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# FACE RECOGNITION AND AGE PROGRESSION USING SUPPORT VECTOR MACHINE AND ORL DATA BASE: A REVIEW

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***Abstract: Human age, as an important personal trait, can be directly inferred by distinct patterns emerging from the facial appearance. Computer-based age synthesis and estimation via faces have become particularly prevalent to picsy because of their explosively emerging real - world applications, such as forensic art, electronic customer relationship management, security control and surveillance monitoring, biometrics, entertainment, and cosmetology. Our objective in this thesis is to develop a human face detection and age progression from face images. Given a face image of the person, we label it with an estimated age. Aging is non-reversible process. Human face characteristics change with time which reflects major variations in appearance. The age progression signs displayed on faces are uncontrollable and personalized such as hair whitening, muscles dropping and wrinkles. Age synthesis is defined to rerender a face image aesthetically with natural aging and rejuvenating effects on the individual face. Automatic age-progression is the process of modifying an image showing the face of a person in order to predict his/her future facial appearance. Age estimation is defined to label a face image automatically with the exact age (year) or the age group (year range) of the individual face. During growth, aging is affected in two main forms, one is the size and shape variation and the other is the textural variation. In this research we are including face detection, face part detection, face detection using orl data base, and age progression.***
***Key Word: Face recognition, Template matching, ORL DATA base, FG-NET,***

## I. INTRODUCTION

The human face holds important amount of information and attributes such as expression, gender and age. The vast majority of people are able to easily recognize human traits like emotional states, where they can tell if the person is happy, sad or angry from the face. Likewise, it is easy to determine the gender of the person. However, knowing person's age just by looking at old or recent pictures for them is often a bigger challenge. Our objective in this thesis is to develop a human face detection and age progression from face images. Given a face image of the person, we label it with an estimated age. Aging is non-reversible process. Human face characteristics change with time which reflects major variations in appearance. The age progression signs displayed on faces are uncontrollable and personalized such as hair whitening, muscles dropping and wrinkles. The aging signs depend on many external factors such as life style and degree of stress. For instance smoking causes several facial characteristics changes. A 30 years old person who smokes a box of cigarettes each day will look like a 42 years old one. Compared with other facial characteristics such as identity, expression and gender, aging effects display three unique characteristics:

- The aging progress is uncontrollable. No one can advance or delay aging at will. The procedure of aging is slow and irreversible.
- Personalized aging variations. Different people age in different ways. The aging variation of each person is determined by his/her genes as well as many external factors, such as health, lifestyle, weather conditions, etc.
- The aging variations are temporal data. The aging progress must obey the order of time. The face status at a particular age will affect all older faces, but will not affect those younger ones. Each of these characteristics contributes to the difficulties of automatic age estimation.
- We have to distinguish between two computer vision problems. Age synthesis which aim at simulating the aging effects on human faces [1] (i.e. simulate how the face would look like at a certain age ) with customized single or mixed facial attributes (identity, expression, gender, age, ethnicity, pose, etc.) which is the inverse procedure of Face detections shown in Figure 1.1. While, Face detection and time domain analysis over time aims at labelling a face image automatically with the exact age (year) or the age group (year range) of the individual face.

Figure 1.1: Age synthesis [1]

### *1.1 Challenges*

There were several challenges encountered when attempting to develop our algorithm, because face images can demonstrate a wide degree of variation in both shape and texture. Appearance variations are caused by individual differences, the deformation of an individual face due to changes in expression and speaking, as well as lighting variations. These issues are explained more in the following points:-

- The Face detection problem is particularly challenging as age depends on many factors, some of them are visual and many others are non-visual such as ethnic background, living style, working environment, health condition and social life. For instance, the effects of ultraviolet radiation, usually through exposure to sunlight, may cause solar aging which is another strong cause for advanced signs of face aging. In particular, Stone [23] stated that aging can be accelerated by smoking, genetic predisposition, emotional stress, disease processes, dramatic changes in weight, and exposure to extreme climates.

- The visual features that can help in evaluating age such as people's facial features are affected by pose, lighting and imaging conditions.
- Males and females may have different general discriminative features displayed in images due to the different extent in using makeup, accessories and cosmetic surgeries which increase the negative influence of individual differences.
- The difficulty of acquiring large-scale databases, which covers enough age range with chronological face aging images, makes the estimation tasks more difficult to achieve. Although AIAA image mining can help the data collection [14], it is usually hard or even impractical to collect a large database of large amount of subjects providing a series of personal images across different ages.

*1.2 Core system module*

In the core system module, our Face detection algorithm consists of two tasks, face representation using the extended bio-inspired features (EBIF) that is based on the bio-inspired features [6] to encode the facial features robustly. Then, age estimation for analysis over the time domain, where we train a cascade of Support Vector Machines (SVM) and Support Vector Regression (SVR) to learn the relationship between the coded representation of the face and the actual age of the subjects. Once this relationship is established, it is possible to estimate the age of a previously unseen image. Some concepts need to be explained first.

We want to differentiate five definitions about human age in this thesis.

- Actual Age analysis: The real age (cumulated years after birth) of an individual.
- Appearance Age: The age information shown on the visual appearance.
- Perceived Age: The individual age gauged by human subjects from the visual appearance.
- Estimated Age: The individual age recognized by machine from the visual appearance.
- Categorization of age: Further are being categorized on the basis of their belonging age progression.

We use the Actual age and Estimate age with progression estimation definitions in this work.

*1.3 Scope and Analysis*

Face detection accuracy depends on how well the input images have been represented by good general discriminative features. The choice of classification or regression has an impact on the result of the estimated age for unknown image. In this chapter, we present a complete Face detection framework with description of each component. The output of this framework is the estimated age for the input face image. Core system module is considered the first module in our three modules system in the Face detection task.

## II. LITERATURE SURVEY

Lanitis et al. [1] extended the AAMs for face aging by proposing an aging function, $age=f\ b$ to explain the variation in age. In the aging function, age is the actual age of an individual in a face image, b is a vector containing 50 raw model parameters learned from the AAMs, and f is the aging function. The aging function defines the relationship between the age of individuals and the parametric description of the face images. The experiments were performed on a database of 500 face images of 60 subjects.Gang et al. [2] introduced Aging pattern Subspace (AGES), which deal with a sequence of an individual's aging face images that will be used all together to model the aging process. Instead of dealing with each aging face image separately.Further he used 200 AAMs features to encode each face image. Yan et al. [3] proposed to use Spatially Flexible Patch (SFP) as the feature descriptor. Since SFP considers local patches and their position information, face images with small misalignment, occlusion and head pose variations can still be handled effectively. Moreover, it can also enrich the discriminating characteristic of the feature set when insufficient samples are provided.Guo et al. [4] proposed a method, called Locally Adjusted Robust Regressor (LARR). They showed that a consistently better performance can be obtained by combining a classifier and a regressor. Using the combination scheme, the MAEs can reach 5.25 and 5.30 years for female and male on the YGA database, and 5.07 years on the FG-NET aging database, respectively.Serre et al. [5] extended the "HMAX" model of Riesenhuber and Poggio [48] to include two higher level layers, called S2 and C2, for object recognition. In the S2 layer, template matching is performed to match the patches of C1 units with some pre-learned prototype patches that are extracted from natural images. This S2 layer gets intermediate features that are more selective and thus useful for discriminating between classes of objects. These S2 units are then convolved over an entire image and C2 units are assigned the maximum response value on S2.

## III. INTEGRATION OF CLASSIFICATION AND REGRESSION

Face detection and progression can be treated as a classification problem, when each age is considered as a class label. Alternatively, Face detection can be treated as a regression problem, where each age is considered a regression value. In our experiments, we use both SVR and SVM methods for Face detection on the FG-NET and the MORPH standard databases. The RBF SVR can address the three limitations of the traditional quadratic regression model [10] :(1) the simple quadratic function may not model the complex aging process, especially for a large span of years, e.g., 0-70; (2) the least square estimation is sensitive to outliers that come from incorrect labels when collecting a large image database; and (3) the least square estimate criterion only minimizes the empirical risk which may not generalize well for unseen. A face feature localizer is used to detect the face in each image using Active Shape Model stage (ASM). Then, the images are cropped and resized to 59×80 gray-level images. For the face representation; we use our extension of the biologically-inspired features method to model each face for the purpose of age estimation, which leads to a total of 6100 features per image. We use cascade of classification and regression. We build six SVR models and one SVM model using the experimentally selected parameter provided .Using SVR or SVM separately cannot adequately estimate age because of the diversity of the aging process across different ages. Hence, we combine SVR and SVM models by selecting which model to use over each age group, based on MSE results over the training. The age of the test image is predicted using a cascade of SVM and SVR models by taking the average over the estimated ages as shown in Figure 3.1. Then, based on the decision nodes, the final age is estimated.

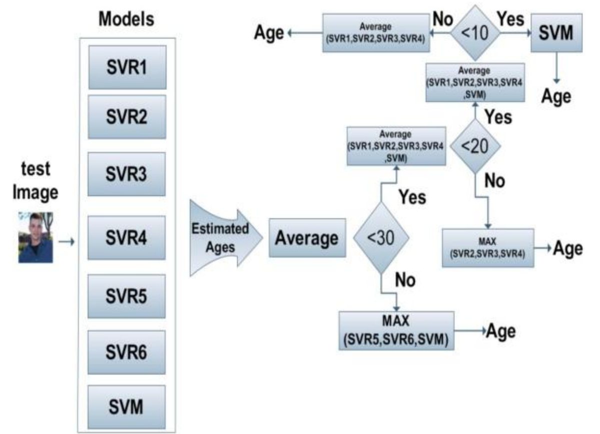


Figure 3.1 Face detection and categorization over the progression process for test images cascade of SVR and SVM models

We used two measures to evaluate Face detection performance: (1) Mean Absolute Error and (2) Cumulative score (CS). The MAE is defined as the average of the absolute errors between the estimated ages and the ground truth ages.

$$\text{MAE}= \sum_{k=1}^{N} \frac{|\hat{l}_k - l_k|}{N}$$

Where lk is the ground truth age for the test is image k and lk^ is the estimated age and N is the total number of test images. The cumulative score CS(j) is defined as Ne≤jN×100% where Ne≤j is the number of test images on which the Face detection makes an absolute error no higher than j years.

*3.1 Aging databases*

Collecting face images is an important task for the purposes of building models for accurate age estimation. However, it is extremely hard in practice to collect large size aging databases, especially when one want to collect the chronometric image series from an individual. In this thesis, we have used two standard aging databases FG-NET and MORPH; we summarize them as follows with other existing benchmark aging databases.

*3.2 FG-NET aging database*

The FG-NET aging database is publically available. It contains 1,002 high-resolution color or grey scale face images of 82 multiple-face subjects with large variation of lighting, pose, and expression. The age range is from 0 to 69 years with chronological aging images available for each subject (on average 12 images per subject).

Fig 3.2 Some sample images from FG-NET

*3.3 MORPH database*

The publically available MORPH face database was collected by the face aging group in the University of North Carolina at Wilmington, for the purpose of face biometrics applications. This longitudinal database records individuals‟ metadata, such as age, gender, ethnicity, height, weight, and ancestry, which is organized into two albums. Album 1 contains 1,724 face images of 515 subjects taken between 1962 and 1998.

Fig 3.3 Some sample images from MORPH album 1

*3.4 YGA database*

The private Yamaha Gender and Age (YGA) is not publically available database. So, we did not use it in our evaluations. YGA database contains 8,000 high-resolution outdoor color images of 1,600 Asian subjects, 800 females and 800 males, with ages ranging from0 (newborn) to 93 years. Each subject has about 5 near frontal images at the same age and a ground truth label of his other approximate age as an integer. The photos contain large variations in illumination, facial expression, and makeup. The faces are cropped automatically by a face detector, and resized to 60x60 gray-level patches.

*3.5 Experiments and results of earlier research work*

A Leave-One-Person-Out (LOPO) test strategy is used on the FG-NET database, i.e., in each fold, the images of one person are used as the test set and those of the others are used as the training set. After 82 folds, each subject has been used as test set once, and the final results are calculated based on all the estimations. In this way, the algorithms are tested in the case similar to real applications, i.e., the subject for whom the algorithm attempt to estimate his/her age is previously unseen in the training set.

## IV. PROPOSED WORKS

*4.1 Algorithm for face recognition*

A template matching process uses pixels, samples, models or textures as pattern. The recognition function computes the differences between these features and the stored templates.

  

It uses correlation or distance measures. Although the matching of 2D images was the early trend, nowadays 3D templates are more common. The 2D approaches are very sensitive to orientation or illumination changes. One way of addressing this problem is using Elastic Bunch Graphs to represent images. Each subject has a bunch graph for each of its possible poses. Facial features are extracted from the test image to form an image graph. This image graph can be compared to the model graphs, matching the right class. The introduction of 3D models is motivated by the potential ability of three dimensional patterns to be unaffected by those two factors. The problem is that 3D data should be acquired doing 3D scans, under controlled conditions. Moreover, in most cases requires the collaboration of the subject to be recognized. Therefore, in applications such as surveillance systems, this kind of 3D data may not be available during the recognition process. This is why there is tendency to build training sets using 3D models, but gathering 2D images for recognition. Techniques that construct 3D models from 2D data are being developed in this context.

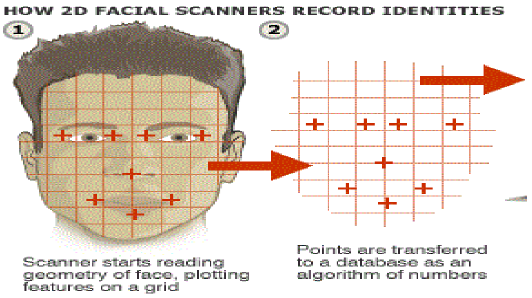


Fig 4.1: Explain how the pixel in grid based face pattern

*4.2 Template matching algorithm Under Active Shape Model.*

A basic method of template matching uses a convolution mask (template), tailored to a specific feature of the search image, which we want to detect. This technique can be easily performed on grey images or edge images. The convolution output will be highest at places where the image structure matches the mask structure, where large image values get multiplied by large mask values.

A pixel in the search image with coordinates $(x_s, y_s)$ has intensity $I_s(x_s, y_s)$ and a pixel in the template with coordinates $(x_t, y_t)$ has intensity $I_t(x_t, y_t)$. Thus the absolute difference in the pixel intensities is defined as $\mathrm{Diff}(x_s, y_s, x_t, y_t) = | I_s(x_s, y_s) – I_t(x_t, y_t) |$.

$$SAD(x,y) = \sum_{i=0}^{T_{\text{rows}}} \sum_{j=0}^{T_{\text{cols}}} \mathrm{Diff}(x+i, y+j, i, j)$$

The mathematical representation of the idea about looping through the pixels in the search image as we translate the origin of the template at every pixel and take the SAD measure is the following:

$$\sum_{x=0}^{S_{\text{rows}}} \sum_{y=0}^{S_{\text{cols}}} SAD(x,y)$$

$S_{rows}$ and $S_{cols}$ denote the rows and the columns of the search image and $T_{rows}$ and $T_{cols}$ denote the rows and the columns of the template image, respectively. In this method the lowest SAD score gives the estimate for the best position of template within the search image. The method is simple to implement and understand, but it is one of the slowest methods. Face part detection is also done through template matching algorithm. further age progression we perform the following steps.

4.2.1 Pose correction: Input face is warped to approximately frontal pose using the alignment pipeline of denote the aligned photo I.

4.2.2 Texture age progress: Relight the source and target age cluster averages to match the lighting of yielding AI s and AI t. Compute flow F source–input between AI s and I and warp AI s to the input image coordinate frame, and similarly for F target–input. This yields a pair of illumination matched projections, Js and $J_t$ both warped to input. The texture difference $J_t - J_s$ is added to the input image I.

4.2.3 Flow age progress: Apply flow from source cluster to target cluster F-target source mapped to the input image, i.e., apply F input–target.F target–source to the texture-modified image I + Jt − Js. For efficiency, we pre compute bidirectional flows from each age cluster to every other age cluster. Aspect ratio progress:

Apply change in aspect ratio, to account for variation in head shape over time. Per-cluster aspect ratios were computed as the ratio of distance between the left and right eye to the distance between the eyes and mouth, averaged over the fiducially point locations of images in each of the clusters. We also allow for differences in skin tone (albedo) by computing a separate rank-4 subspace and projection for each colour channel.

The main focus of this study is to move the research on the human Face detection and progression to real applications and practical usage of life rather than being bounded to the existing databases with their limitations to a single human ethnic group or the well annotated faces. All methods and algorithms should take into consideration a more generalized database that contains various races with different image qualities and conditions.

In this work, we address the following issues:

- Though it is practically difficult or even impossible to collect a huge human Face detection database with correct true labels. But, the internet provides us with the facility to collect such a large amount of face images with possible age information existing in the form of tags or descriptions for a particular image. Popular photo sharing websites such as Flickr can provide a large number of images based on a single age-related query such as 20 years old, the returned results will be in thousands of correct images from different various ancestry groups
- Face misalignment can be rectified by using the Active Shape Model (ASM) to locate the correct facial landmarks for the face images.
- The problem of multi-instance faces in the same image with possibly incorrect labels of the image. This motivated us to design the universal labeller algorithm for efficient and effective image labelling.

  

## V. CONCLUSION AND FUTURE DIRECTIONS

We have developed a fully automatic Face detection and progression frame work in this thesis. A three modelled architecture is proposed: 1) Core system module; 2) Enhancement module; and 3) Application module. In core system module, we have built the main components of our human Face detection system. We introduced a novel face representation schema which has two main steps; face cropping using the Active Shape Model (ASM) to crop the face image to the area that covers the face boundary. We constructed a new database using the internet as a rich repository for image collection. Over many images were crawled, that is based on AIAA image collector using human age-related queries.

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