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An Innovative Approach for Age and Gender Estimation from Facial Images

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Abstract **- In this paper, an innovative approach age estimation method based on decision level fusion of global and local characteristics is proposed. The structure and occurrence knowledge of human faces which are extracted with active appearance representations (AAR) are used as global facial characteristics. The local facial characteristics are the wrinkle characteristics extracted with Gabor filters and skin characteristics extracted with local binary patterns (LBP). Then facial characteristic classification is performed using a Innovative classifier which is the combination of an age group classification and specific age estimation. In the age group classification level, three distinct support vector machines (SVM) classifiers are trained using each characteristic vector. Then decision level fusion is performed to combine the results of these classifiers. The specific age of the classified image is then estimated in that age group, using the aging functions modeled with global and local characteristics, separately. Aging functions are modeled with multiple linear regressions. To make a final decision, the results of these aging functions are also fused in decision level.**

Keywords — SVM, AAR, LBP and FERET;

I. INTRODUCTION

The analysis on facial image preprocessing has received considerable interest in last few years because of the increasing need of dynamic face recognition systems. Face recognition, face detection, facial expression recognition and gender classification are the analysis topics that have been studied by many analyzers in this domain. Facial age estimation is a relatively new topic and the interest in this topic has significantly increased because it has many real time applications. For ex: under ages can be prevented from accessing alcohol, cigarettes or obscene contents on websites using an age estimation system. In addition, age specific target advertising, face recognition and age forecast systems powerful to age progression for finding the missing people and criminals are important age estimation applications.

Facial age estimation is a multi-level classification problem because an age label can be seen as an individual level. This makes age estimation much harder than other facial image preprocessing problems such as gender classification, face detection, etc. Besides, real time age progression displayed on faces is varied and personalized. Aging process of a person is affected by the genetics, race, eating. Facial aging of different individuals drinking habits, living styles, climate, etc. Extent and frequency of facial expressions, emotional stress, exposure to sunlight, extreme weight loss, smoking, usage of anti-aging products, and plastic surgery also affect the person's facial appearance.

Fig:- Facial aging of different individuals

Therefore, influencing the type of facial characteristics that represents the age directly is very complicated. Moreover, the accuracy of age estimation systems are insufficient, even the human skills about age estimation are limited.

The lack of proper huge data set including the chronological image series of individuals is another drawback in these systems. In this paper, an Innovative age estimation method based on decision level fusion of global and local characteristics of facial images both in age group classification and age estimation levels is proposed. The global facial characteristics which contain both the structure and appearance knowledge of human faces are extracted using active appearance representations (AAR). The local facial characteristics are extracted using Gabor filters and local binary patterns

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(LBP). A group of Gabor filters capable of obtaining deep and fine wrinkles in different directions are used to extract wrinkle characteristics and LBP is used to extract the specific skin surface characteristics of facial images. Then dimensionality reduction is performed using principal component analysis (PCA) for each characteristic vector separately.

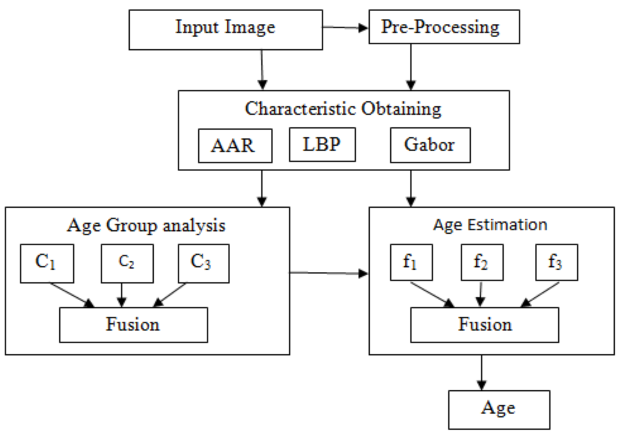


Fig: System structure

After finding the lower dimensional subspaces, three distinct support vector machine (SVM) classifiers are trained using global characteristics, wrinkle characteristics and skin characteristics of facial images. Then the results of these classifiers are integrated to find the age group of the subject. After that, age estimation is performed in that age group in a similar way, in which three aging functions are modeled with global and local characteristics, separately using multiple linear regression. Finally the results of these aging functions are integrated to estimate the age of the subject.

2. METHODOLOGY

Over the years a great number of approaches have been proposed in the field of age estimation from facial images. These approaches typically consist of age image representation and age estimation techniques. Age image representation techniques rely often on structure and surface-based facial characteristics. They can be grouped under the topics of Anthropometric Models, AAR, Age Manifold and Appearance Models. Age group classification or regression methods are performed for age estimation. Recently, Innovative age estimation systems combining the classification and regression techniques are presented. To build a universal human age estimator, powerful multi-instance regress or learning algorithm based on facial knowledge is also used. In anthropometric models only the facial geometry is considered. The initial work using the facial geometry in the age classification domain. They divided the babies from adults using a few ratios of distances on frontal images. However the structure of a human's head significantly changed in the childhood, but not in the adulthood. For this reason their method can be successful in young ages. So the wrinkle knowledge is used to classify the young and senior adults. In the experiments a small database including 54 images is used. Later on other age classification methods using geometrical characteristics based on distance ratios and surface characteristics based on wrinkles are also proposed AAR based methods incorporate structure and appearance knowledge together rather than just the facial geometry as in the anthropometric model based methods. An AAR uses a statistical structure and an appearance model to represent the images. These models are generated by combining a model of structure variations with a model of the appearance variations in a structure-normalized frame. A statistical structure model can be generated with a training set of face images labeled with landmark points. The mean structure is produced with taking the mean of the landmark points in the training set. Then Principal Component Analysis (PCA) is applied to the data to extract the main principal components along which the training set varies from the mean structure.

To build a statistical appearance model, each image has to be normalized, so that its control points match the mean structure. Then, PCA is applied to the gray-level intensities within a pre-specified image region for learning an appearance model. Using the AARs for age estimation was initially proposed.

The interconnection between the age of individuals and the parametric description of face images was defined with an aging function. The classifiers trained using AAR characteristics to distinguish between child/teen and adult. Also different aging functions are used to estimate the age of the classified image. An age estimation approach based on label sensitive learning and age-oriented regression using AAR characteristics. An AGE which uses the sequence of an individual's facial images arranged in chronological order to model the aging process.
The characteristics of face images are obtained with AAR. Then, PCA is used to learn a specific aging subspace for each individual. In AGES method missing age images of individuals can be synthesized with an expectation maximization-like iterative algorithm. Age manifold methods intend to learn a common aging trend

from the images of different individuals at different ages. The aging trend is learned in a low dimensional domain using manifold embedding techniques.

The mapping from the image space to the low dimensional manifold space can be done either by linear or by nonlinear functions such as Y=P(X, L). In this representation is the image space, is the vector contains the age labels associated with images and with is the low-dimensional representation of X in the embedded subspace. In age manifold methods all aging images of different individuals can be used together. But the size of the training data set should be huge enough in order to learn the embedded manifold with statistical sufficiency. Appearance models are mainly focused on the obtaining of global and local aging-related facial characteristics. The obtained aging characteristics from facial images using Fast Fourier Transform. Then the important characteristics are selected using genetic algorithm. As the Local Binary Patterns (LBP) is efficient surface descriptors, they are used in age estimation systems. LBP histograms are obtained from these regions and used for age estimation. Wrinkle knowledge obtained with Gabor filters have also been used as effective surface characteristics on age estimation tasks.

3. PROPOSED METHOD

This paper proposes an innovative age estimation method based on decision level fusion of global and local facial characteristics. This method consists of the image preprocessing, global characteristic obtaining with AAR, and local characteristic obtaining with Gabor filters and LBP, dimensionality reduction with PCA classification with SVM, aging function modeling with multiple linear regression and decision level fusion modules.

A. Image Preprocessing:-

The alignment and the size of original images are different from each other. Also they have nonessential characteristics such as background, cloth and hair which are not associated to the face and can affect the performance of the algorithm. Therefore, image preprocessing step is performed to obtain only the facial regions and to adjust the size and the alignment of the faces. The facial images are cropped, scaled and transformed to the size of 88x88, based on the eye center locations.

B. Characteristic Obtaining:-

The characteristic obtaining module consists of two modules: global characteristic obtaining with AAR, local characteristic obtaining with Gabor filters and LBP. These modules are explained in the following subsections.

1) Global Characteristic Obtaining with AAR:

AAR is a statistical structure and appearance model of facial images. In AAR, a model of structure variations is integrated with a model of the appearance variations in a structure-normalized frame Training samples which are labeled with landmark points are used to generate a statistical structure model.

The landmark points of various facial images. Let represents all the landmark points of training images and represents the mean structure of training images; the main principal components along which the training set varies from the mean structure is obtained with PCA. The projection is chosen to maximize the determinant of the total scatter matrix of the projected samples is the group of eigenvectors with ds largest eigenvalues which provides a linear transformation from Ds dimensional structure space into a dimensional parameter space. The structure parameters are defined by linear formulation. To build a statistical appearance model, each image has to be warped to mean structure. Then, the gray level intensities within a pre-specified image region are used to train an intensity model. Let represents all the gray level intensities of training images, the main principal components along which the training set varies from the mean appearance is also obtained with PCA.

The projection is chosen to maximize the determinant of the total scatter matrix of the projected samples is the group of eigenvectors with dg largest eigenvalues which provides a linear transformation from dg dimensional appearance space into a dimensional parameter space. The appearance parameters are defined by linear formulation and vectors can summarize the structure and appearance of any image.
The integrated structure-appearance parameters are obtained by concatenating and in a single vector and applying a further PCA in order to eliminate the correlations between them.

2) Local Characteristic Obtaining with Gabor Filters:

A Gabor filter is the modulation of a sinusoidal wave with a Gaussian function as shown. Therefore this filter will respond to the frequency which is in a localized part of the signal. 2 dimensional Gabor filters can be viewed. The wavelength, is the alignment, is the level offset, is the standard deviation of the Gaussian kernel and is the spatial ratio of the Gabor function. 2D convolution operation is used to obtain the response of a Gabor filter to an image as follows: Where is the image and is the response of a Gabor filter to the image. In the research the fine and deep wrinkles at different alignments are obtained using a Gabor filter group with 4 scales and 6 alignments.

The responses of these filters for an image are also given in the figure.

3) Local Characteristic Obtaining with LBPs: LBPs are powerful descriptors of image surface.
LBP operator thresholds the center pixel with its neighbors and assigns a binary code for it. Then the occurrence histogram of these LBP codes is used as a surface characteristic. Every pixel of the image is labeled with the following equation, Where xc is center pixel, xp represents one of his P neighbors and R is the radius. In this equation 2P different LBP codes can be generated for the center pixel but all of them are not used. Generally the uniform patterns are used in surface description. Uniform patterns are the ones that contain at most two bitwise transitions from 0 to 1 or vice versa when the binary pattern is considered circular. These patterns account for a bit less than 90% of all patterns when using neighborhood. But holistic descriptions of facial images are not reasonable as the surface descriptors tend to average over the image domain. However it is important to retain the knowledge of spatial relations for facial images.

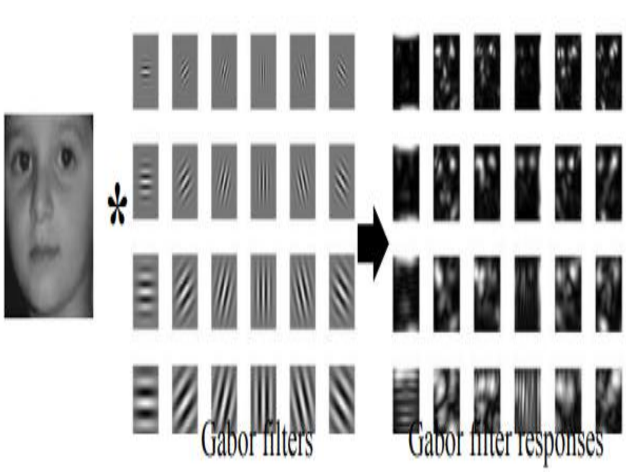


Fig.. Gabor filter process

Furthermore local representations are more powerful to illumination or pose variations than holistic representations. As a result, spatial LBP histograms are obtained for an efficient representation of facial images.
To build a global description of the image, regional histograms are concatenated in a single vector. In this work the specific skin surfaces of facial images are obtained using spatial LBP histograms. Spatial representation of a facial image is obtained by dividing the image into 8x8 regions, producing the LBP histograms of these regions and concatenating them into a single vector.

C. Dimensionality Reduction:
After the characteristic obtaining module, PCA is performed in order to find a lower dimensional subspace which carries significant knowledge for age estimation. The PCA method finds the embedding that maximizes the projected variance. The solution of this problem is given by the group of eigenvectors associated with the largest eigenvalues of the scatter matrix. After influencing the projection subspace, all the samples are projected on it using allowing thus dimensionality reduction.

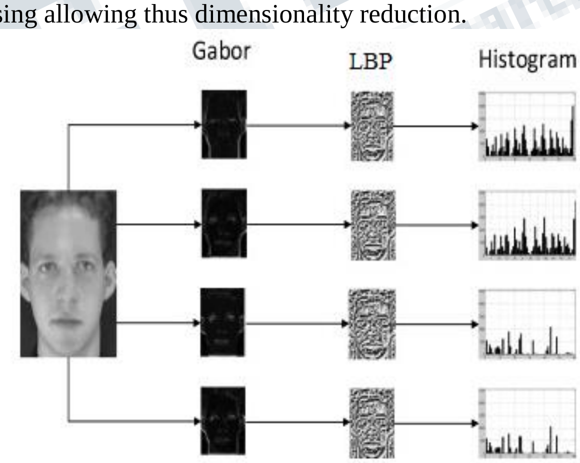


Fig. Spatial LBP histogram generation

D. Classification:
In the age group classification module, the subject is classified into one of the age groups using a SVM classifier. SVM is a supervised learning method which uses support vectors to build a classification or regression model. SVM finds a linear and optimal hyper plane which can separate two classes, providing the lowest separation error and maximum margin between the classes. Consider a two class classification problem with M training point's xi and assigned labels yi.
Linear SVM assumes that there exists a hyper plane separating two classes. The function of this hyper plane,

where w is the normal vector and b is the distance from the origin. In the training level the w and b are found such that this decision rule is valid for all training and test data points. In real world applications, data can rarely be divided by a linear hyper plane. Thus the basic version of SVM only allowing linear classification is changed by applying a so called kernel trick.

The non-linear separable data is transformed into higher dimensional space using a kernel function, which behaves like a scalar product and keeps the computational costs low. The conventional SVM assumes that there exists a linear hyper plane separating two classes. SVM is originally designed for binary classification. To solve multi-class classification problems with SVM, different implementations like one-against-all and one-against-one are used. In the proposed approach one against-one method is used for multi-class classification. For this purpose, k(k-1) binary SVMs representing all possible pairs of k classes are constructed. Each of these classifiers is trained to discriminate only two of the k classes. Then majority voting strategy is used to predict the final output. The data point is assigned to the class that has maximum votes. The optimal parameters for SVM were selected experimentally from the training set.

E. Regression:

After finding the age groups of facial images, the age estimation problem is recast as a multiple linear regression. The data matrix including columns of 1s, B is the unknown parameter vector, L is the age label vector and e is the error vector with zero mean and common variance. During the learning stage the unknown parameters are estimated using least squares, or powerful regression.

F. Decision Level Fusion:

In the proposed method decision level fusion is performed in both classification and regression modules. In the classification module, the age class labels are produced with three distinct classifiers which are trained with global and local characteristics. Then the results of these classifiers are integrated to determine the age group of the subject. In the age estimation module three aging functions are modeled separately in that age group, using global and local characteristics.

4. RESULT ANALYSIS

In the global Characteristic Obtaining step, the coordinates of 68 landmark points on the training samples are used to train the shape model. Also the mean shape is determined from these points. Next, affine transformation is used in the warping process of all images to the mean shape. Then approximately 7000 gray-level intensities in the facial region of the corresponding shape-normalized images are used to train the appearance model. Finally, 277 AAR model parameters are used as global features to represent the images.

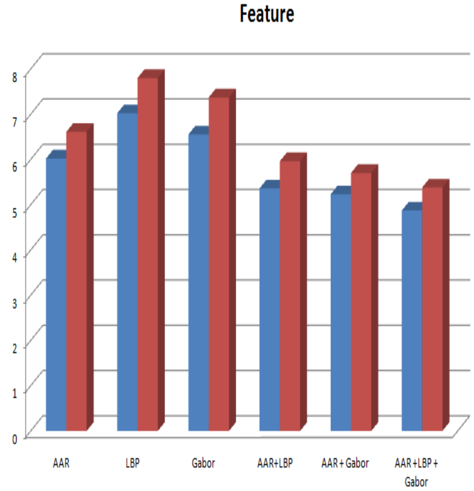
In the local Characteristic Obtaining, wrinkle information of the facial images is obtaining using Gabor filters. The fine and deep wrinkles at different orientations are extracted with Gabor filters applied in 4 scales and 6 orientations. The responses of these filters are concatenated into a single vector and dimensionality reduction is performed using. Furthermore the detailed skin textures of facial images are extracted using spatial LBP histograms. For this purpose LBP histograms are produced from 8x8 sub-regions of facial images and concatenated into a single vector, resulted a spatial representation of the facial image. Also PCA is applied to learn a low dimensional representation of this feature vector.

In the spatial LBP histogram generation phase, the number of sub-regions is determined experimentally. For this purpose, the age estimation performances of the spatial LBP histograms produced with different number of sub-regions are calculated and the results are shown in below Fig.. It can be seen from the figure that using the 8x8 sub-regions gives better results for age estimation. After the feature extraction and dimensionality reduction phase, age group classification is performed using three SVM classifiers. In the experiments, first the age estimation performances of the global, local and fused features are determined using a single level age estimation scheme. In this scheme all the images are used to train the aging functions and the decision level fusion is performed for a final decision for the age. The experimental results on FG-NET and FERET databases are listed in Table. It can be seen from the table that age estimation performance of the AAR features is better than Gabor and LBP features on FG-NET and FERET databases as the AAR features both include the shape and appearance information of facial images.

Feature	FERET	FG-NET
AAR	6.02	6.61
LBP	7.02	7.80
Gabor	6.55	7.37

AAR+LBP	5.36	5.96
AAR + Gabor	5.23	5.70
AAR +LBP + Gabor	4.87	5.38

Fig:- Spatial LBP histogram generation



5. CONCLUSION

In this paper, an Innovative age estimation method relying on decision level fusion of AAR, Gabor and LBP characteristics of facial images is proposed. Its main contribution is decision level fusion of global and local surface characteristics of facial images. Locality is preserved by regional LBP histograms and Gabor filters. In further, local characteristics are integrated with global characteristics of images extracted with AARs.

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