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Facial age range estimation with extreme learning machines

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ABSTRACT

Face image based age estimation is an approach to classify face images into one of several pre-defined age-groups. It is challenging because facial aging variation is specific to a given individual and is determined by the person's gene and many external factors, such as exposure, weather, gender, and living style. Age estimation is a multiclass problem and the number of classes to predict is quite large. There surely is facial aging trend and faces from closed age range have some similar facial aging features. It is difficult to say there are distinct facial aging features for an age. Facial aging features are found to be overlapped among nearby age groups along the aging life and are continuous in nature. In this paper, we emphasised our work on age range estimation with four pre-defined classes. We applied a fast and efficient machine learning method: extreme learning machines, to solve the age categorization problem. Local Gabor Binary Patterns, Biologically Inspired Feature and Gabor were adopted to represent face image. Age estimation was performed on three different aging datasets and experimental results are reported to demonstrate its effectiveness and robustness.

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1. Introduction

Age estimation has many applications, e.g. vending machine can prevent the dispensing of alcoholic drinks or cigarette to an underage customer by finding out the estimated age range of the customer using a computer vision system. Facial aging effects display some unique characteristics [1]: the age progression displayed on faces is uncontrollable, individual and time dependent. Such special characteristics of aging variation cannot be captured accurately due to the prolific and diversified information conveyed by the human faces.

1.1. Motivation

A human face conveys much information that we can easily decipher in our day-to-day communication. This includes the identity of a person, as well as gender, look direction, emotion and age. Developing an automated way to estimate the age of a person from the face image is crucial. This is a key motivation for our work. Such capability, when developed successfully, will enable many applications like automated vending and gaming machines and customized digital signages.

The sooner we know the outcome of any environmental setting changes, the faster we move forward in our research work. We can make the decision quickly whether it is desirable to proceed in a certain direction or not. Fast Extreme Learning Machines (ELM) learning phase attracted us to use it in initial investigation. Furthermore, it was found out to be a good performer as well.

2. Related work

A recent survey on automated age estimation can be found in [2]. Kwon and Lobo [3] first worked on the age classification problem. They referred to cranio-facial research, theatrical makeup, plastic surgery, and perception to find out the features that change with age. A probe gray-scale facial image can be classified into three age groups: babies, young adults, and senior adults. The proposed algorithm is computationally expensive. Adopting the Active Appearance Model (AAM) [4] approach, Lanitis et al. [5] devised a combined shape and intensity model to represent face images. Age is modelled as a function of the vector of the face model parameters. The aging function is defined as linear, quadratic and cubic functions. Later, they [6] reported a quantitative evaluation of the three classifiers (quadratic function, shortest distance, and artificial neural network) using a 400 images database. Geng et al. [1] proposed an aging pattern subspace (AGES) for estimating age from appearance. In order to handle incomplete data such as missing ages in the training

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sequence, the AGES method models a sequence of individual aging face images by learning a subspace representation. The age of a test face is determined by the projection in the subspace that can best reconstruct the face image. Fu et al. [7] constructed a low-dimensional manifold from a set of age-separated face images and use linear and quadratic regression functions on the low dimensional feature vectors from the respective manifolds to estimate the age of a face. Adopting similarly approach, Guo et al. [8] proposed an age manifold learning scheme for extracting face aging features and designed a locally adjusted robust regressor for learning and prediction of human age. Ramanathan et al. [9] proposed a craniofacial growth model that takes into account both psychophysical evidences on how humans perceive age progression in faces and anthropometric evidences on facial growth. The proposed model is used to predict a persons appearance across age and to improve face recognition results. Yan et al. dealt with the age uncertainty by formulating a semi-definite programming problem [10] or an EM-based algorithm [11]. By boosting Local Binary Pattern (LBP) [12] features, Yang et al. [13] identified a sequence of local features which when combined into a strong classifier performs the task of age classification successfully.

Most of the conventional methods for age estimation are intended for accurate estimation of the actual age. However, it is difficult to accurately estimate an actual age from a face image because facial age progression is subject-dependent. Fortunately, it is not necessary to obtain the precise estimates of the actual age for some applications. Most of the age estimation approaches adopted the regression method to predicate exact age from face image. It is difficult to predicate age by using the limited training samples with discrete age values (sparse, not continuous). Moreover, we use Gabor-based features having high dimension and demand for resource will be very high on big dataset. Therefore, in this paper, we pay attention to the mechanism of human age perception, i.e. we limit the estimation to a few age ranges.

One of the problems in facial age estimation is that a large training database is required to represent the variance of the appearance. The training is a time-consuming process. A fast and efficient machine learning method is expected to overcome this problem. Extreme learning machines (ELM) [14] is a simple and efficient learning algorithm driven from single-hidden layer feedforward neural networks (SLFNs). The ELM provides several interesting and significant features over traditional popular gradient-based learning. Not like other feedforward network family, training in the ELM will take an extremely short period. Moreover, it provides better generalization performance over the gradient-based training methods. This motivates us to develop an ELM based facial age range classifier. In this paper, we proposed a novel facial age range estimation framework in which the ELM is employed to classify age groups.

3. Feature extraction

Similar to face recognition, facial features are extracted from original image to represent the faces. In this framework, as shown in Fig. 1, facial features were extracted from face images manually aligned at the two eye corners. Experiment was carried out to compare the results on features obtained by two extraction methods. Biologically Inspired Features [15] has been verified as a good feature for facial age estimation; we adopted it in this paper. In addition, we compared the BIF with another well-established face feature, Local Gabor Binary Pattern [16]. Both features extraction techniques: Biologically Inspired Features (BIF) and Local Gabor Binary Pattern (LGBP), made use of Gabor features extracted with Gabor filter bank of 5 scales and 8 orientations.

All 40 Gabor images generated by Gabor filter bank are divided into processing blocks one after another. Standard deviation or LBP histogram was computed over the block and cascaded into respective vector. Since the extracted feature dimension was too high in both Biologically Inspired Features and Local Gabor Binary Pattern, dimension reduction became a necessary step before they were applied to the ELM. Different feature dimension reduction methods including Principle Component Analysis (PCA), Linear Discriminant Analysis (LDA), Locality Preserving Projections (LPP) and Orthogonal Locality Preserving Projections (OLPP) had been adopted and the performances were compared in this paper.

4. Extreme learning machine

Extreme Learning Machines (ELM) [14] is a simple and efficient learning algorithm in single hidden layer feedforward neural networks (SLFNs). The ELM has several interesting and significant features over traditional popular gradient-based learning algorithms like feedforward neural networks.

Not like other feedforward network family, training can be done by the ELM in an extremely short period. It can overcome the speed barrier faced by classic learning algorithms. Moreover it provides better generalization performance over the gradient-based training methods. The ELM tends to overcome several issues like local minima, improper learning rate and over-fitting problems straightforward. But traditional classical gradient-based learning algorithms may need to use additional methods like early stopping or weight decay to handle such issues [17].

The ELM could be taken as the simplest form of learning algorithms for feedforward neural networks. The present form of ELM algorithm is still only valid for single-hidden layer feedforward networks (SLFNs). However, it was proven that SLFNs can approximate any continuous function and implement any classification application [18]. Thus, we could reasonably assume that

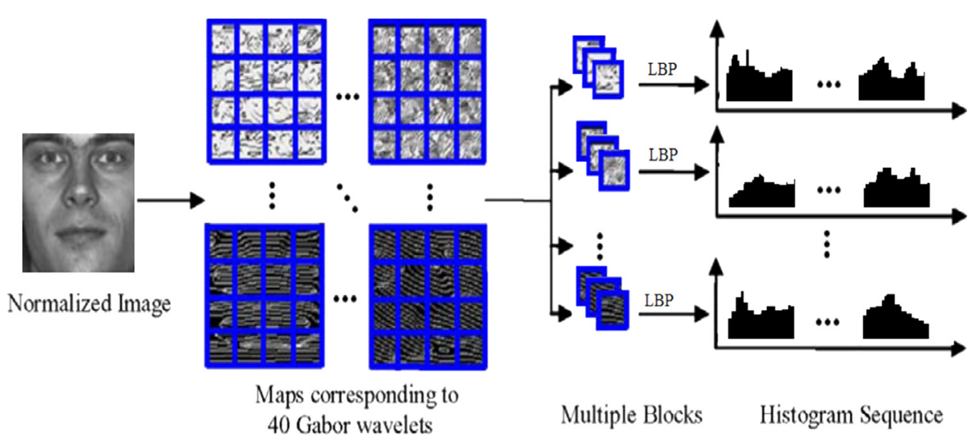

Fig. 1. Local Gabor Binary Pattern processing.

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