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Two-stages based facial demographic attributes combination for age estimation ☆

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ABSTRACT

Automatic age estimation from face images is a topic of growing interest nowadays, because of its great value in various applications. The main challenge in automatic facial age estimation task comes from the large intra-class facial appearance variations due to both gender and race attributes. To this end, in this paper we propose a complete approach for age estimation based on demographic classification. The proposed approach consists of three main parts: (1) Automatic face detection and alignment to extract only the regions of interest. (2) Feature extraction from facial region images using Multi-level face representation. (3) Two-Stages age Estimation (TSE). The main idea of TSE is to classify the input face image into one of demographic classes, then estimate age within the identified demographic class. The experimental results demonstrate that our proposed approach can offer better performance for age estimation when compared to the state-of-the-art methods on MORPH-II, PAL and a subset of LFW databases.

1. Introduction

The widespread topic of automatic demographic classification has been receiving significant attention in recent years. In the facial demographic classification context, gender and race classification has been addressed by several research works. In the recent decade, age estimation has been demanding growing interest, because of its great value in practice such as, business intelligence, access control, human-computer interaction, electronic customer relationship management (*e*CRM). In addition, the estimated age can prevent underages from purchasing cigarettes or alcohol from vending machines [60].

The main goal of age estimation is to predict individuals age based on their face images. In the literature, many methods have been proposed to deal with age estimation. Most of them estimate directly age as a single demographic attribute [10,24]. However, there are some methods which estimate all demographic attributes together [30,11,69]. Despite recent efforts, automatic age estimation still has some difficult problems. Moreover, age estimation has several challenges such as environment settings, temporal variations and especially the large intra-class facial appearance variations due to both gender and race attributes. Fig. 1 shows that race attribute, such as black, white and asian races, could lead to vastly different facial appearances of persons being in the same age. For instance, Guo and Mu in [27], studied the influence of gender and race on age estimation process. They founded that age estimation can be impacted by the gender and race differences considerably.

In this paper, we present a complete framework for age estimation, involving a novel Two-Stages-Estimator (TSE). Our approach consists of three main parts; (1) Automatic face detection and alignment to extract only the regions of interest (facial regions) and to correct the position and the size of faces. (2) Feature extraction from the facial regions image including both global and local texture features. (3) Tow-Stages-Estimator, where the input face is first classified into a specific demographic class using Support Vector Machines (SVM) and then a specific regressor is selected to estimate the exact age using Support Vector Regression (SVR). The performance of our proposed approach is evaluated on MORPH-II, PAL and a subset of LFW databases, and the numerical experiments demonstrate that our TSE obtains better estimation ability in comparison to state of the art methods including Convolutional Neural Networks.

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Fig. 1. Examples of different facial appearances of persons at the same age.

Our work has the following main contributions. (i) A complete framework for age estimation based on demographic classification is proposed; (ii) Three different age estimation methods are evaluated; (iii) Performing a hierarchical age estimation method with two different orders and investigating the order that provides better performances. (iv) Demonstrating that the age estimation accuracy is closely depending on the demographic grouping.

The remainder of this paper is organized as follows. In Section 2, we briefly reviewed related previous works. In Section 3, the proposed approach is presented. Experimental setup and results are shown in Section 4. Finally, the conclusions along with future works are given in Section 5.

2. Related works

In the literature, a lot of approaches have been proposed for facial age estimation. Most of them published prior to 2016 are reviewed in a survey paper [13]. In general, the existing approaches for age estimation can be divided into two categories based on the estimation method: direct age estimation [25,26] and age estimation with demographic attributes [6,5,35]. Direct age estimation is an approach that directly predicts the real age or age group as a single facial demographic attribute. Whereas demographic estimation determines the all facial demographic attributes together (i.g., age, gender and race). In this section, we will briefly review some of these works.

2.1. Age estimation

Age estimation is an automatic process of associating the facial image with a classification (year range) or a regression problem (exact age) [26]. The earliest published paper investigating the age classification was the work of Kwon and Lobo [42], where they presented an age classification method based on facial images by computing distance ratios of different facial features (i.e., eyes, nose, mouth, chin,...etc) and detecting the presence of wrinkles. Their method can classify the input faces into one of three age groups (babies, young adults, and senior adults).

Later the exact age estimation was addressed as a regression problem in [43]. Geng et al. [23] proposed an approach for age estimation based on facial aging patterns. The aging pattern was represented by a method called AGing pattErn Subspace (AGES) [22]. The age is indicated through the position of the face in the aging pattern. In [31] Guo et al. developed biologically inspired aging features, through changing the original bio-inspired models by proposing a novel STD operation in creating C_1 features based on Gabor filter responses. They evaluated their approach on YGA and FG-NET databases. Günay and Nabiyev [24] fused local texture features for age estimation. These features are based on Centrally Overlapped Blocks (COB) approach that captures the related information between the blocks of face image. The features are extracted with three texture descriptors: Local Binary Patterns (LBP) [2], Weber Local Descriptor (WLD) [8] and Local Phase Quantization (LPQ) [59]. Then a specific age is estimated by using the Multiple Linear Regression (MLR). Dibeklioglu et al. [14] addressed the presence of facial expressions in estimating age. They combined the dynamic features that are extracted from facial expressions with the appearance features to train the classifiers/regressors model. Their approach showed that smile dynamics can improve the age estimation accuracy.

Additionally, the hierarchical method [73,35,69], which is a combination of classification and regression techniques is also investigated. In [11] Choi et al. designed a hierarchical age estimator consisting of age groups classification followed by age regression based on facial local features (i.e., the wrinkle and skin features), and facial global features (i.e., the appearance and shape of a face), which are combined into a feature vector. Their experiments are conducted on BERC, PAL and FG-Net databases. Also, Luu et al. [53] introduced a hierarchical age estimation method based on a support vector machine (SVM) and support vector regression (SVR) to discriminate between two stages of human development (adulthood and childhood) and estimate a specific age respectively.

Quite recently, deep learning schemes, especially Convolutional Neural Networks (CNNs) [70], have been successfully used for age estimation issue. Hu et al. [37] proposed a CNNs scheme to facial age estimation without age labels by using the age difference information with three kinds of loss functions (i.e., cross entropy loss, entropy loss, and K-L divergence distance). While Rothe et al. [64] offered a solution to real and apparent age estimation by proposing an approach called Deep EXpectation (DEX). They used a deep CNN network pre-trained on the large ImageNet images [65] with VGG-16 architecture [67] followed by a softmax function to expect value formulation for age regression. Their results are reported on FG-NET, MORPH II and CACD datasets for estimating the biological (real) age. Liu et al. [48], exploited the label correlation among face samples in the transformed subspace and proposed a label-sensitive deep metric learning (LSDML) approach for facial age estimation. Then they extended it to a multi-source LSDML (M-LSDML) by using the correlation of multi-source face aging datasets to learn the label-sensitive feature similarity. Their experimental results showed the effectiveness of their approach on MORPH II, AdienceFaces, FG-NET, FACES and ChaLearn databases.

In addition, feature learning methods were incorporated to achieve better facial age estimation performance. Lu et al. [51], learned discriminative local face descriptor directly from raw pixel values into low-dimensional binary codes and encoded them into a real-value histogram feature for face representation by proposing a cost-sensitive local binary feature learning (CS-LBFL). Also, they proposed cost-sensitive local binary multi-feature learning (CS-LBMFL) method to exploit complementary information. Their CS-LBFL and CS-LBMFL are evaluated on FG-NET, MORPH II, LifeSpan, and FACES databases.

2.2. Demographic estimation

Classifying demographic attributes from the human facial images was first introduced by Yang and Ai [72]. The authors intro-