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Age Estimation Using Classifiers Artificial Neural Network and Support Vector Machine Based on Face Images

Rajan Vishnu Parab
Alamuri Ratnamala Institute of Engineering and Technology, Mumbai
rajanparab09@gmail.com

Prof. Dattatray S. Bade
Vidyalankar Institute of Technology, Mumbai
dattabade@gmail.com

Abstract: ***The most prominent challenge in the facial age estimation is a lack of sufficient and incomplete training data. Aging is slower and gradual process, therefore, faces near close ages look quite similar this can allow us to utilize the face images at neighbouring ages with modeling to a particular age. There are many potential applications in age-specific human-computer interaction for security control and surveillance monitoring. In the last few years biologically inspired features are used for human age estimation for face images but recently more focus put on a method like scattering transform. The proposed approach exploits scattering transform gives more information about features of the facial images. An efficient descriptor consisting scattering transform which scatters the gabor coefficients and pulled with Gaussian smoothing in multiple layer and is evaluated for facial feature extraction. These extracted features are classified using support vector machine and artificial neural network. Results for face based age estimation obtain by the artificial neural network is more effective than support vector machine.***

Keywords: Artificial Neural Network (Ann); Support Vector Machine (SVM); Binary Classifier; Cost-Sensitive Ordinal Hyperplane Ranker (CSOHR); Biologically Inspired Features (BIF); Median Filter (Mf); Scattering Transform (St).

I. INTRODUCTION

Analyzing human face images by automatic age estimation is an important topic in image processing in which person's exact age or age group evaluation is a major task. In the estimator age, group task divides labels roughly into different groups such as child, children, elder, older and exact age task follows age labels densely. Our method mainly focused on the age task and is applied more generally to face images which also outperform with the age group task of the estimator.

Estimator learning and facial feature extractions are too important components to building age estimator effectively. A personage is obtained from classified by only giving the age's value to the estimator as independent labels in multiclass approaches. Accurate age or age group can be predicted by using many approaches like multilayer Perceptron, Support vector machine (SVM). In conventional classifier learning to rank approach for age, estimation is obtained by training the ranking algorithm to adopt the labels ordering property.

Important face related features are obtained by principal component analysis (PCA) where both appearance and shape model are obtained which called as Active appearance model (AAM). BIF consist number of layer of convolution and pooling process thus BIF is a pyramid of Gabor filters for facial images. Gabor filters are used for feature detection as they localize and extract text region from complex data of images (both colour and gray). The wavelet transforms having an inherent multi-resolution representation i.e. scale (window width) and shift (window position) can be varied.

II. RELATED WORK

J. T. Todd, L. S. Mark, R. E. Shaw, J. B. Pittenger [2], different types of the classifier are used for feature representation along with active appearance model. Different classifiers are neural networks quadratic function and shortest distance classifier.

X. Geng, Z. Zhou, and K. Smith-Miles in [3] and X. Geng, Z.-H. Zhou, Y. Zhang, G. Li, and H. Dai [4] say, active appearance model consist face images in a sequence of age ascending for the same person. Therefore propose a method in this paper is (AGES) aging pattern subspace is used for automatic age estimation. Therefore aging models for different persons can be obtained.

Y. Zhang and D. Yeung [5], among the methods which are proposed to data the personalize age estimation method mostly outperform global age estimation by using separate estimator to each person in the training dataset. Typical age databases contain only limited training data for each person, therefore, training a separate age estimator with only training personal data can face the problem of over-fitting the data and therefore degrade the prediction performance. As series of facial images of a single person which showing an aging effect are difficult to obtain. Therefore the performance of the learning personalization for aging process is limited.

Z. Yang and H. Ai [7], not personalize approach such as classifier is trained by using sequence of local binary pattern histogram in which features are obtained by real Adaboost algorithm,

C. Li, Q. Liu, J. Liu, and H. Lu [8], important features are obtained by masking out redundant feature and extracting local region.

III.PROBLEM DEFINITION

The major problem of automatic age estimation from facial images are having a great number of challenges such as uncontrollable environment, incomplete and insufficient training data set, strong personal specificity, higher range variance. The appearance of the face is directly affected by person's facial expression. When images are taken environment such as lighting, camera characteristics affects the appearance of the face. Due to different lighting conditions intensity of facial images are changing.

Age estimation from face images becomes extremely challenging task in computer vision. Age is a crucial factor to identify from a face image of a person. Age of the human from their facial images is estimated from the available database. Thus without reference age of the human from facial images cannot be estimated.

Features obtained from facial images using bio-inspired features to perform fairly well in human age estimation. In bio-inspired features multiple grabber filters of different scales are used and their results are concatenated. In bio-inspired features image patches are first convolved and then pull down and feed to the classifier. In this process, some of the texture information of features is lost. This problem is overcome by using scattering transform. In ordinal hyperplanes ranked when age approaches 1 or k, classifier imbalance problem occurs, where k is age label. This is overcome in proposed system.

IV.EXISTING SYSTEM

1) LEARNING TO AGE RANKS

The class labels are uncorrelated in the multi-class system. But age labels are inherently ordinal. They have strong interrelationship because they are having well order set. Example, if a person of 15-year-old the age labels more likely to be nearby is 14 or 16 years as compared to age label of 10 or 20 years old.

2) RANKING BY AGGREGATING THE PREFERRED BINARY CLASSIFIER OUTPUT

Consider training images I_i , i=1,2 . . . M and x_i is the feature vector extracted to represent I_i and y_i where y_i is a age label of dataset image I_i. In this approach relative order of labels is considered age label y_i as rank order where $y_i \epsilon$ {1, . . .K} K is number of age labels. Dataset denoted by X can be separated into two subsets X_{k+} and X_{k-} as below.

$X_{k+} = \{(x_i, +1) | y_i > K\}$

$X_{k-} = \{(x_i, -1) | y_i \leq K\}$

Thus aggregated two subsets to learn easily binary classifier by questioning (is the face is older than the age K?) to each query gets an answer between positive and negative (1 or 0).

3) COST-SENSITIVE ORDINAL HYPERPLANE RANKER (CSOHR)

Cost sensitivity approach is used in each binary classifier to increase the performance. In age estimation problem in misclassification error as a result of binary classifier (0-1 loss) is reduced and thus total cost is minimized. To state cost for binary classifier cost of individual subproblem are aggregated to estimate rank and thus framework is reduced. Example, when persons exact age is k, the binary classifier (0-1 loss) cannot identify the situation between misclassifying k as a k+1 or k+20, if k+1 is there problem is minor but if k+20 then the mistake is serious.

V. ALGORITHM OF PROPOSED SYSTEM

Learning Phase of proposed Algorithm.

1) [Input] image from the database.
2) [Output] the feature vector of all samples as a database.
3) Filter face image using Median filter by a 5x5 window function, and obtain smooth face image.
4) Crop the smoothened face image to obtain 8 patches (Fiducial Landmarks), as forehead, left eye, right eye, eye center, nose, mouth and chin, left cheek, right cheek.
5) Apply Scattering Transform to 8 patches with (a) option M=2 (scattering order)
   (b) option L=2 (different orientation)
   (c) option J =3
   (d) option. Option =Full (without low pass filter)
6) Concatenate the 8 patches outputs of scattering transform to form final feature vector "V" by equation-1.
   V= (data) = [out 1; out2; out3; out4; out5; out6; out7; out8]
   Feature_S = SUM (data) ---- equation 1.
7) Insert this feature vector and known class (Age group and Age rank) into the database.
8) Repeat above steps for all the samples.

Classification Phase of Proposed Algorithm

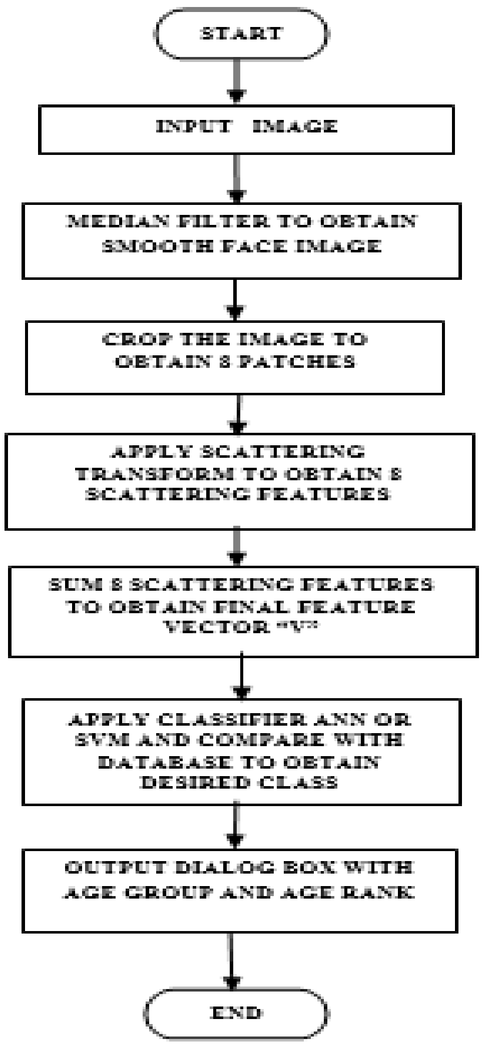
1) [Input] image from the database.
2) [Output] the feature vector of all samples as a database.
3) Filter face image using Median filter by a 5x5 window function, and obtain smooth face image.
4) Crop the smoothened face image to obtain 8 patches (Fiducial Landmarks), as forehead, left eye, right eye, eye center, nose, mouth and chin, left cheek, right cheek.

5) Apply Scattering Transform to 8 patches with (a) option M=2 (scattering order)
   (b) option L=2 (different orientation)
   (c) option J =3
   (d) option. Option =Full (without low pass filter)

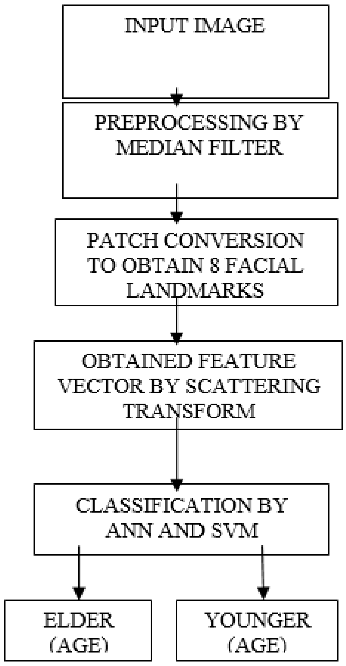
6) Concatenate the 8 patches outputs of scattering transform to form final feature vector "V" by equation-1 for a given unknown face image.
   V= (data) = [out 1; out2; out3; out4; out5; out6; out7; out8]
   Feature_S = SUM (data) ---- equation 1.

7) Apply Artificial Neural Network (ANN) or Support Vector Machine (SVM) and find the class (Age group and Age Rank) for the unknown face image by using a database generated in the Learning phase.

VI. FLOWCHART OF PROPOSED SYSTEM



VII. PROPOSED SYSTEM



1) INPUT IMAGE

In order to train the models, we used images from a database containing colour and grey face images of many individuals. Some of the individual's images in the database supplied a collection of photographs taken over three different age years intervals. The age of the individuals shown in the face images of the database. The range varies between 3 years up to 65 years. Typical images from the database used in experiments. Due to the difficulty in obtaining suitable images for our database, the number of images per individual is not same. For the needs of experiments, the database was split into two parts, used for training and testing (and vice versa) of the age estimation algorithms presented.

2) PREPROCESSING BY MEDIAN FILTER

A Median filter (MF) is a nonlinear filter which removes salt and piper noise from the images effectively. It replaces the pixel value by a median of all pixels in the neighborhood. The median filter removes noise while preserving the sharpness of the image edges. Color images corrupted by noise one cannot apply the median filter directly, therefore the image is divided into three color planes visa red, green, blue and then apply a median filter to three planes individually so that noise can be removed. Effect of removing noise depends on the window size of the median filter. As window size increases noise removed effectively but results into the blurring of images. We place a regular grid i.e. window of 5x5 size on the face images. Such a strategy allows the definition of age invariant discriminatory information in the form of distribution of the edge direction in the face. Thus by using a random sampling technique to improve the performance of linear discriminant analysis (LDA). Thus smoothen face image with facial parts is obtained for further processing.

3) PATCH CONVERSION

We first divide the whole face images into a set of overlapping patches and then apply the selected local image descriptors to each patch. There are eight fiducial landmarks including forehead, middle of the eyebrow, left eye, right eye, nose, mouth and chin, left cheek, and right cheek of the cropped sub-images. The extracted features from these patches are concatenated together to form a feature vector with large dimensionality for further analysis. Given a face image of size H x W, it is divided into a set of s x s overlapping patches that overlap by pixels. The number of horizontal (M) and vertical (N) patches obtained are

$N = (W - s)/ r + 1$

$M = (H - s)/ r + 1$

For each of the M x N patches, we compute a d – dimensional feature vector. These image feature vectors are concatenated into a single M x N x d - dimensional feature vector for a given face image.

We turn the color images into the gray ones, and then we label eye center for each face image. The face images are then cropped and resized into 120 X 120 gray level images.

4) SCATTERING TRANSFORM

To apply ST for face representation, we note that different facial parts would require different sets of scales of the Gabor wavelets. For the parts with tiny details (such as eyes), smaller scales are more appropriate, and vice versa. Hence, it is better to distribute the Gabor wavelets of different scales non-uniformly in a human face image according to the degrees of local details. There are eight masks including forehead, middle of eyebrow, left eye, right eye, nose, mouth and chin, left cheek, and right cheek of the cropped sub-images. ST of m = 0,1 is applied to the holistic face image and all the sub-images. The descriptors obtained for these images are then concatenated into a feature vector.

5) CLASSIFICATION USING SVM

A variety of regression and classification problem can be solved by Support Vector Machine (SVM). While training a classifier statistical learning theory is exploited to reduce the generalized errors. SVM is a classifier which contains binary large margin for machine learning. Analysis of data can be regress with supervised learning model. SVM also shows good performance in the textual category. Thus, SVM contains an algorithm that checks the database and finds existing patterns. 8 facial landmarks are trained with gamma values with 0.25 and thus, prespecified Radial Basis Function (RBF) obtained. SVM can classify age group and rank by training algorithm which can automatically assign the new example. This classifier reduces the errors while training by means of exploiting the statistical learning theory.

The decision function f(x) of a SVM is given as

f(x) = sign(u(x))

u(x) = $\sum_{i}^{N} \alpha_i y_i k(x, x_i) + b$

x is the D- dimension input vector. K(x; xi) is the kernel function between x and support vectors xi.

u(x) is the output where α_i are the weight and y_i are the training labels with x_i respectively.

6) CLASSIFICATION BY USING ANN

Set of learning algorithm consists evaluation function of many inputs which are unknown. Different weights use to update interconnection learning process and finally activation process. Eight facial landmark features obtained by scattering transform are feed to ANN which can make our method most robust to image translation and variation. Due to discriminating information between different facial parts and multi-scale analysis can improve the performance of ANN. Therefore ANN can estimate the age rank and group with higher accuracy.

VIII. PERFORMANCE EVALUATION

Mean absolute error (MAE) and Cumulative score (CS) is used to evaluate the performance of age estimation algorithm. MAE = $\sum_{i=1}^{M} |\widehat{a_i} - a_i| / M$ where $\widehat{a_i}$ = estimated age and a_i = actual age

CS(L) = $\frac{[e_i \le L]}{M}$ where $e_i = |\widehat{a_i} - a_i|$.

Percentage of error for which the error e_i is no higher than a given number of range of tolerance year L, in our system L=4 years. Fig.1.shows the output of the median filter with window function 5X5 of size 256X256. Noise removed and smoothed image obtained. This smoothens image used to detect various facial patches by using bounding boxes as shown in Fig.2.

Fig.1.Median filtered image

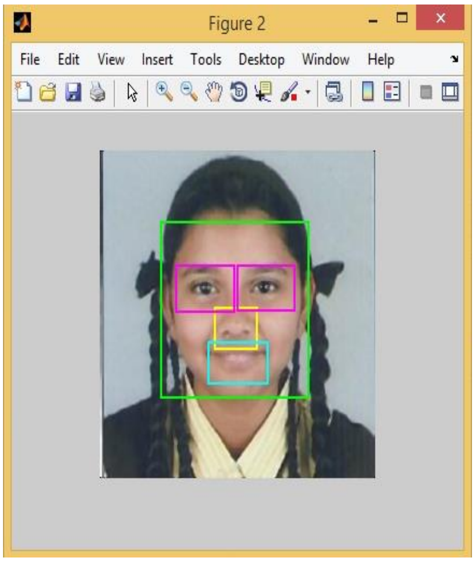


Fig.2.Bounding box of face image

By cropping the bounding box image in different patches 8 facial landmarks are obtained as shown in Fig.3. which then feed to scattering transform to obtain facial features. These 8 facial features are concatenated to obtain final feature vector (v).

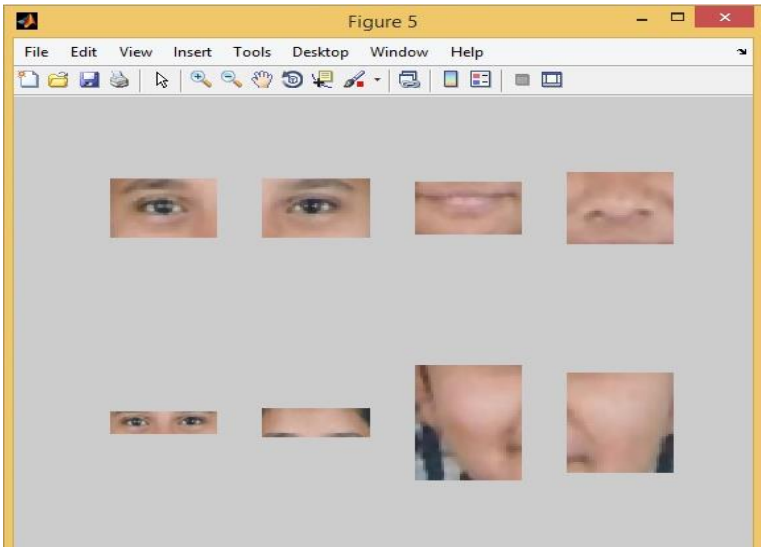


Fig.3.8 facial features obtained using scattering transform

Fig.4. shows the Mean absolute error results for ANN and SVM, ANN achieves lowest MAE value as it exploits the neighboring age discriminative information. Fig.5 shows the Cumulative score. The CS of ANN is better than SVM classifier. Therefore it revels that the proposed algorithm with ANN classifier is more effective than SVM for age estimation of facial images.

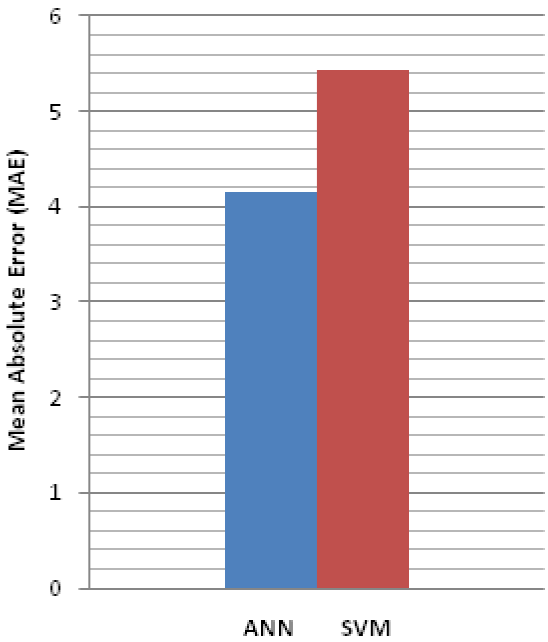


Fig.4.Mean absolute error (MAE) graph

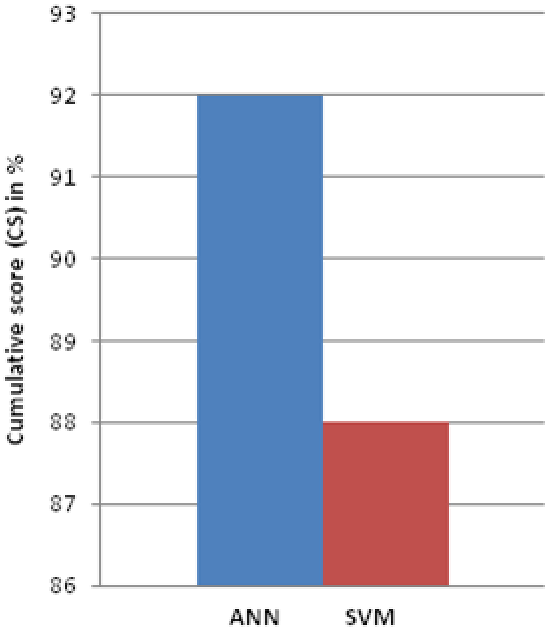


Fig.5.Cumulative score (CS) graph

CONCLUSION

Our approach for human face age estimation employs relative order information within age ranks by aggregating the rank inference. A deformation stable and translation invariant descriptor such as scattering transform along with median filter are used to evaluate feature extraction of the facial component. Features extracted by scattering transform are supplied to support vector machine and artificial neural network.Our proposed method can outperform regression, conventional classification, and ranking approach. Proposed method MF along with scattering transform reduces mean absolute error and increases cumulative score in facial age estimation. Performance achieved by the artificial neural network in terms of MAE and CS are more as compare with support vector machine classifier.

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