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Face Recognition and Retrieval Using Cross Age Reference Coding

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Abstract: This paper introduces an approach for face cognizance throughout age and in addition a dataset containing variations of age in the wild. We use a data-driven system to deal with the go-age face realization challenge, known as cross-age reference coding (CARC). By using leveraging a colossal-scale snapshot dataset freely available on the web as a reference set, CARC can encode the low-degree feature of a face image with an age-invariant reference area. In the retrieval segment, our method most effective requires a linear projection to encode the feature and for that reason it's incredibly scalable. To evaluate our system, we introduce a tremendous-scale dataset known as cross-age dataset. To understand the difficulties of face awareness across age dataset involves 2,000 constructive pairs and a terrible pairs and is cautiously annotated by way of checking each the related photograph and net contents. Our endorse process show that although ultra-modern approaches can gain competitive efficiency compared to normal human efficiency, majority votes of a couple of humans can achieve much higher efficiency on this challenge. The gap between computer and human would imply feasible instructional materials for additional development of move-age face awareness someday.

Keywords: Cross Age Reference Coding (CARC), Face Recognition and Retrieval, DATASET.

1. INTRODUCTION

By means of taking skills of largely available famous person photographs on the internet, we introduce a brand new approach to address this trouble in an extra method from earlier reports. As an alternative of modeling the aging process with robust parametric assumptions, we adopt a data driven procedure and introduce a novel coding process called cross-Age Reference Coding (CARC). Our normal assumption is that if two people seem alike when they are younger, they would also appear similar once they both grow older. Headquartered on this assumption, CARC leverages a set of reference images to be had freely from the internet to encode the low-degree features of a face snapshot with an averaged representation in reference space. By using a pass-age reference set got from the internet, we suggest a new coding method, CARC, which is able to help map low-stage feature into an age-invariant reference area. The outcome exhibit that CARC outperform brand new methods and achieve high accuracy in face cognizance and retrieval across age. Although CARC can obtain superior performance in each DATASET and MORPH datasets, the performance in go-dataset surroundings drops extensively. The drop is probably brought on by means of the large change between the looks distributions of the two datasets. With the intention to evaluating human efficiency on the task of move-age face recognition, we used annotated verification subset referred to as DATASET. Our mission show that although the proposed approaches performs higher than natural human, combing results from multiple human can attain larger efficiency. The human performs better most of the time on rejecting terrible pairs, and acquaintance within the discipline is important to human for attention.

2. SYSTEM ARCHITECTURE

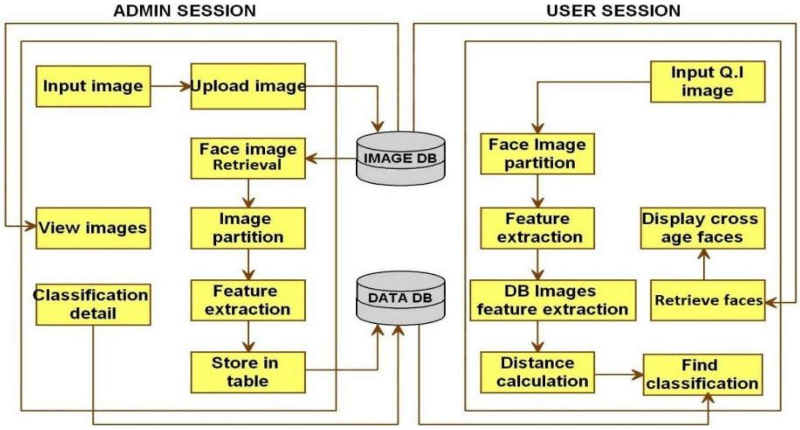

Fig: System Architecture

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3. RELATED WORKS

Face recognition and retrieval have been investigated for a long time in many studies. A thorough survey of this topic is beyond the scope of this paper, and we refer the readers to the survey papers/books [5], [6] for a comprehensive review of this problem. Below we only give a concise survey of several important methods related to our work. Turkand Pentland introduce the idea of eigen face [7] in 1991, Ahonen et al. [8] successfully apply the texture descriptor, local binary pattern (LBP), on the face recognition problem. Wright [9] Propose to use sparse representation derived from training images for face recognition. The method is proved to be robust against occlusions for face recognition. Some researches also use a reference set to improve the accuracy of face recognition and retrieval. Kumaret [3] propose to use attribute and simile classifiers, SVM classifiers trained on reference set, for face verification. Berg et al. [10] further improve the method by using "Tom-vs-Pete" classifier. Yin et al. [4] propose an associate-predict model using 200 identities in Multi-PIE dataset [11] as a reference set. Wuet al. [12] propose an identity-based quantization using a dictionary constructed by 270 identities for large-scale face image retrieval. Although these methods achieve salient performance on face recognition, they do not work well when the age variation exists because they do not consider the age information in the reference set.

Most existing age-related works for face image analysis focus on age estimation [13] and age simulation [14][15]. In recent years, researchers have started to focus on face recognition across age. One of the approaches is to construct 2D or 3D aging models [16]–[17] to reduce the age variation in face matching. Such models usually rely on strong parametric assumptions, accurate age estimation, as well as clean training data, and therefore they do not work well in unconstrained environments. In [18], Wu et al. propose to use a relative craniofacial growth model to model the face shapes for cross-age face recognition and it yields good performance on FG-NET dataset. However, their approach requires age information to predict the new shapes, which is not always available. Some other works focus on discriminative approaches. Linget [19] use gradient orientation pyramid with SVM for face verification across age progression. Li et al. [20] use multi-feature discriminant analysis for close-set face identification. Gong et al. [21] propose to separate the feature into identity and age components using hidden factor analysis. Different from the above methods, we propose to adopt a data-driven approach to address this problem. By taking advantage of a cross-age reference set freely available on the Internet, and using a novel coding framework called CARC, we are able to achieve high accuracy in face recognition and retrieval with age variation. The preliminary results have been published in [22], and the contributions are presented here as a whole. The extensions in this work include: (1) Verification dataset (2) Human evaluations for cross-age face recognition: We use Amazon Mechanical Turk to conduct experiments on face verification in DATASET, in order to understand the difficulties of face recognition across age. (3) More in-depth experiments in face retrieval, verification, and identification and the comparison between human and machine performance.

4. CROSS-AGE REFERENCE CODING (CARC)

1. GREY LEVEL CO-OCCURENCE MATRIX

In statistical texture analysis, texture features are computed from the statistical distribution of observed combinations of intensities at specified positions relative to each other in the image. According to the number of intensity points (pixels) in each combination, statistics are classified into first-order, second order and higher-order statistics. The Gray Level Co-occurrence Matrix (GLCM) method is a way of extracting second order statistical texture features. The approach has been used in a number of applications, third and higher order textures consider the relationships among three or more pixels. A GLCM is a matrix where the number of rows and columns is equal to the number of gray levels, G, in the image. The matrix element P (i, j | Δx, Δy) is the relative frequency with which two pixels, separated by a pixel distance (Δx, Δy), occur within a given neighborhood, one with intensity 'i' and the other with intensity 'j'.

neighbour pixel value ---> ref pixel value:	0	1	2	3
0	0,0	0,1	0,2	0,3
1	1,0	1,1	1,2	1,3
2	2,0	2,1	2,2	2,3
3	3,0	3,1	3,2	3,3

Fig: GLCM Calculation

The matrix element P (i, j | d, ɵ) contains the second order statistical probability values for changes between gray levels 'i' and 'j' at a particular displacement distance d and at a particular angle (ɵ). Using a large number of intensity levels G implies storing a lot of temporary data, i.e. a G × G matrix for each combination of (Δx, Δy) or (d, ɵ). Due to their large dimensionality, the GLCM's are very sensitive to the size of the texture samples on which they are estimated. Thus, the number of gray levels is often reduced. GLCM matrix formulation can be explained with the example illustrated in fig for four different gray levels. Here one pixel offset is used (a reference pixel and its immediate neighbor). If the window is large enough, using a larger offset is possible. The top left cell will be filled with the number of times the combination 0,0 occurs, i.e.

$$\begin{pmatrix} 75 & 23 & 0 & 0 & 0 & 0 & 0 & 0 \\ 23 & 275 & 84 & 17 & 1 & 0 & 0 & 0 \\ 0 & 94 & 1393 & 336 & 61 & 7 & 0 & 0 \\ 0 & 8 & 328 & 3455 & 491 & 60 & 1 & 0 \\ 0 & 0 & 57 & 519 & 4133 & 350 & 5 & 0 \\ 0 & 0 & 5 & 58 & 309 & 4039 & 12 & 0 \\ 0 & 0 & 0 & 0 & 0 & 19 & 18 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix}$$

Fig: Grey level co-occurrence matrix

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how many time within the image area a pixel with grey level 0 (neighbor pixel) falls to the right of another pixel with grey level 0(reference pixel).

2. AVERAGE RGB

Average RGB is to compute the average values in R, G and B channel of each pixel in an image, and use this as a descriptor of an image for comparison purpose.

The following are 3 equations for computing the average R, G, B component of an image I

$$r = \sum_{x=1,y=1}^{x=w,y=h} \frac{R(I(x,y))}{w \times h}$$

$$g = \sum_{x=1,y=1}^{x=w,y=h} \frac{G(I(x,y))}{w \times h}$$

$$b = \sum_{x=1,y=1}^{x=w,y=h} \frac{B(I(x,y))}{w \times h}$$

Here is the equation for distance measure of image I_a and I_b, we use the weighted Euclidean distance The distance between two exact images will be 0 and the distance between to most dissimilar images (blank and white) will be 1 depending on the range of RGB is from 0-255.

$$d(I_a, I_b) = \sqrt{\frac{(r_a - r_b)^2 + (g_a - g_b)^2 + (b_a - b_b)^2}{3}}$$

5. CONCLUSION

With the aid of utilizing a go-age reference set received from the internet, we recommend a brand new coding approach, CARC, which can aid map low-degree characteristic into an age-invariant reference space. The experimental outcome show that CARC outperform brand new approaches and obtain excessive accuracy in face awareness and retrieval throughout age. We additionally introduce a giant-scale face dataset, DATASET, for the rationale of face awareness with age variant. To the pleasant of our capabilities, the dataset is the largest publicly on hand go-age face dataset, and we hope the dataset can support researchers to beef up the outcome of face attention. Even though our experiments exhibit CARC can reap superior efficiency in each DATASET and MORPH datasets, the efficiency in move-dataset atmosphere drops notably. The drop is customarily induced by way of the big difference between the looks distributions of the 2 datasets. One day work, we wish to tackle this problem by introducing domain adoption systems. With the intention to evaluating human efficiency on the assignment of go-age face cognizance, we further built a cautiously annotated verification subset called DATASET and behavior huge experiments. Our experiments exhibit that despite the fact that the proposed approaches performs better than natural human, combing results from a couple of human can obtain better efficiency. Accordingly, there is still a gap on the undertaking. We also exhibit that human performs higher probably on rejecting terrible pairs, and acquaintance within the discipline is worthy to human for recognition. Sooner or later, we need to examine the way to easily select a subset from the reference individuals for additional making improvements to the performance of age-invariant face cognizance and retrieval, and also fin0d out how to lower the false constructive cost in the realization method in an effort to achieve similar efficiency of human.

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