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AGE GROUP ESTIMATION USING MACHINE LEARNING TECHNIQUES: A REVIEW

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ABSTRACT

There has been a growing interest in automatic age estimation from facial images due to a variety of potential applications in law enforcement, security screening and human interaction. machine. However, despite advances in automatic age estimation, this remains a difficult problem. Indeed, the aging process of the face is determined not only by intrinsic factors, e.g. genetic factors, but also by extrinsic factors, e.g. lifestyle, expression and environment. As a result, different people with the same age may have very different appearances because of different rates of facial aging Real-time audience measurement system includes five continuous steps: face detection, face tracking, gender identification, age rating and cloud data data analysis. The challenge of such a system is based on part-time algorithm machine learning methods. The face of the face is determined by various factors: genealogy, lifestyle, expression and environment. That's why people at the same age may have a very different rate of growth. We recommend a novel algorithm that consists of two stages: Local binary patterns and support vector machine classification based adaptive feature. Experimental results on the FG-NET, MORPH and our own database are presented. Estimation of human capability is studied by the ability to use crowd sourcing that allows the ability to combat the capabilities of machines and humans..

KEYWORDS: Facial age estimation, Aging databases, FG-NET Aging.

I. 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 data sets 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 [7] [4] .

Back in 2004 two face aging datasets were made publicly available: The MORPH [6] and the FG-NET Aging Dataset (FG-NET-AD) [2] Automatic video data analysis is a very important problem in the modern society. In recent years computer view and identity identification has been presented in the field of field [1, 1], several different algorithms, principal component analysis, histrogram analysis, 2]. The face image, such as identity, age, gender, nationality, and mark, mark and tattoo can be extracted from a wide variety. Facial Image ID Feature feature is well-searched in real-world applications, such as passport and driver license control [1-3]. Despite the wide interest of face recognition algorithms, only images of photographs (4, 4) have just a limited research to estimate and estimate demographic information (age, gender, nationality).

We focus on the estimation of this paper in this paper, whose goal is to determine the initial age or age group of groups based on the face area. One of its potential applications should mention the electronic customer management (such system automatically collects possible customer information to provide individual advertisements and services to different groups of groups. For the use of interactive electronic devices), security control and surveillance monitoring (for example, can alert or prevent age estimation system Bio Matrix (when using estimation age for any such part), to avoid those who suffer from repeatedly or in the liquor shops, who drink lesser smoking, tobacco products, buy from smoking machines. As well as information about user identification information, and thus reducing the entire system identification error rate). Apart from this, age estimation can be used in the entertainment field, for instance, in order to set photos in many groups or for age-specific human computer-related systems etc. [1].

In order to organize a fully automatic system, classification algorithms are used in combination with a face detection algorithm, which selects candidates for further analysis. In articles [3, 4], we propose a system that extracts all possible information about the people represented in the input video stream, aggregates them and analyzes them to measure different statistical parameters (figure 1). The quality of the face detection step is critical for the final outcome of the entire system, as inaccuracies in the determination of facial position can lead to poor decisions at the recognition stage [5, 6] . To solve the face detection task, an AdaBoost classifier, described in clause [7], is used. Detected fragments are pretreated to align their luminance characteristics and transform them into a uniform scale. In the next step, the detected and pretreated image fragments are transmitted to the input of the gender recognition classifier which makes a decision on their belonging to one of the two classes ("Man", "Woman") [4, 13]. The same fragments are also analyzed by the age estimation algorithm. The proposed gender and age classifiers are based on a nonlinear SVM (Support Vector Machines) classifier with a Radial Basis Function (RBF) kernel [37]. To extract information from an image fragment and to move to a lower-dimensional feature space, Local Binary Patterns (LBP) are used [38-41]. To estimate the length of time a person is in the camera visibility range, the face tracking algorithm [8-11] is used. It is based on the Lucas-Kanade optical flow calculation procedure [12].

The hard part of such a system is the age estimation algorithm based on machine learning methods. A number of studies in the fields of biological, psychological and cognitive sciences have reported on how the

The brain perceives, represents and remembers faces. In particular, various aspects of the estimation of human age have been studied in the field of psychology [15]. Psychological studies are often designed to examine the age, sex, and race of a subject about the accuracy of the age estimate that the subject provides [16]. However, the accuracy of age estimation by large-scale human subjects has not been reported for most of the databases used in the automatic age estimation search [17]. Various studies in the field of age classification have been carried out in recent years [14, 18-34].

The main contribution of this document is as follows. The capacity of human perception in the estimation of the age is studied with the help of an expert opinion in crowdsourcing which allows a comparison of the capacity of machines and humans. We propose a new algorithm consisting of two steps: adaptive feature extraction based on local binary models and the classification of support vector machines. Experimental results on FG-NET, MORPH [35, 36] and our own database are presented.

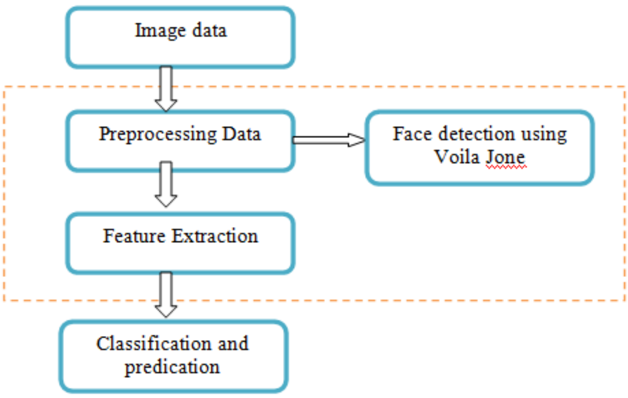

Fig.1. Real-time audience measurement system based on computer vision and machine learning algorithms

II. FACE AGING DATABASE

There are conventional databases that are widely used in the field of estimating age from facial images. Each image in these datasets contains information about the biological age of a person in that image. The most commonly used database is MORPH [35]. It contains more than 55,000 facial images of more than 13,000

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different people: men and women of different races, nationalities and ages. The MORPH database is quite large and suitable for both training and testing. Images of Caucasians (around 17000) were selected from the MORPH database. Faces were automatically assigned using the boosting algorithm. Further, the false positive samples were removed. In addition, a large number of fragments of unsatisfactory quality were thrown away manually. These fragments contained images with significant lightning defects, repeated images of the same person of the same age, faces with unnatural facial expression (closed eyes, grimacing, etc.) and faces of people whose age is significantly different from the biological. To select images, a group of experts was involved. The result is the creation of a set of images from the MORPH database. This set contains 6513 fragments that are best suited to perform experiments on automatic age estimation. The statistical distribution of faces by age is shown in Figure 2.

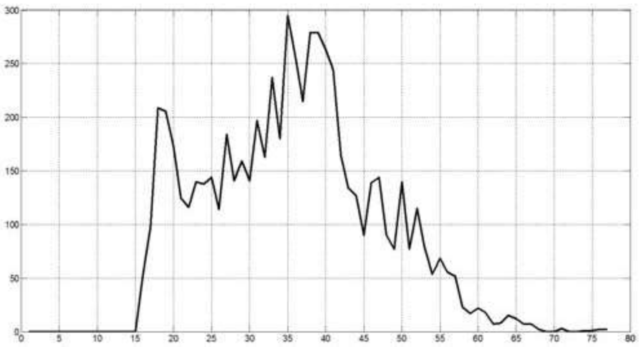


Fig. 2. Statistical distribution of faces depending on the age for the set of images that was selected from MORPH database

It should be noted that the age distribution in the final database of selected fragments is non-uniform. There are no images of people under 16, and for people over 57, the number of fragments available in the classroom is insufficient for training or testing. Most of the images fall on the age range of 30 to 40 years old Thus, the base MORPH has the necessary number of images (approximately 100 per class) only in the range of 16 to 55 years. For the range extension, it is necessary to develop its own database. Special attention should be given to images of people under 16 and over 57 years old.

Another conventional database is FG-NET [6]. It contains 1002 images of 82 people (about 12 images of different ages for each person). This database is not large enough for training, yet FG-NET is widely used as a test database in the literature.

For the purpose of the search, faces were automatically assigned. In addition, false positives have been manually removed. The resulting set contained 841 people (the selection level for the stimulation algorithm was 84%). The distribution of the faces as a function of age for FG-NET is shown in Figure 3.

The distribution is non-uniform: most images are less than 20 years old. For other age groups, the number of images decreases. Such a distribution can distort the statistics of the test algorithm and make an analysis of his work unreliable. For this reason, there is the important task of developing face test equipment with uniform age distribution. Because of these challenges, the task of developing our own database with a uniform distribution is of current interest.

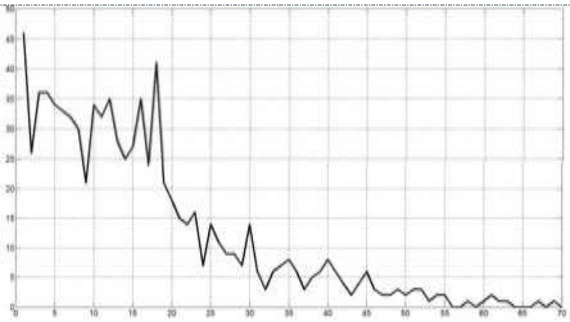
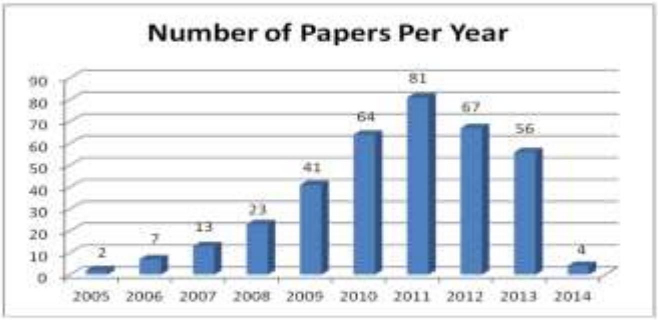


Fig. 3. Statistical distribution of faces depending on the age for the set of images that was selected from FG-NET database



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

The main problem in creating the specialized database for age recognition task is the lack of information about the actual biological age of people on the images. However, it is possible to use a visually perceived age as a reference. For this purpose, a group of experts is involved to determine the approximate age of each person in the database in the crowd sourcing experience. A database labeled in such a way is suitable for both training and testing algorithms. This experiment was performed for a new database (10,500 images) that was previously used for training and testing of the gender classifier. Each image was evaluated by five experts. The final value of age was obtained by averaging taking into account possible errors that were not taken into account. The statistical distribution for the resulting database is shown in FIG. 4.

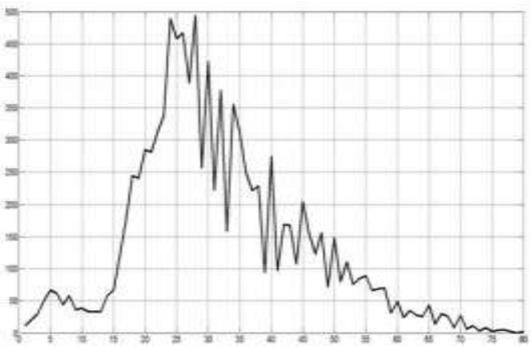


Fig. 4. Statistical distribution of faces depending on the age for own database

The distribution is non-uniform, most images fall on the age range of 16 to 40 years. The developed database is more suitable for training and testing algorithms because it has a wider age range than the MORPH database. However, the database developed contains an insufficient number of pictures of young and old people. This challenge leads to creating another database with a controlled number of images for each age.

Russian Faces Database Control (RUS-FD) which has been selected from free information sources (social network Vkontakte with the age of the person avatar image) contains 150 images of the low resolution of real life (60x60 pixels on each face) each age (from 6 to 60 years old). The biological age of the people on the images was known in advance. The accuracy of this information has been verified by the expert group. Thus, four

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different databases were prepared for the training and testing of age estimation algorithms. Their main parameters are given in the table. I.

Table I. Parameters of testing and control face aging databases

Database	**Number of images**	**Age range**	**Distribution by age**	**Labeling of age**	**Purpose**
Image set from MORPH	6513	16-75	nonuniform	real biological age	training and testing
Image set from FG-NET	841	1-70	nonuniform	real biological age	testing
Own database	10500	1-80	nonuniform	subjectively perceived age	training and testing
Control database (RUS-FD)	8100	6-60	uniform (150 images per each age)	real biological age	training and testing

A. Age Estimation Algorithm

1. The proposed age estimation algorithm performs a multiclass classification approach where for each age (from 1 to N) a binary classifier is constructed by deciding whether a person on the input image looks older whether given age or not. The input fragments are pretreated to align their luminance characteristics and transform them into a uniform scale. Preprocessing includes the transformation and scaling of the color space, both similar to those of the gender recognition algorithm.
2. In addition, image normalization was performed by a histogram equalization procedure. The LBP feature space transformation and the SVM training procedure are used for the construction of binary classifiers. To predict the outputs of the direct age binary classifier are analyzed statistically and the most likely age becomes the output of the algorithm.
3. To test the age estimation algorithms, the standard performance measures were calculated:
4. Means Absolute Error (MAE) - mean absolute difference between estimated and actual ages.
5. Cumulative score (CS) - the probability that the estimated age is within a range dx of the actual age.
6. Probability Density Function of the estimation error of age.

Estimate the proposed algorithm in a real-life test performed first on the FG-NET database. The age on the FG-NET data base was manually scored by a group of experts to compare the subjective estimate with the performance of the algorithm. The corresponding dependencies for the simulation of the LBP-SVM algorithm are shown in Figure 6 and Figure 7.

The proposed algorithm shows comparable results to subjective evaluation in a range of ages from 20 to 35 years. The average absolute error in this range is about 6 years. The precision of the LBP-SVM algorithm decreases in the elderly due to the growth of the MAE. In this interval (45-60 years), the proposed algorithm gives an expert assessment of about 10-15 years in terms of average error.

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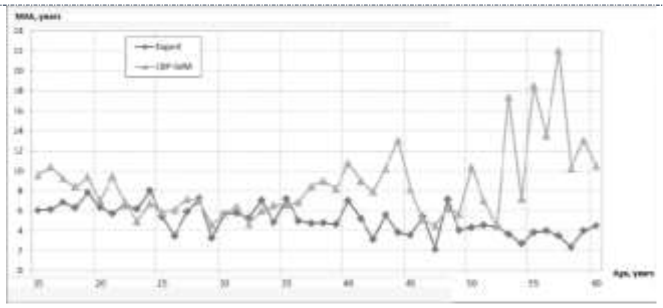

Fig. 6. MAE on FG-NET database for LBP-SVM algorithm

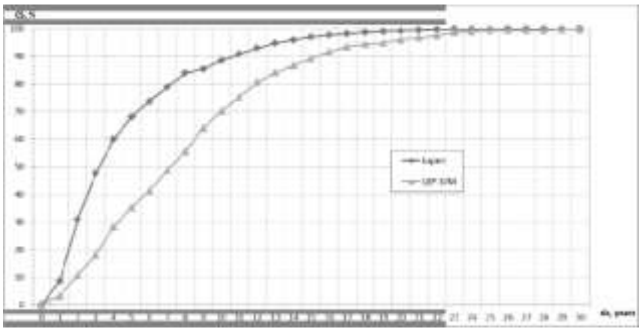

Fig. 7. CS on FG-NET database for LBP-SVM algorithm

The cumulative score shows that about 40% of estimates are less than 5 years apart from actual age and 70% - less than 10 years apart. The subjective evaluation curve in Figure 7 gives us the possible limit for the future improvement of the age estimation algorithm.

The analysis of the error probability density function shows that the proposed algorithm has an error distribution close to symmetry. Objective results are not likely to overestimate the actual age, which is typical for expert evaluation. The MAE and CS comparison for the LBP-SVM algorithm on different test databases is shown in FIG. 8 and Fig.9.

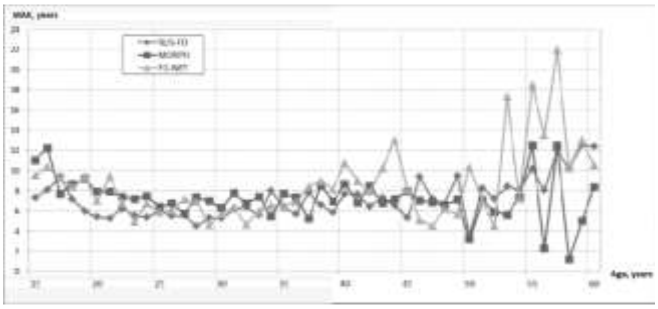

Fig. 8. MAE comparison on different databases for LBP-SVM algorithm

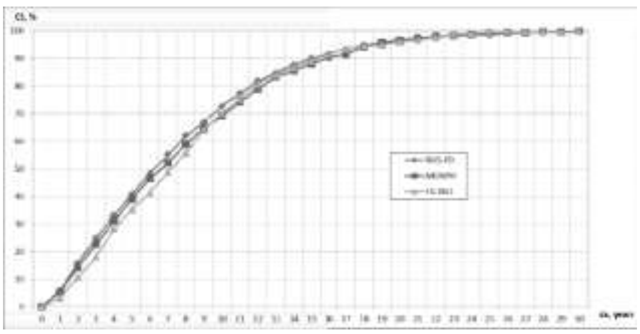

Fig. 9. CS comparison on different databases for LBP-SVM algorithm

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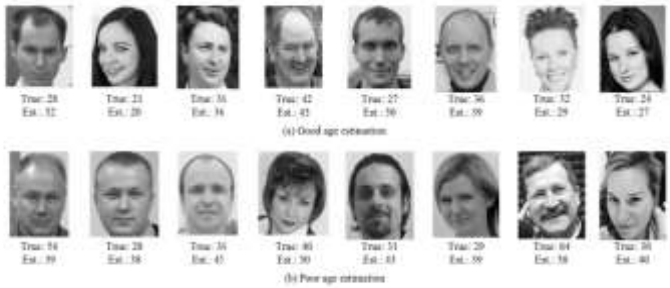

Fig. 10. Examples of age estimation using the proposed algorithm

The MAE range of the LBP-SVM algorithm on the RUS-FD data is 6.94, the MORTH database -7.29, the FG-NET -7.47 database. MAE's subjective estimate is 4.2 indicating that the proposed algorithm still requires much more improvement to show results comparable to a human. It is important to note that if we learn and test the LBP-SVM algorithm on the MORTH database, we get a total MAE score of 4.86 because the simplicity of the MORTH database (the same light condition for the faces). Possible ways to improve the accuracy of the age classifier are the extension of the set of features, the use of SVM learning procedures, the pre-processing and post-processing steps.

Example of the face image where the LBP-SVM algorithm has a good and poor age estimate are shown in Figure 10.

B. Age Estimation Algorithm

We summarize the published methods and results for the age estimation of different face databases in Table II. As you can see from the review, the most popular features are Biological, Inspired Characteristics (BIF) and their modification, Gabor and the local binary model and its modification, except for MORTH and the FG-NET database in some papers. PAL, LFW + and some private database age estimates can reach a total AEM score of between 4 and 5. CS in the same column reflects the percentage of correct age estimates in a 5-year absolute error. In some documents, researchers prefer to calculate MAE and CS separately for the male and female sub-databases. Our age estimation algorithms provide a world-class result for the MORTH database, but focus on the actual audience measurement application in which faces can be more or less similar to the private database RUS-FD. In this case, we can achieve a total MAE score of less than 7.

III. CONCLUSION

This article addresses the problem of automatically estimating age from actual acquired face images. We proposed an age estimation algorithm consisting of two steps; Adaptive feature extraction based on a local binary model and a vector support vector classification. Experimental results on the FG-NET, MORPH and our private face aging database RUS-FD are presented. The ability of human perception in estimating age is studied using a crowd sourcing experiment that allows a comparison of the capacity of the machine and humans. The results of experiments remain a very difficult problem. The age estimation algorithms described in this article have integrated into the audience measurement system that can collect and process image data in real time

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Publication	**Features extraction**	**Using face aging database**	**Performance measure and**
Fu and Huang [14]	Holistic appearance	Private YGA (1600, 8000)	MAE: 5~6 CS Female:55% CS Male:
Thukral et al. [19]	Landmark based hierarchical approach	FG-NET	MAE: 6.2
Han et al. [17]	Component and holistic biologically inspired features (BIF)	FG-NET MORTH II PCSO (1802, 10036)	FG-NET/MORTH II/PCOS MAE: 4.6 / 4.2 /5.1 CS: 74,8% / 72.4% / 64%
Geng et al. [24]	Holistic appearance, principal component analysis (PCA)	FG-NET MORTH	FG-NET/MORTH MAE: 6.8 / 8.8 CS: 65% / 46%
Suo et al. [25]	Holistic and local topology, 2D shape, color, and gradient	FG-NET Private (NA, 8000)	FG-NET/Private MAE: 6.0 / 4.7 CS: 55% / 66%
Guo et al. [26]	Holistic BIF	FG-NET Private YGA (1600, 8000)	MAE: 4.8 / F: 3.9, M: 3.5 CS: 47% / F: 75%, M: 80%
Choi et al. [27]	Holistic appearance, Gabor, LBP	FG-NET PAL (NA, 430)	FG-NET/PAL/BERC MAE: 4.7 / 4.3 /4.7
Guo and Wang [28]	Holistic BIF, partial least squares (PLS)	PAL (590, 844) FACES (171, 1026)	PAL/FACES MAE: 6.1 / 8.1
Chao et al.[29]	Label-sensitive relevant component analysis	FG-NET	MAE: 4.4
Nguyen et al. [30]	LBP, multilevel LBP, Gabor	PAL (NA, 430)	MAE: 6.53
Han et al. [31]	BIF	Images of Groups LFW+ FG-NET	Images of Groups / LWF+ Age Group: 68.1%, 66.7% FG-NET
Shan [32]	LBP, Gabor	Images of Groups	Age Group: 55.9%
Ylioinas et al. [33]	LBP	Images of Groups	Age Group: 51.7%
Alnajar et al. [34]	Orientation histogram of local gradients	Images of Groups	Age Group: 56.5%
Proposed	LBP	Private RUS-FD, MORTH FG-NET	RUS-FD/ MORTH MAE: 6.94 / 4.86 CS: 42% / 56%

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