Analysis of facial growth patterns for forensic investigation of missing children

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Abstract : Face age prediction system is the simulation of prediction of face and face age. To predict the face of any person, age plays an important role and the various models are built on age parameter. Yet, growth-related shape variations during developmental years are considered for face prediction. Image processing is utilized for the face prediction. Anthropometric pieces of evidence gathered from the face are used as the core facial features with respect to age. The anthropometric studies are used to describe the facial growth with the help of growth parameters characterized by the facial landmarks. These age-based models have different useful applications like finding the missing persons, especially in the case of missing kids. In this paper, anthropometric features are extracted from the face of the child. These features are compared with the face of the same person but at different age intervals.

IndexTerms **– Face prediction, Facial features, Facial landmarks, Anthropometry, Craniofacial growth**

I. INTRODUCTION

Crime is increasing at an alarming rate in the world [10]. It is believed that kids are the most vulnerable victims with regards to crime. Targeting kids for kidnapping have an undeniable benefit for the criminal that, if they succeed hiding them for a few number of years, their facial features will generally drastically change with the passing days. Therefore, the kids untraced for a long time will remain untraced forever. Thus, Face age prediction system assumes a vital part of this sort of applications. The main objective for all applications is to re-create the face with the lapse of time and to produce aging effects that are generally possible without changing the identity of a person. IMDB-WIKI and 300W iBug datasets are used for the experiments. Python and OpenCV are utilized for the implementation process. The assumption that is taken in the proposed methodology, is that the subject has not undergone any plastic surgery.

The noteworthy applications of the process of developing age in human faces are national security, ages based human-computer interaction for parental restriction and finding the missing persons [3]. It is a challenge to create the models that describe the process of developing age in human faces. It is observed that the shape of face generally changes during earlier growth period. On the contrary, in the later ages, textural differences like wrinkles are observed on the face [3]. Hence, face anthropometry and craniofacial models are very important in face prediction.

Anthropometry deals with extraction of facial features. These features provide important landmarks and their position as well as measurements on the face. The anthropometric features are believed to differentiate one individual from another. Craniofacial model shows the growth pattern of the face with respect to age. It is also to be understood that saturation is found in both anthropometric features and craniofacial growth after reaching adulthood. Methods to suggest techniques to build the process of developing age in faces have already been explored by many researchers [7, 5] etc. Most of the methods avoid the psycho-physical pieces of evidence gathered on the process of developing age. Face anthropometric studies provide a better understanding of craniofacial growth [5] and it is consequently utilized by the physician in handling craniofacial diseases. By utilizing such data, the face recognition system are developed.

The remaining part of the paper is arranged as follows, Section I contains the introduction of the paper, Section II highlights the literature survey of different papers related to the face age prediction system, Section III briefs about how face anthropometry and craniofacial growth are utilized for face prediction, Section IV provided details of the proposed methodology, Section V concludes research work with future scope of the paper.

II. LITERATURE SURVEY

This section explores the efforts put forth by researchers across the globe in the area of face prediction. In the year of 1999, A. Lanitis et al. proposes a parameterized statistical model to explain the impact of aging on a face in “modeling the process of aging in face images”. And later on in 2006, N. Ramanathan et al. uses anthropometric pieces of evidence and craniofacial growth model to predict the face in “modeling age progression in young faces”. In the year of 2009, N. Ramanathan et al. discusses the issues in age estimation, appearance prediction, face verification in the paper of “age progression in human faces: a survey” and the transformational model for face shape and textural changes are used in the paper “how would you look as you age?” In 2009, the paper “automatic child face age progression based on haritability factors of familial faces” describes how siblings and parents facial features are utilized for predicting the face of a missing person. In the year 2010, Jinli Suo et al. proposes a “compositional and dynamic model for face aging” is based on various leveled And-Or chart in each age group. In 2012, Hsuan Chang et al. extract 6 facial RoIs and from that predicted new RoI to override on the original image in facial image prediction using an Exemplar-based algorithm and non-negative matrix factorization. The details about these papers are as mentioned in table 1.

Table 1. Literature Survey

Paper Name	Author Name	Publication Name	Dataset	Description
Facial Image Prediction using Exemplar-based algorithm and Non-negative Matrix Factorization	Hsuan T. Chang, Hsiao W. Peng	Signal and information processing IEEE	Aging database: FG-NET, GF-NET database contains face pictures	In this paper, the author proposes Exemplar-based algorithm and it examines the human growth. They predict 6 RoIs with the help of non-negative matrix factorization and linear interpolation methods [1].
Modelling Age Progression in Young Faces	N. Ramanathan, R. Chellapa	Computer vision and pattern recognition IEEE	Aging database: FG-NET	The author proposes craniofacial growth model that shows growth related changes in shape saw on human faces during developmental years. The growth patterns on human face and anthropometric pieces of evidences are collected in the proposed model. The anthropometric studies use growth parameters characterized by facial landmarks [5].
A Compositional and Dynamic Model for Face Aging	Jinli suo, Song-Chun Zhu, Shiguang Shan, and Xilin Chen	IEEE Transactions on pattern analysis and Machine Intelligence	MORPH, aging database: FG-NET	The compositional and dynamic methods for facial aging is proposed by the authors and it constitutes faces by a various levelled And-Or chart in each age group. The decomposition of the face parts to defines the extensive variety of faces by elective choices. Markov procedure on the parse diagram is used to characterize facial aging. The parameters of dynamic method are learned through the large face dataset and the face aging stochasticity is also displayed [9].
Age Progression in Human Faces: A Survey	N. Ramanathan, R. Chellapa and Soma Biswas	Journal of Visual Languages and Computing	Aging database: FG-NET, passport, FERET, PIE dataset	The authors have done the detailed analysis of the issue of facial aging and give a full record of the numerous interesting research that has been performed on the subject from various area. The age estimation, appearance prediction, face verification [2] etc. are the major issues and the author propose an analysis of different methodologies on these issues [7, 11].
Modelling the Process of Aging in Face Images	Andreas Lanitis, Chris Taylor, Timothy F.Cootes	Computer vision, IEEE	350 images used for training	Depict in this paper, they use a parameterized statistical model to explain how the impacts of aging on facial appearance. They proposed the framework which is reproducing the face images with aging impacts and it is utilized for predicting that how a person might look like after few years, or how a person used to look before some time [4].
Automatic Child-Face Age-progression Based on Heritability Factors of Familial Faces	Anonymous Submission	Biometrics, Identity and Security (BIdS) IEEE	BGC database	The hereditary facial features of brothers, sisters, mother, and father are used to predict the way that how children might look up to growing period. The familial data is first time used directly with the Active Appearance Models (AAM) [8].
HOW WOULD YOU LOOK AS YOU AGE?	N. Ramanathan, R. Chellapa	Image Processing (ICIP) IEEE	87 separated images of adults	The transformational methods for facial shape and texture are constituted by the facial growth model. For developing transformation models, they gathered information related to facial growth from the datasets of age-separated facial images [6].

III. FACE ANTHROPOMETRY AND CRANIOFACIAL GROWTH MODEL

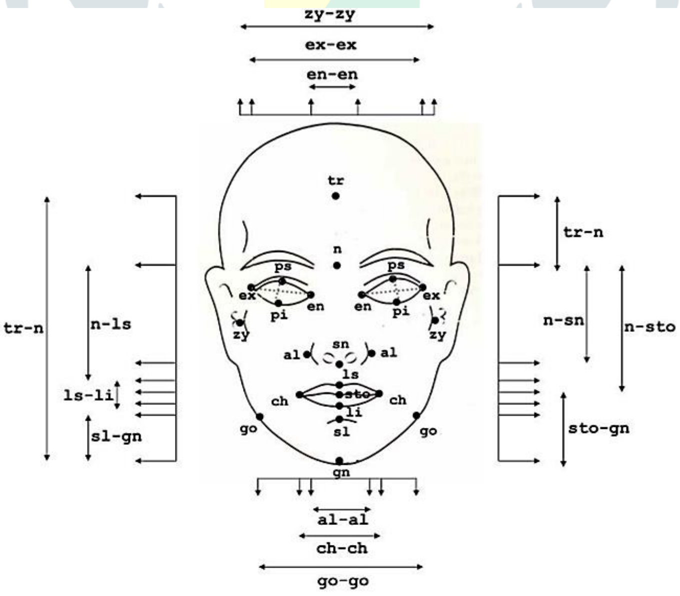

Figure 1. Face Anthropometry with detected Facial Landmarks [5]

Figure 1 demonstrate the face image with detected 24 facial and the key facial measurements are utilized for creating growth model. Ramanathan et al. used face anthropometry for computing the ratio of several facial landmarks. A quantitative interpretation of the craniofacial complex is achieved by the computation taken between key landmarks on human faces across age and it is consequently utilized for characterizing face growth [5]. The craniofacial growth model provides age-based facial computation and portion of distances between facial landmarks. Proportion indices are used to study the facial growth and to develop craniofacial growth model. The important proportion indices that were utilized as a part of the study are as under [5]:

$$Facial\ Index: \frac{n-gn}{zy-zy} \quad (1)$$

$$Mandibular\ Index: \frac{sto-gn}{go-go} \quad (2)$$

$$Intercanthal\ index: \frac{en-en}{ex-ex} \quad (3)$$

$$Orbital\ width\ Index: \frac{ex-en}{en-en} \quad (4)$$

$$Eye\ fissure\ Index: \frac{ps-pi}{ex-en} \quad (5)$$

$$Nasal\ Index: \frac{al-al}{n-sn} \quad (6)$$

$$Vermilion\ height\ Index: \frac{ls-sto}{sto-li} \quad (7)$$

$$Mouth-face\ width\ Index: \frac{ch-ch}{zy-zy} \quad (8)$$

Table 2 describes various growth patterns noticed for men and women. The growth patterns are different for men and women for various parts of faces. Relative Total Increment (RTI) is defined as (l18-l1)/l1 where, l1 and, l18 correspond to mean value of the measurements obtained at ages 1 and 18 respectively. The age of maturation and the period of growth spurt are evaluated by observing relative changes in facial measurements with passing years.

Table 2. Growth pattern in different facial regions for Male and Female

Feature	RTI (%)		Growth Spurt (yrs)		Maturation age (yrs)	
	M	F	M	F	M	F
n-gn	50.5	44.8	1-4	1-5	15	13
zy-zy	38.7	35.9	3-4	3-4	15	13
en-en	20.5	17.5	3-4	3-4	11	8
al-al	30.9	21.2	3-4	3-4	14	12
n-an	71.5	67.5	1-2	3-4	15	12

Figure 2 demonstrates the correlation between pressure distribution in a fluid filled spherical object and face profiles acquired by using above transformation. Ramanathan et al. took the assumption that some of the identifiable manner of remodeling is indicated by geometric invariants described below. According, the 'revised' cardioidal strain transformation method is defined with the help of

$$P \propto R_0 (1 - \cos(\theta_0)) \quad (9)$$

$$R_1 = R_0 + k (R_0 - R_0 \cos(\theta_0)) \quad (10)$$

$$\theta_1 = \theta_0 \quad (11)$$

Here, P demonstrates pressure at the specific point on item surface acting radially towards the outside, (R_0, θ_0) and (R_1, θ_1) demonstrate angular coordinates of a point on the surface of the item and k demonstrates growth related constant. For different growth parameter k, the variation of face closely took which is seen in real facial growth. With increased growth parameter k, the observable age of each person face profiles increased. The authors have preferred to use the age transformation method on frontal face of the kids.

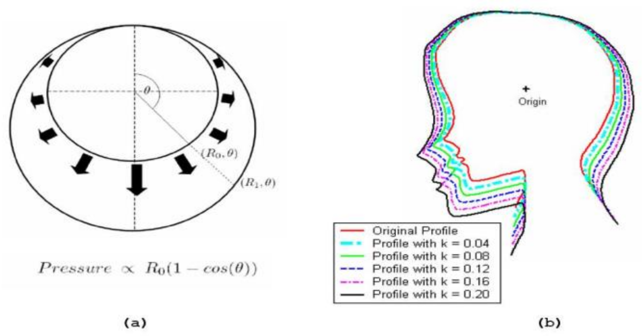

Figure 2. Modeling Growth patterns on Young Faces [5]

According to face anthropometry, the various face regions reach maturation at different years because some face attributes vary less with compared to other face attributes as age grows. The 'revised' cardioidal strain transformation method concludes that various regions of human faces have various growth parameters across age, thus we consider anthropometric affirmation gathered on face growth while developing the model.

IV. Proposed Methodology

In this paper, the implementation methodology is focussing on feature extraction and craniofacial growth model. Anthropometric features are extracted under the feature extraction process and craniofacial growth model includes growth of face with respect to age.

Figure 3 displays the flow of the proposed methodology. The first step is to identify the face in the image or face detection. Next, the key facial landmarks on the image are detected and localized. The key facial landmarks are used to find the key facial features which are then used to find the Region of Interest (ROIs). These ROIs are extracted with the help of key facial features. The key facial landmarks are also used for determining the (x,y)-coordinates of landmarks detected on the facial image. The origin point is taken from the detected landmarks and their distances from the origin for analyzing the growth patterns on the face are determined. The distance measurements are increased with increasing age. In future, the distance measurements may be used for implementing growth patterns on the facial images of children.

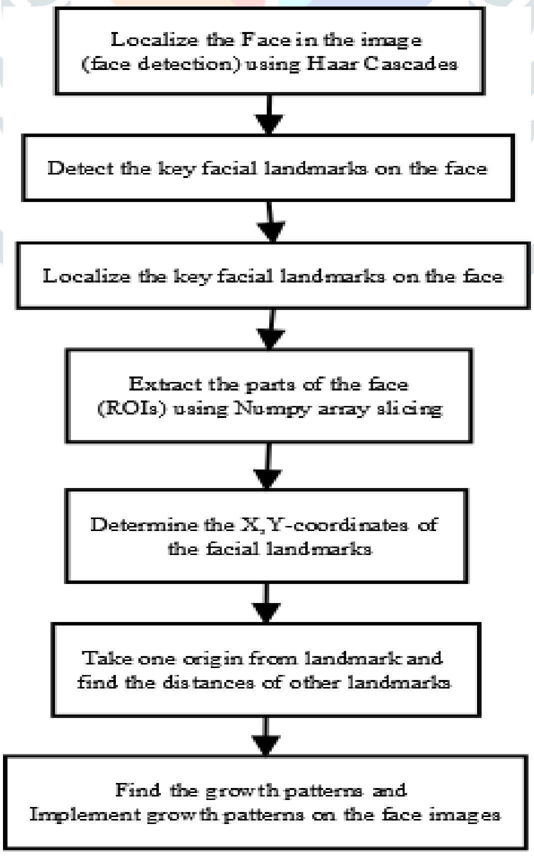

Figure 3. Proposed Methodology

The facial landmark detection is the part of shape prediction problem. The shape prediction methods are used for finding facial structures on the face. The process of finding facial structures includes locating the face in the picture followed by detecting the key facial structures on the face RoI. The important point in the face detection method is that obtaining the face bounding box or the (x,y)-coordinates of the face in the image. There are various facial landmarks detectors but all of these are trying to localize and label seven main RoIs viz. mouth, right eyebrow, left eyebrow, right eye, left eye, nose, and jaw. A training set of labeled facial landmarks on images is used for this implementation. The images are manually labeled, specific (x,y)-coordinates of regions neighboring every face structures are enumerated along with the chances of the distance between pairs of input pixels. To determine facial landmark locations directly from the pixel intensities from the training data, a group of regression trees is trained. The last outcome is the facial landmark detector that can be utilized for the detection of facial landmarks in real-time. The next process is to extract face RoIs and the facial regions can be retrieved with the help of python indexing. Table 3 indicates the relevant feature points to be considered for various facial features.

Table 3. Relevant facial points for facial features

Sr. No.	Facial features	Relevant facial points
1	Mouth	48 to 67
2	Right eyebrow	17 to 21
3	Left eyebrow	22 to 26
4	Right eye	36 to 41
5	Left eye	42 to 47
6	Nose	27 to 35
7	Jaw	0 to 16

V. EXPERIMENTAL RESULTS

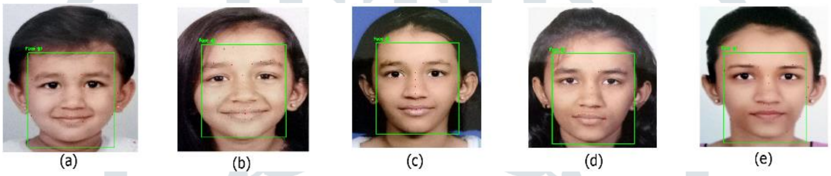

Figure 4. Face Detection and Detection of key Facial landmarks at different ages

Figure 4 displays the outcomes of the face detection. It also shows the detection and localization of key facial landmarks on the facial images. We consider the images of a person from age 1 to 25. Figure 6 illustrates how RoIs would be extracted from the face images and at the left corner of the image, it has written the RoI name which would be extracted from the image.

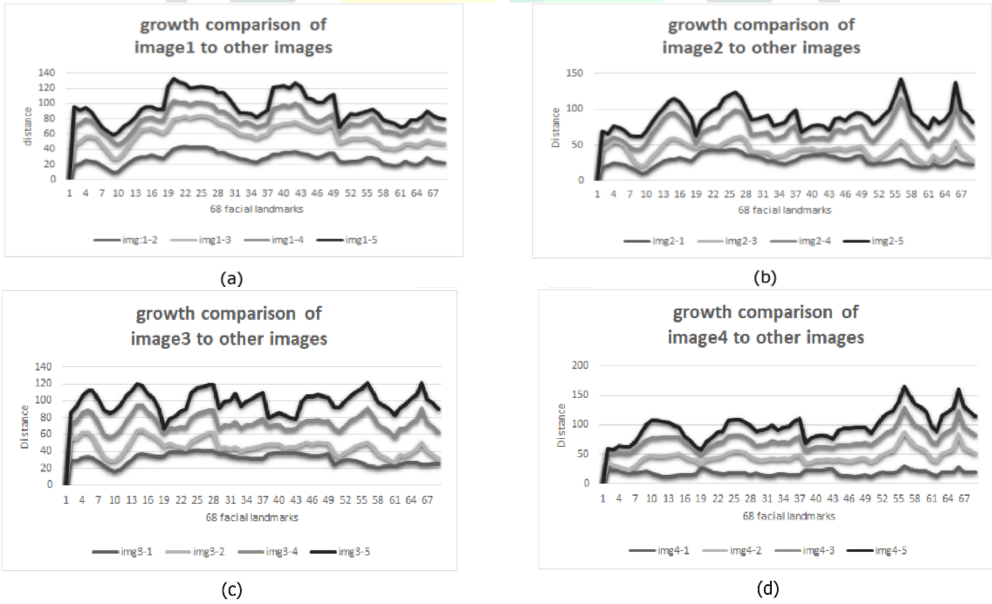

Figure 5. Growth comparison of face images for different ages

The graph 5(a) shows the results of the distances for 68 (x,y)-coordinates of images 4(a) to 4(b), (c), (d), and (e). Also the graph 5(b) shows the results of the distances for 68 (x,y)-coordinates of image 4(b) to 4(a), (c), (d), and (e). From the graph 5(a), when we consider the image 4(a) of age 1 to 5, we can say that the growth will be increased with increase in age. From the graph 5(b), when we consider the image 4(b) of age 6 to 10, we can say that the growth will be increased less with the age increases. The graph 5(c) and 5(d), display the other distance matrix for image 4(c) and 4(d). We would find the growth patterns in accordance with the graph analysis and from the 68 (x,y)-coordinates. The growth patterns would be useful for prediction of the facial image displaying growth over a period of time.

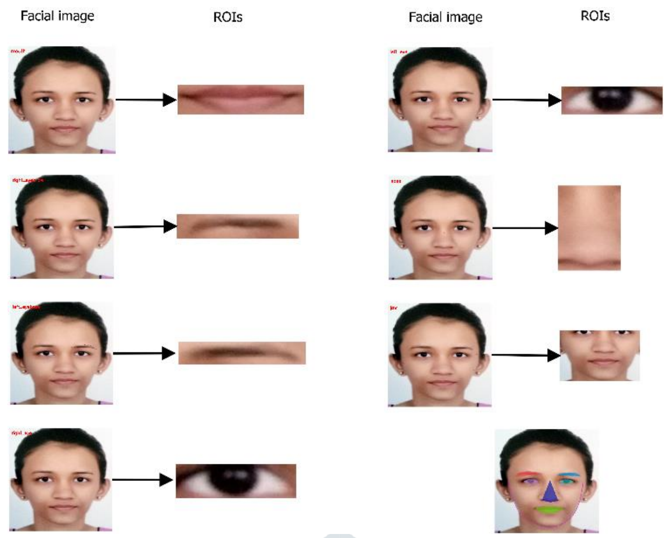

Figure 6. Extraction of RoIs from facial images

VI. CONCLUSIONS

The paper presents different growth patterns observed across age. The facial measurements are different for males and females. Visual and quantitative results are presented to validate implementation methodology for predicting the face. Change in facial appearance is demonstrated in accordance with the face shape and aging effects. In future, the growth patterns will be utilized for implementing the growth of the face on the facial image. Future work includes aging effects like wrinkles on face images. Texture transformation on the face age in the later stage is not considered.

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