Journal of Industrial Information Technology and Application Vol. 2 No. 4

ISSN(Online) : 2586-0852

Age and Gender Estimation based on Multiple patterns and Multiple features

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Abstract. Human age and gender are valuable demographic characteristics. They are also important soft biometric traits useful for human identification or verification. In this paper, we propose an age and gender estimation framework based on multiple patterns and multiple features. The proposed approach consists of three process. First step is landmark based face alignment. Second step is feature extraction step. In this process, we define multiple patterns from face region. And then, we combine multiple features extracted from multiple patterns. Finally, we classify age and gender using a multi-layered Support Vector Machines (SVM) for efficient classification. Rather than performing gender estimation and age estimation independently, the use of the multi-layered SVM can improve the classification rate by constructing a classifier that estimate the age according to gender. Moreover, we collect a dataset of face images, called by DGIST_C, from the internet. Our dataset consists of about 20K Korean celebrities, labeled for age, gender.

Keywords; age estimation; gender estimation; feature fusion approach; multi-layered approach

1. Introduction

Recently, techniques for analyzing and understanding a user's face as a core technology for human and machine interaction have been actively researched. In particular, automatic demographic classification has found its way into industrial

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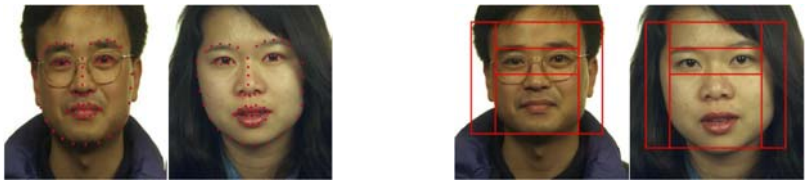
Received: 2017.10.10; Accepted: 2017.11.10; Published: 2018.12.30

applications such as surveillance monitoring, security control, and targeted marketing systems [1]. A comprehensive survey of methods and data has previously been offered by [2, 3, 4]. Gao et. al. [5] used Gabor descriptors along with a Fuzzy-LDA classifier that considers a face image as belonging to more than one age class. Guo et. al. [6] used a combination of Biologically-Inspired Features (BIF) and various manifold-learning methods for age estimation. Choi. et. al, [7] used Gabor and LBP features along with a hierarchical age classifier composed of a Support Vector Machine (SVM) to classify the input image to an age class followed by the support vector regression (SVR) to estimate a precise age. Moghaddam et. al. [8] used a SVM with a Radial Basis Function (RBF) and Baluja et. al. [9] used an AdaBoost classifier. Fazl-Ersi et. al. [10] proposed a feature-based method using a SVM and a LBP operator. Beikos-Calfa et al. [11] proposed a holistic but resource intensive strategy that employed a Linear Discriminant Analysis (LDA) and a Principal Component Analysis (PCA) for gender recognition.

In this paper, we propose age and gender estimation framework using a combining the combination of multiple feature and multiple patterns in order to have a better facial representation for age and gender estimation. The rest of this paper is organized as follows: we will describe the details of proposed approach in Section II. Experimental results will be demonstrated in Section III. Finally, conclusion of our work will be presented in Section IV.

2. Methods

Face alignment is one of the important stages of face analysis, such as face recognition, age and gender estimation, and facial expression. Previously, a popular approach for face alignment was the positioning of a frontal face image into an upright canonical pose based of the position of the eyes. However, the previous face alignment method is unsuitable for age and gender expression estimation since the eye distance is various in an uncontrolled environment. Thus, we devise a landmark based face alignment method to acquire the detailed face region [1]. To obtain the landmarks, we use the open-source OpenFace library [12], which is a real-time and accurate facial landmark detector. Fig. 1(a) shows some detected facial landmark points using the OpenFace library.



(a) (b)

Fig. 1 Sample result images: (a) example of detected facial landmark points, (b) example of multiple patterns

In feature extraction process, we combine the combination of multiple patterns and multiple features. First, we define multiple patterns: left-side(LS), right-side(RS), forehead(F), eyes(E), and mouth(M). All those patterns are automatically cropped from the aligned face region. Fig. 1(b) shows some example of cropped multiple patterns. And then we extract multiple features from each pattern. As feature, we do not define any new local descriptor, but evaluate a collection of local descriptors. Local descriptors are currently being extensively applied for facial analysis, making use of a histogram representation to reduce the feature vector dimension. As descriptors, we have considered the well known HOG, LBP, and some alternatives. Considering the combination of multiple patterns and multiple features, we design a two layered architecture. Each first layer expert in the architecture is built using a SVM classifier with RBF kernel. Its output is a score indicating the proximity of the sample to the border between both classes. The second layer fuses those scores feeding a single second layer SVM classifier.

In age and gender estimation process, we employ a novel multi-layered approach to improve the performance and tackle the complexity problem. In the gender classification layer, we classify gender from the input image using a two-class SVM classifier with an RBF kernel. We then calculate the probability of gender by applying a sigmoidal function to the signed margin distance. In the age classification layer, we classify age using two separate classifiers using a multi-class SVM classifier with an RBF kernel. We subsequently determine the final predicted age by the weight average of the predicted age. The rationale behind this method lies in the differences of facial structures among different genders. For example, middle-aged females and males generally do not show the same facial aging signs due to better skin care and cosmetic use by females.

3. Results

We perform age and gender classifications on the DGIST_C database. Our age classifier categorizes four age groups: 0-19, 10-19, 20-29, 30-39, 40-49, 50-59, 60-69, and 70+ years old. Table 1 shows the composition of the data used in the experiment.

The proposed approach is evaluated using a five-fold cross-validation protocol with overall classification accuracy. Our system was implemented using c++ and tested it on a computer with an Intel i7-2600K CPU @3.40GHz and 32GB RAM. Moreover, several standard routines from the OpenCV Library [13] have been integrated into our framework for face detection and SVM training.

Here, we refer to "exact" classification as the mean accuracy, across all age groups, of predicting the true age label. "1-off" implies counting labeling errors, one age group removed from the true label, as correct. Table 2 shows the result of proposed method with DGIST_C database. The combination of all patterns reaches a gender estimation accuracy over 95%. Moreover, the proposed method achieves an age estimation accuracy over 79%, 93% response to "exact" and "1-off", respectively.

TABLE I. THE DETAILED INFORMATION OF DATABASE

Gender		Age Group (male + female)							
Male	Female	0-9	10-19	20-29	30-39	40-49	50-59	60-69	70+
16017	10669	56+ 375	456+1 096	5070+ 6670	4221+ 1505	4134+ 612	1473+ 171	369+ 69	238+ 171

TABLE II. RESULT OF PROPOSE METHOD

	Combination of multiple patterns and multiple features					Accuracy(%)	
	Left-side	Right-side	Forehead	Eye	Mouth	exact	1-off
Age	ULBP+WLD +LSP2	FPLBP+HOG +LSP2	ULBP+HOG +LSP012	ULBP+HOG +LSP2	ULBP+LSP1 +LSP2	79.8425	93.6621
Gender	ULBP+HOG +LSP1	ULBP+LSP2 +LSP012	LPQ+HOG +LSP2	LPQ+HOG +LSP2	ULBP+HOG +LSP0	95.1059	-

4. Conclusion

In this paper, we proposed age and gender estimation framework using a combining the combination of multiple patterns and multiple features. First, we detect facial landmark points and perform face alignment using these landmarks. We then define multiple patterns of the face that is related with age and gender estimation and extract multiple features. And then, we combine these combination using two layered architecture. By combining the multiple patterns and multiple features, we have a better facial representation for age and gender estimation. Finally, we classify age and gender using multi-layered SVM. By using the multi-layered SVM, we can improve the classification accuracy by constructing a classifier that estimate the age according to gender. The experimental results demonstrate that the proposed approach classifies age and performs gender estimation very efficiently and accurately. In the future, the

proposed method will be applied to digital signage to provide customized service for advertising and marketing.

Acknowledgment

This research was supported by the DGIST R&D Program of the Ministry of Science and ICT (17-IT-01). It was also supported the technology transfer and commercialization Program through INNOPOLIS Foundation funded by the Ministry of Science, ICT and Future Planning (2017DG0002).

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