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Research paper

Fusion of Active Appearance Model and Histogram of Oriented Gradient for Age Estimation

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Abstract

In recent years, automated age estimation through face images has attracted the interest among the research due to its variety applications in law enforcement, human computer interaction etc. This paper presents the fusion of Active Appearances Model (AAM) with Histogram of Oriented Gradients (HOG) to form the face descriptors for automatic age estimation. AAM and HOG are known to be reliable feature extraction techniques for shape and texture images. The weaknesses of both are minimized and the strengths of both are utilized in the proposed method for better age estimation model. The proposed method is evaluated using two benchmarked age estimation datasets and promising results is generated.

Keywords: *AAM, AGE ESTIMATION, FACE RECOGNITION, HOG*

1. Introduction

Biometrics contain the physical information of an individual's identity information. Among different biometric modalities, facial features are widely used to recognize different types of demographics information such as ethnicity, age and genders recognition. In this context, age estimation is one of growing interest area due to its widely practical applications. For examples, Internet access control, security control, buying alcohol, cigarette, firms and others.

Age estimation is the determination of a person's age based on biometric features. Human is having different variety information from facial such as face, eyes, or nose. It is essential to extract the most meaningful features from a human's face image in order to better represent the age of the person.

In this paper, an age estimation method through the fusion of Active Appearance Model (AAM) [1] and Histogram of Oriented Gradients (HOG) [2] is proposed. The proposed method is able to extract better representative face features by exploiting the strengths of AAM and HOG while compensating the weaknesses of both. Some of the related works are discussed in Section 2 and the implementation of the proposed method is detailed in Section 3. Section 4 introduces the face aging databases. The experimental results are presented in Section 5 and lastly, a conclusion of this paper is drawn in Section 6.

2. Related Works

Nowadays, a lot of facial based age estimation techniques have been studied over the last few years. Narayanan Ramanathan [3] examined the problem from more wide point of view which is the analysis of the basis of human face aging and what have been done there so far. The study has summarized the problem of age estimation methods, which can be categorized in Shape vs Textures, Features selection and Factors. Timothy F. Cootes, Gareth J. Edwards, and Christopher J. Taylor [4] proposed active appearance models to improve the efficiency direct approach to match the shape and texture simultaneously.

Khoa Luu et al. [1] used Active Appearance Model (AAM) to extract the facial image to form a combined feature vectors. They divided the classifier into two main categories between (0-20) and (21-69). A classifier build by SVMs is used to distinguish between youth (0-20) and adults (21-69). Based on this work the authors modified the classifier construction by adding a supervised spectral regression after the extraction of the combined AAM.

Sethuram et al. [5] studied the AAM performance related to facial aging and compared the performance by building a general model based on gender. They run the experiments according to two ethnic groups: American and African with two age groups 18-45 and 46-65 groups.

There are also popular feature extraction techniques in literature such as Principle Component Analysis (PCA) [6], Hierarchical Multiscale Local Binary Pattern (H-LBP) [7] and Scale Invariant feature transform (SIFT) [8]. These techniques are sometimes known as feature descriptors. These methods are invariant to translation, rotation and scale transformation in image domain to moderate perspective and transformation. There is also a well-known feature descriptor technique named Histogram of Oriented Gradients (HOG) [2].

3. Proposed Solution

Apart from the feature representation problem discussed in the previous section, there are also other problems found from the existing age estimation methods such as high computational cost due to the high requirement of processing device to perform the recognition. Other than that, most of the existing methods could be further enhanced to perform well in estimating a person's age.

In this paper, we propose a simple yet efficient method, dubbed H-AAM for estimating age through facial images. Figure 1 and Figure 2 illustrates the overview of H-AAM, In the proposed pipeline, AAM is applied at the beginning of the process in order to extract the region of the face for training. Then, HOG is used to extract salient faces with occlusions, pose and illumination changes and transform the AAM feature into a 1D local histogram of gradient as the face feature descriptors. Feature descriptors is able to provide a compact representation of the face image. SVM is applied as the last stage for age classification.

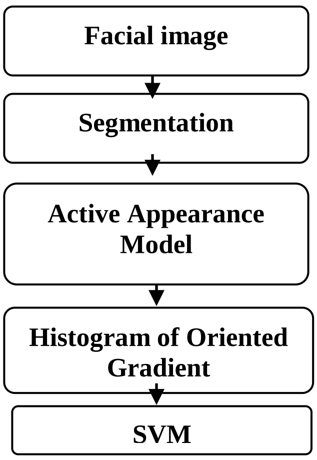

Figure 1: Block diagram of propose method

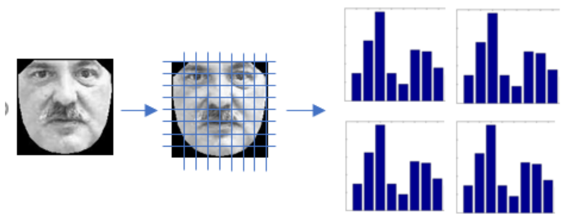

Figure 2: Partitioning and Extracting Process using H-AAM for Generating Histogram

Local histogram is implemented on each level of the image, I_0, I_1, *and* I_2. I_0, which is then filtered using the following filter kernel $D_x = [-1, 0, 1]$ and $D_y = [-1, 0, 1]^T$. The results of the filtering process are $I_{0x} = I_0 * D_x$ and $I_{0y} = I_0 * D_y$. Then, the filtered image I_{0x} and I_{0y} are divided into *m* number of overlapping cell. In each cell, the calculation of the magnitude and angles (orientation) is performed.

The magnitude of the gradient is calculated as,

$$|G_0| = \sqrt{{I_0}_x^{\,2} + {I_0}_y^{\,2}}$$

The orientation, θ of the gradient is computed as,

$$\theta_0 = \arctan\left(\frac{I_{0_y}}{I_{0_x}}\right)$$

4. Face Aging Database

There are several face-aging databases available publicly which contain age information and facial images. The benchmark databases: FG-NET [9] and MORPH [10] are used in the experiment.

FG-NET [9]: Face and Gesture Recognition Research Network. This database consists of newborns to 69 years old facial image and landmarks. There are average 12 pictures of 82 subject ages from 0 to 69. There are 1002 images colored or gray with variation of resolution, quality and expression. Each of the facial images was manually annotated with 68 landmarks points. Figure 3 shows some sample facial images with landmarks points.

Figure 3: Sample facial Images with landmarks points from FG-NET Database.

MORPH [10]: Craniofacial Longitudinal Morphological Face Database. The database consists of two parts: Album1 and Album2. Album1 consists of 1690 greyscale images of 631 subjects between 15 and 68 years old. Every image consists of additional information about race, gender, facial hair, glasses and age. Album2 consists of 55608 images of 13673 subjects between 16 to 99 years old. Figure 4 shows sample facial images from MORPH database.

Figure 4: Sample images from MORPH Database

5. Experimental Evaluation

This section presents the experimental results of the proposed method based on the MAE using FG-NET and MORPH databases with different parameter settings. MAE is used to determine the performance of the proposed method. It is the mean difference of the predicted age and the real age. Lower score of MAE represents better performance of age prediction.

The calculation of MAE is as follows:

$$MAE = \frac{\sum_{i=0}^{n} |EA_i - RA_i|}{n}$$

Table 1 shows the result of MAE based on different parameter settings: image size, window per bound box, *winx* and *winy* and histogram bins. The best setting can be found at window per bound box 5 and window per bound box 10 with size of feature [15 20] and histogram bins 6 which produces MAE result of 4.1953.

Table 1: MAE based on different parameter settings of MORPH database

Size	win x	win y	Histogram bins	MAE Result
[25 24]	3	6	10	4.7581
[30 10]	3	10	10	4.2135
[30 10]	8	10	10	4.2174
[30 10]	5	5	10	4.2127
[15 20]	5	10	6	4.1953
[30 10]	5	10	9	4.2053
[30 10]	5	10	8	4.1993
[30 10]	5	10	7	4.203
[25 24]	5	10	9	4.7575
[25 24]	5	10	10	4.7563
[30 10]	5	10	10	4.2081

After determining the best image size at 25 x 12, experiments are conducted to find the optimum setting for histogram bins. Figure 5 shows the MAE results on MORPH for the image partitioned into dimension of 25 x 12 pixels with window per bound box, *winx* = 5 and *winy* = 5 using different setting of histogram bins. From Figure 5.1, the best MAE score with 4.2094 can be attained by histogram bins = 6. This shows that more meaningful information can be extracted at this setting.

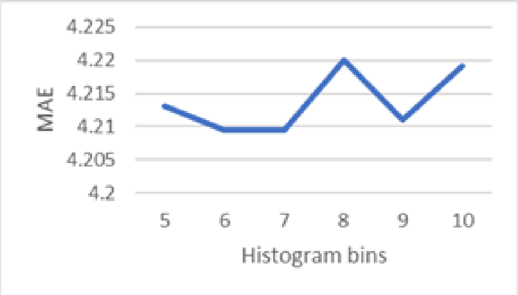

Figure 5: MAE results on MORPH using different histogram bins for the image separated into 25 x 12 pixel with winx = 5 and winy = 5.

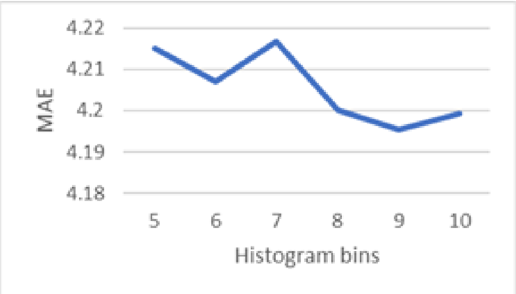

Figure 6: MAE results of the image separated into 25x12 with winx = 5 and winy = 10.

Figure 6 and Figure 7 show different histogram settings with window per bound box, *winx* = 5 and window per bound box, *winy* = 10 on the image sizes of 25 x 12 and 20 x 15 tested on MORPH database respectively. For the dimension of 25 x12, the best MAE 4.1953 is at the bin of 9. For the dimension of 20x15 as shown in Figure 7, the best parameter setting falls on histogram bins of 6.

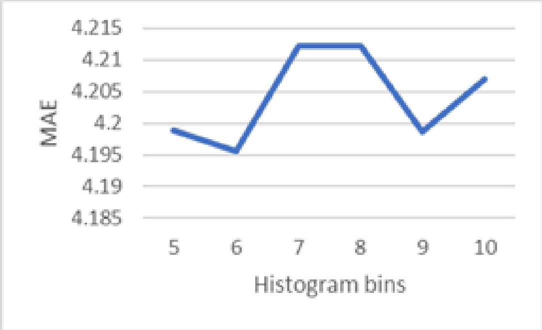

Figure 7: MAE results of the image separated into 20x15 with winx = 5 and winy = 10.

Table 2 shows the differences of the histogram setting and the MAE result. The highest MAE is with histogram bins 6 for size 20x15 with *winx* = 5 and *winy* = 10.

Table 2: MAE of different histogram bins with size [20 15] and *winx* = 5 and *winy* = 10.

Histogram bins	MAE
5	4.1993
6	4.1953
7	4.2002
8	4.2168
9	4.2071
10	4.2151

Table 3: Comparison with other state-of-the-art methods for MORPH database

Techniques	MAE (years)
AAM [1]	4.72
$AGES_{lda}$ [11]	6.22
RUN1 [12]	8.34
SVR [13]	5.91
H-AAM	**4.1953**

Table 4: Comparison with other state-of-the-art methods for FG-NET database

Techniques	MAE (years)
AAM [1]	4.766
KAGES [14]	6.18
AGES [11]	6.77
H-AAM	**4.6327**

Table 3 and Table 4 presents the MAE results of the proposed H-AAM method and other state-of-the-art methods using MORPH and FG-NET respectively. It is shown that H-AAM performs better than Active Appearance Model AAM proposed by Khoa Luu et al [1] for both databases. H-AAM achieves MAE of 4.1953 using MORPH and 4.6327 using FG-NET. To be fair in comparison, same configurations are applied on both datasets. In Table 3, other state-of-the-art methods score higher MAE compared to H-AAM using MORPH dataset. In addition, other state-of-the-art methods such as Kernel AGing pattErn Subspace, KAGES [14], AGES [6], AAM [7] using FG-NET also perform slightly poorer than H-AAM. This proves that H-AAM is able to extract more meaningful information from the images for predicting age and the difference of the actual age and the predicted are minimised effectively.

Cumulative score is also calculated in the experiments. Cumulative score of an age difference *d* describes the percentage of estimations which have estimation error of less than or equal to *d* years and can be calculated as:

$$CS(d) = \frac{N(|EA_i - RA_i|)_{\leq d}}{n} \times 100$$

where *N(|EAi-Rai|)* $\leq d$ is the number of estimations with an estimation error less than or equal to *d*. Figure 8 shows the cumulative score of H-AAM and AAM using MORPH database. The cumulative score of H-AAM and AAM using FG-NET database is illustrated in Figure 9. From the figures, it is obviously shown that H-AAM performs better than AAM in average as the curves of H-AAM are nearer to the top left corner. This attests that H-AAM is more powerful in extracting meaningful features that better discriminate ages of a person, in comparison to AAM.

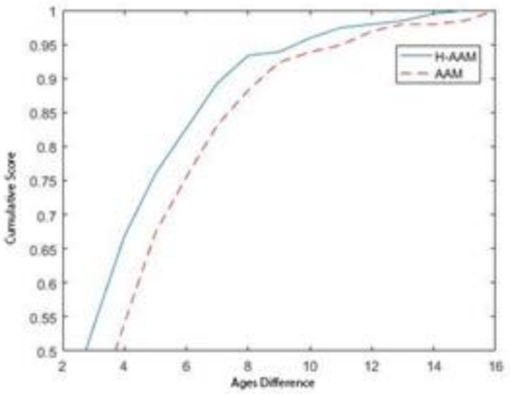

Figure 8: Cumulative Score of H-AAM and AAM using Morph Database.

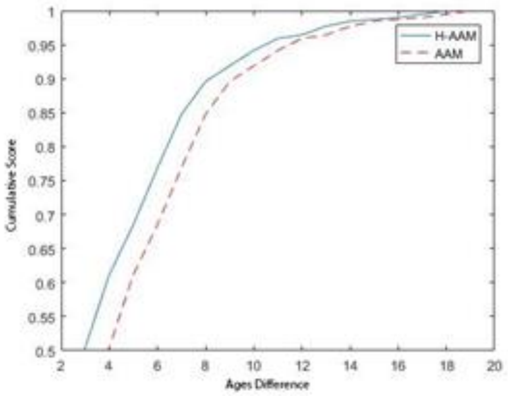

Figure 9: Cumulative Score of H-AAM and AAM using FG-NET Database.

6. Conclusions and Future Work

In this paper, we present an age estimation method through facial image based on the fusion of the active appearance model and local histogram. By utilizing the strengths of both, more meaning features can be extracted from the face images and this in turns enhance the accuracy in predicting the human's age. To be specified, AAM is first applied to extract the features from the original face images. Then the local histogram is locally computed to determine the magnitude value of gradients to form the image descriptors. The proposed method is evaluated using two benchmark datasets: MORPH and FG-NET and promising results of low MAE 4.193 and 4.6327 can be achieved compared to other state-of-the-art methods.

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