Person Recognition through Age Progression

Sowrabhi Ravi#1, Sneka Antony*2, Farjana Farvin, Assitant Professor#3
#*studenst, Department of Computer Science and Engineering,*
Anjalai Ammal Mahalingam Engineering College, kovilvenni
Thiruvarur-614403, Tamilnadu, India.

Abstract

Face Recognition is widely known as biometric method used for recognizing and identification. Face recognition is used in emergent research on image analysis and for security purposes. A new challenge in face recognition is aging progression. Human faces undergoes variation with aging, it is strenuous challenging to identify .we build our system to detect the childhood image even in unusual poses and extract the occluded face of image by ROI(Rectangle of Interest) cropping. It leverages multiple image regions like eyes and mouth including non-cooperative subjects by using object based face tracking method, these extracted images are compared with those of registered faces in dataset and closest registered face is selected as the person's. Recognizing images in spite of age progression is challenging because, the growth in each individual is personal and not predictable. This experiment result shows advantage of the proposed method on aging progression and avoids detrimental effect of the shape change of faces caused by growth.

Keywords - *Age progression, face recognition, face detection*

I. INTRODUCTION

Human identification or person identification is the task of matching images with the existing images on our database based on the appearance of the person. Human faces have the ability to appear different depending upon the pose, facial expression, and the activity the human is engaged in as well as the makeup. Human eyes have the natural ability to identify humans and other objects by analysing facial features, costumes, hair styles etc. Training the computer system to identify humans in different styles and poses is a tedious task. Identifying humans through age progression is even more challenging. Human faces undergo growth related changes that show differences in the form of shape and appearance. Hence, the analysing variations in a photograph due to factors such as lighting, pose, facial expressions, aging etc. is a significant metric in evaluating face recognition systems.

Modelling age progression in human faces is a very challenging task. Facial aging happens in different forms in different age groups. Variations in human faces are due to the cranium's growth from infancy to teen years. The most common feature analysed in age progression is wrinkles and other skin artefacts in adult faces. Apart from biological factors, factors such as climatic conditions, ethnicity, mental stress etc. are often attributed to play a role in the process of aging.

Figure [1.1] shows some examples that show variation of faces in the same person. Aging is an irreversible process and it happens to everybody. The age progression signs displayed on faces are uncontrollable and personalized such as hair whitening, muscles dropping and wrinkles. Figure [1.1] shows the aging of two young boys and their pictures after 10 years. The aging of the two have similar characteristics including increase in height, growth of facial hair and tightening of the muscles. But, there are several differences in their aging. For example, the first boy's nose length has increased considerably, whereas, the second boy's face remains almost the same. The second boy has become tanned, whereas the first boy's skin tone is the same

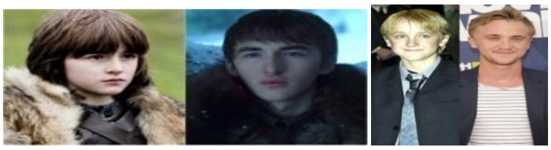

Fig 1.1 shows examples of variations of facial features due to age progression

The computer vision system cannot always recognize two photos of the same person at different ages. So, we propose a system that would recognize and group the photos of the same person irrespective of the change in physical appearance. This is done by analysing the linear and non-linear constraints on growth parameters.

II. RELATED WORKS

A. Age progression

The topic of human aging and automated face recognition is a popular field [1]. The face recognition is used in real world in case of missing people [18], or identifying children [13]. Normally, for identification of humans, Anthropometry is used. Anthropometry refers to the measurement of the human individual. It has been used by the forensic department for identification, for the purposes of understanding human physical variations. Such automatic identification of human physical characteristics are majorly data driven [19]. Humans undergo a lot of physical changes as they age. Age progression is achieved by adding differences between age prototypes on a given face image.

Many methodologies have been proposed to predict the age progression [8]. There is no standard method for it because of it complexity [7]. Each researcher computes a different methodology, none of which has been proved to be the most efficient.

Kemelmacher-Shlizerman et al. [20] describe an age progression method based on age prototypes derived from 40000 images collected from the internet. A key element of the method is the illumination normalization technique used, which ensures the generation of normalized age prototypes. Since, this aging is different for each individual; Tsai et al. [11] proposed an approach based on the use of the Expectation Maximization algorithm.

The model used for modelling aging [10] was by considering training samples with limited age separation as polynomials and the training samples with long term age separation as Markov Model.

U. Park, Y. Tong and A.K. Jain considered 3D age progression by utilizing either datasets with 3D reconstructed faces [9].

A model that compares the input image and registered faces from dataset uses Block matching method [3] that compensates the position shift of face component in case of the image shot at a different age than the registered image.

B. Datasets

In order for the system to automatically recognize images, the system needs to undergo a lot of training. This training involves a huge set of datasets. Humans tend to look different in different poses, or when a person is engaged in some kind of activity [4]. Cues such as changes in hairstyle, or poses may affect the automated age progressions. The dataset used for analyzing poses and angles called Person in Photo Album (PIPA) [5] and Faces in the Wild (LFW) [6] datasets contains over 4000 images of person at some different poses. Our model uses a dataset similar to PIPA.

The major changes in humans happen because of aging. One of the major applications for recognizing photos across age progression is verification of passports. FG-NET [2, 14,15]is a dataset that contains a large dataset of passport datasets. Datasets called aging dictionary [16] that holds linear combination of face patterns, expresses a particular personalized aging process.

C. Age Prediction

The dataset has a large collection of different faces of people belonging to different age groups. The dataset is indexed by means of the age of the person. So, the system should be capable of predicting the age of the input image so that it is easier to get the related photos from the dataset.

Conditional adversarial auto encoder (CAAE)[12] is a method that learns a face manifold, traversing on which smooth age progression and regression can be realized simultaneously. The growth curve is studied that gives a clear difference of each feature at different age[17]. This methodology is usually employed for images that have a short age difference.

III.PROPOSED SYSTEM

A. Overview of Face Recognition through Age Progression

In this work, we study the problem of face recognition through age progression. Aging is a monotonous involuntary process that is unpredictable in every living creature. Building a simple face recognition system, where the image is expressed as a superposition of age and some common components is proposed by us. We propose a system, given an input image of a person that would retrieve all the other images irrespective of their ages stored in the database. We show how respective ages and gender are predicted (given an input face image) and through the predicted data as a parameter, an automatic invariant face verification method is employed to recognize the person. A number of algorithms for face detection, age and gender estimation and recognizing through age progression are used for the system. The system completely based on the photos uploaded by the users and are stored in a dataset called Person in Photo Albums (PIPA Dataset).Furthermore,through the extensive experiments we show that the proposed method outperforms the state-of-the-art methods both qualitatively and quantitatively.

B. Face detection

The first step after converting the input image to grayscale is face detection. Face detection is finding the face from the image which will later be used to detect the face. One of the most efficient methods for identifying faces from the image is by using object based face tracking method proposed by viola-jones method. The face detection algorithm usually involves the sums of image pixels within rectangular areas. The value of any given feature is the sum of the pixels within clear rectangles subtracted from the sum of the pixels within shaded rectangles

The face detection method involves the following 4 stages, namely: Haar Feature, Creating an integral image, Adaboost Training, and cascading classifiers.

- Human faces contain similar properties (such as the eye region is darker than the upper-cheeks). Those regularities can be matched by using haar features.
- An image representation called the integral image evaluates rectangular features in constant time.

- Object detection framework employs a variant of the learning algorithm AdaBoost to both select the best features and to train classifiers that use them.
- Cascading is used to identify whether the identified rectangle is a face or not a face.

Algorithm

Input: Set of *N* positive and negative training images with their labels (x^i, y^i) . If image *i* is a face$y^i = 1$, if not $y^i = -1$

1. Initialization: assign a weight $w_1^i = \frac{1}{N}$ to each image i.
2. For each feature f_i with j = 1,….,M.
   a. Renormalize the weights such that they sum to one.
   b. Apply the feature to each image in the training set, and then find the optimal threshold and polarity θ_j, s_j . That minimizes the weighted classification error. That is θ_j, s_j
   $$= arg \min_{\theta,s} \sum_{i=1}^{N} \omega_j^i \, \varepsilon_j^i \quad where\ \varepsilon_j^i$$
   $$= \begin{cases} 0 \ \ if\ y^i = h_j\left(x^i, \theta_j, s_j\right) \\ 1, \qquad otherwise \end{cases}$$
   c. Assign a weight α_j to h_j that is inversely proportional to the error rate. In this way best classifiers are considered more.
   d. The weights for the next iteration, i.e. ω_{j+1}^i , are reduced for the images *i* that were correctly classified.

3. Set the final classifier to

$$h(x) = sgn\left(\sum_{j=1}^{M} \alpha_j h_j(x)\right)$$

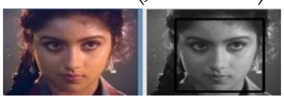

Fig 3.1 shows detected faces

C. Age Estimation

Once the face has been detected, the next step is to estimate the person's age and gender. Once we classify the age group of the input face, it will be easy to fetch other images from different age groups. Age estimation is a complex process, and it is very difficult to estimate it accurately. Growth analysis and Wrinkle analysis are calculated first and based on the value obtained, age is detected.

1) Growth Analysis

Craniofacial growth suggests that the face changes from circular to oval due to growth. This causes slight changes in the position of the primary facial features. For example, in babies the distance between eyes are closer whereas in adults the distance is far apart. So, distance between facial features can be used as a basic parameter to detect faces. Depending on the distance between two features, we define 7 important ratios:

$$ratio\ 1 = \frac{D(eyes_{left}, eyes_{right})}{D(Middle\ of\ eyes, nose)}$$
$$ratio\ 2 = \frac{D(eyes_{left}, eyes_{right})}{D(Middle\ of\ eyes, lip)}$$
$$ratio\ 3 = \frac{D(eyes_{left}, eyes_{right})}{D(Middle\ of\ eyes, chin)}$$
$$ratio\ 4 = \frac{D(Middle\ of\ eyes, nose)}{D(Middle\ of\ eyes, lip)}$$
$$ratio\ 5 = \frac{D(Middle\ of\ eyes, lip)}{D(Middle\ of\ eyes, chin)}$$
$$ratio\ 6 = \frac{D(eyes_{left}, eyes_{right})}{D(Top\ of\ head, Chin)}$$
$$ratio\ 7 = \frac{D(Side\ of\ face_{left}, side\ of\ face_{right})}{D(Top\ of\ head, Chin)}$$

Where D(A,B) is the minimum distance between the features A and B.

2) Wrinkle Analysis

The wrinkle geography map is used to determine where edge detection algorithms should be applied in order to search for wrinkles. To quantify the degree of the skin creases, wrinkle density is defined. Aged people often have clear wrinkles on the forehead, eye corners, below cheeks, and upper lip. Since the human face is symmetrical, it is sufficient to analyze only one side of the face. We define formulae for locating each of the above mentioned feature, based on the location of the eye.

- The formula to locate the forehead region from face:
  $$Width = \frac{4}{3} \times D_{eyes}\ , Height = \frac{1}{4} \times D_{eyes}$$
- The formula to locate the eye corner region from face:
  $$Width = \frac{1}{6} \times D_{eyes}\ , Height = \frac{1}{4} \times D_{eyes}$$
- The formula to locate the left cheek corner region from face:
  $$Width = \frac{1}{2} \times D_{eyes}\ , Height = \frac{4}{5} \times D_{eyes}$$

Once each wrinkle prone areas are detected, it is indispensable to measure the wrinkle density. Wrinkle density can differ in humans depending upon their respective ages. Children and young adults have zero or very less wrinkles. In older adults the wrinkles are evident and show clearly. Based on this, if a pixel belongs to an edge it is labelled as a wrinkle pixel.

Wrinkle in each of the three regions is detected by using Canny Edge Detector. The output is in the form of a binary image that shows only wrinkles.

3) Age Estimation

Age is estimated using Feed Forward Back Propagation neural network that takes the 7 ratios and 3 wrinkle features as input. The neural network has 7 neurons namely AG1,AG2, AG3,AG4,AG5,AG6,AG7 corresponding to age groups 2-6, 7-13, 14-24, 25-34, 35-50, 51-65,66-80. The highest neuron value among the 4 groups determines which age group the person belongs to.

D. Calculating Growth Parameter

Given an input image of a 2 year old, we automatically generate the image of a 20 year old by computing the difference in the texture and flow difference between the two groups AG1 (2-6) and AG3 (14-24) and applying it to the input image. The following three steps are involved to calculate the growth parameter. They are: Texture age progression, flow age progression, and aspect ratio progression.

1) Texture Age Progression

Given an input image I, relight the source and target age cluster averages to match the lighting of I as IS and IT. Compute flow Fsource–input between IS and I and warp IS to the input image coordinate frame, and similarly for Ftarget–input. This yields a pair of illumination matched projections, Js and Jt both warped to input. The texture difference Jt −Js is added to the input image I.

GROUP NAME	AGE GROUPS	PHOTOS IN DATASET
AG1	TODDLER (2-6)	**10**
AG2	CHILDREN(7-13)	**25**
AG3	TEENAGERS(14-24)	**15**
AG4	YOUNG ADULTS(25-34)	**20**
AG5	MIDDLEAGERS(35-50)	**25**
AG6	SENIORS (51-65)	**10**
AG7	OLD PEOPLE(66-80)	**8**

2) Flow Age Progression

Apply flow from source cluster to target cluster Ftarget–source mapped to the input image, i.e., apply Finput–target ◦Ftarget–source to the texture-

With the dataset as mentioned above, and given a random image input, the system should be able to recognize and retrieve all other images stored in the database. Given a random set of inputs, and their corresponding output we calculated accuracy.

modified image I + Jt − Js. For efficiency, we precompute bidirectional flows from each age cluster to every other age cluster.

3) Aspect Ratio Progression

Apply change in aspect ratio, to account for variation in head shape over time. Per-cluster aspect ratios were computed as the ratio of distance between the left and right eye to the distance between the eyes and mouth, averaged over the fiducially point locations of images in each of the clusters.

E. Face Recognition

We use a simple and straightforward method for Face recognition. We train the SVM algorithm with the different 7 age group sets of people belonging to different age. The SVM algorithm will generate a linear decision surface and identify the person. Given an input image and the estimated person's age, we search only in the age set belonging to the age group. If the image search provides no result, then we compute growth parameter and convert the image to a different age group and search again in that set. Similarly the system automatically searches in each group and retrieve images if other images found. The result is matched if, $w \times i + b \leq 0$,

IV. EXPERIMENTS

After training the system at each step the system is able to recognize images across age progression. The system is tested and experimented with various inputs. We have a total collection of 113 identified images in our PIPA (Person in Photo Album) dataset. The system is designed in such a way that, the system will be able to recognize only the images stored the dataset. However, when the input is an image that is not a part of the PIPA dataset, the system asks the user to identify the person and it adds the details and the image to the PIPA dataset. The PIPA dataset has collections of different celebrities taken at different ages. The ages are grouped into the following 7 categories in Table 1:

TABLE 1

NAME	AGE OF IMAGE	NO. OF PHOTOS IN THE DATABASE							VERIFICATION PERCENTAGE
		AG1	AG2	AG3	AG4	AG5	AG6	AG7	
JEN ANISTON	13	1	2	3	2	2	0	0	**85%**
EMMA WATSON	27	1	4	4	1	0	0	0	**90%**
MATHEW PERRY	45	0	1	3	2	2	2	0	**97%**
MAGGIE SMITH	2	1	1	1	3	1	2	3	**60%**

VI RESULT

Thus various celebrity images along with their random age images are tested and the various outputs are found. The system recognizes and retrieves efficiently by 83%. Thus it achieves the state of art performance.

VII CONCLUSION

In this paper, we studied a method to verify a person from face image which was registered in database many years ago across age progression is proposed. We have investigated efficacy of various cues, including the face recognizer HOG and their histogram values .For better analysis, we proposed deep convolution neural network which measure the degree of linear relationship between features, images matched with PIPA dataset. In dataset the face components are shifted in face area with age progression, block matching, which takes correlation between the blocks in the captured face and the registered one with the position shift, is powerful to get the same person's face in the database. Further some changes in texture of skin are considered. But in that case, thoroughness of skin, such as wrinkles spots can be removed, while keeping the features of the face sharp, using a nonlinear smoothing filter, thus the influence of the change of the texture can considered to be small enough.

This system is more efficient and very skillful for real-time system. In future we decided to improve the performance of age progression and reduce the complexity of face recognition.

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