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AGE-INVARIANT FACE RECOGNITION BASED ON LOCAL K-MEANS ENSEMBLE

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Abstract. *Face recognition across age progression is an important problem that has not been widely addressed. For the aging effect, the shape and texture changes degrade the performance of face recognition. To solve the issue in across age face recognition, an age-invariant face recognition based on local K-means ensemble is proposed. First, the gradient angle provides a simple but effective representation. This representation is further improved when hierarchical structure is used, which leads to the use of the K-means pyramid (KMP). When combined with supervised learning, KMP demonstrates excellent performance. Our work differs from previous studies in the representation, K-means pyramids (KMPs), and the ensemble classification frameworks. Experimental results show that the proposed methods outperform the existing techniques.*
Keywords: Face recognition, Age progression, K-means pyramid

1. **Introduction.** Face recognition is an important problem in computer vision and has many applications such as human-computer interaction, image retrieval, and surveillance. However, there exist more difficult problems in the recognition, including illumination change, pose, expression, accessory, and aging. In this paper, we focus on across age problem. Due to the lack of robustly identifiable features that are stable across age, the precision of current age-related facial image recognition is still very limited. Most of these works study age simulation [1,2] and age estimation [3-5]. Besides, some researchers focus on the effect of age progression on face profiles and appearances [6,7].

Face recognition across age has received relatively little attention. To overcome aging problem, some previous work applies age progression for face verification studies. When comparing two photos, these methods either transform one photo to have the same age as the other, or transform both to reduce the aging effects. Lanitis et al. [1] proposed one of the earliest works, where a statistical model is utilized to capture the variation of facial shapes over age progression. The model is then used for age estimation and face verification. A recent work proposed by Biswas et al. [8] studies feature drifting on face images at different ages and applies it to face verification. Other studies using age transformation for verification include [4,5,9].

The above methods can be roughly categorized as generative methods since aging needs to be modeled. On the other hand, discriminative approaches have been used for face verification across age progression [10]. The study most related to our work is [11]. They proposed a model of gradient orientation pyramid (GOP) algorithm combined with the support vector machine (SVM) to face verification tasks. Note that gradient-based representations recently have been used in computer vision and pattern recognition tasks such as the scale invariant feature transfer (SIFT) [12] for object and category classification, and the histogram of orientation (HOG) [13]. In [14], they considered the problem of determining functions of an object that are insensitive to illumination changes and successfully applied to face verification. In recent years, the ensemble of local feature based classifiers for face verification has been well studied and achieved good performance [15,16]. Xu et al. [17] utilized regions around eyes for age invariant face verification and illustrated that local features inherently possess spatial locality.

Inspired by the works mentioned above, we propose age-invariant face recognition based on local K-means ensemble. The proposed methods incorporate two different stages, training stage and testing stage. At training stage, the framework of the proposed methods is based on unsupervised learning of local features in different layers. The last classification results from the layer N are further integrated into one feature. Then, the task is to assign the pair as either extra-personal or intra-personal. The pair is classified by using supervised learning. At testing stage, the framework of the proposed methods is the simplified structure of the method at training stage. The contributions of the proposed age-invariant face recognition approach are that our algorithm is different from previous ones in the representation, K-means pyramids (KMPs), and the ensemble classification frameworks. Experimental results will demonstrate that the proposed methods outperform the existing techniques.

The rest of the paper is organized as follows. Section 2 presents face verification framework. Experimental results are demonstrated in Section 3. Finally, Section 4 draws the conclusions.

2. Face Verification Framework.

2.1. Local classifier training. In previous studies, researchers could extract facial features from the entire face, which leaded to high dimensionality of features and completely ignored the probability that facial parts may change in different ways as age progression. This motivates us to find effective local features for face representation. In our methods, therefore, we extract KMPs according to local facial parts.

First, we input face image, and extract local features for the K-means classifier training of the first layer. In the second layer, the previous classification results are considered as a new representation for each individual. The local features of this representation are further extracted for the K-means classifier training of the second layer. The following layers are operated similarly to the second layer.

As previously described, using the entire face ignores the probability that different parts of human face may change in totally different ways as age progression. Mao et al. [16] extracted GOPs according to local facial parts. Our approach uses the local two eyes $(E1, E2)$ in facial image for features' representation of individual.

Each of the gradient angles, θ, is calculated from each pixel of $E1$ and $E2$ in Layer-1, respectively. The gradient angles' representation of the eye is further divided into $r1 \times t1$ overlapping sub-patches of the same size ($b1 \times b1$ sub-patches' size). We collect m local feature sets ($m = r1 \times t1$) from each sub-patch of the eye image. Afterward, all of the local feature sets of the right eye and the left eye are trained by K-means, respectively. For example, the eye image size is 5×4, and size of sub-patches is 3×3. We collect m (3×2) local features from overlapping sub-patches (shift 1 pixel), and each sub-patch contains n (3×3) features.

The local K-means classifier of Layer-1 is generated, when the operations of Layer-1 schema are finished. In next layer, we repeat the first three steps in Layer-1, including inputting training image set, preprocessing and feature extraction. Now, we generate the new representation of the eyes $(E1, E2)$ from the local K-means classifier of Layer-1, respectively. Next, we resample the new local features from the new representation of the eyes in Layer-2. The procedures of resampling are to divide the new representation into $r2 \times t2$ overlapping sub-patches of the same size ($b2 \times b2$ sub-patches' size). Afterward, the concept of training procedures in the following layers (Layer-3, ..., Layer-N) is similar to the Layer-2.

2.2. **Classifier ensemble framework.** The framework is described using an ensemble feature model for the training task. We generate the new representation of the eyes (E_1, E_2) from the local K-means classifier of the last layer, respectively. After finishing the previously hierarchical unsupervised learning procedure (Layer-1, ..., Layer-N), we integrate the new representation of the eyes (E_1, E_2) into a feature set, respectively.

Given a pair of two eyes (E_1, E_2) and corresponding integrating feature set (F_1, F_2), the ensemble feature vector $x(I) = f(E_1, E_2)$, defined in Equation (1), is computed as the element-wise product of the difference between new eyes representation in the same image.

$$x(I) = f(E_1, E_2) = (F_1 \odot F_2) \tag{1}$$

where $\odot$ is the element-wise product, and I is an inputting facial image.

Face verification as a two-class classification problem has been studied for general face analysis. For example, Moghaddam et al. [18] used a Bayesian framework for the extra-personal and intra-personal face verification. Phillips [19] used SVM for face verification problems and observed good results on the FERET database [20] compared to component-based approaches. Jonsson et al. [21] used SVM for face verification problems.

As in [11,18,19,21], we also model the face verification tasks as a two-class classification problem. Given an input image pair I_1 and I_2, the task is to assign the pair as either extra-personal (i.e., I_1 and I_2 from different individuals) or intra-personal (i.e., I_1 and I_2 from the same people).

Given an image pair (I_1, I_2) and corresponding ensemble features $(E_{f1} = x(I_1),\ E_{f2} = x(I_2))$, the feature vector $X = F(I_1, I_2)$, defined in Equation (2), is computed as the element-wise product of the difference between ensemble features in extra-personal or intra-personal, respectively.

$$X = F(I_1, I_2) = (E_{f1} \odot E_{f2}) \tag{2}$$

2.3. **Testing framework.** We describe the framework using KMPs for the testing task. The verification task needs to establish integrating features of the eye by processing in hierarchical K-means classifier (Layer-1, Layer-2, ..., Layer-N). We generate the ensemble features from the last layer, and assign all the pairs as either extra-personal or intra-personal from training set and testing set. Afterwards, we randomly select several extra-personal pairs and intra-personal pairs, respectively, as testing subjects.

Note that the hierarchical structure of verification task is to be established by K-means classifier and resampling procedures. These procedures are directly used in each training stage layer. Afterwards, the ensemble feature is computed as in Subsection 2.2 and then discriminative task is processed by using SVM for each of pairs.

3. **Experimental Results.** The MORPH is a public face-with-age database. It is widely used for research of age-related facial image analysis. These photos are taken under various illumination and facial expression conditions, spanning from 2003 to late 2007. The MORPH is composed of 55,000 unique facial images of more than 13,000 individuals. The ages range from 16 to 77 with a median age of 33.

In addition, the FG-NET Aging Database [22] is publicly available. It is widely used for research of age-related facial image analysis, since photos are taken under various illumination conditions. Illumination is the most significant factor affecting face appearance in addition to pose variation. The FG-NET database includes 1002 high-resolution color or gray-scale face images of 82 multiple-race subjects with large variation of lighting, pose, and expression. The age range is from 0 to 69 years old with chronological aging images available for each subject.

For verification tasks, we use the CAR and the CRR as the critical criteria [11]. It is expected to be as high as possible [23]. The LibSVM library [24] is used in the experiment. We tested the proposed approach on MORPH database. Comparison of our face verification results with those in [16], at the age gap of 1, 2, 3 and 4-6, is also conducted. The CAR and CRR results at the age gap of 4-6 years are shown in Figures 1 and 2, respectively. Experimental results show that our proposed approach is much better than GOP+SVM and LCEM (local classifier ensemble model). We also tested the proposed

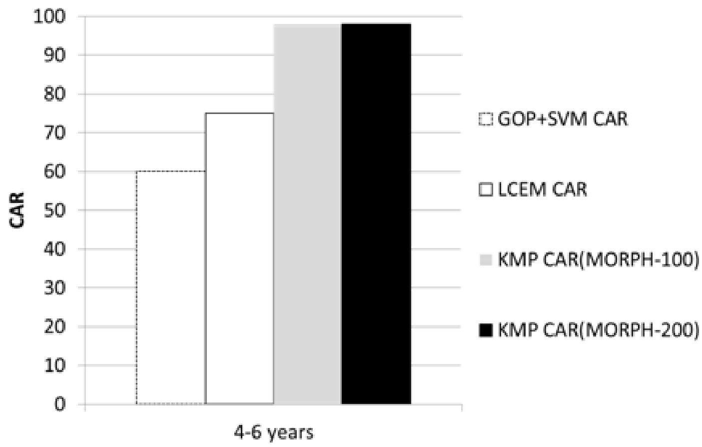

Figure 1. The CAR result at the age gap of 4-6 years

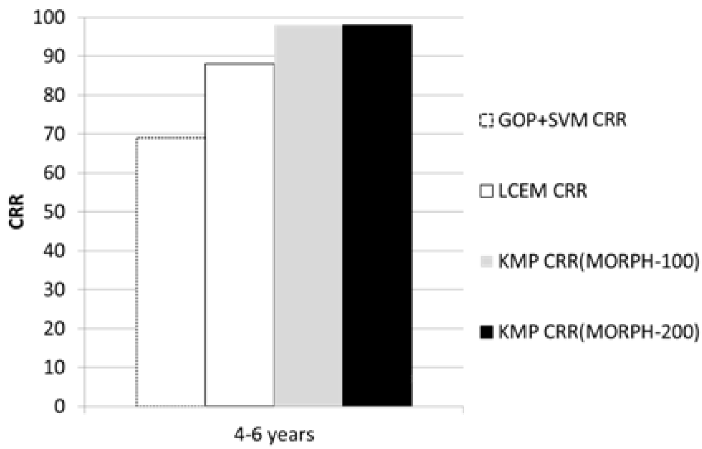

Figure 2. The CRR result at the age gap of 4-6 years

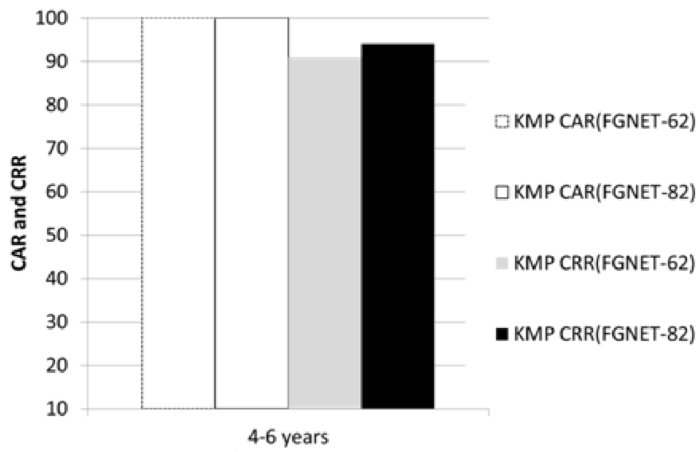

Figure 3. The FG-NET experiment at the age gap of 4-6 years

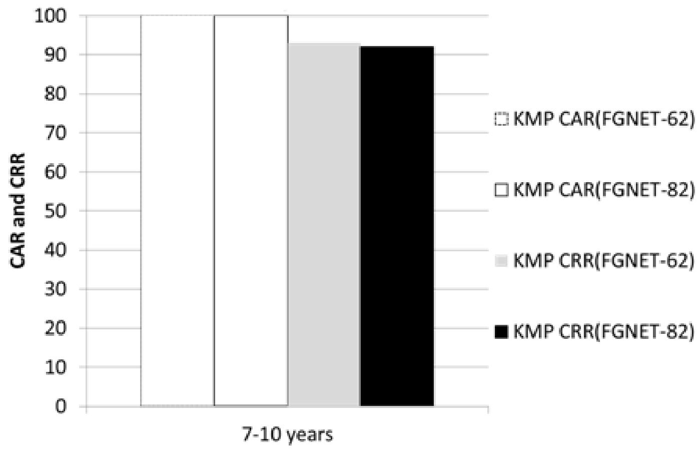

Figure 4. The FG-NET experiment at the age gap of 7-10 years

approach on FG-NET database. These impressive experiment results, at the age gap of 4-6 and 7-10 years, are shown in Figures 3 and 4, respectively.

4. **Conclusions.** Age-invariant face recognition based on local K-means ensemble has been proposed. The framework of the proposed method, at training stage, is based on unsupervised learning of local features in different layers. The last classification results from the layer N are further integrated into one feature. Then, the task is to assign the pair as either extra-personal or intra-personal. The pair is classified by using supervised learning. Our work differs from previous studies in the representation, K-means pyramids (KMPs), and the ensemble classification frameworks.

Experimental results show that the proposed framework can be significantly improved compared to the method proposed in [16]. In the experiments, we observe the results are significantly improved at the age gap of 1, 2, 3 and 4-6. At the age gap of 7-10, the results are still impressive. In addition, we also show that ensemble of local classifiers achieves significant performance on MORPH and FG-NET databases.

In future work, we will focus on unconstrained environment (i.e., real world). Then, for deeper understanding of the proposed methods, testing on a large public database will be conducted.

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