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A NOVEL APPROACH FOR AGE CLASSIFICATION FROM FACE USING AAM AND SVM

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ABSTRACT: This paper presents the age group classification based on facial images. We perform age-group classification by dividing ages into four age groups
According to the incremental regulation of age.Features are extracted from face images through Active Appearance Model (AAM), which describe the Shape and color value variation of face images.Support vector machine (SVM) classifier with Gaussian Radian Basis Function (RBF) kernel is trained. Experimental results that SVM can improve the performance of age classification.

Keywords: AAM, SVM, Image Processing.

I. INTRODUCTION

As humans, we are easily able to categorize a person’s age group from an image of the person’s face and are often able to be quite precise in this estimation. This ability has not been pursued in the computer vision community. In order to begin researching the issues involved in this process, this research addresses the limited task of age classification of a mugshot facial image into a baby, young adult, and senior adult. Any progress in the research community’s understanding of the remarkable ability that human’s have with regard to facial image analysis will go a long way towards the broader goals of face-recognition and facial-expression recognition. In the long run, besides leading to a theory for automatic precise age identification which would assist robots in numerous ways, analysis of facial features such as aging-wrinkles will assist in wrinkle analysis for facial-expression recognition. However, in the shorter term too, an improvement of our understanding of how humans may classify age from visual images can be used in the domain of indexing into a face database by the person's age, in the area of newspaper-story understanding [10, 11], and in the application areas such as gathering population age-statistics visually (for example, getting the ages of patrons at entertainment and amusement parks or in television network viewer-rating studies.) To gain an understanding for the aging process of the face, we consulted studies in cranio-facial research [1], art and theatrical makeup [2, 7], plastic surgery, and perception [5].

Limitation of Face Age Classification

Even though current machine recognition systems have reached a certain level of maturity, their success is limited by the conditions imposed by many real applications. For example, recognition of face images acquired in an outdoor environment with changes in illumination and/or pose remains a largely unsolved problem. Ambient lighting changes greatly within and between days and among indoor and outdoor environments. Due to the 3D structure of the face, a direct lighting source can cast strong shadows that accentuate or diminish certain facial features. However, it is still a difficult task for a machine to recognize human faces accurately in real-time, especially under variable circumstances such as the 3D head pose, Illumination (including indoor / outdoor), Facial Age group, occlusion due to other objects or accessories (e.g., sunglasses, scarf, etc.), Facial hair, aging. The similarity of human faces and the unpredictable variations are the greatest obstacles in face-recognition.

The illumination problem is basically the variability of an object's appearance from one image to the next with slight changes in lighting conditions and viewpoint. This often results in large changes in the object's appearance. This recognition problem is made difficult by the great variability in head rotation and tilt, lighting intensity and angle, facial expression, aging, etc.

Some other attempts at facial recognition by machine have allowed for little or no variability in these quantities.

Problem Definition

An improved approach to Age Classification using modified AAM algorithm.

In our algorithm we focused on main three constraints are Time, accuracy, number of recognized Age Group. Because previous algorithms are not focused on all three constraints together so, our aim is to design an algorithm which focus on these basic and make the algorithm efficient than previous algorithms.

Issues we will focus on:

- Time constrain: The performance time for the feature extraction and time of classification.
- Accuracy: The accuracy of the Age classification still needs to be improved. The accuracy decreases when more ages are needed to be recognized.
- Number of the recognized age group: Although there are varieties of age group states to describe the human's feelings, until now only limited types of Age Group can be recognized. But our algorithm recognized at least 4 Age Group.

II. Related Work

Caused by the growing interest a lot of papers have been published over the last years, which deal with the problem of age estimation. They outline some different and interesting approaches.

The work of Narayanan Ramanathan et al. [38] provides a good introduction to the topic. They examine the problem from a more wide point of view, namely the analysis of the basics of human face aging and what has been done there so far. The rst steps in understanding the morphological changes associated with growth in biological forms were made by D'arcy Thompsons's study of morphogenesis (1917) [47]. Based on Thompson's work, Shaw et al. [43] studied facial growth as an event perception problem and discovered the Cardioidal strain and the A ne Shear transformation to describe facial growth. Further Pittenger and Shaw [35] enhanced this approach and distinguish the importance of three force conjurations, named: the shear, strain and radial forces and identi ed the cardioidal strain forces (containing the radial components) to be the most important one. Todd et al. [50] developed the 'revised' cardioidal strain transformation model, by comparing the human head growth with the modeling of a uid-lled spherical object with pressure Xin Geng et al. [17] developed an age estimation method named AGES (AGing pattErn Subspace), based on the following assumptions:

1. The aging progress is uncontrollable.

2. Every person ages differently.

3. The aging progress must obey the order of time.

Therefore they introduced the so called aging patterns, as a sequence of personal facial images sorted in chronological order. The images are represented by their feature vector, extracted by the Appearance Model described in [10]. Instead of using isolated pictures for training, a subspace of the aging patterns is learned, using Principal Component Analysis (PCA). A big problem was the lack of complete aging patterns, which led to highly incomplete training data. To deal with this they developed an iterative learning algorithm, which is able to estimate a part of the missing personal aging pattern with each iteration, using the global aging pattern model learned so far. Karl Ricanek et al. [40] used the Active Appearance Model (AAM) described in [46], to locate relevant aging features. In the next step they applied Least Angle Regression (LAR) by Efron et al. [11] to identify the most important features. The reduced feature vectors of the training set are then used for Support Vector Regression (SVR) by Vapnik [51]. While training, the age estimation acts as a feedback for the LAR. They also tried to incorporate information like race and gender into their training, but got the best performance, when only using the results of the LAR.

Feng Gao and Haizhou Ai [14] collected thousands of frontal or near frontal face images and labeled them with a subjective age. The training samples were divided into the following four age groups: 0-1, 2-16, 17-50 and 50+. To get a descriptor vector they used Gabor features by C. Liu et al. [26]. Then they utilized the linear discriminant analysis (LDA) technique [4], to build the Classifier. They further improved it by implementing Khoa Luu et al. [29] used Active Appearance Model (AAM) to extract a combined feature vector of the facial images. The Classifier is divided into two main steps. First a binary Classifier f is build by SVMs to distinguish between youths (0-20) and adults (21-69). In the second step a growth and development function f_1 and an adult aging function f_2 are separately trained with Support Vector Regression (SVR) [27], on youth and adult datasets, respectively. When classifying, the test image is rst assigned to one of the two age groups and then handed to the corresponding age function, to estimate the exact age. Based on this work Khoa Luu et al. modi ed the Classifierconstruction by adding a supervised spectral regression after the extraction of the combined AAM feature vector [28]. It should improve the correlation information among the feature vectors of the same class and decrease it for different classes. Also it should help to reduce the dimension of the feature vector.

Based on a recent work, Sethuram et al. [41] improved their analysis-synthesis face-model approach, which is based on Active Appearance Models (AAM). They used Support Vector Regression (SVR) to learn age-based properties of the AAM parameters and gradient-regression-based AAMs, to represent the texture information. After this a Monte-Carlo simulation is run, which generates random faces, which are then classified based on the age estimated by the SVR, to get the feature information learned by the support vectors. Finally bins are created and averaged for each age, to get a table of AAM parameters, that can be used to morph a face to a desired age.

Young H. Kwon and Niels da Vitorie Lobo [21] developed an algorithm based on ratios of different facial features and a wrinkle analysis, including the automatic extraction of the required features. Their approach only needs a manually initialized center position of the head to t an oval around the face. With this information initial position of iris, mouth and nose are set and optimized with the image potential technique. This information allows the computation of different ratios, which they discussed regarding to their reliability and robustness. For the wrinkle analysis they searched in different regions, like eyes and forehead, by dropping randomly oriented snakelets [20] to these regions. For the Classification, the ratios are used to differentiate between baby and non baby and the wrinkles between adults and seniors. So for example a person, who is not a baby and has no wrinkles is an adult.

III. PROPOSED SYSTEM

An improved approach to age classification using modified AAM algorithm. In our proposed algorithm we focused on main three constraints are Time, accuracy, number of recognized Age group. Because previous algorithms are not focused on all three constraints together so, our aim is to design an algorithm which focus on these basic and make the algorithm efficient than previous algorithms.

Issues we will focus on:

1. Time constrain: The performance time for the feature extraction and time of classification.
2. Accuracy: The accuracy of the age classification still needs to be improved. The accuracy decreases when more age group are needed to be recognized.
3. Number of the recognized age group: Although there are varieties of age group to describe the human age, until now only limited types of age can be recognized. But our algorithm recognized at least 4 age group.

A. Proposed System Architecture

In our proposed methodology for this paper we categorize the process on two parts first on is training dataset for Age Feature Extraction using AAM algorithm .Training is the process how to learning of data set take place for future comparison. Second part is testing the new dataset with trained dataset; it helps to detect the Age of image and finally Age Group according to Age detected by the system. Here we explain the working methodology of proposed system.

1. First part shows how we train our data set for the Age Classification. First we input the different face images then we extract the features of the images using AAM (Active Appearance Model) and then we train our dataset using SVM (Support Vector Machine) and finally we take a test for the correctness of the age detection.

Second part shows how we detect Age. First we capture image and then queue these samples in database and then detect age and then comparing the detected Age to the trained database. When the age is detected then the Classify Age Group According to detected Age.

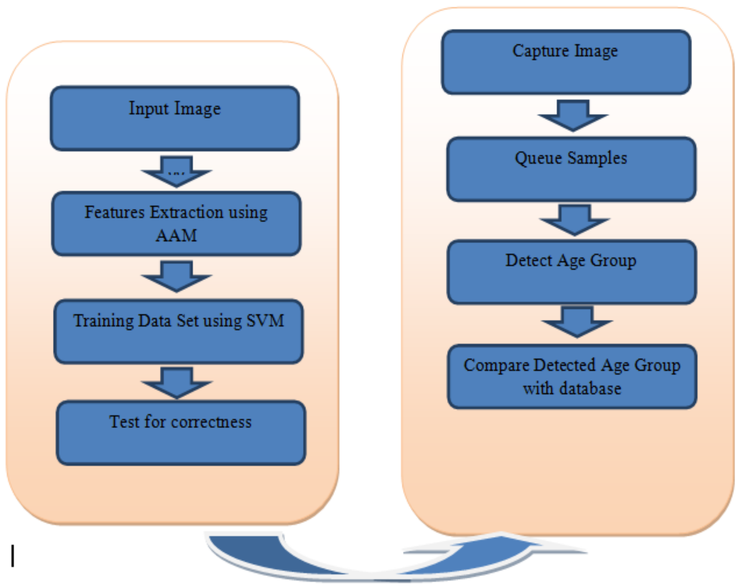

Figure: Proposed System Architecture

B. Features Extraction using AAM

The Eigen Object Recognizer class applies AAM on each image, the results of which will be an array of Eigen values that a Neural Network can be trained to recognize. AAM is a commonly used method of object recognition as its results, when used properly can be fairly accurate and resilient to noise. The method of which AAM is applied can vary at different stages so what will be demonstrated is a clear method for AAM application that can be followed. It is up for individuals to experiment in finding the best method for producing accurate results from AAM. To perform AAM several steps are undertaken:

Stage 1: Subtract the Mean of the data from each variable (our adjusted data)

Stage 2: Calculate and form a covariance Matrix

Stage 3: Calculate Eigenvectors and Eigen values from the covariance Matrix

Stage 4: Chose a Feature Vector

Stage 5: Multiply the transposed Feature Vectors by the transposed adjusted

C. Feature Extraction

Feature extraction converts pixel data into a higher-level representation of shape, motion, color, texture, and spatial configuration of the face or its components. The extracted representation is used for subsequent expression categorization. Feature extraction generally reduces the dimensionality of the input space. The reduction procedure should (ideally) retain essential information possessing high discrimination power and high stability. Such dimensionality reduction may mitigate the „curse of dimensionality‟. Geometric, kinetic, and statistical- or spectral-transform-based features are often used as alternative representation of the facial expression prior to classification.

D. Classification

Age categorization is performed by a classifier, which often consists of models of pattern distribution, coupled to a decision procedure. A wide range of classifiers, covering parametric as well as nonparametric techniques, has been applied to the automatic Age recognition problem. The two main types of classes used in facial age recognition are action units (AUs), and the prototypic facial expressions defined by Ekman. The 4 prototypic age groups relate to the age group of child, younger, elder, older. However, it has been noted that the variation in complexity and meaning of age group covers far more than these four age group categories.

E. Training via SVM

To perform automated age recognition, our system needs to deal with the issues of face localization, facial feature extraction and the training as well as the classification stages of the SVM.

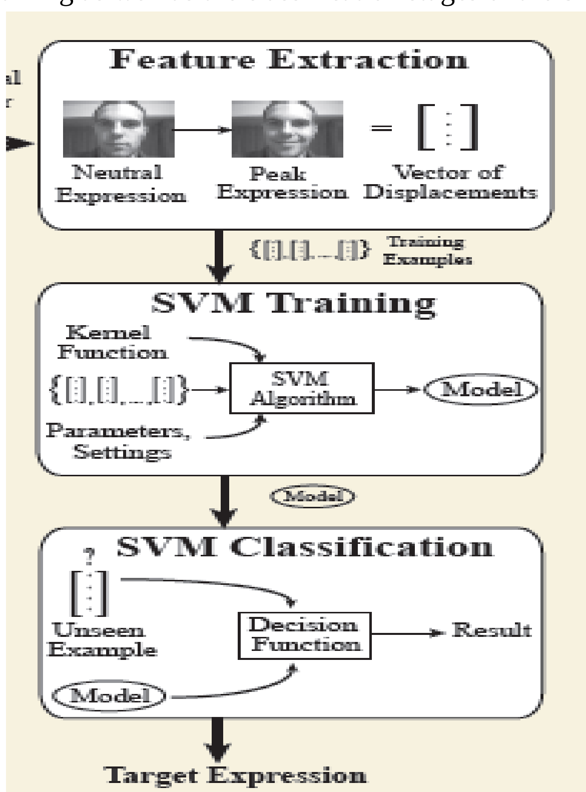

Figure2:SVM classification

F. Training & Classification

The labeled vector of displacements of each example expression supplied is used as input to an SVM classifier, resulting in a model of the training data, which is subsequently used to dynamically classify unseen feature displacements. The result is then returned to the user. SVMs are maximal margin hyper plane classifiers that exhibit high classification accuracy for small training sets and good generalization performance on very variable and difficult to separate data.

IV. EXPERIMENTAL RESULTS

In order to verify the proposed method, we employ the database of FG-NET AGING Database and FERET Database .There are 60images in each age group. In the first step of the experiment, we mark 52 features manually on the facial image, including 8 points in mouth, 7 points in nose, 16 points in eyes,8 points in eyebrows and 13 points in face contour .Then we divide the warped images into two parts, one is the training set and the other is the test set. In this experiment, we randomly select 30 images per age group as training set and the others 30 images as test set.

In order to compare the effects of different type of feature representation, four kinds of features (grayscale value, edge image, grayscale value with edge image and horizontal edge

image) are extracted to test in our proposed system. First, the grayscale value of the original warped image is used as features to recognize the age group. Here 30 images in each age group

are used to test. In this experiment, only gray level images are used to recognize. The experimental result is shown as Table I. Here the average recognition rate using gray level image is 81.1 %. It can be seen that the recognition result of adult group is better than the one of child and elder group. 9 elder images are recognized as adult image due to the elder image is seen like the adult image.

Input Age Group	Recognition Results			
	Child	Adult	Elder	Recognition Rate
Child	26	3	1	86.7%
Adult	1	28	1	93.3
Elder	2	9	19	63.3%

V. CONCLUSION

The optimally design Singular Value Decompositions tested on the training dataset. The results obtained are excellent. The recognition rate for all four principal ge group namely child, younger, elder, older along with Neutral is obtained which is more than previous existing techniques. Finally the network is tested on the real time dataset with excellent recognition rate.

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