HUMAN AGE IDENTIFICATION VIA MACHINE LEARNING

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ABSTRACT: *A crucial point in Human Age Identification via Machine Learning is basically about automated systems learning to classify patterns and interactions in digital data sets. To achieve our objective, the paper is indicated a face model for appearing at low, middle and high resolution respectively. On age estimation, The Group Sparse Representation Based on Robust Regression (GSRBRR) formulation for mapping feature vectors to its age label. The different kind of regression methods are used to justified the testing results.*
Keywords: Sparse Representation, Low Resolution, High Resolution, Face Features

1. INTRODUCTION:

In automatic facial age estimation the aim is to use dedicated algorithms that enable the estimation of a person's age based on features derived from his/her face image. The facial age estimation problem shares several similarities with other typical face image interpretation tasks where the execution stage includes the process of face detection, location of facial characteristics, feature vector formulation and classification. According to the application for which an age estimation system is intended to be used, the output of the classification stage can be an estimate of the exact age of a person or the age group of a person or even a binary result indicating whether the age of a subject is within a certain age range. Among the three variations in age-group classification is the most widely used as in most applications it is only necessary to obtain a rough estimate of a subject's age rather than his/her exact age. Another important factor pertaining to the age estimation problem is the range of ages considered. This parameter is an important aspect of the problem as different aging characteristics appear in different age groups; hence a system trained to deal with a specific age range may not be applicable to more diverse age ranges.

An important aspect of the age estimation problem is the formulation of suitable metrics for assessing the performance of age estimators. The most widely used error metric is the Mean Absolute Error (MAE) between actual and estimated ages of faces in a test set. Also propose the use of the cumulative score (CS) that shows the percentage of cases among the test set where the age estimation error is less than a threshold. The CS measure is regarded as a more representative measure in relation with the performance of an age estimator. In the case that age-group classification is considered, the percentage of correct age-group classifications can also be used for performance evaluation. 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. Both age estimation and age progression need to take into account age-related facial deformations encountered during the lifetime of a subject. However, the two problems are in effect inverse problems since in age estimation information extracted from face images is used for determining the age of a subject whereas in age progression given a target age a face image that displays typical aging characteristics associated with the target age group is synthesized.

The rest of this paper is structured as follows. In Section 2 is presented the algorithm development. The experiment and results are presented in Section 3. We conclude this paper in Section 4.

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2. ALGORITHM DEVELOPMENT

Consider a linear model

$$\boldsymbol{y = x\beta + e} \qquad \textbf{(1)}$$

In classical statistics the error term e is taken as a zero-mean Gaussian noise. A traditional method to optimize the regression is the least squares problem

$$\boldsymbol{arg\ min_{\beta}\ \sum_{j=1}^{m} r_j^2} \qquad \textbf{(2)}$$

Where $r = y - x\beta, r_j$ the jth component of the residual is vector r and β is the sparse coefficient vector. Linear least squares estimates can be behave badly when the error distribution is not normal. In this situation, robust methods are to be preferred. The most common method of robust regression is M-estimation. M-estimators have shown superiority due to their generality and high breakdown point. Primarily M-estimators are based on minimizing a function of residuals

$$\boldsymbol{arg\ min_{\beta}\ \sum_{j=1}^{m} p(r_j)} \qquad \textbf{(3)}$$

where ρ(r) is a symmetric function with a unique minimum at zero. In this paper, we consider the bisquare function, i.e.,

- ***Input***: Training set $x = x_1, x_2, \dots \dots, x_c$ parameter $\sigma_1, \sigma_2, \lambda$; test sample y
- ***Output***: w, β
  1. Compute similarity matrix D
  2. Initialize $\beta = \beta^0$
  3. Start from $t = 1$:
     I. Compute residual $r^t = y - x\beta^t$
     II. Estimate weight as
     $$w_t(r_j^t) = \begin{cases} \left[1 - (\frac{r_j^t}{k})^2\right]^2, & |r_j^t| \le k \\ 0 & |r_j^t| > k \end{cases} \quad j = 1,2,3 \dots \dots, m$$
     III. Weighted regularized robust coding:
     $$\beta^t = argmin_{\beta} \left\| {}_{t}^{-\frac{1}{2}}(y - xD\beta) \right\|_2^2 + \lambda$$
     IV. Go back to step I until the condition of convergence is met, the maximal number of iteration is reached.

$$\boldsymbol{p(r)} = \begin{cases} \boldsymbol{\frac{k^2}{6}\left[1 - (1 - (\frac{e}{k})^2)^3\right]} & \boldsymbol{for\ |e|\ \le k} \\ \boldsymbol{\frac{k^2}{6}} & \boldsymbol{for\ |e|\ \le k} \end{cases}$$

Figure 1. Algorithm for GSRBRR

k is a positive tuning threshold. Such threshold *k* adaptively controls the objective function's behavior to differently penalize small and large residuals.

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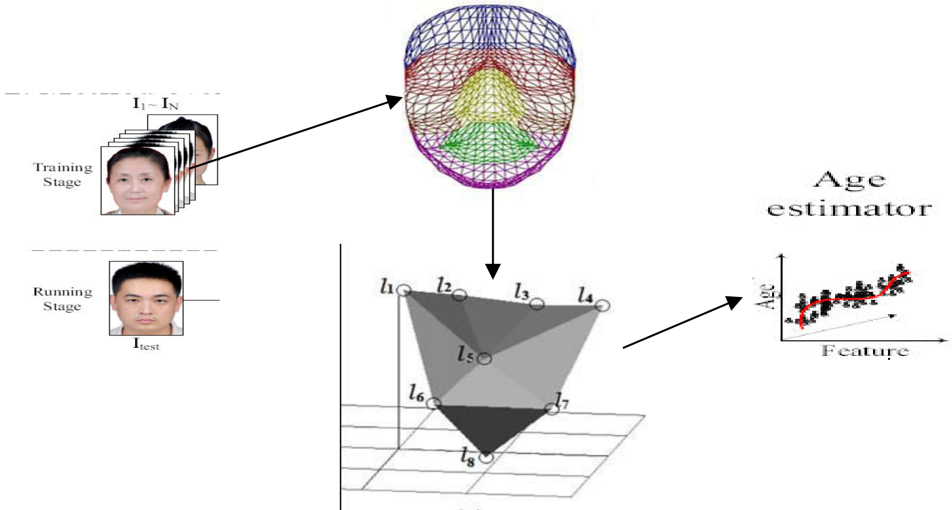

Figure 2. Systematic Diagram

3. EXPERIMENT AND RESULTS:

According to the algorithm (Figure 01), we setup the experiment with two stages. Such as training stage and running stage (Figure 02). The systematic diagram shows that, the age estimator evaluated with facial features.

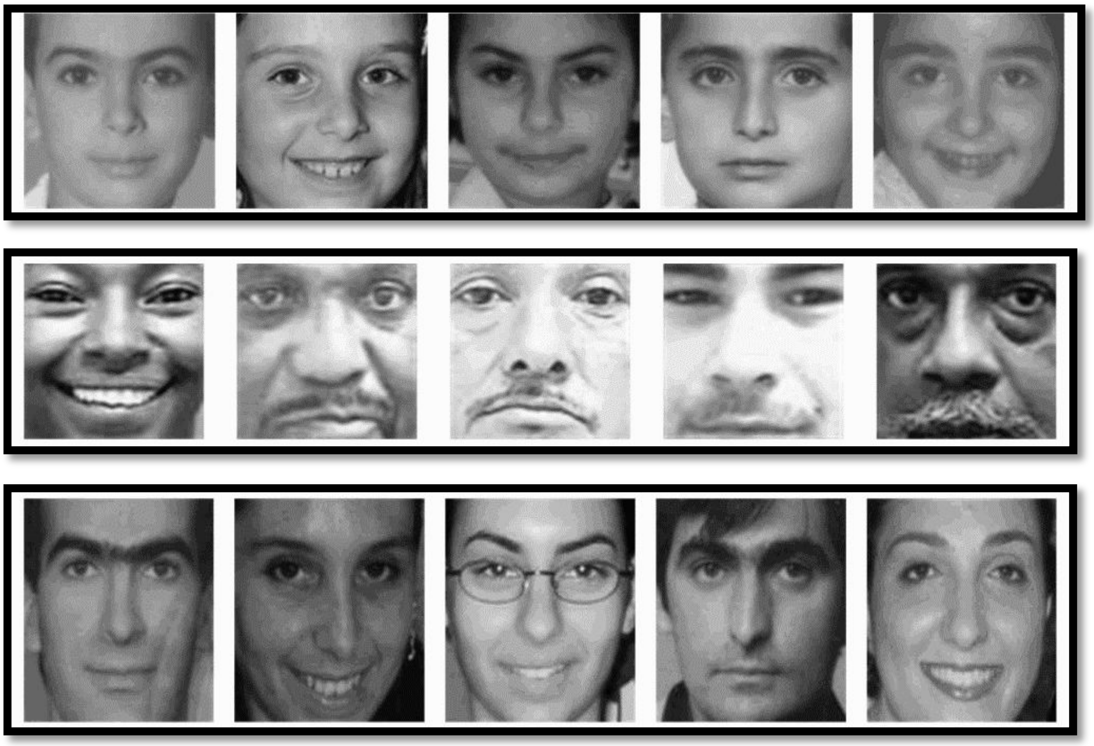

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Figure 3: Example of aging effects input images of different ages

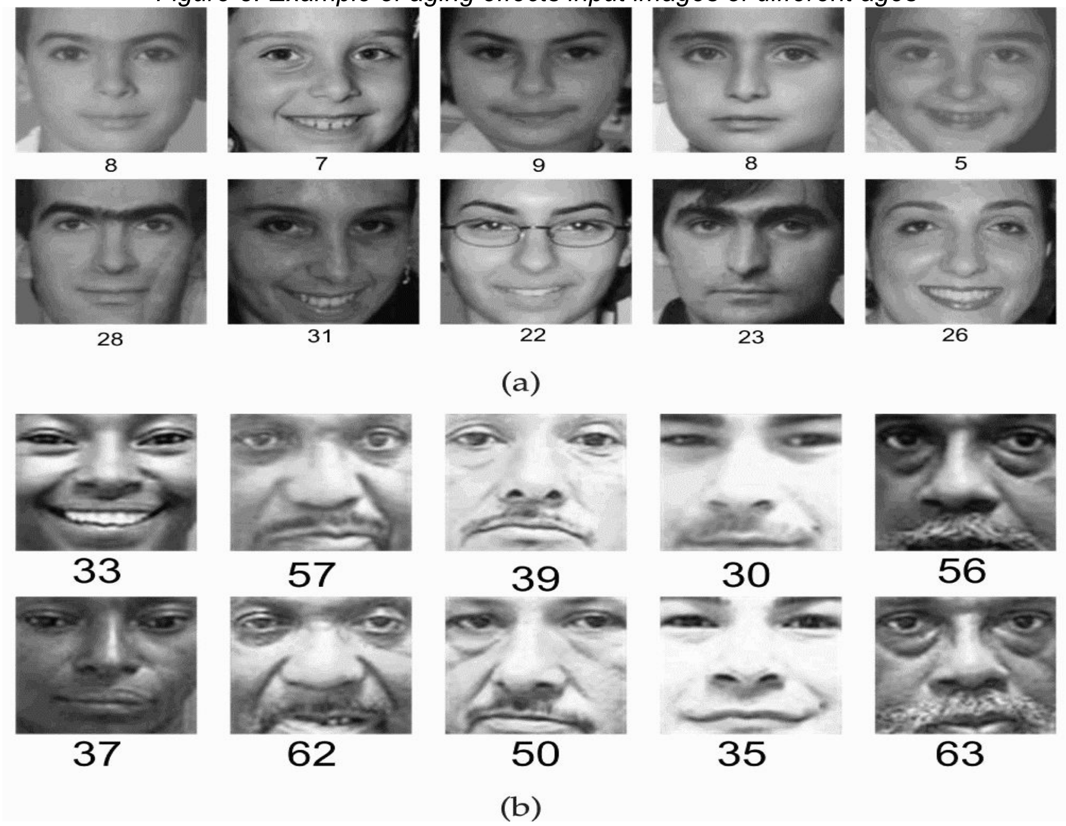

Figure 4: *Result of our method a) Age group 0- 30 b) Age group 30- 70*

4. CONCLUSION:

This work has presented a human age identification via machine learning-based features extraction method for single 2D low-resolution face image with 2D face training image pairs based on age estimator. The experiments show that, it could be applicable to identify the age version of the 2D low-resolution input face image in absence of 2D high-resolution face image in the training sets.

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