HUMAN FACIAL AGE ESTIMATION BY POSITIONAL TERNARY PATTERN AND GRAY-LEVEL CO-OCCURRENCE MATRIX

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Abstract: -Human facial age estimation is done using image processing. Many applications like forensics, security, and biometrics have attracted much attention in human facial age estimation. Multiclass classification and regression problem are the existing approaches that cast facial age estimation. We propose a positional ternary pattern algorithm that inherits the craniofacial shape with wrinkle and micro texture pattern. And then Gray-Level Co-occurrence Matrix plays a major role in revealing properties of gray levels in texture image. Age estimation based on human face remains a problem in computer vision and pattern recognition. To estimate an accurate age most of the existing system is used and it requires a huge data set attached with age labels. In addition to the proposed approach we proposed the probabilistic neural network that is widely used in classification and pattern recognition problem.

Key words: - Image processing, Positional Ternary Pattern, gray-Level Co-occurrence Matrix, Probabilistic Neural Network.

1 Introduction

The biometric features are unique for each human beings. One useful method to identify any person by features of the face is face recognition. In olden days identification of documents such as land registration, passports and identification of a person in high security zone where the only areas where face recognition was used. Now a days, with the growing popularity of photo sharing websites such as Face book and Flickr, there has been a growing interest in facial age estimation. Age progression is generally indicated by skin texture, face structure and skin color. The challenging problem is that the appearance of human faces that exhibits remarkable changes with the process of aging, and different people may have very different aging processes as well.

Aging is a non- reversible process. With time, the human face characteristics changes which reflect major variations in appearance. The signs that indicate the age progression are uncontrollable and personalized such as hair, whitening, muscles dropping and wrinkles. Some other external factors include life style and degree of stress.

This paper provides a method to estimate the age of a human by analyzing wrinkles and face lines of face images. The proposed system involves four stages- pre-processing feature extraction, classification and age estimation. The number of training sets available such as FG-NET, MORPH, Refined-MORPH and Web Face.

2 Literature surveys

2.1 Age Synthesis

Y. Fu, G. Guo, and T. S. Huang [1] proposed age synthesis and estimation via faces. Human age can be directly inferred by distinct patterns emerging from the facial appearance. Derived from rapid advances in computer graphics and machine vision, computer-based age synthesis and estimation via faces have become particularly prevalent topics recently because of their explosively emerging real-world applications, like forensic art, electronic customer relationship management, security control and surveillance monitoring, biometrics, entertainment, and cosmetology. Age synthesis is defined to rerender a face image aesthetically with natural aging and rejuvenating effects on the individual face. Age estimation is known to label a face image automatically with the exact age or the age group of the individual face. Because of their particularity and complexity, both problems are attractive yet challenging to computer-based application system designers. Large efforts from both academia and industry have been devoted in the last a few decades. In this paper, they survey the complete state-of-the-art techniques in the face image-based age synthesis and estimation topics.

2.2 Classification based on facial features

W.-B. Horng, C.-P. Lee, and C.-W. Chen[2] proposed Classification of age groups based on facial features. The process of ageing causes significant alterationsin the facial appearance of individuals. When compared with other sources of variation in face images (e.g. variation due to changes in pose and expression), appearance variation due to ageing displays some unique characteristics. For example ageing variation is specific to a given individual, it occurs slowly and it is affected significantly by other factors, such as the health, gender and the lifestyle of the individual. In this paper they describe how the effects of ageing on facial appearance can be explained using a parameterized statistical model. They present experimental results to show that reasonably accurate estimates of age can be made for unseen images. They also show that we can improve our results significantly by taking into account the fact that different individual's age in different ways and by considering the effect of lifestyle. They also demonstrate how the proposed framework can be used for simulating ageing effects on new face images, in order to predict how an individual might look like in the future, or how he/she used to look in the past. Experimental and visual results on simulation of age effects are presented.

2.3. Support Vector Machine

Lanitis, C. J. Taylor, and T. F. Cootes[3] proposed Modeling the process of ageing in face images. In this paper, they introduce a novel age estimation technique that combines Active Appearance Models (AAMs) and Support Vector Machines (SVMs), to dramatically improve the accuracy of age estimation over the current state-of-the-art techniques. In this method, characteristics of the input images, face image, are interpreted as feature vectors by AAMs, which are used to discriminate between childhood and adulthood, prior to age estimation. Faces classified as adults are passed to the adult age-determination function and the others are passed to the child age-determination function. Compared to published results, this method yields the highest accuracy recognition rates, both in overall mean-absolute error (MAE) and mean-absolute error for the two periods of human development: childhood and adulthood. It involves an understanding of the human aging process, the biomechanical factors that influence the general patterns of aging that the idiosyncratic nature of aging, which is evident in the facial aging differences of identical twins. This paper will present an overview of the prior works in age estimation (determination) and a novel approach based on a hierarchical model, which infuses a classification system with multiple age estimator functions to create an industry age-estimation algorithm. The aging factors for adults, ~ 21 years and older, does include some cranial changes, but the primary drivers are the development of wrinkles, lines, creases, and sagging of the skin. As with synthetic face aging techniques, great care should be taken to separate the aging process into growth and development and adults as the factors that contribute to the changes that are being modeled are vastly different.

2.4 Human Computer Interaction

K. Luu, K. RicanekJr, T. D. Bui, and C. Y. Suen[4] proposed the age estimation by active appearance models and support vector machine regression. Extensive studies on human faces in the Human–Computer Interaction (HCI) field reveal significant potentials for designing automatic age estimation systems via face image analysis. The success of such research may bring in many innovative Human–Computer Interaction tools used for the applications of human-centered multimedia communication. Due to the temporal property of age progression, face images with aging features may display some sequential patterns with low dimensional distributions. Such a processing has been evaluated by extensive simulations and compared with the state of-the-art methods. Experimental results on a large size database demonstrate the effectiveness and robustness of the framework.

2.5 Age Classification

Y. H. Kwon and N. D. V. Lobo[5] proposed Age classification from facial images. The ability to classify age from a facial image has not been implemented in computer vision. This research addresses the limited task of age classification of a facial image into a baby, young adult, and senior adult. This is the first reported work to classify age, and to successfully extract and use natural wrinkles. To gain an understanding for the aging process of the face, we consulted studies in cranio-facial research, art and theatrical makeup, plastic surgery, and perception. Cranio-facial research suggests that the growth of a human head is best described by the revised cardioidal strain transformation. We present a theory and practical computations for visual age classification from facial images, based on cranio-facial changes in feature-position ratios, and on skin wrinkle analysis.

3 Motivation

The existing age estimation system involves the use of age ranking using accelerated gradient algorithm and label ranking. The major drawback of the existing system is that the Mean Absolute Error (MAE) is high. To overcome this problem a proficient system that uses Positional ternary Pattern (PTP), Principal Component Analysis (PCA) can be used to find the estimated age range. Neural Network is used for classification of age group.

4 Proposed Scheme

The proposed system uses a combination of Positional Ternary Pattern (PTP) and Principal Component Analysis (PCA) for feature extraction. Gray Level Co-occurrence Matrix (GLCM) algorithm is used to identify the texture of the image. The classification of the age is done using Probabilistic Neural Network (PNN).

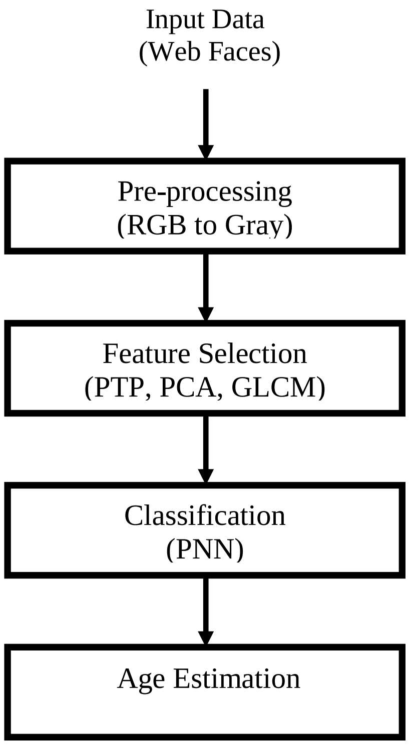

Figure 1 Architectural Design of Proposed System

4.1. Data Pre-processing

Data pre-processing is a technique that involves transforming raw data into an understandable format. Real-world data is often incomplete, inconsistent, and lacking in certain behaviors, and is likely to contain many errors. Data pre-processing is a proven method of resolving such issues. Different region of face like eye pair, nose, mouth, and chin are detected. The data set may have images of all different sizes. The first step in preprocessing is to convert the entire training image into specific size; here the images are converted into 256x256 size. The RGB color of the image makes it complex to find out the texture, gradient values. So to reduce complexity all the RGB color images are converted into gray-scale images. First, the face part of the image is detected using CascadeObjectDetector function in Matlab. The cascade object detector uses the Viola-Jones algorithm to detect people's faces, noses, eyes, mouth, or upper body. The trainCascadeObjectDetector function can also be used to train a custom classifier to use with this System object. The face part of the image is cropped out for better accuracy. Then the facial features to identify the age are cropped out. Then the image is ready for further processing. Pre-processing of the data set is so important because it helps to reduce complexity. The pre-processed image is converted into gray scale and of standard size 256x256.

4.2 Feature Selection

Feature selection, is the process of selecting a subset of relevant features for use in model construction. Extraction of global and local features is made from face images. The global features include various distance ratios of all crucial facial objects like left eyeball, right eyeball, nose, chin, lip, and forehead. The feature that is mainly used here is wrinkle feature of the face like forehead region, eye corners regions, eyelids, mid of eyebrows. The dataset have facial images of people of all ages, races, gender. Feature selection is done so as to simplify the process that is to focus on the terms that help to find the result faster. Here in human face, the wrinkles face line and the fading of skin color. The human skin loosen it tightness and the shape changes with respect to age. But age processing is a slow process, so in some cases the main facial features may not change with respect to age. Finding age in such cases makes it difficult. There are some exceptional cases where the changing happens faster or slower. In such cases, Age range can be found instead of accurate age. The features of the pre-processed image are identified using detectFaceParts function in Matlab. The output is that the eyes, nose and mouth area in the face are identified or marked.

4.2.1 Positional Ternary Pattern

In this paper, we propose a novel appearance based method, Positional Ternary Pattern (PTP), as edge based one for automatic age recognition with the notion that, both shape (the craniofacial growth) and skin (wrinkles and blemishes) changes during aging, are efficiently detected on regions of face image with high edge response. Our method is not only robust to noise but also describes face aging accurately and efficiently owing to adapting edge operators for generating patterns. In addition to, our proposal it achieves more stability than existing edge based methods by incorporating a ternary pattern which provides high discriminating power in flat and high-textured area. For successful recognition of age, it is needed to adequately represent shape and skin changes of the face according to aging. Existing edge based descriptors proves their superiority in facial expression recognition in which, detecting shape changes of facial features is the main issues, and wrinkles and blemishes as remarkable skin aging cue, are able to be found effectively by high edge response. From these observations, we adopt edge operators in our proposed method so as to represent face aging accurately and efficiently. The proposed Positional Ternary Pattern (PTP) assigns eight bit binary code to each pixel of an image. Then, we select the primary and secondary direction from those edge responses. Here, we take a further step to select the secondary direction in such a way that, it can represent better corner structure of that pixel. At last, we introduce a ternary pattern of the primary direction, which distinguishes the flat and edge-based region.

4.2.2 Principal Component Analysis

PCA tool is used in exploratory data analysis and for making predictive models.PCA used an orthogonal transformation to convert a set of observations of correlated variables into a set of linearly uncorrelated variables called principal components. PCA is done by Eigen value decomposition of a data covariance matrix, usually after mean centering the data matrix of each attribute. It is the simple true eigenvector based multivariate analyses. Its operation can be thought as revealing the internal structure of the data that best explains the variance in the data. It is closely related to factor analysis. Factor analysis typically incorporates more domain specific assumptions about the underlying structure and solves eigenvectors of a slightly different matrix. The steps involved in PCA algorithm includes:

1. Take the whole dataset consisting of d-dimensional samples ignoring the class labels.
2. Compute the dd-dimensional mean vector (i.e., the means for every dimension of the whole dataset)
3. Compute the scatter matrix (alternatively, the covariance matrix) of the whole data set
4. Compute eigenvectors (ee1,ee2,...,eedee1,ee2,...,eed) and corresponding eigenvalues (λλ1,λλ2,...,λλdλλ1,λλ2,...,λλd)
5. Sort the eigenvectors by decreasing eigenvalues and choose kk eigenvectors with the largest eigenvalues to form a d×kd×k dimensional matrix WWWW(where every column represents an eigenvector).
6. Use this d×kd×k eigenvector matrix to transform the samples onto the new subspace. This can be summarized by the mathematical equation: yy=WWT×xxyy=WWT×xx (where xxxx is a d×1d×1-dimensional vector representing one sample, and yyyy is the transformed k×1k×1-dimensional sample in the new subspace.)

4.2.3 Gray-Level Co-occurrence Matrix

Gray-level co-occurrence matrix (GLCM), are gray-level spatial dependence matrix is one of the statistical methods to examine the texture that considers the spatial relationship of the pixels. The GLCM functions defines the texture of an image by calculating how often pairs of pixel with specific values and in a specified spatial relationship occur in an image, creating a GLCM, and then extracting statistical measures from that matrix. After GLCM is created, using gray comatrix, we can derive several statistics from them using gray coprops. These statistics provide information about the texture of the image. The following table lists the statistics.

Statistics	Description
Contrast	Identifies local variations in Gray-Level Co-occurrence Matrix
Correlation	Identifies joint probability occurrence of the specified pixel pairs
Energy	Provides the sum of squared elements in GLCM. also known as Uniformity or angular second moment
Homogenecity	Identifies the closeness of distribution of elements in the GLCM to the GLCM Diagonal

The steps involved in GLCM algorithm are:

1. Quantize the image data. Each sample on the echogram is treated as a single image pixel and the value of the sample is the intensity of that pixel. These intensities are then further quantized into a specified number of discrete gray levels as specified under Quantization.
2. Create the GLCM. It will be a square matrix *N* x *N* in size where *N* is the **Number of levels** specified under **Quantization**. The matrix is created as follows:

   a. Let *s* be the sample under consideration for the calculation.

   b. Let *W* be the set of samples surrounding sample *s* which fall within a window centered upon sample s of the size specified under **Window Size**.

   c. Considering only the samples in the set *W*, define each element *i*,*j* of the GLCM as the number of times two samples of intensities *i* and *j* occur in specified **Spatial relationship** (where *i* and *j* are intensities between 0 and **Number of levels**-1) . The sum of all the elements *i*, *j* of the GLCM will be the total number of times the specified spatial relationship occurs in *W*.

   d. Make the GLCM symmetric:

      i. Make a transposed copy of the GLCM

      ii. Add this copy to the GLCM itself

   e. Normalize the GLCM:

3. Divide each element by the sum of all elements. Calculate the selected **Feature**. This calculation uses only the values in the GLCM. See:

   - Energy
   - Entropy
   - Contrast
   - Homogeneity

- Correlation
- Shade
- Prominence

4. The sample *s* in the resulting virtual variable is replaced by the value of this calculated feature.

4.5 Probabilistic Neural Network

The algorithm which is used for classification and pattern recognition problems is Probabilistic Neural Network (PNN). It's a feed forward neural network.A Parzen window and a non-parametric function is used to approximate the parent Probability Distribution Function (PDF) of each class. By using PDF of each class, the class probability of the new input data is estimated. Then the Baye's rule is used to allocate the class with highest posterior probability to the new input data. This method helps to reduce the probability of mis-classification. In a PNN, the operations are separated into four layers:

- Input layer
- Hidden layer
- Pattern layer/Summation layer
- Output layer

PNN algorithm is often used for classification problems. The first layer calculates the distance between the input vector and the training input vector. This results in a vector whose elements indicate how close the input is to the training input. The next layer adds the contribution for each class of inputs and produces a net output as a vector of probabilities. The neuron that represents the hidden neuron category. The pattern neurons sum the values of the class they represent. The last layer called the output layer compares the votes of each category and the one with largest votes is assigned as the target category.

Neural network is used on the training set to classify the age group according to the specific feature values. The input image is compared with the stored training datasets. The class with maximum similarity is chosen to be its class or estimated age group.

5 Experiment Results

This section presents the experiment results after testing the proposed system. It explains first the experimental setup then shows the results on different test. The proposed system uses a set of different faces of all race, gender and age. The proposed system estimates the age range of the given input. Figure 2 shows a set of web faces. The proposed system uses the passport size of human facial images.

Figure 2 Web Faces

The first step in the process in pre-processing the facial images. All the images are converted into gray scale image and cropped to standard 256x256 sizes. Figure 3 shows the preprocessed image.

Figure 3 Preprocessed image

The feature selection is done on the face. This includes the wrinkles, face line around eyes, nose and chin. The texture value of the features are found using PTP for further processing. Figure 4 shows the output of the feature selection.

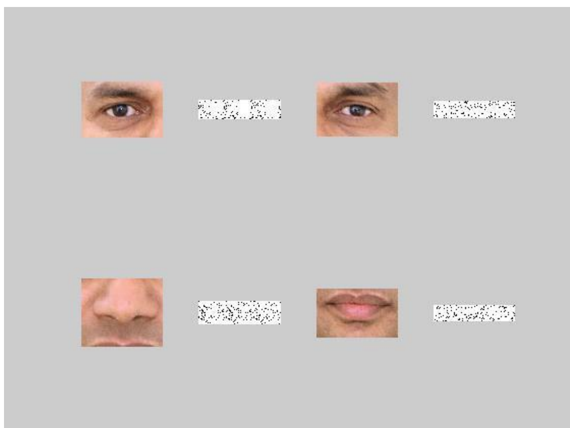

Figure 4 Feature Selection

The texture value of the entire face is found using Positional Ternary Pattern (PTP) algorithm. Figure 5 shows the output of the algorithm.

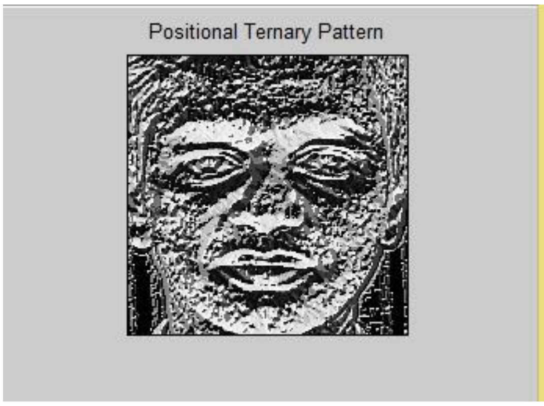

Figure 5 Texture Extraction

Neural Network is used for classifying ages. The features of the training and test sets are compared to get the result. Figure 6 shows the complete output of the proposed system.

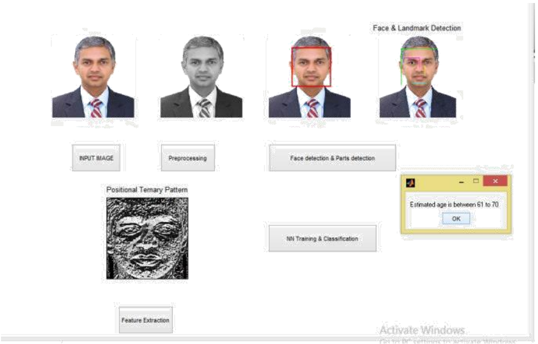

Figure 6 Age Estimation

6 Conclusion

In this paper, we have proposed a novel approach for age classification in face images The classification of human age from facial images plays a vital role in Computer vision, cognitive science and Forensic Science. The various computational and mathematical models, for classifying facial age, using Positional Ternary Pattern (PTP) have been proposed yields better performance. This paper proposes a novel method of classifying the human age group using Artificial Neural Network. This is done by pre-processing the face image at first and then extracting the face features using PTP. Then the classification of human faces is done using Probabilistic Neural Network (PNN). The process of combining PTP and PNN can improve optimization rather than using separately. From this technique we successfully classified humans according to the age category by using positional ternary pattern.

In future development we can accurately estimate the person's age by using Edge Deduction of facial part and classify using K-NN .This will reduce the Mean Absolute Error(MAE).

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