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An Analysis of Different Ethnic Age Group Estimation from Facial Images

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Abstract: ***Today's intelligent systems in this digital era, require a high demand for Internet and multimedia computing that focuses images mostly. Images contain human conveys valuable information. Especially, Face is a prolific information source through which people can effortlessly extract many kinds of useful information from a face image, such as identity, expression, emotion, gaze, gender, age, etc. But, automatic detection by computers is still a herculean task. The automatic extraction of most of the useful information has been extensively studied in several research areas including multimedia, HCI, computer vision, pattern recognition, machine learning and neural networks. Images containing faces has received a great attention over the last few years, because of its applications in all the domains. Based on the analysis of the information contained in the face images, there are a lot of research efforts in processing of human face images that tries to build a fully automated system. It is confident that the outcome this proposal definitely supports the future prospective researchers to have a clear vision on age group estimation from facial frontal images.***

Keywords: Medical Imaging, Image Forensics, Face detection, Feature extraction, Skin detection, Video processing, Bio-metrics.

1. INTRODUCTION

In this modern world, cognitive vision plays vital role where making machines to think and act like human beings. For this objective, the artificial system needs to perform the high-level tasks of understanding and interacting with the physical world, it needs, among other things, to be able to perceive, represent and reason about its environment. Computer vision uses visual perception to observe the world analogous to the visual system in humans that allows individuals to assimilate information from the environment based on the visible light reaching the eye. However, knowing person's age just by looking at old or recent pictures for them is often a bigger challenge. Human face characteristics change with time which reflects major variations in appearance. The age progression signs displayed on faces are uncontrollable and personalized such as hair whitening, muscles dropping and wrinkles [2].

2. MOTIVATION

All the human faces form a class of fairly similar objects. Each face consists of the same facial components in the same geometrical configuration with slightly varying sizes. The facial age estimation problem shares similarities with the age progression problem. Age progression is the prediction of the future facial appearance of a subject based on images showing his/her previous facial appearance; whereas face estimation estimate age / age group from the facial features/ appearance [1][2]. Both age estimation and age progression need to take into account age-related facial deformations encountered during the lifetime of a subject. In recent years, age as an attribute related to human faces is being increasingly studied and there has been a growing interest in problems such as face recognition across ages, automatic expression from face images, and appearance prediction across aging, etc [3][4].

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3. CHALLENGES IN AGE GROUP ESTIMATION

In age estimation, problem of estimation of pose or shape is severely under-constrained due to many factors such as: the image formation process, occlusions, changes in appearance, and the complexity of the human body structure itself. There were several challenges encountered when attempting to develop a methodology, because face images can demonstrate a wide degree of variation in both shape and texture. Appearance variations are caused by individual differences, the deformation of an individual face due to changes in expression and speaking, as well as lighting variations [1][2]. While developing a system for human age estimation entails characterizing certain attributes that are inherent to human faces such as (i) the 3D structure of human faces, (ii) the reflective properties of facial skin[3] color, wrinkles, landmarks etc., (iii) the uniqueness of different facial features of human, (iv) the global and local configuration of facial features, etc. in combination with scene-centric and hardware specific attributes such as illumination, lighting conditions, environment and viewpoint. (v) Age estimation systems, often encounter facial images of individuals taken from real-life conditions, where facial appearances are affected by the inter play of multiple factors such as pose, facial expressions, races, occlusions, etc. make it more even more difficult [3][4]. [vi] Limited inter-age group variation: In certain cases, differences in appearance between adjacent age groups are negligible, causing difficulties in the process of age estimation. This problem is escalated when dealing with mature subjects.[vii] Diversity of aging variation: Both the rate of aging and type of age-related effects differ for different individuals. For example the amount of facial wrinkles may be significantly different for different individuals belonging to the same age group. As a result of the diversity of aging variation, the use of the same age estimation strategy for all subjects may not produce adequate performance. Several factors could influence the aging process including race, gender and genetic traits. For this reason different age estimation approaches may be required for different groups of subjects.[viii] Physiological factors: The Face detection problem is particularly challenging as age depends on many factors, some of them are visual and many others are non-visual such as ethnic background, living style, working environment, health condition and social life. For instance, the effects of ultraviolet radiation, usually through exposure to sunlight, may cause solar aging which is another strong cause for advanced signs of face aging. In particular, Stone stated that aging can be accelerated by smoking, genetic predisposition, emotional stress, disease processes, dramatic changes in weight, and exposure to extreme climates [5]. [ix] Visual features: The visual features that can help in evaluating age such as people's facial features are affected by pose, lighting and imaging conditions [1]. [x] Gender: Males and females may have different general discriminative features displayed in images due to the different extent in using makeup, accessories and cosmetic surgeries which increase the negative influence of individual differences. [xi] Benchmark Database: The difficulty of acquiring large-scale databases, which covers enough age range with chronological face aging images, makes the estimation tasks more difficult to achieve. Although, Artificial Intelligence based image mining can help the data collection, it is usually hard or even impractical to collect a large database of large amount of subjects providing a series of personal images across different ages[2].These difficulties can be overwhelmed by employing simplifying assumptions and domain specific knowledge, or by engineering the environment appropriately.

Fig. 1.Some facial images from the FG-NET (top) and MORPH-II (bottom) databases.

4. PROPOSED METHODOLOGY

The Face detection system must be robust against the This research proposes an innovative hierarchical age estimation method based on score and decision level fusion of global and local facial features. This research proposal consists of image preprocessing, global feature extraction with AAM, GIST, GLCM and local feature extraction with LBP, PLBP, LPQ, PLPQ,

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PHOG and LGBP. After the feature extraction stage, classification with multiclass support vector machines (SVM), age grouping with multiple support vector regression are done. Finally, age group of the input face image, is estimated automatically using the prominent features. In the literature, different approaches have been proposed to characterize facial their physical description. For instance, Collins et al., [82] proposed a gender recognition approach by combining HOG and LHSV features within a SVM classifier. Galdi et al [83] used gaze analysis for gender and age categorization by extracting features from a sequence of eye images, using AdaBoost and SVM classifiers. Specifically, for age recognition, Ge et al., [84] presented an approach that uses HOG, SIFT and LBP descriptors in a prediction system, which uses a regression model with a multi-view canonical correlation analysis. Dong et al [85] proposed a deep learning based framework, which extracts related visual features from a set of face images for age-group prediction. Facial images are used for the classification of age groups and the classification is done mostly using Local Descriptors. One way to achieve the texture classification in gray scale images is to use the texture descriptors to build several local descriptions of the facial image and concatenate them into a global description. These local feature based methods are more robust against variations in pose or illumination than holistic methods. Holistic description of a face using texture methods is not reasonable since texture descriptors tend to average over the image area [86]. Momeni -K et al., demonstrated that anatomical information is highly correlated with the physical features [87]. Most of the approaches only consider image descriptors which are not directly related with the anatomical structure of the face and just attempt to extract one feature at a time. Hence, there is a doubt whether a single feature information could be useful to decide the facial representation fully. All the selected global (AAM, GIST and GLCM) and local descriptors (LBP, PLBP, LPQ, PLPQ, LGBP and PHOG) are applied in every cropped and normalized skin region, and once the local features of every region have been extracted independently, the feature vectors are concatenated into a single vector. In addition, several combinations between different techniques are performed in an attempt to capture unique advantages of each descriptor. Score level and Feature-level fusion has been successfully applied in images, to avail the fused feature descriptor. Since, the local feature vector extracted by the LBP, PLBP, PHOG, LPQ, PLPQ and LGBP is high dimensional, only the principal components are chosen with the PCA. The z-score is then applied to normalize the lower dimensionality features. The fusion of features, is built up through the concatenation of the normalized feature vectors. Aging differs according to the age groups of a person. Wrinkles are usually found in senior and advisor subjects, while geometric features normally change during childhood and adulthood. The Hybrid fused feature using the two-stage age prediction based on age-group specific classifiers separate groups more precisely. It has shown good results and better ability to deal with these age-related adopted hybrid facial features.

5. EXPERIMENTS AND DISSCUSSION

The performance of an age group estimation system, with respect to both accuracy and computational speed, is not solely based on feature extraction algorithms, but also with gender and ethnicity. More importantly, some local features are not varied with pose, facial expression variations and lighting direction, but others vary with age progression. Additionally, evidences from proved that hybrid features are more appropriate for machines to recognize human faces than holistic ones.

Table: 1 Different Ethnicity Comparison

		Accuracy (%)				
S.No	**Age Group**	**Asian**	**Black**	**Hispanic**	**Middle**	**White**
1	Child	94.1	99.9	99.9	100	99.9
2	Teen	93.66	99.5	99.9	97.6	99.7
3	Young	94.1	97.45	95	97.6	99.6
4	Middle	75.15	92.3	80	90	94.9
5	Senior	76.11	92.3	77.5	88.5	95
6	Advisor	95.5	98.4	94. 8	96.9	98.5

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Table 2. MAE on different age group

Age group	MAE
0-10	5.084
11-20	5.156
21-35	5.216
36-50	4.083
51-65	4.862
Above 65	3.375

Table 3. Failure rate of proposed scheme

Measure	Estimation
TPR (Correct Detection)	94.5%
FPR (Wrong Group Estimation)	0.1%
FNR (Failure)	5.4%

Note: TPR-True Positive Rate, FPR-False Positive Rate, FNR-False Negative Rate

For age group estimation, there are concrete ways to evaluate the performance of different algorithms. The output of an age group estimation can be an estimate of the exact age group range of a person. Considering the results of this research, the following discussion points can be drawn. Accuracy is appreciably good even multiple features taking computation time. The accuracy of the system improved with increased number of features that are contributing towards classification. This proposal achieved equally good or better accuracy with significantly reduced dimension. With dimension reduction and selective hybrid features on region of interest are applied, thus the processing time is less and hence the system is fast enough.

6. CONCLUSION

The performance of proposed scheme may affect and deteriorate the performance include pose, image quality, lighting conditions, gender and age difference. Number of experiments are conducted in the cited studies to define the effect of each factor. Based on the results, the proposed approach is suitable for human age-group estimation in real time. Since the time taken on average is 28 milliseconds, which is appropriate in the context of real-time performance. For measuring the performance of age estimation algorithm MAE and CS is used. It is usually based on the mean average error (MAE) between real and estimated ages and Cumulative Score (CS) that shows the number of test cases, which have an absolute error smaller

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than a given threshold. In the case of age-group, age estimation errors usually refer to the percentage of correct classifications. Analysis carried out on previous research in facial age estimation and hybrid techniques with shape, appearance, texture and skin features adapted to the facial aging problem. Overall, the proposed method performs the best with MAE of 3.14and accuracy of 96.17 respectively. Also, it gives good results in both gender of different races. Overall, evaluation shows that this proposed scheme is better to the state of the art for facial age group estimation.

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