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Age Estimation, A Gabor PCA-LDA Approach

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Abstract

Automatic human age estimation has considerable potential applications in human computer interaction and multimedia communication. In this paper the Gabor wavelet and its characteristics as a powerful mathematical and biological tool, was used for feature extraction. A combination of Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) was used to reduce dimension and enhance class separability. *Finally Euclidean distance was used to classify the images into one of three major groups. These groups are: Group1 (0 to 3 years), Group2 (5 to 10 years) and Group3 (20 to 80 years). The robustness and accuracy of the proposed system was tested on the FG-NET [1] and MORPH [2] public face aging databases. This system was able to achieve 90% accuracy.*

Keywords: *age classification, Gabor features, PCA, LDA*

I. INTRODUCTION

Human faces are important. One can distinguish a person's gender, mood, race, age category, and identity from the face. As a result, the face is expected to play a significant role in human computer interaction (HCI), security, sales and marketing. One can conclude that future computer interfaces may use the face to monitor security passes; or content of instant-messaging, email and chats; or to restrict access by children to adult content found on the Web. Therefore automatic human face age estimation is a field that is now becoming popular.

Though the literature on the automatic estimation of human face age is very few, an attempt was made to provide a comprehensive review of the existing materials. The materials assessed were categorized into three main groups. These reveal that automatic estimation of human face age may use the anthropometric model [3], the Aging pattern Subspace (AGES) [4] model and the regression model [5] [6]. This stratification was derived from Guo's classification [5] in conjunction with additional literature published since the release of

Guo's paper. The anthropometric model has been proven to be very successful for human age estimation and was the model selected for the present work.

Hence in this research, human face texture (part of anthropometric model) was chosen as the dominant feature for human age estimation. The texture information was extracted using Gabor Wavelets. The human face images were first processed in the spatial domain by applying Gaussian filters to them. Then by using different scales and orientations, in the frequency domain Gabor faces were extracted. These Gabor faces, sufficiently mimic the pattern recognition abilities of the human visual cortex. A combination of Principal Component Analysis (PCA) and Linear Discriminate Analysis (LDA) was applied on the Gabor faces for dimension reduction and to enhance the class separability. By applying PCA to the Gabor face images, low dimensionality images were obtained and processed using LDA. The vectors obtained from the LDA are representative of each image. These vectors were divided into *train vectors* and *test vectors*. The *train vectors* were used to train the system. Finally Euclidean distance between the *test vectors* and the *train vectors* classified the *train vectors* into one of three age groups namely Group1 (0 to 3 years), Group2 (5 to 10 years) and Group3 (20 to 80 years).

II. PROPOSED AGE ESTIMATION METHOD

The proposed age estimation method consists of five parts. Each is described below.

A. Preprocessing

Since input images are affected by the type of camera, illumination conditions, background information the images need to be normalized before feature detection and extraction. To combat the effect of any unwanted variations, the steps of pre-processing are:

1. For each face image select the facial regions of importance (ROI). Here, the region containing the eyes, nose and mouth was manually cropped, since these features are necessary for automatic age estimation. This region is also representative of data for texture analysis.

2. Normalize all the cropped regions of importance to a size of 64 x 64 pixels.

3. The FG-NET face database has a collection of colored images so finally the normalized colored images were converted to grey scale.

B. Feature Extraction

Holistic feature extraction methods extract features from the whole face image and were extracted by Gabor wavelets. The Gabor wavelets (kernels, filters) can be defined as follows [7]:

$$\psi_{\mu,v}(Z) = \frac{\|k_{\mu,v}\|^2}{\sigma^2} e^{\frac{\|k_{\mu,v}\|^2\|z\|^2}{2\sigma^2}} \left[e^{ik_{\mu,v^z}} - e^{-\frac{\sigma^2}{2}}\right]$$

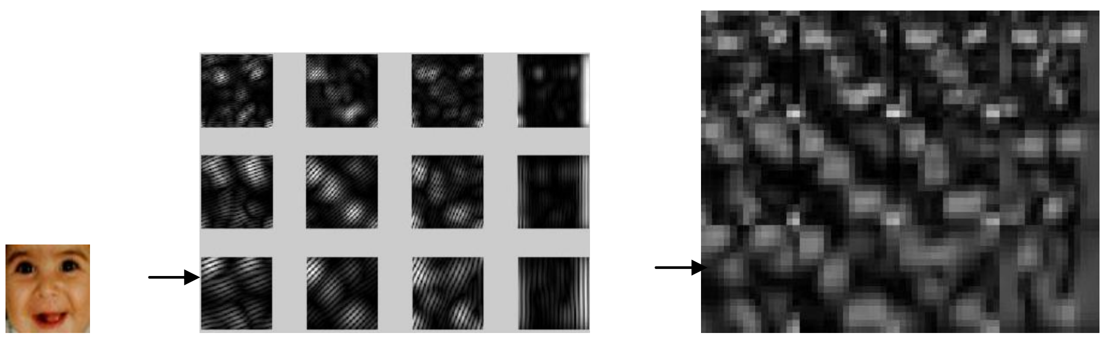
The Gabor kernels are all self-similar since they can be generated from one filter by scaling and rotation. This scaling and rotation is done by the wave vector $k_{\mu v}$. In most cases one (1) Gabor wavelet of five different scales $v \in \{0, \ldots, 4\}$ and eight orientations $\mu \in \{0, \ldots, 7\}$ are used. These scales and orientations will give forty (40) Gabor kernels. If I (x, y) is the gray level distribution of an image, then the convolution of image I and a Gabor kernel $\psi_{\mu v}$ is defined as follows [7]:

$$O_{\mu,v}(z) = I(z) * \psi_{\mu,v}(z)$$

To capture different scales and orientation concatenate all the representation results to obtain an augmented feature vector. Before the concatenation down-sample each $O_{\mu,v}(z)$ by a factor P to reduce the space dimensions. Normalize it to zero mean and unit variance. Then construct a vector out of the $O_{\mu,v}(z)$ by concatenating its rows (or columns). The augmented Gabor feature vector represents the Gabor wavelet set. In the development of the automatic human face age estimation system, research shows that only twelve (12) of the above mentioned forty (40) Gabor kernels were necessary for application to each face image. These twelve (12) Gabor kernels have accurately extracted the necessary features for automatic human face age estimation. The human face age estimation system uses Gabor wavelets of three different scales and four orientations with a down sampling factor p of 64. These twelve (12) Gabor wavelets demonstrate properties similar to the original family of forty (40) Gabor wavelets. They exhibit:

1) Real Part
2) Imaginary Part
3) Magnitude Part

In the proposed system only the twelve (12) magnitude parts of the Gabor wavelets were necessary to extract the holistic facial features for age estimation, from each image in both the training and testing class. The magnitude part of the generated twelve (12) Gabor wavelets was used and each Gabor wavelet down sampled to 16 x 16 pixels. Illustrated below (Fig 1) is the convolution of these twelve Gabor Wavelets (only magnitude part) on a sample image (from the FG-NET face aging database [1]). After convolution with the image, an augumented Gabor feature vector was generated. It is the concatenation of twelve (12) images, which were the result of the convolution of the twelve (12) Gabor wavelets on the original image.



12 MAGNITUDES OF SAMPLE IMAGE

C. Principle Component Analysis (PCA) Dimension Reduction

The augmented Gabor feature vector introduced above resides in a space of very high dimensionality. There were a total of ninety (90) images in the dataset used to design the system, with thirty (30) images for each of the three classes. The images were courtesy of the FG-NET [1] and MORPH [2] face aging database. The classes are:

1. Class 1 (1 to 3 years)
2. Class 2 (5 to 15 years)
3. Class 3 (20 to 80 years)

FIG 1: AUGUMENTED GABOR FEATURE VECTOR

Of the maximum ninety (90) i training and the remaining thirty (30) images for testing. Since, there are twelve (12) Gabor magnitude feature images for every one image in the dataset a vector of size 256 x 1 pixels represents each image. Totally, this resulted in a Gabor feature vector with a very high dimensionality of size 256 x 720 pixels for training images and 256 x 360 for testing images. Thus Principal Component Analysis (PCA) [8] was used to reduce the dimensionality of the Gabor feature vector. The first eigenvector was eliminated and the resulting eigenvector was of size 3072 x 59. A Gabor PCA feature vector was obtained with reduced dimension of 59 x 60 pixels for all sixty (60) training images and 59 x 1 for each testing image.

D. Linear Discriminant Analysis (LDA) Enhance Class Separability

The Fisher linear Discriminant (LDA, FLD) was used for achieving high separability between the different patterns for classification. The LDA projection space has been created [9], and applied to the testing and training images. The final Gabor PCA LDA feature vector for the training set of size 59 x 60 pixels is compared with the Gabor PCA LDA feature vector of the test image, whose size is 59 x 1 pixels. This comparison for classification into one of the age groups is done by Euclidean distance.

E. Euclidean Distance

While the simple Euclidean distance measure seems to be enough, research does suggest that different distance measures may affect the performance of system. Thus an appropriate distance measure has to be chosen to reflect the nature of the problem being solved [10]. More complex classifiers, e.g. Support Vector Machine could also be used for improvement of accuracy. However, systems become more complex and the improvement is not often guaranteed [10]. Thus the Euclidean Distance was identified as the maximal means of classification for the system. A novel competitive nearness approach was implemented using the average class distances. The average for each of the three training class was calculated. Then for any test input image, the distances to these three class average sets were computed. The class which had the least distance was considered to be the winner. And the age range label was assigned based on the label of the winning group.

Fig 2, demonstrates the flow of the proposed age estimation steps.

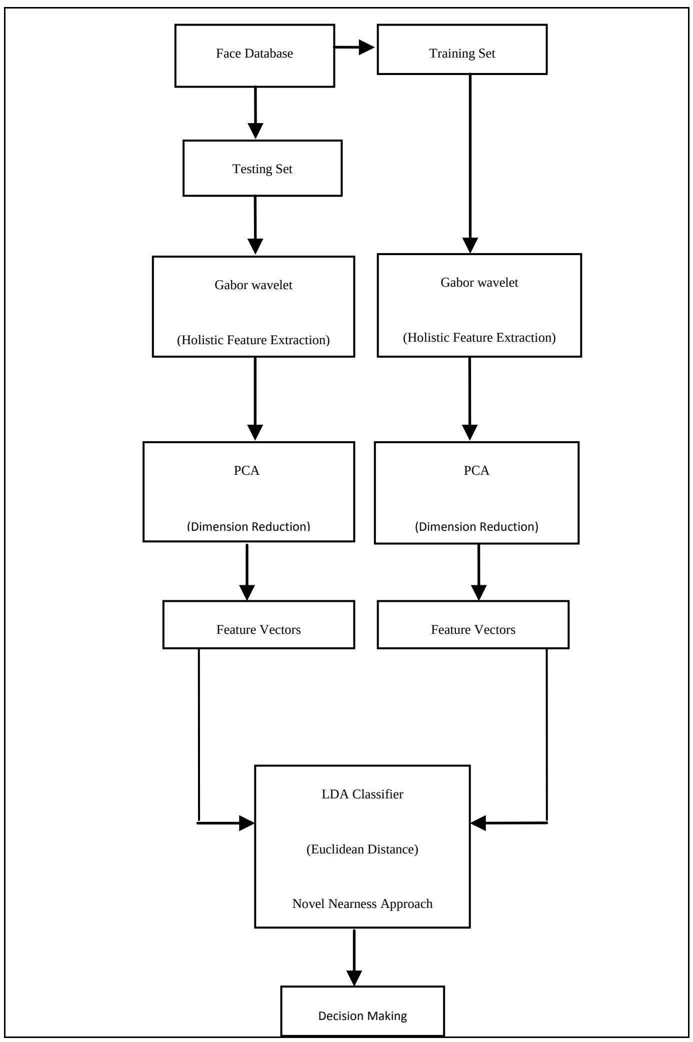


FIG 2: FLOWCHART OF THE HUMAN FACE AGE ESTIMATION SYSTEM

III. EXPERIMENT RESULTS

Experiments

Step One – *Train the system*: Twenty (20) images were selected for each class from the FG-NET face database [1]. The system was trained with these images using the Gabor PCA approach described above, to derive the Training Feature Vector.

Step Two - *Gather the testing images*: Ten (10) images were selected for each class from the FG-NET [2] and MORPH [2] face database. The images were processed for classification by using the Gabor PCA approach described above, to derive the Testing Feature Vector.

Step Three: *Classification*: The LDA classifier was used to enhance class separability. The minimum Euclidean distance of the Testing feature vector from the average distance of the three Training feature vectors was computed. The class with the minimum distance was defined as the winner. Thus the image was labeled with the age group of that particular class.

Performance Measure

The performance of age estimation algorithms is normally tested with two different measures: the mean absolute error (MAE) and the cumulative score (CS). However, since the proposed system is concerned with coarse age estimation, these measures could not be adopted to accurately reflect the results since the final output of coarse estimation system is the age range and not the exact age of the human face. Hence, the percentage of accuracy achieved during the experiments was tabulated, charted and presented.

Results

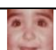
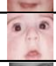
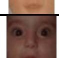
Subjects	Distance from Baby Training Class	Distance from Child Training Class	Distance from Adult Training Class	Minimum Distance	Result
	13.15	14.85	14.86	13.15	Baby
	13.85	15.03	16.05	13.85	Baby
	14.05	14.80	15. 20	14.05	Baby
	14.20	15.80	15.60	14.20	Baby
	13.80	15.50	15.80	13.80	Baby
	14.30	14.90	14.60	14.30	Baby
	15.60	16.00	16.20	15.60	Baby
	15.40	15.60	14.80	14.80	Adult
	16.20	17.40	17.60	16.20	Baby
	14.00	15.70	15.80	14.00	Baby
Average	**14.46**	**15.56**	**15.65**	**14.40**	

TABLE 1: RESULTS ON BABY TEST CLASS

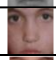
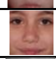
Subjects	Distance from Baby Training Class	Distance from Child Training Class	Distance from Adult Training Class	Minimum Distance	Result
	15.60	14.10	14.50	14.10	Child
	15.20	14.60	14.90	14.60	Child
	14.90	14.20	15. 10	14.20	Child
	14.80	14.70	15.20	14.70	Child
	15.00	14.10	14.15	14.10	Child
	15.20	14.40	14.70	14.40	Child
	15.60	14.10	14.60	14.10	Child
	14.20	15.70	15.00	14.20	Baby
	15.60	14.60	15.40	14.60	Child
	15.80	14.40	15.00	14.40	Child
Average	**15.19**	**14.49**	**14.86**	**14.34**	

TABLE 2: RESULTS ON CHILD TEST CLASS

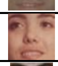
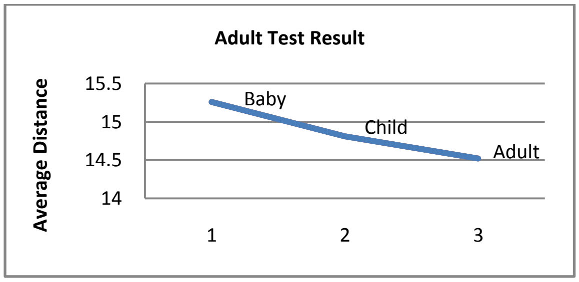
Subjects	Distance from Baby Training Class	Distance from Child Training Class	Distance from Adult Training Class	Minimum Distance	Result
	14.00	14.30	13.80	13.80	Adult
	15.60	14.70	14.20	14.20	Adult
	15.35	14.38	14. 35	14.35	Adult
	16.45	15.85	14.95	14.95	Adult
	15.70	15.35	15.30	15.30	Adult
	15.80	14.60	14.50	14.50	Adult
	15.50	15.30	15.45	15.30	Child
	14.70	14.50	14.35	1435	Adult
	15.05	14.70	14.50	14.50	Adult
	14.50	14.45	13.80	13.80	Adult
Average	**15.26**	**14.81**	**14.52**	**14.50**	

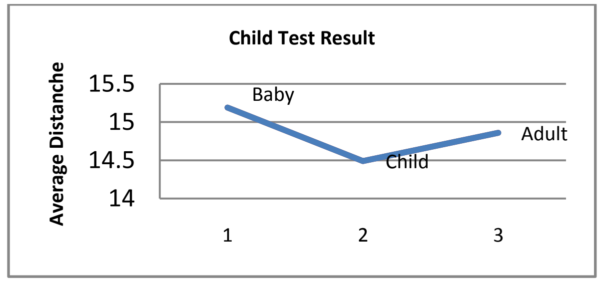
TABLE 3: RESULTS ON ADULT TEST CLASS

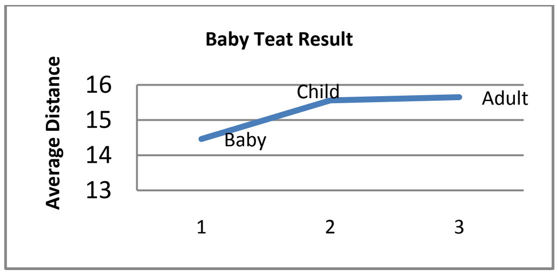
The tables above show the minimum Euclidean distance with every test image and the average Euclidean distances of each training class. From the table the overall system success rate of 90% is evident. Of the thirty (30) test images, only three (3) were misclassified. A minimal error rate of 10% was encountered.

IV. CONCLUSION

The hypothetic automatic human face age estimation system initially conceptualized was successfully created and classified the images into three groups namely; Group1 (0 to 3 years), Group2 (5 to 10 years) and Group3 (20 to 80 years). It was found to be robust against changes in variation, illumination and pose, since images were taken from different data sources. This system was able to achieve 90% accuracy.







REPRESENTATION	I – BABY	II– CHILD	III – ADULT
Correct Categorization	9	9	9
Incorrect Categorization	1	1	1
Average: 90%			

TABLE 6.4: OVERALL SYSTEM PERFORMANCE

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