

# Age Estimation Based on Color Facial Texture

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**Abstract** — Automatic age estimation via faces is one of the dominant topics nowadays. In this paper, we proposed a novel approach for age estimation from RGB color face image. Despite the large number of methods for age estimation, their performance remains unsatisfactory for RGB images. The idea is to extract features from three color band instead of extract features from gray-scale. The experimental results show the superiority of our approach compared to that of the state-of-the-art methods that use the PAL dataset.

**Keywords** — Age estimation, Biometric, Color image, Texture, ML-LBP, SVR.

## I. INTRODUCTION

THE purpose of age estimation has recently become an active research topic in computer vision. That provides ancillary information of an individual's identity information. It can be used in many real-world applications such as electronic customer relationship management [2], security control and surveillance monitoring [10, 16, 20], biometrics [21, 19], and entertainment. For example, if the user's age is estimated by a computer, an age specific human computer interaction (ASHCI) system ensures young kids have no access to internet pages with adult materials. A vending machine, secured by the ASHCI system, can refuse to sell alcohol or cigarettes to the underage people [4].

Most of previous works in age estimation field have utilized gray-scale face images. So far, however, no research has studied the age estimation based on RGB face image, which uses color space for sensing, representation and displaying of color images. However, its application in image analysis is quite limited due to the high correlation between the three color components (red, green and blue).

In this paper we propose an approach based on the RGB face images which can achieve age estimation, through extract facial features by using local binary pattern method (LBP), after feature extracted we start in regression phase using SVR. This paper is organized as follows. Section 1 is this introduction and discusses relevant related works from the literature. Local binary pattern discuss in section 2. Section 3, details of proposed framework are presented. Section 4, provides the details of the conducted experiments along with results. The paper concludes with a brief summary of results and proposal of future research directions in section 5.

## II. RELATED WORKS

In the past years, a lot of techniques have been proposed to estimate age from face image. The first work was introduced by Kwon and Lobo [4]. in late 80s propose approach was based on geometric ratios of key face features and wrinkle analysis for classification of the images into one of three age groups: babies, young adults or senior adults. Their method achieved 90% in a database of 47 high-resolution images.

Later, Jun-DaXia and Chung-Lin Huang [5] investigated an age classification method where they extract the regions of age features by Active Appearance Model (AAM). They method achieved 73 % accuracy on MOPHY image database.

Ricanek et al. [6] focuses on the development of a generalized multi-ethnic age-estimation technique. They used the active appearance model (AAM) due to its ability to capture relevant aging features.

Ranjan Jana et al.[7] estimate the real age of a human by analyzing wrinkle area of face images. Wrinkle geography areas are detected and wrinkle features are extracted from face image. Depend on wrinkle features, each face image is clustered using fuzzy c-means clustering algorithm.

Nguyen et al. [8] present a method for age estimation based on a multilevel LBP (MLBP) and support vector regression (SVR). However, they consider the global features for age estimation. Their experiment on PAL database. Their method can estimate the human age with MAE 6.58 years.

Choi and Lee et al. [9] is strongly dependent on the method of choosing skin regions (where the frequency components are extracted), which are determined by the facial feature points.

Baddrud Z. Laskar et al. [10] Use facial features based on Neural Networks (ANN) and Gene Expression Programming GEP to classify ages of the FGNET database into four categories.

## III. LOCAL BINARY PATTERN

Ojala et al [16] proposed the local binary patterns (LBP). The LBP method has been widely used in many applications, such as finger-vein, gender classification,

facial expression recognition, and face recognition [11], in addition to age estimation. It is a powerful method to extract skin detail features that contain the wrinkle and other features, such as edge-end, corner, age spots, and flat areas, etc..

The basic LBP operator labels the pixel of the image by comparing it with the surrounding pixels in its  $3 \times 3$ -neighbourhood and considering the result as a binary number. The LBP operator is defined as [2].

$$LBP_{R,P} = \sum_{i=0}^{i=P-1} s(g_i - g_c) \times 2^i \quad (1)$$

Where  $P$  is the number of neighboring pixels,  $R$  is the radius of the LBP circle (the distance from the center pixel to the neighboring pixels),  $g_c$  is the value of the center pixel ( $x_c, y_c$ ), and  $g_i$  is the value of the 8 neighboring pixels, and function  $s(x)$  is the threshold function, defined as:

$$\text{Where } s(x) = \begin{cases} 1, & \text{if } x \geq 0 \\ 0, & \text{if } x < 0 \end{cases} \quad (2)$$

The binary codes extracted from (2) can be classified into uniform and non-uniform patterns. The uniform patterns are the micro-textures that contain at most two bitwise transitions from 0 to 1 or 1 to 0. Other patterns with a larger number of bitwise transitions are regarded as the non-uniform pattern. The reason for this classification derives from the observation that uniform patterns are useful for describing age texture features, such as wrinkles, corner, and spots, whereas non-uniform patterns do not have sufficient information to describe these texture features. In our work, we used  $LBP_{(8,1)}^{u2}$  which have 58 uniform patterns. (See Fig 1)

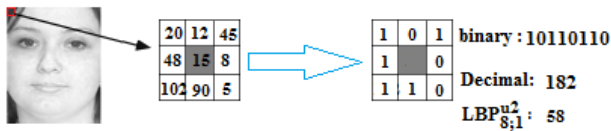


Fig. 1. Example of  $LBP_{(8,1)}^{u2}$

#### IV. PROPOSED APPROACH

Our proposed approach for age estimation from RGB facial image works in four steps (see figure 2). First, we conversion the region of interest (ROI) of RGB face to R, G, and B bands. Second, in our approach uses the Multi-Level Local Binary Pattern (ML-LBP) method to extract the feature from each color band and concatenated them in feature vector. Finally, the SVR is used for age estimation. We will explain the details of these procedures in the next.

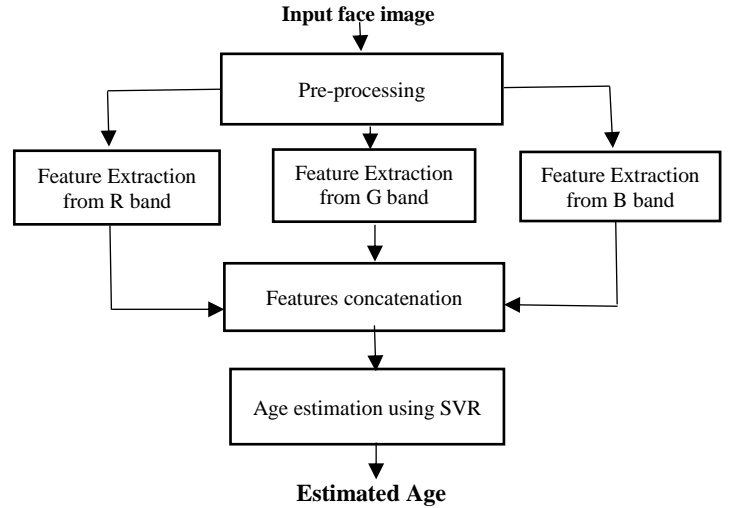


Fig. 2. Overview of our proposed approach.

##### A. Pre-processing

Normally, the input face image is color. Therefore, the first step of face image-based age estimation systems is the convert input face to three-color components (red, green and blue). [12]

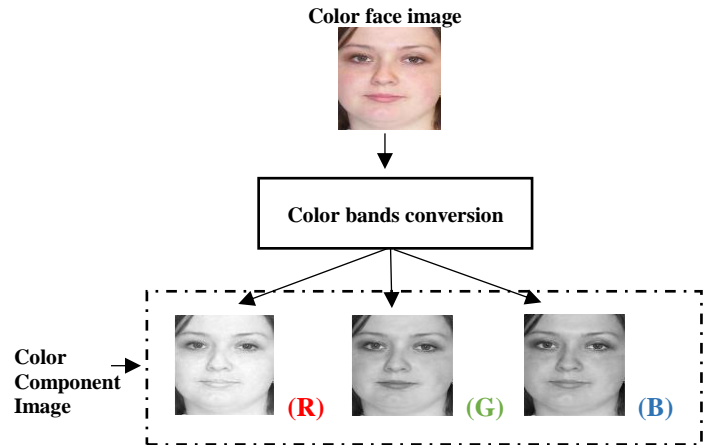


Fig.2. Example of face color image conversion.

##### B. Feature Extraction Based On ML-LBP

In order to extract feature we divided each color band of face ROI (region of interest) into sub-blocks, and obtain the histogram features from each sub-block by applied the LBP operator on each color b. For example, in the first level, we can obtain one histogram from the whole input color bands without segmenting it into the sub-block. In the second level, we can divide it into the sub-blocks of  $2 \times 2$ , and obtain the four histograms from 4 sub-blocks. In the third level, we can divide it into the sub-blocks of  $3 \times 3$ , and obtain the nine histograms from 9 sub-blocks. The 14 (1+4+9) histograms obtained are concatenated to form the final color space descriptor as depicted in Figure 4

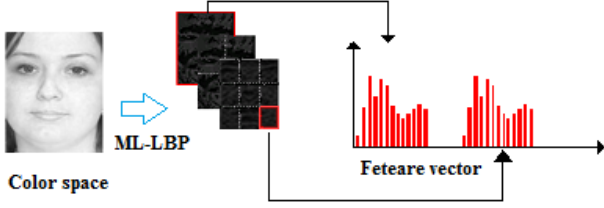


Fig. 4. Example of ML-LBP features extraction with 3 level.

### C. Age Estimation

The last step estimation age using the multi-class Support Vector Regression (SVR) with a non-linear RBF kernel. We can obtain the best relation between the extracted features and the ground-truth age of human in input image. For implementation, we used the LibSVM software package [13,14] in our experiments.

## V. EXPERIMENTS AND RESULTS

### A. Database Description

We use a public database for evaluating the performance of our system, called PAL database [17,19]. Was obtained from 576 people, the age of the people used for the PAL database ranges from 18 to 93 years old. For each person. We used 1045 face cropped of these images. Some sample images from the PAL database are shown in Fig 5.



Fig.5. Examples of images in PAL database: (a) age 22; (b) age 58; and (c) age 72.

In addition, work, we divided the PAL database into tearing and testing databases. In order to perform two-fold cross-validation to evaluate the performance of the age estimation system.

### B. Performance Evaluation

There are two measures to evaluate the performance of age estimation. The Mean Absolute Error (MAE) and the Cumulative Score (CS).

Mathematically, MAE is the measure of the average of the absolute error of the estimated ages compared with the ground-truth ages. The mean absolute error is given by (3) [19].

$$MEA = \sum_{i=1}^N |age_i - \widehat{age}_i| / N \quad (3)$$

$age_i$  : The ground-truth age of subject  $i$ .

$\widehat{age}_i$  : The estimated age,

$N$  : The total number of subject.

MAE is only an indicator of average performance for age estimators, it does not provide enough information of how accurate the estimators might be.

The cumulative score (CS) can estimate the accuracy that is defined as (4) [15]:

$$CS(j) = \frac{N_{e \leq j}}{N} \times 100$$

Where  $N_{e \leq j}$  is the number of test images is the number of test images on which the age estimation makes an absolute error no higher than  $j$  years.

### C. Results

In this experimental work, apply ML-LBP on the PAL database. To gain the best results we changed the level until the results began to fall. Table 1 shows the changing in the results between different levels. Multi-class Support Vector Regression (SVR). Evaluates all these experiments.

TABLE 1: COMPARISONS OF THE MAE AND CS RESULTS ON THE PAL DATABASE

ML-LBP level	MAE	CS
2	8.86	65.58%
3	7.87	70.08%
4	7.28	72.37%
5	7.08	74.57%
6	6.86	76.67%
7	6.78	76.60 %
<b>8</b>	<b>6.70</b>	<b>75.81%</b>
12	6.82	75.81%

For the next experiment we Detailed estimation performance MAE for this experiment is indicated in Table 1. The SC curves are shown in Fig 6. As we observed that the level 6 gives the best results.

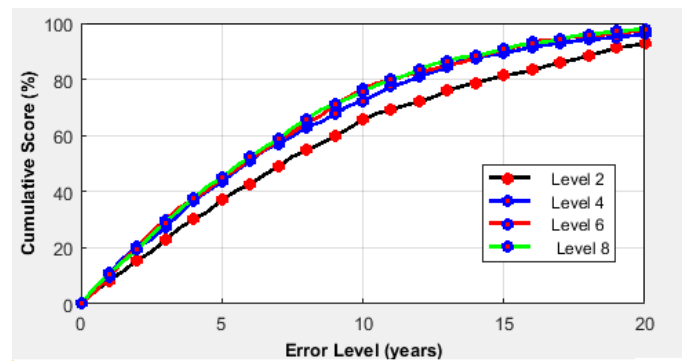


Fig.6. Age estimation performance on the PAL DB

Table 2 Show comparisons MAE of the proposed approach with previously published work. the smallest MAE is obtained by using ML-LBP-method with SVR for facial RGB image From this experimental result, we can confirm that our approach outperforms the previous approach, also

TABLE 2: COMPARISONS OF THE MAE AND CS RESULTS ON THE PAL DATABASE

<i>METHODS OF AGE ESTIMATION</i>	<i>MAE</i>	<i>CS</i>
SVR/SVM+LBP [21]	8.44	N/A
KRR+LBP [19]	9.61	64 %
SVR+ MLBP [20]	6.78	N/A
SVR+LBP [19]	8.87	62%
<b>Our approach</b>	<b>6.70</b>	<b>75.81%</b>

## VI. CONCLUSION

In this paper, we have proposed an approach for age estimation. Our approach takes advantages of RGB image for extracting facial features based on multi-Level Local Binary Patterns (ML-LBP) and multi-class Support Vector Regression (SVR). The color face ROI (region of interest) was separated to R, G, and B bands. Histogram features for age estimation are extracted for each band by the ML-LBP, and the final age is obtained using the input histogram features and the trained SVR. The proposed approach was trained by using 936 color images and tested by 110 color images ranges from 18 to 93 years old, from the PAL database. Experimental results show that our approach works well with the color faces and outperforms other methods. Our approach achieved MEA= 6.70 years. In the future work, we would enhance the accuracy of age estimation from RGB facial image by considering the effect of gender, ethnicity, and facial expression.

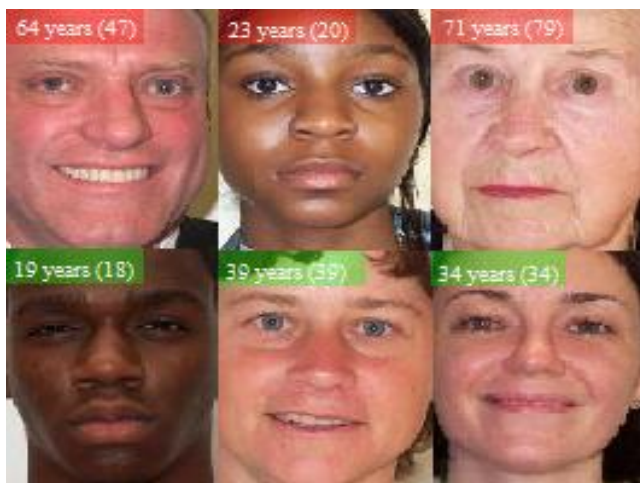


Fig.7. Comparisons results of age estimation by the proposed approach.

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