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Human age classification using facial skin aging features and artificial neural network

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Abstract

In this paper a novel method based on facial skin aging features and Artificial Neural Network (ANN) is proposed to classify the human face images into four age groups. The facial skin aging features are extracted by using Local Gabor Binary Pattern Histogram (LGBPH) and wrinkle analysis. The ANN classifier is designed by using two layer feedforward backpropagation neural networks. The proposed age classification framework is trained and tested with face images from PAL face database and shown considerable improvement in the age classification accuracy up to 94.17% and 93.75% for male and female respectively.

Keywords: Skin aging features; Artificial Neural Network (ANN); Local Gabor Binary Pattern Histogram (LGBPH); Wrinkle analysis; Age classification

1. Introduction

Human face conveys considerable amount of non-verbal information for day-today communication such as gender, age, expression, etc. Human face image also reflects such type of information. This type of information can be extracted from face images by applying suitable algorithms. Researchers have developed numerous algorithms for extracting such type of information from face images to be used for the applications over a wide range in the field of computer vision. Researchers contributed for developing potential applications by using most of the information from human face images. But there is less contribution of researchers by using the age information as compared to the other information conveyed by human face image. Because, age progression varies from person to person as it depends on persons' internal factors such as gene and gender and external factors such as weather condition, living style, consuming habits, etc., unable to control it and the database collection i.e. collecting face images of individuals' over a wide age range is very difficult (Geng, Zhou, & Smith-Miles, 2007; Ramanathan & Chellappa, 2005). Hence it becomes very intricate to study the age progression by capturing the similarities and discrepancies in the aging patterns shown by face image. Therefore human age classification via face images is more complicated not only for human being but also for a machine. But human age classification via face images by a machine has potential applications in ASHCI (Age Specific Human Computer Interaction), intelligent ICU (Intensive Care Unit) (Geng, Zhou, Zhang, Li, & Dai, 2006; Lanitis, Draganova, & Christodoulou, 2004) ECRM (Electronic Customer Relationship Management), etc. (Fu, Guo, & Huang, 2010). Therefore this topic attracted numerous researchers from

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both industry and academic world, even though it is complicated.

Main contribution of this paper is summarized as follows. A novel framework is presented in this paper to solve the human age classification problem via face images by a machine by using facial skin aging features and Artificial Neural Network (ANN). The facial skin aging features are extracted by using Local Gabor Binary Pattern Histogram (LGBPH) and wrinkle analysis. The age classifier is designed by using two layer feedforward backpropagation neural networks. The novelty of the proposed age classification framework consists of following three ways. Firstly, the proposed age classification framework has shown great improvement in the age classification accuracy. Secondly, illumination, rotation, scale and translation invariant efficient facial skin aging features are extracted by using LGBPH and wrinkle analysis. Lastly, only eight region of interest are used for extracting facial skin aging features which are not only less in count but also differ in dimensions as compared to (Fard, Khanmohammadi, Ghaemi, & Samadi, 2013). The proposed age classification framework is trained and tested with face images from PAL face database (Minear & Park, 2004). This database includes images in the age range from 18 years to 93 years, which shows age progression from adulthood to senior adults. During the age progression from adulthood to senior adults, the perceptible changes occur in the skin texture but imperceptible changes occur in the shape of human face (Geng et al., 2007). Therefore the facial skin aging features of region of interest in face images are used to differentiate between age groups.

The rest of the paper is organized as follows. Existing age classification systems are summarized in Section 2. Facial skin aging features and ANN are enlightened in Section 3. Section 4 describes the proposed age classification framework. Section 5 elaborates the experimental results and conclusion is drawn in Section 6.

2. Related work

Kwon and da Vitoria Lobo (1999) are the foremost researcher to deal with age classification problem. They designed an age classification system for classifying 47 face images from their private database into three age groups by using geometric features and skin wrinkle analysis and achieved 100% accuracy. Kanno, Akiba, Teramachi, Nagahashi, and Agui (2001) developed an age classification system to classify 440 face images of young males from their private database into four age groups by using mosaic features and neural network and achieved accuracy of 80%. Horng, Lee, and Chen (2001) designed an age classification system for classifying 230 face images from their private database into four age groups by using geometric ratios, skin wrinkle analysis and neural networks and achieved 81.6% accuracy. Iga, Izumi, Hayashi, Fukano, and Ohtani (2003) designed an age classification system for classifying 101 face images from HOIP (Human and Object Interaction Processing) database (Yamamoto & Niwa, 2002) into five age groups by using six different kinds of information i.e. Gabor wavelet, skin color, etc. and SVM (Support Vector Machine) and achieved 58.4% accuracy. Takimoto, Mitsukura, Fukumi, and Akamatsu (2006) designed an age classification system for classifying 252 face images consisting of 113 male images and 139 female images from HOIP database (Yamamoto & Niwa, 2002) into six age groups using Gabor wavelet, PCA (Principal Component Analysis) and neural network and achieved 57.3% and 54.7% accuracy for male and female database respectively. Gunay and Nabiyev (2008) designed an age classification system for classifying the face images from FERET (Face Recognition Technology) database (Phillips, Moon, Rizvi, & Rauss, 2000) and 350 images from their private database into six age groups by using LBP and Nearest Neighbour ($k-NN$) classifier and achieved 80% accuracy. Dehshibi and Bastanfard (2010) designed an age classification system for classifying 498 face images from IFDB (Iranian Face Database) (Bastanfard, Nik, & Dehshibi, 2007) into four age groups by using geometric features, wrinkle analysis and ANN and achieved 86.64% accuracy. Hajizadeh and Ebrahimnezhad (2011) designed an age classification system for classifying 377 face images from IFDB (Bastanfard et al., 2007) into four age groups by using HOG (Histograms of Oriented Gradients) and PNN (Probabilistic Neural Network) and achieved 87.025% accuracy. Fard et al. (2013) designed an age classification system for classifying 575 face images from PAL (Productive Aging Lab) face database (Minear & Park, 2004) by using HOG, LBP and ANFIS (Adaptive Neuro-Fuzzy Inference System) and achieved 88.01% accuracy. Gao and Ai (2009) designed an age classification system for classifying 6386 web images into four age groups by using Gabor features and fuzzy LDA classifier and achieved accuracy of 91%. Yang and Ai (2007) developed an age classification system to classify 13236 face images consisting of 9000 snapshot images, 3540 images from FERET (Phillips et al., 2000) database and 696 images from PIE (Pose, Illumination, and Expression) database (Sim, Baker, & Bsat, 2003) into three age groups by using LBP (Local Binary Pattern) histograms and AdaBoost (Adaptive Boosting) classifier and achieved 92.12% and 87.5% accuracy for FERET (Phillips et al., 2000) database and PIE database (Sim et al., 2003) respectively. Izadpanahi and Toygar (2014) designed an age classification system for classifying 1104 face images consisting of 425 images form FG-NET (Face and Gesture Recognition Research Network) database (FG-NET) and 679 images form IFDB (Bastanfard et al., 2007) into seven age groups by using geometric ratios, wrinkle analysis and SVC (Support Vector Classifier) and achieved 92.62% overall accuracy. The outline of existing age classification systems as described earlier is given in Table 1.

After surveying the existing age classification systems it has been observed that the age classification accuracies of