A Study on a Structure Based Human Facial Age Estimation

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Abstract: Researchers have shown more interest in the soft biometrics area to fill the communication gaps between humans and machines with the growth of real-world application has increased day to day life. Soft-biometric consists of age, gender, ethnicity, height, facial measurements and etc. This paper contains a detailed discussion about the contribution of the researchers in the area of gender classification and age estimation using neural networking. Most of the work is done using Convolutional neural networks and auto encoders. Various elements related to neural network models such as dataset, findings, calculative metrics and results are embraced for effortless interpretation of tabular correlation research. Finally, the authors summarize germane tasks for future various research aspects. We plan a primary study on increasing the performance of pre-trained deep networks by applying post-processing strategies. The main advantage with respect to fine-tuning strategies consists of the simplicity and low computational cost of the post-processing step. To the best of depart our knowledge, this paper is the first study on age estimation that proposes these of post-processing strategies for features extracted using pre-trained deep networks. Our method exploits a set of pre-trained Convolutional Neural Networks (CNNs) to extract features from the input face image. The method then performs a feature level fusion, reduces the dimensionality of the feature space, and estimates the age of the individual by using a Feed-Forward Neural Network (FFNN). We evaluated the performance of our method on a public dataset (Adience Benchmark of Unfiltered Faces for Gender and Age Classification) and on a dataset of non-ideal samples affected by controlled rotations, which we collected in our laboratory. Our age estimation method obtained better or comparable results with respect to state-of-the-art techniques and achieved satisfactory performance in non-ideal conditions. Results also showed that CNNs trained on general datasets can obtain satisfactory accuracy for different types of validation images, also without applying fine-tuning methods

***Index Terms* – Soft Biometrics, Neural Nets, CNN, Gender recognition, Age estimation.**

I. INTRODUCTION

A Human face provides a lot of information about the age, gender, mood etc. It is affected by many dynamic factors that get changed over a period of time such as aging, hair style, expressions, etc. Gender and Age are considered an important biometric attribute for human identification. Biometric recognition is the method of gathering information about a person's physiological and behavioural characteristics for human identification and verification (security models). Biometrics consists of soft biometric (age, gender, ethnicity, height and facial measurements) and hard biometric (Physical, behavioural and biological). Soft-biometric attributes like skin, hair colour, distance between eye and nose, face shape, and etc can be accessed to accelerate data traversing, or to classify unlabelled subjects for various gender and age classes.

Accurate age group estimation has many applications in fields such as homeland security, forensic science, and passport services; it can also be used for locating missing persons, determining the age of asylum seekers with missing legal documents, controlling paedophilia, conducting statistical analysis (e.g., class wise age distribution), limiting access to the purchase of certain commodities (e.g., alcohol and tobacco), and controlling some human–computer interactions (HCI) (e.g., limiting Internet access to certain age groups).

The motivation for age estimation systems has grown over the past few decades, given the rise of the digital age and the increase in human–computer interaction. Recently, the Face Recognition Vendor Test (FRVT) evaluated the performance of facial age estimation as a new area of study with Still Images Track. The main objectives of this evaluation include the assessment of current age estimation technology and the investigation of the estimation accuracy on large-scale datasets across demographic variations.

Among the various biometric recognition technologies, face recognition is a biometric recognition technology with great development potential, and has broad application prospects in information security, public safety, and other Field. In academia, research topics related to classical face analysis usually include face detection, face recognition, face verification, face tracking, 3D facial expression recognition, etc. Among them, the analysis of face attributes such as age estimation, gender recognition, and ethnic recognition has attracted the interest of many researchers .The face aging process generally follows some common aging modes. During the growth stage of children, the biggest change is the shape change caused by the growth of the skull. The aging process in adulthood is mainly reflected in changes in facial skin texture such as the appearance and deepening of wrinkles, loose skin, increased spots, etc. However, due to the complex facial features and slow aging process, the degree of aging depends not only on the increase in age, but also due to various factors such as gender, race, genes, living habits, and health status . In addition, the collection of face age images is very burdensome.

The existing public face age datasets have many problems such as an imbalance in age, gender, and ethnicity, which makes it difficult to meet the requirements of most research work. The above reasons mean that the research on face age estimation still faces great challenges. Although facing huge challenges, face age estimation technology has a wide range of potential applications in the fields of surveillance and investigation, information management systems, intelligent human–computer interaction, social entertainment, and other fields. The face age estimation process roughly includes image pre-processing, feature extraction, and age estimation. Image pre-processing methods include human face detection, face correction, and image cropping.

Before neural network training in deep learning methods, image augmentation methods can be used to augment the dataset to alleviate the overfitting of the network. Image augmentation methods include filtering, sharpening, histogram enhancement, flipping, rotation, and scale transformation. In the feature extraction stage, traditional methods mostly use explicit feature extraction to obtain age features based on manual design. Due to the limitations of hand-designed features, the extracted age features are not necessarily optimal.

The modern feature extraction method based on convolutional neural networks can well capture the face-related feature information in the image, and has a strong robust adaptability to the noise in the image, which means the final estimation in the age estimation stage is more accurate. In the age estimation stage, there are roughly classification, regression, blending, and distributed learning methods. If age is regarded as a separate label, then age estimation is a classification problem. In addition, the age of the human face has a certain order, so that the age estimation can also be regarded as a regression problem. Some people have suggested that the facial features of adjacent ages have similarities. If the age correlation between adjacent ages is fully considered, the age estimation can be regarded as a distribution learning problem, so that multi-label learning or distribution learning can be used in the training of neural networks. Then, neighbouring age tag information contributes to real age tags during the network training phase. However, current convolutional neural networks (CNNs) are becoming larger and more complex, exposing many shortcomings such as too many model parameters, large footprints, large training dataset, long training time, and inconvenient deployment on mobile terminals. Therefore, a more lightweight network is needed, but at the same time, the accuracy of age estimation must be guaranteed. Aiming at the above problems, this paper proposes an age estimation model based on ShufflfflffleNetV2. Experiments show that the network proposed in this paper converges quickly during the training phase, has high accuracy during the age estimation phase, and has a small footprint of the network model. The contributions of this article are summarized as follows:

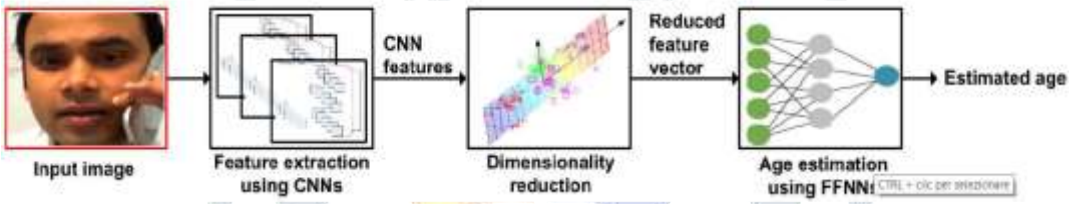
(1) A lightweight convolutional neural network age estimation model based on the mixed attention mechanism is constructed.

(2) The age estimation method combining classification and regression is easy to implement and the final age estimation accuracy is very high.

(3) Perform face detection and correction on the input face image, and perform image augmentation, so that the feature information related to the face age is amplified, which is helpful for network learning.

II. BACKGROUND

Age estimation based on face images plays an important role in a wide range of scenarios, including security and defence applications, border control, human-machine interaction in ambient intelligence applications, and recognition based scheduled soft biometric information. Recent methods based on deep learning have shown promising performance in this field. Most of these methods use deep networks specifically designed and trained to cope with this problem. There are also some studies that focus on applying deep networks pre-trained for face recognition, which perform a fine-tuning to achieve accurate results



III. LITERATURE SURVEY

Lanitis, C. Draganova and C. Christodoulou, "Comparing different classifiers for automatic age estimation", IEEE Trans. Syst. Man Cybern. B Cybern., vol. 34, no. 1, pp. 621-628, Feb. 2004

We describe a quantitative evaluation of the performance of different classifiers in the task of automatic age estimation. In this context, we generate a statistical model of facial appearance, which is subsequently used as the basis for obtaining a compact parametric description of face images. The aim of our work is to design classifiers that accept the model-based representation of unseen images and produce an estimate of the age of the person in the corresponding face image. For this application, we have tested different classifiers: a classifier based on the use of quadratic functions for modeling the relationship between face model parameters and age, a shortest distance classifier, and artificial neural network based classifiers. We also describe variations to the basic method where we use age-specific and/or appearance specific age estimation methods. In this context, we use age estimation classifiers for each age group and/or classifiers for different clusters of subjects within our training set. In those cases, part of the classification procedure is devoted to choosing the most appropriate classifier for the subject/age range in question, so that more accurate age estimates can be obtained. We also present comparative results concerning the performance of humans and computers in the task of age estimation. Our results indicate that machines can estimate the age of a person almost as reliably as humans

X. Geng, Z.-H. Zhou, Y. Zhang, G. Li and H. Dai, "Learning from facial aging patterns for automatic age estimation", Proc. 14th Annu. ACM Int. Conf. Multimedia, pp. 307-316, 2006.

Age Specific Human-Computer Interaction (ASHCI) has vast potential applications in daily life. However, automatic age estimation technique is still underdeveloped. One of the main reasons is that the aging effects on human faces present several unique characteristics which make age estimation a challenging task that requires non-standard classification approaches. According to the speciality of the facial aging effects, this paper proposes the AGES (AGing pattErn Subspace) method for automatic age estimation. The basic idea is to model the aging pattern, which is defined as a sequence of personal aging face images, by learning a representative subspace. The proper aging pattern for an unseen face image is then determined by the projection in the subspace that can best reconstruct the face image, while the position of the face image in that aging pattern will indicate its age. The AGES method has shown encouraging performance in the comparative experiments either as an age estimator or as an age range estimator.

F. Gao and H. Ai, "Face age classification on consumer images with Gabor feature and fuzzy lda method" in Advances in Biometrics, Berlin, Germany: Springer, pp. 132-141, 2009.

As we all know, face age estimation task is not only challenging for computer, but even hard for human in some cases, however, coarse age classification such as classifying human face as baby, child, adult or elder people is much easier for human. In this paper, we try to dig out the potential age classification power of computer on faces from consumer images which are taken under various conditions. Gabor feature is extracted and used in LDA classifiers. In order to solve the intrinsic age ambiguity problem, a fuzzy version LDA is introduced through defining age membership functions. Systematic comparative experiment results show that the proposed method with Gabor feature and fuzzy LDA can achieve better age classification precision in consumer images.

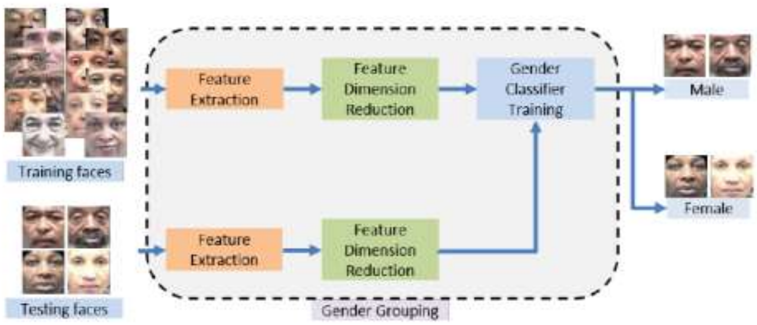
K.-H. Liu, T.-J. Liu, H.-H. Liu and S.-C. Pei, "Facial makeup detection via selected gradient orientation of entropy information", Proc. IEEE Int. Conf. Image Process. (ICIP), pp. 4067-4071, Sep. 2015.
This work presents a novel facial makeup detection method, which includes four steps: entropy information computation, feature extraction, feature selection and classification. To carry out this objective, first all face images are subject to the entropy information computation. Once the entropy images of faces are obtained, a feature extraction step is applied to the entropy images instead of original face images. The extracted features are further processed to reduce the redundant information on the feature vector, which is done by a feature selection procedure. A statistical analysis approach is chosen to realize this feature selection purpose, which aims to lower the feature dimension and maintain higher discrimination. In the last step, the makeup is detected by classifying faces into two groups: makeup and no-makeup. The experimental results on two databases indeed demonstrate the superiority of the proposed method.

T.-J. Liu, K.-H. Liu, H.-H. Liu and S.-C. Pei, "Comparison of subjective viewing test methods for image quality assessment", Proc. IEEE Int. Conf. Image Process. (ICIP), pp. 3155-3159, Sep. 2015.
This paper presents a comparison study on subjective quality scores obtained by both single stimulus (without reference) and triple stimulus (with reference) methods. The TID2013 database is reevaluated by single stimulus approach, which is realized by absolute category rating (ACR). And the mean opinion score (MOS) provided along with TID2013 represents the results from triple-stimulus pair comparison (3-stimulus PC) method. In the end, the correlation coefficient and hypothesis testing are used to determine if there is a significant difference between both sets of scores. The experimental results show that the differences exist and are significant for some specific distortion types or image contents. We believe the findings in this work can benefit and facilitate the future subjective visual quality viewing tests.

W.-J. Suen, H.-H. Liu, S.-C. Pei, K.-H. Liu and T.-J. Liu, "Spatial-temporal visual attention model for video quality assessment", Proc. IEEE Int. Symp. Circuits Syst. (ISCAS), pp. 1-5, May 2019.
Objective assessment for videos has developed with mature technique. However, there are still some challenges, such as mimicking the behavior that human-beings do when they watch a video. In this paper, we introduce a model for full-reference (FR) video quality assessment (VQA) which is based on visual attention, optical flow, spatio-temporal slice (STS) images and center bias map. The experimental results show that our proposed model has better performance in wireless transmission distortion than other models in the LIVE video quality database

IV. PROPOSED SYSTEM

In this work, the primary features such as eyes, nose, mouth, chin, virtual top of the head and the sides of the face are considered at the first step. From these features, ratios that differentiate babies from young adults and seniors are computed. In secondary feature analysis, wrinkle geography is used for detection and measurement of wrinkles. The wrinkle index is used to differentiate senior adults from young adults and babies. Later, Horng et al. improved the work by classifying the images into four age-groups, i.e., babies, young adults, middle-aged adults and old-aged adults. It consists of three steps like localization of feature, extraction and classification. The above methods give a clear idea about age-group classification, but do not convey specific age estimation Gender grouping, age grouping, and age estimation at the same time.The proposed solutions are efficient and can be applied to real world age estimationOur framework is expandable in its structure, and also modifiable on the facial features and learning algorithms.



Procedure of the gender grouping system

V. METHODOLOGY

DATA PREPROCESSING

Data preprocessing is very important and normally performed before feature extraction. It involves cropping, pose correction, RGB to grayscale conversion, scaling, normalization and transformation of two-dimensional image to one-dimensional vector. Cropping Using Golden ratio Cropping facial region from an image using Golden ratio-based measurement seems to preserve maximum information about the face, irrespective of age, gender, race of a person [14,31–33]. The size of a face varies from infancy to adulthood, gender to gender, race to race, but Golden ratio remains constant [14,34]. The Golden ratio is defined as below. Definition Let a and b are two quantities and a < b; if the ratio of b to a is same as the ratio of (a + b) to b, then it is called as Golden ratio φ and the value is 1.61803…

$$\phi = \frac{b}{a} = \frac{(a+b)}{b} = \frac{1+\sqrt{5}}{2} = 1.61803\ldots$$

The Golden ratio3-based cropped and scaled faces of different age, gender and race are depicted in Fig. 4. Let ai j(j=1,2) and bi j(j=1,2) be the vertical and horizontal cuts of ith image, respectively; then, the Golden ratio for the faces in Fig. 4 is related as below:This implies that φ remains constant irrespective of age, gender, race of a person and preserves uniformity among subregions of faces, i.e.,

$$\phi = \frac{a_{i2}}{a_{i1}} = \frac{b_{i2}}{b_{i1}} = \frac{(a_{i1} + a_{i2})}{(a_{i2})} = \frac{(b_{i1} + b_{i2})}{(b_{i2})} = 1.61803\ldots$$

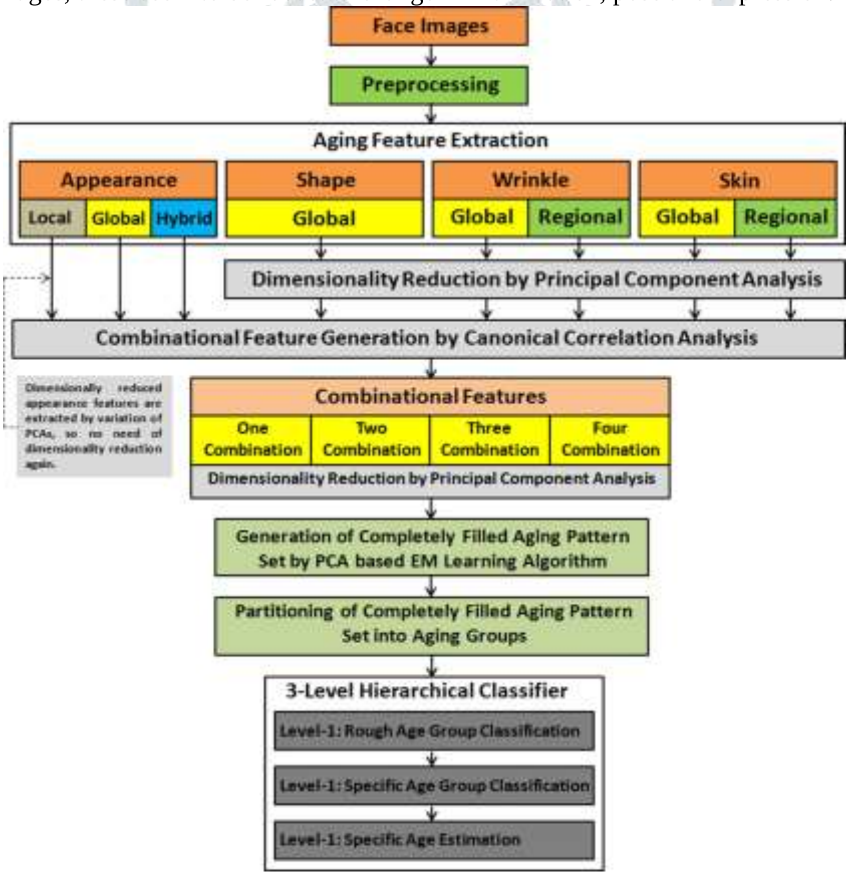
Definition Let a and b are two quantities and a < b; if the ratio of b to a is same as the ratio of (a + b) to b, then it is called as Golden ratio φ and the value is 1.61803… i(Rk) ≈ j(Rk), where i(Rk) and j(Rk) are kth subregion of ith and jth image, respectively. For age estimation prospective, the Golden ratio-based cropping is important, as the subregions containing discriminative aging features occupy the same location in all faces after cropping. So by localizing common subregions using Golden ratio, it is easy to apply regionspecific feature extractor in a standard and effective way. The pose correction involves rotation, warping, skewing a face image. Grayscale conversion converts the RGB color image into 0–255 intensity image. Scaling operation scales an image to a fixed dimension. For the present experiment, all images are scaled to 124×100-dimensional images.

Image normalization is a process of changing the intensity value of pixels. In this paper, a contrast limited adaptive histogram equalization (CLAHE) for normalization of a grayscale image is used. CLAHE operates on a small area of an image called tiles rather than the whole image. The contrast of each tile is enhanced by CLAHE. The neighboring tiles are then combined using bilinear interpolation to eliminate artificially induced boundaries. The contrast, especially in homogeneous areas, can be limited to avoid amplifying any noise that might be present in the image [26]. After normalization, the two-dimensional image of dimension 124×100 transforms to a vector of dimension 12400×1 by taking each row of two-dimensional image in sequence.

APPEARANCE FEATURE

The appearance of a face is very informative and important for age estimation, as it changes smoothly over age, irrespective of child, adult, gender, lifestyle and race. In some works in the literature , the appearance feature is extracted by active appearance model (AAM) based on principal component analysis (PCA). It combines appearance feature with shape feature to generate final feature known as AAM feature .

Since the AAM uses classical global PCA, the AAM feature is global in nature. But, from age estima-tion point of view, facial appearance changes regionally as well as globally, but shape changes globally. So, we need a appearance feature extractor that preserves local as well as global appearance of a face. To tackle the above challenges, the current approach uses hybrid PCA for appearance feature extraction. One way of extracting hybrid appearance feature is cross-correlating sub-pattern covariance matrices, and the other way is crosscorrelating sub-pattern and whole pattern covariance matrices. The first method is called SubXPCA , and the second method is called as ESubXPCA. Since both methods extract appearance feature by considering local and global variations of images, these seem to be robust to change in illumination, pose and expression.



FACIAL GENDER AND AGE ESTIMATION: APPLICATION AND CHALLENGE'S

Automation has covered wide area in real-world application area. Similarly, age andgender estimation can also be devised automatically. Age and gender classification techniques can improve computer's perceptional and interactional capabilities. Various applications for age and gender classification includes human-computer interaction (HCI) can provide users appropriate and customized services based on gender and age ground. Electronic customer relationship management is an internet-based technology; here personal data is examined for all class of consumers without intruding data privacy. Major aim of automation for classify age and gender is to predict age and gender class for each customer based on their facial images taken through camera and for demographic data. Age and gender classification can provide knowledge to improve the user experience in gaming and phone application. It can also be used for the verification or authentication accuracies based on soft biometric techniques. Age classification can control entry to unwanted content in televisions and Internet from children. In employment like police, military and government employments require age estimation during recruitment and while retirement age.

CONVALUTIONAL NEURAL NETWORK

CNN is an active architecture of approach of profound learning which takes input as multimedia like images, videos or various 2D/3D data. It is evident that gender and age estimation on basis of facial features deals with images and video data. Thus, various researches done by the researcher's and scientist lies on facial gender and age estimation focuses on CNN models. CNN model consists of different weights for every hidden neuron expressed in mathematical expression of multi-dimensional matrix. Further image transfers through hidden layers of CNN, dimensions of weights and matrix gets remodel after every convolutional layer. CNN frameworks are designed by a well-fixed combination of layers such as narrow layers, sub sample layers, and full layers. Concentrated layers serve as building block to CNN and it is used to perform the basic function of convolution. Sub-sample layers perform major function for controlling over fitting issues by reducing the parameters and size by using max operation for maximum pooling. At last the fully connected layer of neurons is maps to all activation function of previous layers. There exists an additional RELU layer that helps in implementing the nonpurity function and correction in CNNs. The last layer is usually utilized as softmax layer that provides decimal feasibility to each output neuron. Researchers have proposed several interactive CNN architectures for basic neural network concept. Predefined CNN architectures were investigated for this research keeping into account the recognition of gender as well as the estimation of the age from facial images, such as: VGG19 and VGGFace, ResNet, AlexNet and GoogLeNet.

FACIAL GENDER CLASSIFICATION AND AGE ESTIMATION BASED ON NEURAL NETWORK

Brief summary of research covering each individual neural net based facial characteristics, gender and age estimation.Author has recommended CNN architecture for classifying gender and age using benchmark database of adience facial images with a better performance. The architecture is built up of one output layer and three fully connected layers. A part of starting two layers of convolutional layers contains local response normalization layer and connected to repaired linear operation (ReLU) along with the max-pooling layer for each convolutional layer. Smaller network design has been introduced to reduce over fitting problem. Every entirely associated layer encloses 512 neurons all. Output of the neural network is depending upon SoftMax layer for which input is provided through output of previous entirely associated layer. Cropped and over sampled facial mugshots where used for gender and age estimation. Author noted Mean accuracy ± Standard error for age as well as the gender, where classification of the age using misperception matrix. Literal efficiency of single cropped image for estimating age results to 49.5 ± 4.4 and for 1-OFF the efficiency results to 84.6 ± 1.7. Whereas, over-sample method results efficiency of 50.7 ± 5.1 and 1-OFF efficiency of 84.7

CNN WITH MULTIPLE OUTPUT

A numerous output convolutional neural network for solving various classification problems. Collective binary classification problems are secured through an ordinal regression issue. For both MORPH and AFAD dataset results have been appraised as expected. For feature extraction module biologically, inspired features can be accessed and undergoes back propagation procedure. Proposed architecture works on three convolution layers, two Pool layers, 3 normalization layers along with a single fully connected layer. Metric along with the ordinal regression methods are correlated and acknowledged for both datasets by applying MAE metrics on datasets respectively for propose research. These values can be used for any data specific schemes like colour images. Best results have been achieved from Ordinal Regression
CNN (OR-CNN) and study of Cumulative score in a graphical manner. Authors have also tested the approach model on grayscale images versus colour images.

CONCLUSION

In this paper, we obtainable a innovative age estimation method designed to increase the presentation of pre-trained deep networks by applying post-processing approaches. Our process uses pre-trained sets of CNNs to extract structures from the face images. It then implements a dimensionality reduction of the feature set, a feature level fusion, and estimates the age value using feedforward neural networks. We estimated our method by training it on a public dataset and testing it on images acquired in a less-constrained scenario. The completed results show that the method achieved satisfactory performance for non-ideal images acquired in unconstrained scenarios. We also compared the accuracy of our age estimation method with that of state-of-the art techniques by using a challenging public dataset. The obtained results show that our method achieved better or comparable results with respect to the state of the art. Results also demonstrated that CNNs trained on general datasets can obtain satisfactory accuracy for different types of validation images. Furthermore, results proved that pre-trained deep networks can be considered as general feature extractors for age estimation, also without applying computationally expensive fine-tuning techniques. As future work, we should test the suitability of the pro-posed method for estimating other soft biometric information, such as gender or pose. Moreover, we should evaluate other feature reduction strategies widely used by face recognition systems

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