Physical quantification: Age

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1 Description

Face analysis is a field of deep interest in machine vision. Although the literature provides several examples of studies about face interpretation [3] and emotion recognition [2]; age estimation [1] has not been well explored yet. Automatic age estimation is a growing field for different reasons. Some applications are: human computer interfaces, recognition efficiency, automatic age progression systems and aged-based indexing of images.

The goal of age estimation is to determine the age of a subject from a face image. There are different approaches to attack the problem but most of the models apply machine learning techniques. When a new image comes, the features involved in age detection are extracted. Then, a technique to evaluate the features is applied and a machine learning technique is used to estimate the age. The correct selection of the features to use is one of the key aspects in age classification. An overview of the process is presented by Figure 1.

2 Example

2.1 Method overview

An example of age estimation is presented by [10] where an Active Appearance Model (AAM) model [4] is used.

AAM [4] models the appearance by combining a model of shape variation with a model of texture variation. The appearance model has parameters, c, controlling the shape and texture (in the model frame) according to

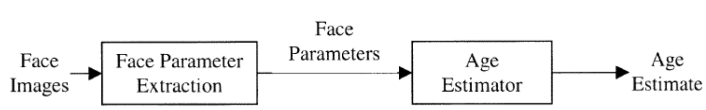

Figure 1: Block diagram of the age estimation approach from [6].

$$x = \overline{x} + Q_s c$$
$$g = \overline{g} + Q_g c \quad (1)$$

where $\overline{x}$ is the mean shape, $\overline{g}$ the mean texture and Q_s, Q_g are matrices describing the modes of variation derived from the training set.

The authors extend the model to build a graph model of the face with three levels: (i) The first level is a global AAM model for face images at low resolution. (ii) At second level, each facial component is clustered into different types and a separate AAM model is added for each type. This accounts for middle resolution. (iii) The third model describes facial details perceptible at high resolution such skin zones that are refined with some details (e.g.wrinkles and blobs). Figure 2 exemplifies the three levels.

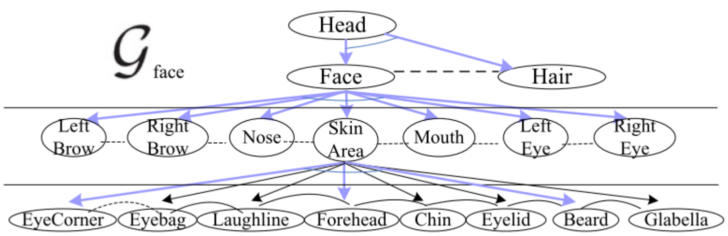

Figure 2: Graph of the face with three levels of [10].

In a training stage a set of images I and ages A is collected. N denotes the number of samples. A set of graphs G_1 to G_N is extracted from each image I_1 to I_N. A set of feature vectors for age estimation is created F_1 to F_N using the joint probability of the graphs representation and the age of an image $P(G, A)$. At the end, an age estimator is trained from the feature vectors and their correspondent age labels A_1 to A_N. The process is divided in four different stages: (1)Computation of graph representation, the model decomposes the face into semantically meaningful parts where the edges describe constraints and spatial relationships; (2)Learning statistics of graph parameters, the joint probability of $P(G, A)$ is calculated; (3)Feature design, the observation that humans usually perform about age estimation including general face and skin attributes, wrinkles, ratios between metrics from facial landmarks; and (4)Age estimation in feature space, the estimation of the age from designed features as a regression problem. Figure 3 shows the process.

2.2 Model and features design

Given a graph model G of a face, a face instance I is generated.

$$G \longrightarrow I \quad (2)$$

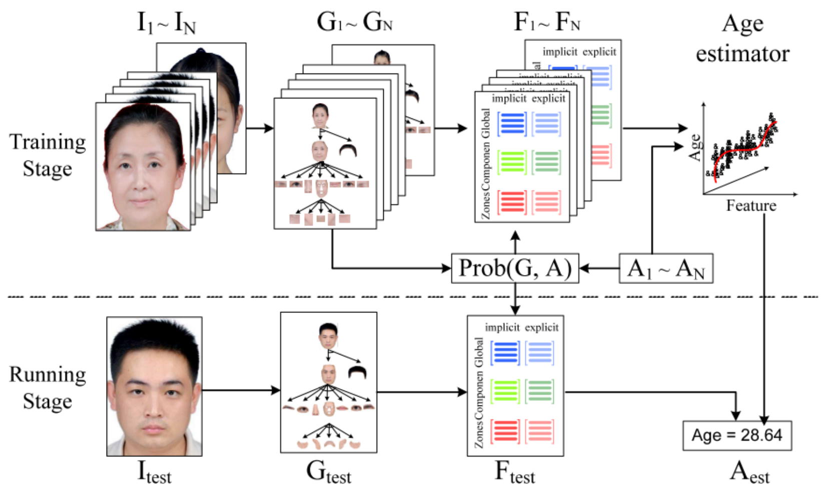

Figure 3: Framework of [10].

The graph is controlled by three hidden variables as follows:

$$G = \{w_1, w_2, w_3\} \tag{3}$$

where w_1 decribes the general appearance of the face and the hair, w_2 refines the appearance of facial components (eye, nose, etc) and w_3 controls the attributes of different facial zones, including wrinkles, pigments, etc.

At each level four features are described: topology, geometry, photometry, and configuration.

$$w_i = \left\{ t_i^{top}, t_i^{geo}, t_i^{pht}, t_i^{cfg} \right\} \tag{4}$$

At the three levels from top to bottom, topological features represent the index of hair styles, the cluster belonging of each facial component and the existence of wrinkles and marks. Geometric features describe the face geometry by a set of landmarks. Within the age, geometric changes occur especially in formative years. For adult people, the eye-corner and mouth-corner and the grow of wrinkles denote the age. Some filters that include areas, size and angles are applied to obtain information of this feature. From the photometric parameters, statistics about the skin and hair atributes, the gradients of facial components, and details of skin zones are computed. Three different types of images are used for this feature: color, low-frequency intensities and high frequency intensities. The configural metrics refer to ratios among facial components (specially effective to calculate age in children [8]). Figure 4 illustrates the different four types of features.

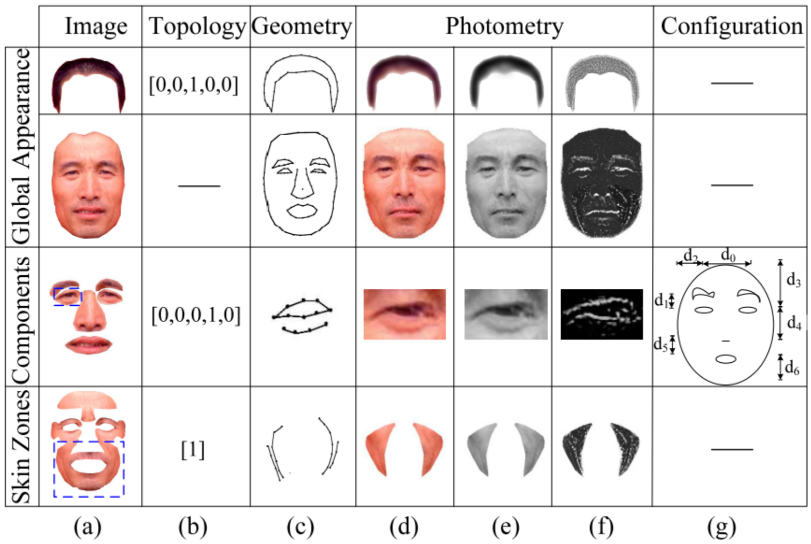

Figure 4: Four types of features at three levels of estimation.

For a given image I, the objective is to estimate its age A, which is inferred from a regression model.

$$A = R\left[F(I)\right] \in [0, 100] \tag{5}$$

where R is the regression function and $F(I)$ is the feature set extracted from I.

$$F(I) = \left\{(M_i^k, W_i); K = 1, 2..., D \;\; i = 1, 2, 3\right\} \tag{6}$$

where i indexes the graph and M are the filters operated in variable ω which is the hidden variable for the graph representation of I. D is the total number of features.

The hidden variable ω is computed by maximum posterior probability:

$$\omega^* = argmax\, p(\omega|I) \tag{7}$$

With today's techniques the estimation error varies around a five years range. In this case a regression model is used for the prediction but there are many other techniques that can be used at this point. More examples are in [5, 6]. Also the Keith Price Repository [1] offers a deep collection of articles related to this topic such as [7, 9].

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