國立台灣科技大學
資 訊 工 程 系

碩士學位論文

階層式年齡估測方法利用人臉特徵以及皺紋偵測之研究

A Study of Hierarchical Age Estimation Using Facial Features and Wrinkle Detection

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中華民國 一百 年 六 月 十四 日

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中華民國　100年　6月　14日

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論文摘要

人臉年齡的估測一直是一個不容易從外觀上判斷的問題。因為人的外觀會因為很多因素而有不同的變化，例如年齡的成長、不同人種之間的差異、性別的差異、生活環境、天氣等等因素都會有所不同。在年齡預測的研究中有兩個廣為人知的資料集分別是 Face and Gesture Recognition Research Network (FG-NET) [18] 和 Morphology (MORPH) [17]，我們從中擷取部份的資料來進行實驗，實驗的對象在零到六十九歲之間。

基於 Luu et al. [10] 提出的架構，以六種人臉特徵集合逐一實驗並與原始主動外觀模型 [20] 提供的 68 個點的結果做比較最後歸納出最佳的特徵集合。二十一歲到六十九歲年齡區間的實驗結果並不令人滿意，因此我們將年齡區間再分為二十一歲到四十歲以及四十一歲到六十九歲，並提出我們在年齡預估的方法。

基於我們的架構之下針對資料集 1 以及資料集 2 以六種人臉特徵點實驗，此架構首先由支援向量機 [4] 將影像資料分為三個年齡集合，分別是零到二十歲、二十一到四十歲、四十一到六十九歲，再根據支援向量迴歸 [8] 對上述三個年齡集合的每張測試影像預測迴歸值，最後根據此迴歸值去推估年齡。

我們也和其他優秀的年齡預估方法做比較，由實驗結果顯示我們的方法確實有助於改善人臉年齡推估。

關鍵詞: 臉部特徵擷取、主動外觀模型、皺紋偵測、支援向量機、支援向量迴歸

A Study of Hierarchical Age Estimation Using Facial Features and Wrinkle Detection

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Abstract

Age estimation is not an easy problem from facial appearance. Because the facial appearance may be changed by many factors such as age, race, gender, living environment, weather, etc. There are two well established aging data sets, the Face and Gesture Recognition Research Network (FG-NET) [18] and the Morphology (MORPH) [17], for age estimation research. We utilize these two data sets and extract a part of them for our experiments with the subjects of age from 0 to 69 years old.

Based on Luu et al. [10] we implement six sets of facial features. We then compare each set of facial features with the Active Appearance Model (AAM) [20] using the original 68 features. From the result we conclude the sets of facial features that we will use. Furthermore, we find that the Mean Absolute Error (MAE) in the 21 to 69 years old age group is unsatisfactory. Hence we propose to divide this age group into 21 to 40 years old and 41 to 69 years old age groups and our age estimation architecture is also presented.

After that, we implement our architecture in six sets of facial features with dataset 1 and dataset 2. The image datasets are divided into three age groups which are 0 to 20 years old, 21 to 40 years old, and 41 to 69 years old by Support Vector Machine (SVM) [4] and get the regression value of each test image by Support Vector Regression (SVR) [8]. We then predict age by the prediction value of each test image. We also compare our result with other state-of-art age estimation methods. The experiment result shows that our propose method certainly improve the MAE in age estimation.

Key words: Facial features extraction, Active Appearance Model, Wrinkle Detection, Support Vector Machine, Support Vector Regression

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Chapter1. Introduction

The organization of this thesis is as follows: Chapter 1 introduces the motivation of the thesis and the aging data sets. Chapter 2 is related research in age estimation. In Chapter 3, we discuss the methods for age estimation and the facial features that we use. Chapter 4 shows the architecture of our age estimation method and the experiment results. Chapter 5 concludes our study and discusses future work.

1.1 Motivation

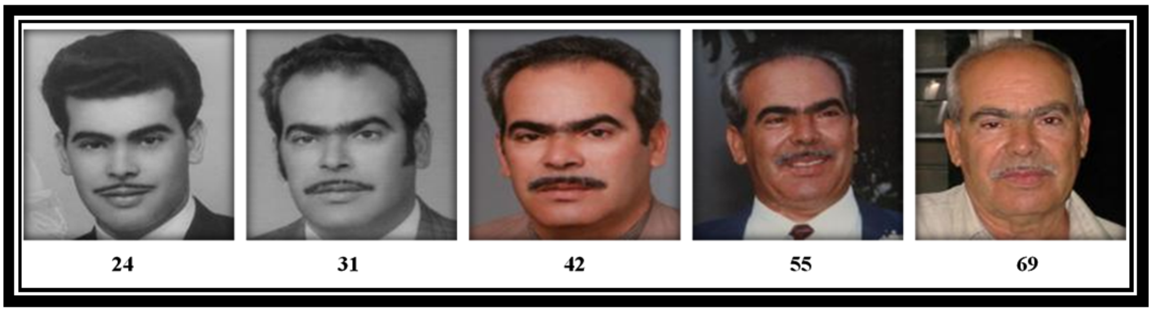

Figure 1.1 Image of a subject and his real age

There are many researches about face recognition, facial expression, etc. Age estimation is also an important research among them. In recent years, age estimation research has significantly increased, because it has more and more applications in several aspects. For example, there are age limit for buying alcohol, cigarettes, driving a car, watching video program, etc. The same technique can also apply to aging missing children to estimate their current appearances. Our main motivation is to automatically generate the age tag of the character in the image. Figure 1.1 indicates one person's process of growth. However, it is difficult for us to recognize his real age. Because the aging pattern is different among people and even in the same person, so it is hard for us to determine the real age by examining the appearance only. Also the aging pattern may be influenced by gender, health, race, etc. If there is an automatic age estimation system then it will be very helpful many applications.

1.2 Aging database

There are many public databases which included age information. The FG-NET and the MORPH are two of the well known datasets which will be used in our experiments. The FG-NET contains 1002 images provided by 82 subjects. The FG-NET dataset varies from 0 to 69 years old, and it is about 12 images per subject. Each FG-NET image contains 68 landmarked points. Figure 1.2 shows the age distribution of the FG-NET dataset.

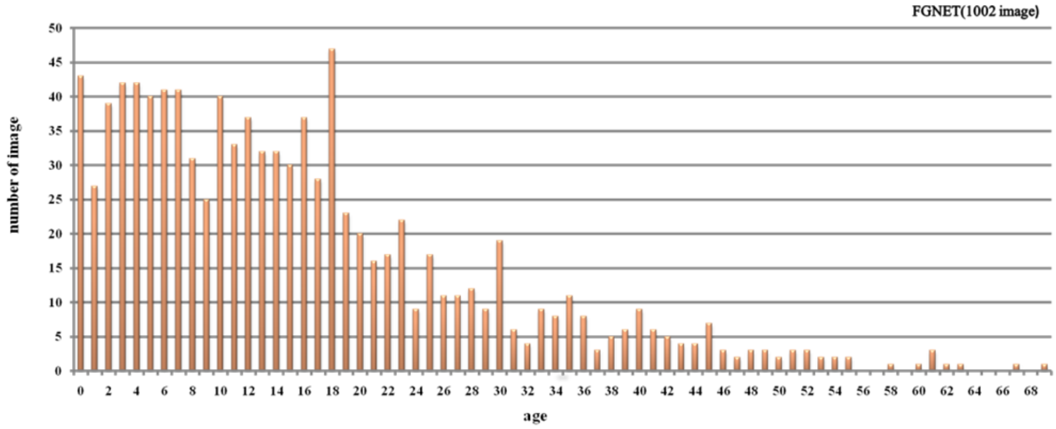

Figure 1.2 The age distribution of the FG-NET dataset

Figure 1.2 indicates that the age distribution mostly concentrate before 20 years old. This biased distribution would cause a problem of over-learning the 0 to 20 years old age group. On the other hand, the MORPH dataset consists of album 1 and album 2. Album 1 contains 1690 gray images of 631 subjects from 15 to 68 years old. Album 2 consists of 55608 images of 13673 subjects from 16 to 99 years old. For the 0 to 20 years old age group, the MORPH dataset contains only subject images between 16 to 20 years old. This is similar to the FG-NET set which shares the same problem.

To compare with other age estimation methods, we select 632 images from the MORPH dataset which are Caucasian entirely for the comparison dataset (named dataset 1 afterward).Figure 1.3 represents the age distribution of dataset 1.

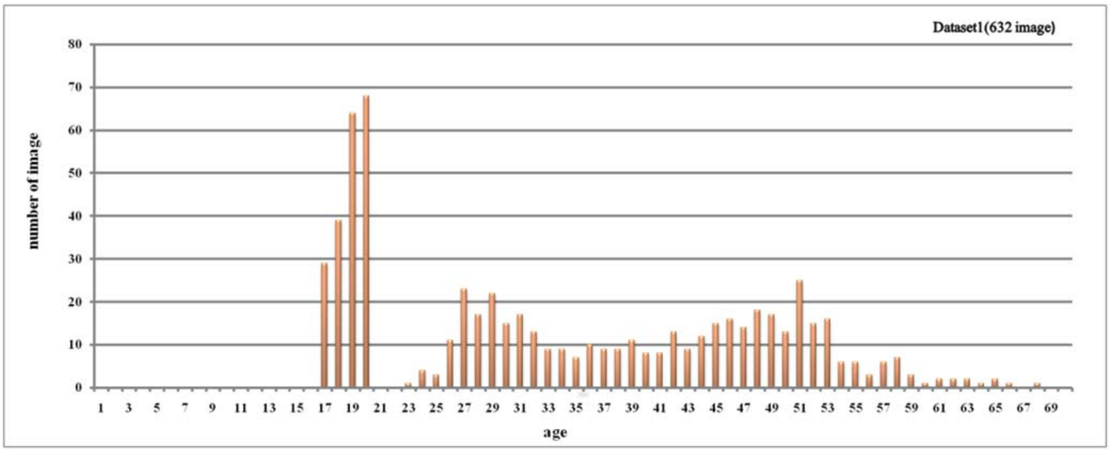

Figure 1.3 The age distribution of dataset 1

We divide the dataset into three age groups, first one is 0 to 20 years old, the second one is 21 to 40 years old, and the last one is 41 to 69 years old. In dataset 1, there are 200 images from the 0 to 20 age group, 206 images from the 21 to 40 age group, and 226 images from the 41 to 69 age group.

We also choose 500 Caucasian images from the MORPH dataset album 2 and combine the FG-NET dataset 300 images to become total 800 images (named dataset 2 afterward). Figure 1.4 represents the age distribution of dataset 2.

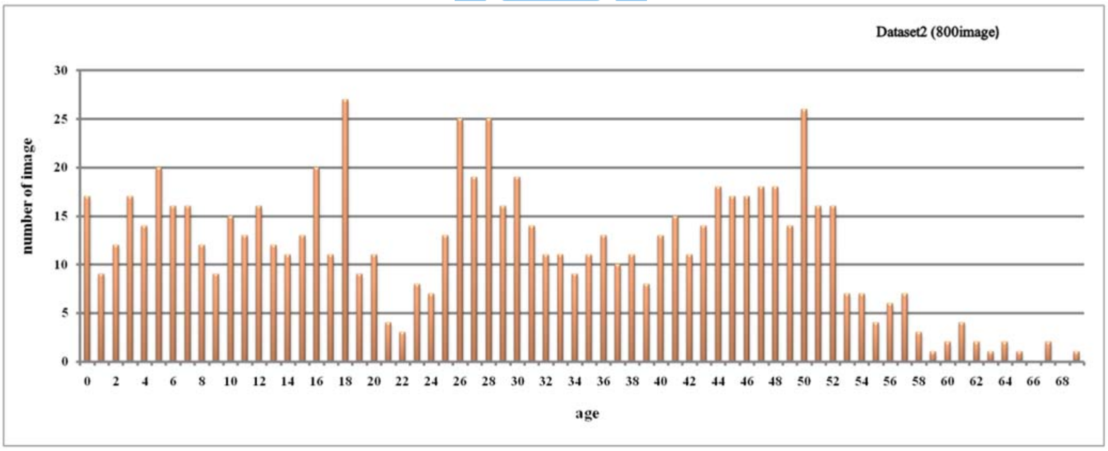

Figure 1.4 The age distribution of dataset 2

The first age group has 300 images, and the second, the third age groups also have 250 images. Both datasets will be used in our experiments later.

Chapter2.　Related Work

There were many earlier researches about age estimation. Geng et al. [21] proposes an automatic age estimation method named AGES (AGing pattErn Subspace) which is based on three characteristics:

I. The aging progress is uncontrollable

II. The aging patterns are personalized

III. The aging patterns are temporal data

An aging pattern is a sequence of personal face images sorted in time order. Figure 2.1 shows the aging pattern of their work, where m means the missing part. The first step of AGES is, facial features extraction by the AAM. Then learn a subspace of aging patterns by Principal Component Analysis [9] (PCA). But the problem is the lack of missing part of aging pattern, which will cause the training data to be incomplete. To deal with this problem, they proposed an algorithm to construct a model to learn the missing data.

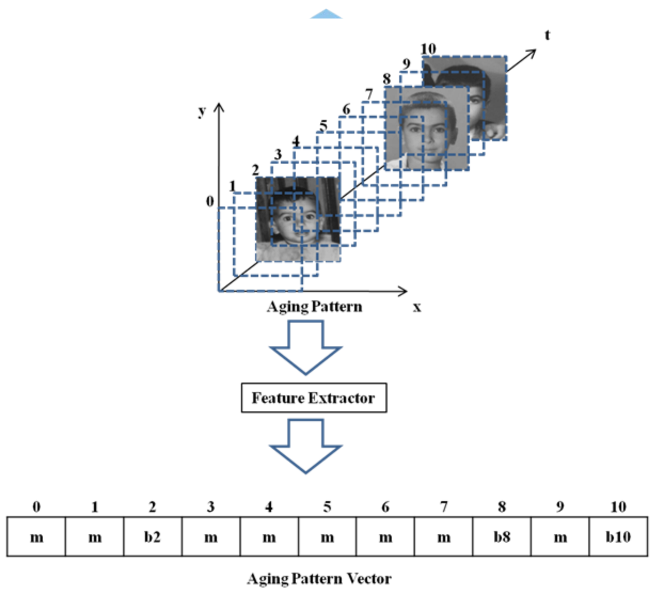

Figure 2.1 Age estimation step of AGES

Then a global aging pattern will be learned by their proposed algorithm. In the next step, the feature vector is calculated from the test image to get a proper aging pattern by minimizing the reconstruction error. The position of the test image in aging pattern will then indicate its real age. Figure 2.1 shows the age estimation steps of AGES.

Moreover, [1] designed classifiers that accept representation of unseen images and produce an estimate age of these images. They use the classifiers for each age group and the classifiers for different clusters of subjects within their training dataset. In this way, the age estimation accuracy will improve. Similar to [1], the framework of [2] can be used for simulating a new face of image. It can predict a subject will look like in the corresponding age.

In [16], Zhang et al. proposed an approach by formulating age estimation as a multi-task learning problem. This approach is multi-task extension called multi-task warped Gaussian process (MTWGP). For each learning task refers to estimation of the age function for each person. The MTWGP regression functions are implicitly defined by the kernel function and all its model parameters can be learned from the data automatically.

In [3], Xiao et al. investigated the problem of learning a distance metric. They measured the semantic similarity of input data for regression problems. They combined the regression method, k nearest neighbors (kNN), and their learned metric named mkNN to apply to age estimation problem.

[6] introduced the learning scheme for extracting facial features and designed a regressor for learning and prediction of human ages. Experiments using the proposed method in [6] over different datasets such as FG-NET and UIUC-IFP-Y were presented.

[15] aimed at a problem of rank label prediction with uncertain labels. A ranking model is designed as the candidate kernels and there are parameters for feature selection and kernels. Expectation-Maximization (EM) method is used to decide these parameters. Their work is validated by FG-NET and Yamaha database.

Besides, Kwon et al. [22] proposed a method for age classification from facial images. It is based on facial cranio-facial development and wrinkle analysis. In their research, the primary features are eyes, nose, mouth, chin, virtual top of the head and the sides of the face. The facial ratios were obtained from the above features and distinguish babies from young adults and seniors. In the second feature, wrinkle information is employed to distinguish seniors from young adults and babies. The above two features would categorize the image into three classes. We will refer these ratios into our work.

Similar to [22], Ramanathan et al. [13] propose a craniofacial growth model that characterizes growth related shape variations of face images under 18 years of age. They use growth parameters to characterize facial growth and also show the age-based anthropometric constraints on facial proportions, and then propose methods to calculate optimal growth parameters.

Hewahi et al. [14] proposed a methodology based on neural networks in age estimation. They build a system that estimate age within certain age ranges but not estimate the exact age. There are two stages in this system. In the first stage, the age is classified into four categories which are child, young, youth and old. In the second stage, classify each age category into two more specific ranges. Figure 2.2 indicates this age estimation system.

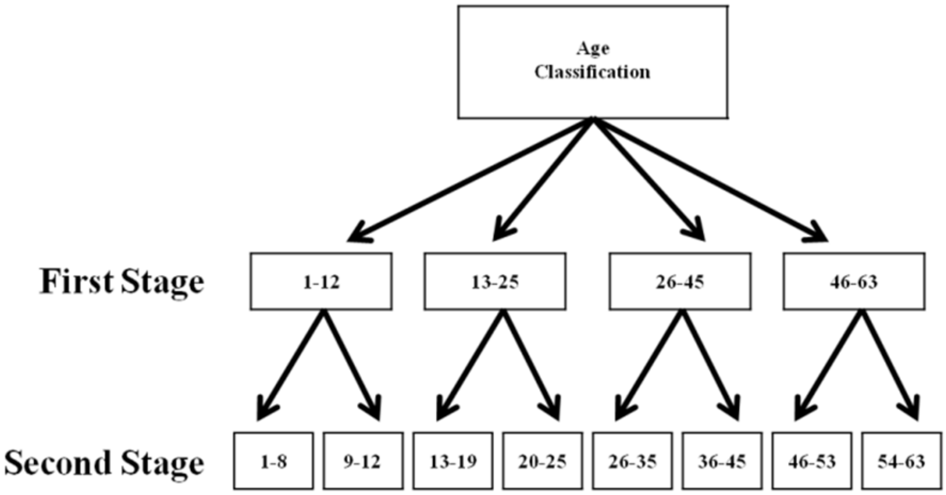

Figure 2.2 Age estimation system in [14]

Chen et .al [6] developed an age estimation system by model selection. They determine the best selection methods among Least Angle Regression (LAR), PCA, and Locality Preserving Projections (LPP) for age estimation. Besides, they also proposed an operator named "graph age preserving" (GAP) to construct a neighborhood graph for LPP.

Most of aforementioned publications have the similar framework: first, extract the facial features from the image; second, construct a well-behaved age estimation system to predict age.

Chapter3. Age Estimation Methods

Based on the architecture in [10], we propose to use the AAM to extract facial feature and the SVM to classify the dataset into 0 to 20 (named young afterward) and 21 to 69 (named adult afterward) age group. From the above two age group, the SVR in employed to get the aging function for each group. When given a test image, from the above SVM classifier this image can be assigned into the suitable age group. After that, according to the corresponding aging function to predict age.

In the following sections, we present methods for facial feature extraction by AAM, SVM classifier, and SVR. We then implement the architecture in [10] with dataset 2 in the same experiment settings and evaluate suitable facial features.

3.1 Active Appearance Model

Section 3.1.1 will discuss the concept of the AAM training process and Section 3.1.2 will introduce the principle of fitting process.

3.1.1. AAM Training Process

The AAM is based on the Active Shape Model (ASM) by Cootes et al. [19]. The AAM is a statistical model which use shape and texture of object and iteratively deform to fit a new object of image. Different from the ASM, the AAM also combine a model of texture variation.

After that, a statistic shape model generated by using PCA as shown in Equation 1.

$$x = \bar{x} + P_s b_s \tag{1}$$

Where x represents landmarks as a vector, $\bar{x}$ is the mean shape, P_s are the set of orthogonal variances, b_s are the parameters of the model. Each image is warped so that each control point matches the mean shape to obtain a “shape-free patch”. Then, sample gray-level information and apply PCA to generate a texture model is built by Eigen-analysis as shown in Equation 2.

$$g = \bar{g} + P_g b_g \tag{2}$$

Where $\bar{g}$ is the mean gray value, P_g are the set of orthogonal variances of gray value, b_g are the parameters of the model. The shape and texture models then concatenate into a combined appearance model as shown in Equation 3.

$$\begin{aligned} x &= \bar{x} + Q_s c \\ g &= \bar{g} + Q_g c \end{aligned} \tag{3}$$

Where $\bar{x}$ and $\bar{g}$ are the mean shape and mean texture individually, Q_s 、 Q_g are matrices that describe the modes of variation, and c are the parameters that dominate the shape and texture. This model can be generated by our dataset 1 or dataset 2 which include the 68 facial features in AAM.

3.1.2. AAM Fitting Process

The AAM fitting process is an iterative algorithm as follow:

I. Project the texture sample into the texture model frame

II. Evaluate the error vector by

$$\begin{aligned} r &= g_s - g_m \\ E &= |r|^2 \end{aligned} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(4)$$

Where g_s is the texture information, g_m is the model texture parameter, r is the error vector, E is the current error.

III. Compute the predicted displacements

IV. Update the model texture parameter

V. Calculate the model frame texture

VI. Calculate a new error vector

The above procedure will repeat if there is no improvement made to resulting error. More detail can be found in [20].

3.2 Support Vector Machine

The SVM is an effective technique for data classification. Usually, there are training and testing sets in data classification. The objective of the SVM is from the training data to produce a model which predicts the target value of the testing data. For a two-class classification task, the SVM tries to find a hyper-plane H which separates these two class data with the maximum margin. Suppose a series training dataset N includes n points defined as the following equation:

$$N = \{(x_i, y_i) | x_i \in R^n, y_i \in 1 \vee -1, \forall i = 1 \ldots n\} \tag{5}$$

Where x_i is a n-dimensional real number vector in feature space, y_i represents the class in which x_i belongs.

Figure 3.1 shows an example of separating two groups of data points. H_2 has the maximum margin between the three Hyper-plane.

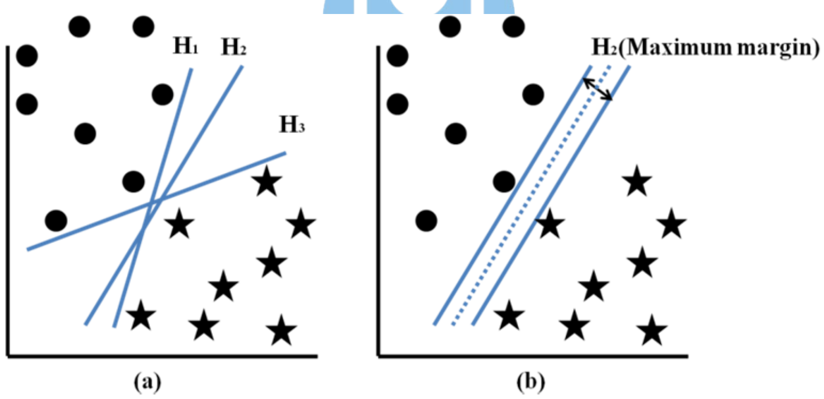

Figure 3.1 (a) Three Hyper-plane separating the two class data, (b) The maximum margin Hyper-plane

The Hyper-plane H which separate x_i into two groups, G_a and G_b as in Equation 6:

$$\begin{aligned} G_a &= \{(x_a, y_a) | x_a \in R^n, y_a \in 1\} \\ G_b &= \{(x_b, y_b) | x_b \in R^n, y_b \in -1\} \end{aligned} \tag{6}$$

The Hyper-plane H satisfying:

$$H : w^T x - b = 0 \tag{7}$$

Where w is a normal vector of *H*, it is perpendicular to *H*, and b is the offset of the Hyper-plane.

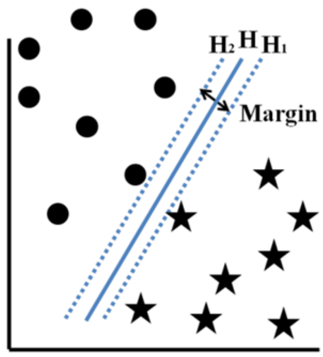

Figure 3.2 The Hyper-plane has the maximum margin

Figure 3.2 represents two support Hyper-plane H_1 and H_2, H is the optimal separating Hyper-plane. Define H_1 and H_2 as:

$$\begin{aligned} w^T x - b - \delta = 0 \\ w^T x - b + \delta = 0 \end{aligned} \tag{8}$$

Scale Equation 8 using a constant factor and derivate this Equation into Equation 9 as follow:

$$\begin{aligned} w^T x - b - 1 = 0 \\ w^T x - b + 1 = 0 \end{aligned} \tag{9}$$

The distance between two support Hyper-plane d is $2/\|w\|$, so the margin= $2/\|w\|$. Hence we want to maximize $2/\|w\|$ or to minimize $\|w\|^2/2$, the SVM is employed to solve this problem.

The Lib-SVM [5] is an easy, fast, powerful package that supports many programming language. In our experiment, we use the Radial Basic Function (RBF) kernel to train our two classifiers.

3.3 Support Vector Regression

The SVM can also deal with regression problem. This kind of SVM is called SVR [8]. Similar to SVM, the goal of SVR is to find the optimal hyper-plane. The difference is this hyper-plane that predicts the data distribution but not separate the data into two class. Suppose there is a training data N includes n points like:

$$N = \{(x_i, y_i) | x_i \in R^n, y_i \in \text{regression value of } x_i, \forall i = 1 \ldots n\} \tag{10}$$

Where x_i is a n-dimensional real number vector, y_i represents the regression that x_i belongs. Define a function $f(x)$ as:

$$f(x) = w \cdot x + b \tag{11}$$

where $w \in R^n$, $b \in R$, for each x_i, if the subtraction between $f(x_i)$ and y_i is small enough, then the function $f(x)$ can predict y_i from x_i. w ,which is the hyper-plane that we want. In the mathematical representation, the above problem can be expressed as:

$$\| y_i - (w \cdot x_i - b) \| \le \varepsilon \tag{12}$$

where $\varepsilon \ge 0$, ε represents the gap between SVR prediction and the true value. This is called ε-SVR, the gap between prediction and true value must be smaller than ε.

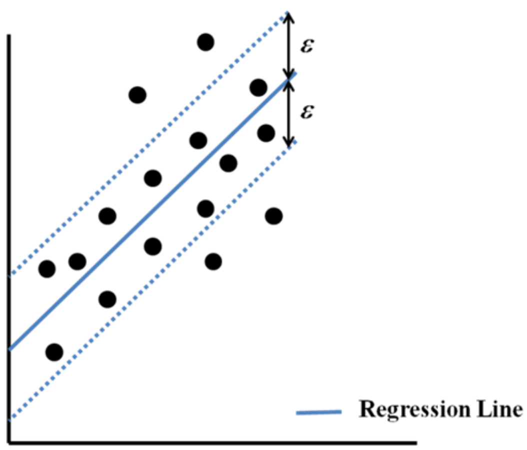

Figure 3.3 SVR linear regression with epsilon-insensitive

Figure 3.3 indicates the linear ε-SVR with its regression line. The Lib-SVM, which also offers ε-SVR, is employed in our experiments to get the regression value of the test images. We then can determine that the test image belongs to which age level by the regression value.

3.4 Experiment with Different Facial Feature

The experiments based on [10] work in dataset 2 and we apply different facial feature trying to find the suitable feature. Dataset 2 includes 300 images in young group, and 500 images in adult group. Each experiment randomly selects 250 images from young group and 250 images from adult group building SVM model, the rest of images for testing the model. Afterwards, we randomly choose 200 images from young group to build the SVR young model and use the rest of 100 images to test this model. Similar to the young group, we randomly select 400 images from adult group to build the SVR adult model and use the rest of 100 images to test this model. We repeat the above process eight times and calculate the average value. For each kind of facial feature, the image sets are different from test1 to test8. But between different facial feature sets, the image sets are identical. In the following section, we will implement the experiments and compare the result with different facial feature sets.

3.4.1. The original 68 features in AAM

A standard AAM landmarked image provides 68 points. Figure 3.4 and Table 3.1 show the 68 landmarked image points and their corresponding descriptions.

Figure 3.4 AAM 68 landmarked points image

Facial feature	ID	Number of points
Face side	1-15	15
Left eyebrows	16-21	6
Right eyebrows	22-27	6
Left eye	28-32	5
Right eye	33-37	5
Nose	38-48	11
Lip	49-67	19
Nose center	68	1

Table 3.1 The description of landmarked points in Figure 3.4

The Mean Absolute Error (MAE) is a well known performance comparison in age estimation. MAE is defined as follow:

$$\mathrm{MAE} = \frac{\sum_{i=1}^{n} |\overline{\mathrm{ai}} - \mathrm{ai}|}{\mathrm{N}} \tag{13}$$

Where $\overline{\mathrm{ai}}$ is the testing sample predict age, ai is the ground truth age, and N is the total number of testing images.

The experiment result uses the AAM original 68 landmarked points is as shown in Table 3.2 and Table 3.3 respectively. The c_{1_68} is the classification accuracy of classifying young and adult group by using the 68 features. The y_{68} is the MAE of using the 68 features in young group, and a_{68} is the MAE in adult group.

	test1	test2	test3	test4	test5	test6	test7	test8	Avgerage
c_{1_68} (%)	89	90	87	89	85	89	88	88	88.13

Table 3.2 The SVM accuracy using the original 68 features

	test1	test2	test3	test4	test5	test6	test7	test8	Avgerage
y_{68} (MAE)	3.35	3.1	3.55	3.36	3.5	4.66	3.32	3.34	3.52
a_{68} (MAE)	7.96	7.02	7.01	7.79	6.7	8.33	7.04	7.87	7.47

Table 3.3 The MAE using the original 68 features

As shown in Table 3.2, the SVM using the original 68 features produces about 88% accuracy in classifying young and adult groups. And Table 3.3 shows that a_{68} is about twice as great as y_{68}. This experiment is employed as the baseline comparison for the following experiments.

3.4.2. Modified 49 features excluding lips

In this experiment, we consider that the mouth motion may be an influence factor, so we remove the 19 landmarked points of lip from the original AAM 68 features. Figure 3.5 and Table 3.4 show the landmarked image and the corresponding description respectively.

Figure 3.5 Modified 49 facial features excluding lips

Facial feature	ID	Number of points
Face side	1-15	15
Left eyebrows	16-21	6
Right eyebrows	22-27	6
Left eye	28-32	5
Right eye	33-37	5
Nose	38-48	11
Nose center	68	1

Table 3.4 The Description of landmarked points in Figure 3.5

Using the above facial feature, Table 3.5, Table 3.6, and Table 3.7 show the experiment result and compare with using the original 68 feature. The c_{1_49} is the classification accuracy of classifying young and adult group by using the 49 features. The y_{49} is the MAE of using the 49 features in young group, and a_{49} is the MAE in adult group.

	test1	test2	test3	test4	test5	test6	test7	test8	Avgerage
c_{1_68} (%)	89	90	87	89	85	89	88	88	88.13
c_{1_49} (%)	90	90	87	89	85	89	88	88	88.25

Table 3.5 The SVM accuracy comparison between c_{1_49} and c_{1_68}

	test1	test2	test3	test4	test5	test6	test7	test8	Avgerage
y_{68} (MAE)	3.35	3.1	3.55	3.36	3.5	4.66	3.32	3.34	3.52
y_{49} (MAE)	3.27	3.52	3.65	3.48	3.4	5.36	3.44	3.28	3.68

Table 3.6 The MAE comparison between y_{49} and y_{68}

	test1	test2	test3	test4	test5	test6	test7	test8	Avgerage
a_{68} (MAE)	7.96	7.02	7.01	7.79	6.7	8.33	7.04	7.87	7.47
a_{49} (MAE)	7.81	6.96	6.74	7.24	6.76	8.64	7.41	7.96	7.44

Table 3.7 The MAE comparison between a_{49} and a_{68}

As shown in Table 3.6 and Table 3.7, y_{49} is smaller than y_{68} in several experiments and a_{49} is smaller than a_{68} on average. In addition, c_{1_49} is slightly more accurate than c_{1_68}. The above results support our assumption that these 19 landmarked points of lip can be an influence factor for age estimation.

3.4.3. Modified 32 features excluding eyebrows

In this experiment, we try to remove the eyebrows and choose some part of eyes, mouth, and nose as shown in Figure 3.6 and Table 3.8. Because some subjects may have their eyebrows altered cosmetically, we conjecture that the eyebrow information will not be helpful. We assume that the removed landmarked points might be the influence factors.

Figure 3.6 Modified 32 facial features excluding eyebrows

Facial feature	ID	Number of points
Face side	1-15	15
Left eye	28、30、32	3
Right eye	33、35、37	3
Nose	38、39、40、42、44、45、46	7
Nose center	68	1
Lip	49、55、67	3

Table 3.8 The Description of landmarked points in Figure 3.6

The experiment results are shown in Table 3.9, Table 3.10, and Table 3.11 respectively. The c_{1_32} is the classification accuracy of classifying young and adult group by using the modified 32 facial features. The y_{32} is the MAE of using the modified 32 features in young group, and a_{32} is the MAE in adult group.

	test1	test2	test3	test4	test5	test6	test7	test8	Avgerage
c_{1_68} (%)	89	90	87	89	85	89	88	88	88.13
c_{1_32} (%)	89	90	87	88	85	90	88	89	88.25

Table 3.9 The SVM accuracy comparison between c_{1_32} and c_{1_68}

	test1	test2	test3	test4	test5	test6	test7	test8	Avgerage
y_{68} (MAE)	3.35	3.1	3.55	3.36	3.5	4.66	3.32	3.34	3.52
y_{32} (MAE)	3.28	3.02	4.89	3.65	3.36	4.94	3.07	3.42	3.70

Table 3.10 The MAE comparison between y_{32} and y_{68}

	test1	test2	test3	test4	test5	test6	test7	test8	Avgerage
a_{68} (MAE)	7.96	7.02	7.01	7.79	6.7	8.33	7.04	7.87	7.47
a_{32} (MAE)	8.67	7.3	6.41	7.11	6.95	8.96	8.9	6.92	7.65

Table 3.11 The MAE comparison between a_{32} and a_{68}

As shown in Table 3.9, c_{1_32} is bit more accurate than c_{1_68} on average which suggests that the modified 32 features and the original 68 facial features have the same effect for classifying young and adult. As shown in Table 3.10 and Table 3.11, y_{32} is smaller than y_{68} in several experiments but a_{32} is higher than a_{68} on average. The above results do not support our assumption that by removing landmarked points of eyebrows can improve the accuracy for age estimation.

3.4.4. 6 features of facial ratios

As discussed earlier, [22] considered six kinds of facial ratios as a principle for classification. We propose six ratios to be used for age estimation: ratio 1 to ratio 5 are similar to [22] but ratio 6 is completely new. These six ratios are show in Figure 3.7 and the corresponding distance calculated from the AAM landmarked points are shown in Table 3.12.

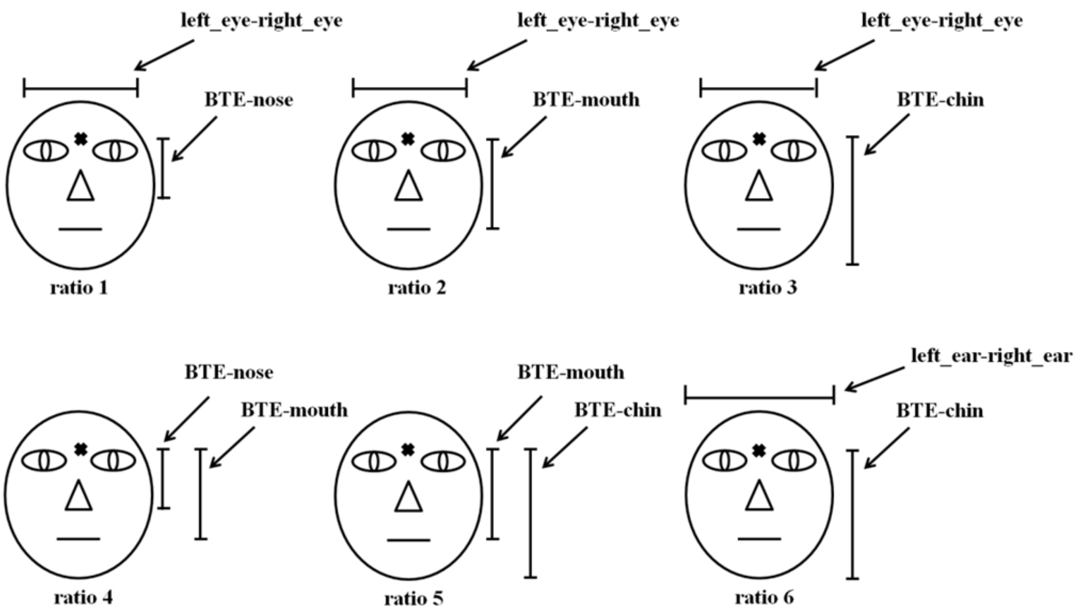

Figure 3.7 The six ratios of facial features

Distance of facial feature	AAM ID
Left eye to right eye	Distance(28,33)
BTE to nose	Distance(midpoint(19,25),42)
BTE to mouth	Distance(midpoint(19,25),67)
BTE to chin	Distance(midpoint(19,25),8)
Left ear to right ear	Distance(2,14)

Table 3.12 The Distance of six ratios by AAM landmarked points

These ratios are not affected by any facial expressions or facial motions. According to Farkas et al. [12], facial feature cab be varied especially in young group. Hence our intuition is to combine the six ratios as a part of facial feature for classification. Ratio 1 is the distance from the left eye to the right eye divided by the distance between the eyebrows (named BTE afterward) and nose. Ratio 2 is the distance from the left eye to the right eye divided by the distance of BTE to mouth. Ratio 3 is the distance from the left eye to the right eye divided by the distance of BTE to chin. Ratio 4 in the distance from BTE to nose divided by the distance of BTE to mouth and ratio 5 is the distance from BTE to mouth divided by the distance of BTE to chin. And ratio 6 is the distance from the left ear to the right ear divided by the distance of BTE to chin.

We consider only the six ratios as features in this experiment. Table 3.13,Table 3.14, and Table 3.15 show the experiment results. The c_{1_6} is the classification accuracy of classifying young and adult group by using the modified 32 facial features. The y_6 is the MAE of using the modified 32 features in young group, and a_6 is the MAE in adult group.

	test1	test2	test3	test4	test5	test6	test7	test8	Avgerage
c_{1_68} (%)	89	90	87	89	85	89	88	88	88.13
c_{1_6} (%)	68	72	70	76	66	71	73	70	70.75

Table 3.13 The SVM accuracy comparison between c_{1_6} and c_{1_68}

	test1	test2	test3	test4	test5	test6	test7	test8	Avgerage
y_{68} (MAE)	3.35	3.1	3.55	3.36	3.5	4.66	3.32	3.34	3.52
y_6 (MAE)	3.69	3.6	3.82	4.29	3.55	3.99	4.01	4.03	3.87

Table 3.14 The MAE comparison between y_6 and y_{68}

	test1	test2	test3	test4	test5	test6	test7	test8	Avgerage
a_{68} (MAE)	7.96	7.02	7.01	7.79	6.7	8.33	7.04	7.87	7.47
a_6 (MAE)	9.59	9.11	8.32	9.07	8.24	8.53	8.92	8.22	8.75

Table 3.15 The MAE comparison between a_6 and a_{68}

The experiment results suggest that only using the six ratios as features is not suitable. In most cases, the result is inferior in the adult group, but still useful in the young group, which supports the conclusion in [12].

3.4.5. Hybrid 21 features with facial ratios

Similar to the last experiments, we now consider combining the 15 facial features as shown in Figure 3.8 and Table 3.16. The BTE point can be decided as the midpoint between the original AAM feature point 19 and point 25. These features simplify the original 68 features and combine the six ratios to become the hybrid 21 features.

Figure 3.8 Modified 15 facial features

Facial feature	ID	Number of points
Face side	2、8、14	3
between the eyebrows	none	1
Left eye	28、30、32	3
Right eye	33、35、37	3
Nose	40、42、44	3
Nose center	68	1
Lip	67	1

Table 3.16 The Description of landmarked points in Figure 3.8

The experiment results of using the hybrid 21 features are shown in Table 3.17, Table 3.18, and Table 3.19. The c_{1_21} is the classification accuracy of classifying young and adult group by using the modified 32 facial features. The y_{21} is the MAE of using the modified 32 features in young group, and a_{21} is the MAE in adult group..

	test1	test2	test3	test4	test5	test6	test7	test8	Avgerage
c_{1_68} (%)	89	90	87	89	85	89	88	88	88.13
c_{1_21} (%)	87	89	86	88	83	89	87	86	86.88

Table 3.17 The SVM accuracy comparison between c_{1_21} and c_{1_68}

	test1	test2	test3	test4	test5	test6	test7	test8	Avgerage
y_{68} (MAE)	3.35	3.1	3.55	3.36	3.5	4.66	3.32	3.34	3.52
y_{21} (MAE)	3.28	3.29	4.01	3.69	3.45	4.17	3.15	3.45	3.56

Table 3.18 The MAE comparison between y_{21} and y_{68}

	test1	test2	test3	test4	test5	test6	test7	test8	Avgerage
a_{68} (MAE)	7.96	7.02	7.01	7.79	6.7	8.33	7.04	7.87	7.47
a_{21} (MAE)	8.43	7.84	6.99	7.38	7.64	8.68	7.85	7.64	7.81

Table 3.19 The MAE comparison between a_{21} and a_{68}

As shown in Table 3.17, the SVM accuracy is about equal between c_{1_21} and c_{1_68}. In Table 3.18, the MAE between y_{21} is really close to y_{68} or better. Now we focus on the adult group, Table 3.19 suggests that neither the hybrid 21 features nor the original 68 feature is effective. So in the following experiments, we plan to improve it.

3.4.6. Hybrid 33 features with facial ratios

Following the last experiment, we want to improve MAE in adult group. Therefore, from the AAM 68 facial features, we again remove some points and reserve 27 points shown in Figure 3.9 and Table 3.20. These 27 points reserve the most important features of the original 68 features.

Figure 3.9 Modified 27 facial features

Facial feature	ID	Number of points
Face side	1-15	15
between the eyebrows	none	1
Left eye	28、30、32	3
Right eye	33、35、37	3
Nose	40、42、44	3
Nose center	68	1
Lip	67	1

Table 3.20 The Description of landmarked points in Figure 3.9

Following the last experiment, we combine the six ratios and the 27 features to become 33 features. The experiment results show in Table 3.21, Table 3.22, and Table 3.23 respectively. The c_{1_33} is the classification accuracy of classifying young and adult group by using the modified 32 facial features. The y_{33} is the MAE of using the modified 32 features in young group, and a_{33} is the MAE in adult group.

	test1	test2	test3	test4	test5	test6	test7	test8	Avgerage
c_{1_68} (%)	89	90	87	89	85	89	88	88	88.13
c_{1_33} (%)	88	90	86	89	85	90	88	86	87.75

Table 3.21 The SVM accuracy comparison between c_{1_33} and c_{1_68}

	test1	test2	test3	test4	test5	test6	test7	test8	Avgerage
y_{68} (MAE)	3.35	3.1	3.55	3.36	3.5	4.66	3.32	3.34	3.52
y_{33} (MAE)	3.3	3.34	4.36	3.59	3.49	4.64	3.13	3.42	3.66

Table 3.22 The MAE accuracy comparison between y_{33} and y_{68}

	test1	test2	test3	test4	test5	test6	test7	test8	Avgerage
a_{68} (MAE)	7.96	7.02	7.01	7.79	6.7	8.33	7.04	7.87	7.47
a_{33} (MAE)	8.13	7.26	6.67	7.67	7.06	9.47	8.86	7.64	7.85

Table 3.23 The MAE comparison between a_{33} and a_{68}

As shown in Table 3.21, the SVM accuracy is comparable between c_{1_33} and c_{1_68}. The MAE in young group is similar to the last experiment that y_{33} and y_{68} is almost equal in several testing cases. However, as suggest by the results shown in Table 3.23, a_{33} does not improve MAE compared to a_{68}. In next section, we will try to add new features to improve MAE in the adult group.

3.4.7. Hybrid 36 features with wrinkle detection

From all the previous experiment, MAE in young group is almost the same by using 6 features, 21 features, and 33 features. On the other hand, MAE in adult group is not satisfactory. So now we plan to use wrinkle detection to improve MAE in the adult group. There are three regions of wrinkle detection in our work. Figure 3.10 indicates the three regions of facial wrinkle detection.

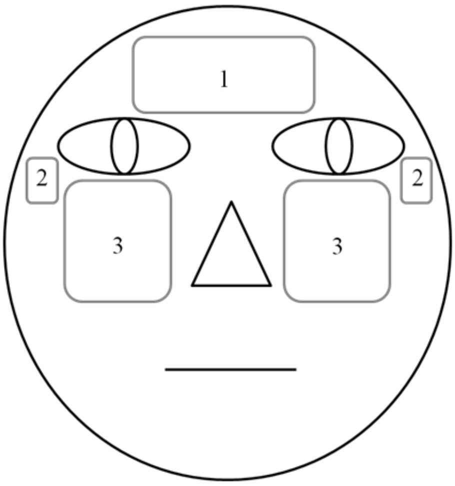

Figure 3.10 The three parts of facial wrinkle detection

The first region is the forehead, the second region is the fishtail, and the third region is below the eye to the nose. For a test image, we compute the edge map by Sobel operator. The Sobel operator use two 3 by 3 matrixes. One of the matrixes is detecting the horizontal gray level value variation of test image, and the other is detecting the vertical gray level value variation. After that, we extract the line for the three regions of face using the Hough transform for line detection. First, Hough-transform transform the 2-dimentional space into $r-\theta$ space, defined as follows:

$$r = x\cos\theta + y\sin\theta \tag{14}$$

We set a threshold as a voting basis and calculate the r value of edge points from an edge map to decide strait lines above this threshold.

In the first region, we extract the horizontal lines in the edge map. For the second and third regions, we extract the lines with angles between 25 to 65 degrees in left side of face and the lines with angles are between 115 to 155 degrees in right side of face. These three regions of line information will be combined into the adult images as a part of features. Figure 3.11 indicates the test image of our wrinkle detection method and Figure 3.12 is the result of the test image. The red lines in Figure 3.12 represent the detected wrinkles.

Figure 3.11 The test image of the wrinkle detection

Figure 3.12 The result of our wrinkle detection method

We combine the six ratios which mentioned before and 27 features in Figure 3.9, and the three wrinkle features. The result is a set of total 36 features, which will be used only in the adult group. Following the above experiments, the results are shown in Table 3.24 and Table 3.25. The c_{1_36} is the classification accuracy of classifying young and adult group by using the modified 32 facial features. The y_{33} is the MAE of using the modified 32 features in young group, and a_{36} is the MAE in adult group.

	test1	test2	test3	test4	test5	test6	test7	test8	Avgerage
c_{1_68} (%)	89	90	87	89	85	89	88	88	88.13
c_{1_36} (%)	89	90	87	90	86	90	89	87	88.50

Table 3.24 The SVM accuracy comparison between c_{1_36} and c_{1_68}

	test1	test2	test3	test4	test5	test6	test7	test8	Avgerage
a_{68} (MAE)	7.96	7.02	7.01	7.79	6.7	8.33	7.04	7.87	7.47
a_{36} (MAE)	7.38	6.29	5.89	6.38	6.57	7.33	7.89	6.65	6.80

Table 3.25 The MAE comparison between a_{36} and a_{68}

Table 3.25 suggests a great improvement of MAE in the adult group. As shown in Table 3.24, the SVM accuracy is comparable between c_{1_36} and c_{1_68}. As shown in Table 3.26, the average SVM accuracy using different feature sets, only the 6 features produces inferior accuracy and the 36 hybrid features produces the highest accuracy. Table 3.27 shows that the average MAE between young and adult group using different features sets. The results in Table 3.27 suggest that by using 36 features we can achieve the least MAE among all the features sets.

	Accuracy(%)
68 features	88.13
49 features	88.25
32 features	88.25
6 features	70.75
21 features	86.88
33 features	87.75
36 features	88.50

Table 3.26 The SVM average accuracy comparison among 7 sets of facial features

	MAE
68 features	5.49
49 features	5.56
32 features	5.68
6 features	6.31
21 features	5.68
33 features	5.75
36 features	5.23

Table 3.27 The Average MAE comparison among 7 sets of facial features

From the above experiment results, we decide to use the hybrid 36 features as our main features in SVM and SVR. In the following chapter, we will present our proposed age estimation architecture and will experiment with dataset 1 and dataset 2.

Chapter4. Experiments

In this Chapter, we present the framework of the proposed age estimation method and the experiment results.

4.1 Framework

From the previous experiment results, we consider the MAE in adult group is unsatisfactory, so we decide to divide the adult group further into 21 to 40 years old age group (named junior adult afterward) and 41 to 69 years old age group (named senior adult afterward). Figure 4.1 represent the architecture of our propose method.

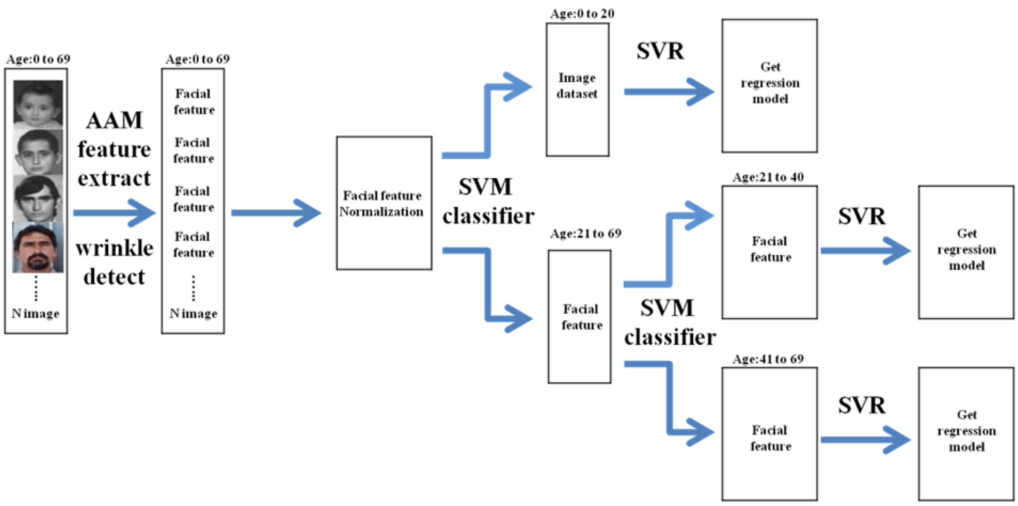

Figure 4.1 The Training step of the propose method

Figure 4.1 is the training step of our method. First, we employ AAM to extract facial features from the image and calculate the six ratios of facial features. In the next step, these facial features will be normalized by translation, rotation, scaling. And train the first level two-class SVM classifier by these normalization features. Besides, the wrinkle information is extracted and the above normalization features are combined to train the level 2 two-class SVM classifier. In the final step, we utilize the six sets of facial features to train the SVR regression model for each corresponding age group.

Given a new image to estimate age, Figure 4.2 indicates the testing step of the process.

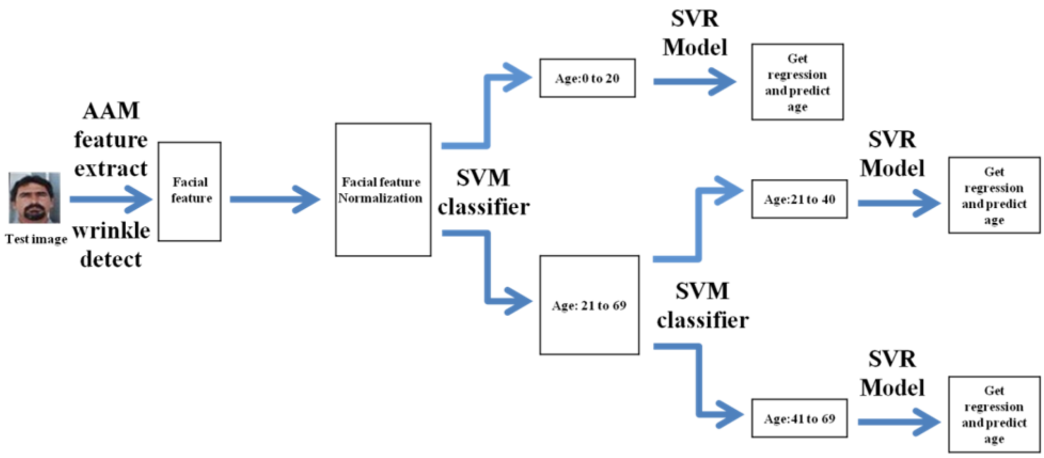

Figure 4.2 The Testing step of the propose method

First, facial features from AAM are extracted and normalized. Then according to classification result by the first level SVM classifier, the test image will be assigned to an age group of young or adult. If the test image is assigned to young age group, we apply the SVR model to compute the regression value of the test image and predict the age accordingly to. Otherwise, if the test image is assigned to adult age group, then it will be further assigned to junior adult age group or senior adult age group by the second level SVM classifier. Similar to the step of young age group, the following SVR model also return the regression value for junior adult age group and senior adult age group. Then the age of the test image is estimated by the returned regression value. The detailed implementation of our propose method will be presented in the next section.

4.2 Experiment Result

While detecting wrinkles on subject images, there are some restrictions in our experiment:

I. The subject cannot wear glasses that will occlude the detection region 2.

II. The subject cannot cover the forehead bangs that will occlude the detection region 1.

III. The subject must be Caucasian. Because the training sets are composed of images of Caucasian only.

However, every subject images may have different poses and the size of images may not be the same. Hence we need to calibrate the AAM landmarked points before the training and testing process. There are three steps in the calibration process:

Translation, rotation, and scaling

First, we select the youngest age image among all images as the reference image for calibration. In the translation step, we select the nose as the pivot to translate all other points. After translation, a vector V_a is defined as follows:

$$V_a = (x_8, y_8) - (x_{68}, y_{68})$$
$$V_b = (x_8, y_8) - (x_{68}, y_{68}) \tag{15}$$

V_a is a reference vector in the reference image, and V_b is a vector in the image to be calibrated. In the rotation process, the rotation angle is computed as shown in Equation 16:

$$\cos\theta = \frac{V_a \cdot V_b}{|V_a| \cdot |V_b|} \tag{16}$$

From Equation 16, we rotate all 68 points with rotation angle θ in the rotation step. In the scaling step, from the first point to the 67^{th} point we obtain 67 vectors as shown in Equation 17:

$$V_1 = (x_1, y_2) - (x_{68}, y_{68})$$
$$\vdots$$
$$V_{67} = (x_{67}, y_{67}) - (x_{68}, y_{68}) \tag{17}$$

We then calculate the scaling ratio with respect to V_a and V_b. All 67 vectors are scaled by this ratio individually. Now the calibration process is completed by translation, rotation, and scaling.

In the first experiment, we implement our method with dataset 2 and experiment with different sets of facial features. At first, we randomly pick 250 images from young age group, 250 images from adult age group. These images are employed to train the level one SVM classifier and the rest of images are employed to test the resulting classifier. The experiment repeats eight times and the average result is shown in Table 4.1.

	Accuracy(%)
68 features	88.25
49 features	88.38
32 features	88.38
6 features	71.13
21 features	86.75
33 features	87.38
36 features	88.00

Table 4.1 The average accuracy of level one SVM classifier with seven different sets of facial features

The accuracy in Table 4.1 is comparable between five sets of facial features and the AAM original 68 facial features, with the exception of using only the 6 ratios as features. In next step, we pick 200 images from the junior adult group and 200 images from the senior adult group to train the level two SVM classifier. The rest of images are employed to test the resulting classifier. Same as the experiment with the level one classifier, the average accuracy is shown in Table 4.2. And the average accuracy of level one and level two classifiers is shown in Table 4.3.

	Accuracy(%)
68 features	71.88
49 features	72.88
32 features	70.50
6 features	63.38
21 features	68.00
33 features	69.63
36 features	74.38

Table 4.2 The average accuracy of level two SVM classifier with seven different sets of facial features

	Accuracy(%)
68 features	80.06
49 features	80.63
32 features	79.44
6 features	67.25
21 features	77.38
33 features	78.50
36 features	81.19

Table 4.3 The average accuracy of level one and level two SVM classifier with seven different sets of facial features

In Table 4.3, the results indicate that the hybrid 36 features indeed produces the highest accuracy as stated in the conclusion of the previous chapter. Similar to the above step, we randomly select 200 images from young, 150 images from junior adult (named *ja* afterward), and 150 images from senior adult (named *sa* afterward). For the rest of images in each group, we test each group by these images correspondingly. The experiment repeats eight times, and the MAE results of each set of facial features is shown in Table 4.4,Table 4.5, and Table 4.6.

	MAE
y_{68}	3.26
y_{49}	3.39
y_{32}	3.41
y_{6}	3.48
y_{21}	3.20
y_{33}	3.30
y_{36}	3.30

Table 4.4 The average MAE in young comparison among 7 sets of facial features

	MAE
ja_{68}	4.14
ja_{49}	4.15
ja_{32}	4.26
ja_{6}	4.40
ja_{21}	4.28
ja_{33}	4.34
ja_{36}	4.26

Table 4.5 The average MAE in junior adult comparison among 7 sets of facial features

	MAE
sa_{68}	4.41
sa_{49}	4.41
sa_{32}	4.43
sa_{6}	4.40
sa_{21}	4.34
sa_{33}	4.57
sa_{36}	3.96

Table 4.6 The average MAE in senior adult comparison among 7 sets of facial features

In Table 4.4, Table 4.5, and Table 4.6, y_{21} has the lowest MAE than others which suggests that the six facial ratios are really helpful. And the sa_{36} has significant lower MAE than using other feature sets in the senior adult group.

Original architecture	MAE	Our architecture	MAE
68 features	5.49	68 features	3.93
49 features	5.56	49 features	3.98
32 features	5.68	32 features	4.03
6 features	6.31	6 features	4.09
21 features	5.68	21 features	3.94
33 features	5.75	33 features	4.07
36 features	5.23	36 features	3.84

Table 4.7 The average MAE comparison between [10] and the proposed two-layer architecture

Table 4.7 shows the average MAE result of original architecture [10] and the proposed two-layer architecture. The MAE results clearly indicate great improvement in dataset 2.

In the second experiment, we implement the architecture with dataset 1 to compare the result with other age estimation method. At first, we randomly pick 150 images from young and 150 images from adult. These images are employed to train the level one SVM classifier and the rest of images are employed to test the accuracy of this classifier. The experiment repeats three times and the average results are shown in Table 4.8.

	Accuracy(%)
68 features	71.67
49 features	73.00
32 features	68.00
6 features	54.33
21 features	64.33
33 features	68.33
36 features	68.00

Table 4.8 The SVM average accuracy of level one classifier comparison among 7 sets of facial features

In the next step, we pick 150 images from the junior adult group and 150 images from the senior adult group. These images are employed to train the level 2 SVM classifier and the rest of images are employed to test the accuracy of this classifier. The average accuracy of the level two SVM classifier is shown in Table 4.9 and the average accuracy of level one, level two SVM classifier are shown in Table 4.10.

	Accuracy(%)
68 features	74.33
49 features	73.33
32 features	71.33
6 features	58.67
21 features	67.00
33 features	71.33
36 features	74.33

Table 4.9 The SVM average accuracy of level two classifier comparison among 7 sets of facial features

	Accuracy(%)
68 features	73.00
49 features	73.17
32 features	69.67
6 features	56.50
21 features	65.67
33 features	69.83
36 features	71.17

Table 4.10 The SVM average accuracy of level one classifier and level two classifier comparison among 7 sets of facial features

In Table 4.9 and Table 4.10, the AAM original 68 features, the modified 49 features, and the hybrid 36 features almost show the same accuracy. After that, we randomly select 100 images from young, 100 images from junior adult, and 100 images from senior adult to train the SVR model of each age group. The rest of images in each group are used to test their corresponding SVR models. The experiment repeats three times and the results are shown in Table 4.11,Table 4.12, and Table 4.13.

	MAE
y_{68}	4.83
y_{49}	4.45
y_{32}	4.84
y_{6}	4.09
y_{21}	4.97
y_{33}	4.73
y_{36}	4.73

Table 4.11 The average MAE in young group comparison among 7 sets of facial features

	MAE
ja_{68}	3.55
ja_{49}	3.70
ja_{32}	3.73
ja_{6}	4.06
ja_{21}	3.88
ja_{33}	3.78
ja_{36}	3.71

Table 4.12 The average MAE in junior adult group comparison among 7 sets of facial features

	MAE
sa_{68}	4.65
sa_{49}	4.53
sa_{32}	4.62
sa_{6}	4.29
sa_{21}	4.26
sa_{33}	5.34
sa_{36}	4.01

Table 4.13 The average MAE in senior adult group comparison among 7 sets of facial features

In Table 4.11, the y_6 has the least MAE, and the y_{49}, y_{33}, and y_{36} are more accurate than the y_{68}. As shown in Table 4.13, the sa_{36} produces the least MAE. The average MAEs of the three age groups are shown in Table 4.14.

	MAE
68 features	**4.35**
49 features	**4.24**
32 features	**4.40**
6 features	**4.15**
21 features	**4.35**
33 features	**4.66**
36 features	**4.13**

Table 4.14 The average MAE of three age groups comparison among 7 sets of facial features

From Table 4.14, the hybrid 36 features have the least MAE. The modified 49 features and the 6 ratios of facial features are also more accurate than the original 68 features. With identical experimental settings used in dataset 1, we compare our results with WAS, AAS and AGES in [21]. Moreover, we compare the results with MTWGP, LARR, RUN1 and mkNN in [16]. The comparison results are shown in Table 4.15.

	MAE
Our propose method	**4.13**
MTWGP[16]	**6.28**
LARR[16]	**7.94**
RUN1[16]	**8.34**
AGES[21]	**8.83**
WAS[21]	**9.32**
mkNN[16]	**10.31**
AAS[21]	**20.93**

Table 4.15 The MAE comparison of our method and other age estimation methods ("proposed" method in the first row)

In Table 4.15, our proposed method compares favorably to other state-of-the-art age estimation methods using the MORPH database. This finding concludes that our proposed method can improve MAE in age estimation.

Chapter5. Conclusion and Future Work

We propose a novel age estimation method based on [10] with six different sets of facial features and compare the estimation accuracy with the original AAM 68 features using dataset 2. The estimation results may be influenced by pose, motion, or facial expression so we propose to normalize every image to alleviate this problem. Through experiments, we find that the estimation accuracy in the adult age group is always inferior to the estimation accuracy in the young group.. Hence we propose a multi-layer architecture to alleviate this problem and implement the architecture with dataset 1 and dataset 2. The method divides age group from 21 to 69 years old into 21 to 40 years old age group and 41 to 69 years old age group by using two level of SVM classifiers. For each age group, we obtain the regression value of each image by epsilon-SVR to predict the corresponding age. From the experiment results with dataset 2, we find that the hybrid 36 features set with wrinkle detection is more accurate than other sets of facial features. We also compare our result with other state-of-the-art age estimation methods using dataset 1 and the results show that our proposed method compares favorably with others.

In the future work, because every race have different aging pattern so it may be helpful to build different aging models for different races. Also, gender is another influence factor hence it may also be helpful to build different aging models for male and female.

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