research directions in age estimation will focus on the following issues:

i) Dealing with unconstraint face images: Developing age estimation algorithms that can deal with images captured under completely unconstraint images such as the ones captured by surveillance cameras. The ability of performing age estimation using unconstraint images will extend the range of possible applications where age estimation systems can be used.

ii) Age estimation based on video sequences: Currently almost all research efforts in age estimation deal with static images. However, temporal information that includes both face movements and expressions can also provide important age-related clues. A similar scenario was encountered in expression recognition that gradually moved away from dealing with static images as it became obvious that facial movements are also important for interpreting expressions [6].

iii) Multi-modal age estimation: Apart from the face, aging also affects other parts of the body [24] hence information fusion from different modalities could lead to more accurate age estimation systems. Although some attempts of developing age estimation based on individual biometric modalities, such as gait [29], head movements [23] and fingerprints [14] were reported in the literature it is anticipated that the topic of multi-modal biometric age estimation will attract substantial research interest in the near future.

iv) Age estimation results have reached error levels that make them suitable for several applications. However, there is still room for further improvements in age estimation tasks involving ages traditionally used as age thresholds (i.e age of 12, 15 and 18). For these particular ages additional research is required in order to further minimize age estimation errors.

In order to support the scenarios stated above, there is a clear need for developing new aging datasets that contain unconstraint images, video sequences and multi-modal biometric samples.

6 Conclusions

The FG-NET-AD was released back in 2004 in an attempt to encourage and promote research in the new (at that time) research topic of facial aging. It was fortunate that the release of the FG-NET-AD coincided with the release of the MORPH aging database [36] that provided different type of data and as a result supported complementary experimental investigations. Based on the analysis of published work, review of several key age estimation papers and analysis of the results reported, it is evident that the scopes that lead to the generation and distribution of the FG-NET-AD are fulfilled. A large number of researchers have benefited from using the database and as a result the topic of facial age estimation is now an established and well studied research area in computer vision and the emerging field of soft biometrics in particular. Although the FG-NET-AD can still be used for supporting research related to facial aging, it is imperative that new aging databases are made available in order to support new types of experimentations that will further advance research in age estimation.

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