Age groups classification based on ratios in facial images

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Abstract

Age classification from human face is a very challenging problem because the appearance of a particular face varies due to changes in pose, expressions, illumination, and other factors such as make-up, occlusions,or image degradations caused by blur and noise etc.This paper explains a method for age groups classification based on the primary face features extraction,then calculate the ratios of the distance between these features to distinguish age groups of the input imageinto one of three groups : baby , young adults or senior adults.

Keywords : Digital Image Processing , Face Image analysis , Age estimation, Age categories , Craniofacial

1. Introduction

Human face includes rich amount of information usable in many interesting applications, one of the most fascinating being automated age classification[1]. Among the first to research age prediction were, Kwon and Vitoria Lobo who proposed amethod to classify input face images into one of the following three age groups: babies, young adults and senior adults [5]. Their study was based on geometric ratios and skin wrinkle analysis. Their method was tested on a database of only 47 high resolution face images containing babies, young and middle aged adults. They reported 100% classification accuracy on these data. Craw, Tock, and Bennett [8] designed a system to locate the features in a face using statistical knowledge to create an ideal template. This system is capable of labeling the hair, the eyes, the mouth, and the nose in a mug shot image.

Khaung and Myint [9] developed an automatic classification of the face aging system of following steps : Face region extraction, noise filtering, resizing image and histogram equalization process are included in enchaining step. Eigen faces for each age group are stored in Database. The minimum different is computed among the input face and mean faces of all age groups for classification age. Finally, in age classification stage, the simulated face is produced by the mean structure of the desire age groups.Ling *et al*. [1] proposed a method based on a combination of local binary pattern (LBP) variants encoding the structure of elongated facial micro-patterns and their strength. The experimental analysis points out the complexity of the age classification problem under uncontrolled settings. The proposed method provides state-of-the-art performance that can be used as a reference for future investigations.

Depending on what side you are, aging may be a threat to youra-lgorithm or an interesting research opportunity. Looking from the face recognition point of view, aging brings confusion to the algorithms. In fact, in order to call a biological measurement qualify to be a biome-tric, it should satisfy the permanence requirement [3]. In this paper our aim is to simulate the ability of human brain to categorize a person's age group from an image of the person's face .An improvement of our understanding of how humans may classify age from visual images, is shed light on studies in craniofacial research .Which is constructed a mathematical model that describes the growth of a person's head from infancy to adulthood [5].Head growth can be visualized as a series of ever grow-ing circles all attached at a common tangent "base point" , with this theory the growth of lower parts [nose ,mouth, and chin] of the face is more pronounced than that the upper part[forehead ,eyes] ,that means with aging the face space will be longer and more extended the eye occupy a higher position in an adult than in an infant. Another cons-equence of this development into adulthood is that, relative to the margins formed by the eyes and the mouth, the position of the nose drops [5]. To distinguish baby face from the two older groups we have compute a set of ratios , these ratios require the automatic localization of primary features [the eyes , nose, mouth , chin and virtual top face] [5]. the input of our system is frontal face images without expressions after preprocessing and feature extraction, in the preprocessing stage the interest in acquire the image and eliminate the addition unwanted details such as backgr-ound, great part of the head and chin, then the face image which contain only the main face features (eyes, nose ,top, chin and mouth) is aligned so the two eyes is located on an imagine horizontal line .

2. Face features and it's ratios

Face recognition across ages is an important problem and has many applications, such as passport photo verification, image retrieval, surve-illance, etc. This is a challenging task because human faces can vary a lot over time in many aspects, including facial texture (e.g. wrin-kles), shape (e.g. weight gain), facial hair, presence of glasses, etc. In addition, the image acquisition conditions and environment often undergo large changes, which can cause non-uniform illumination and scale changes[4]. The aging process affects the structure and appearance of people in different ways. One of such is the change in craniofacial-morphology (CM) of individuals. The subject of a person's CM and age estimation is by itself insuffic-iently researched. Especially on the analysis of children's CM at differ-rent ages ,because it hasn't been considered thoroughly,One of the changes during a persons agingpr-ocess is the change in CM. Differ-entcraniofacialcharacteristics appear at different age and change during the aging process. Analysis of CM can be widely used and has great potential: determining the age of imigrants in situations in which there are no documents that can prove their actual age, for web pages that allow access only for persons above a certainage, for historical photography analysis etc. It can improve face recognition systems (most of face recognition systems are sensitive to changes caused by aging), and can also be used for finding missing people during several years(especially children). Analysis of CM can also improve the human-machine interaction based on age of a person, predict the way a person ages, and facilitate the fight against pedophilia by removing photos of underaged children from theInternet and personal computers[2].In infant years, the body develops very fast and the algorithms focus on changes on skull size and ratios among facial features. In young adults, there's no change in skull size or ratios and wrinkles start to appear. In the senior adulthood, wrinkles mostly determine the age[3]. The skull size can be represented by mathematical model that calculate six ratios of face features (see figure 1)

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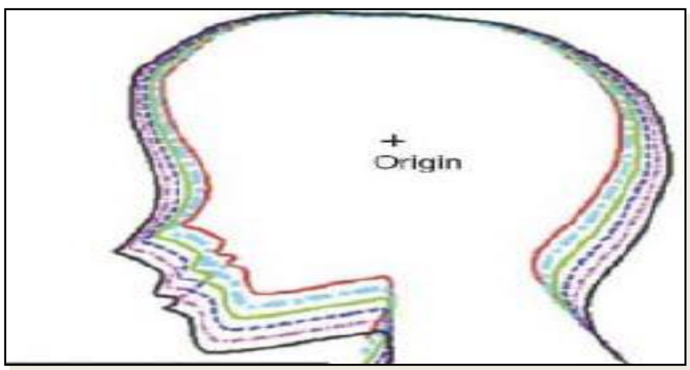

Fig .2 head growth [2]

After statistical analysis of these ratios on different age groups input images the values describe that changes caused by craniofacial growth are: Forehead slopes back, shrinks and releases spaces on the surface of the cranium, Facial features expand their areas and cover the interstitial spaces, Cheeks extend to larger areas, Chin becomes more protrusive, while the growth of human head is represented by two different coordinates.One for the base point and the other is for the growth line of the skull[7].facial angel changes during growth , this angel is defined by the intersection between two lines , one line the Frankfurt horizontal passes through the top of the earhole and the bottom of the eye socket, the other connects the most prominent part of the chin with the deepest part of the depression just above nose [7].(see fig .3)

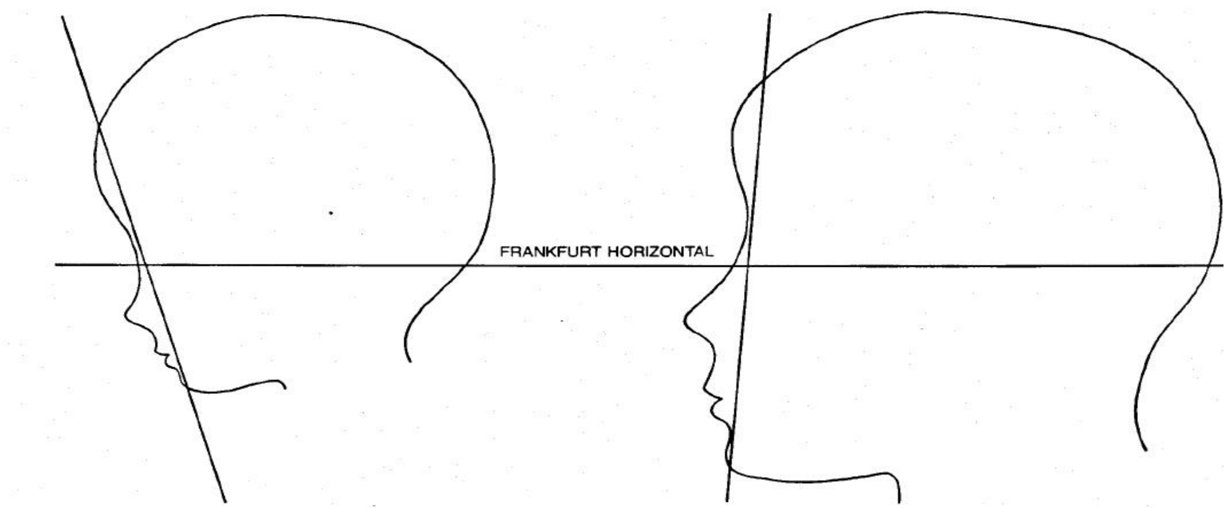

Fig .3 . Facial angel change with head growth

3. Suggested System

A high level description of the steps in the approach are taken in this paper are presented as follow:

Stage 1: Image acquisition

Stage 2: Preprocessing .

Stage 3: Compute facial feature.

Stage 4: Compute ratios .

Stage 5: Classify input image into one of three groups {Baby ,Young ,Senior}

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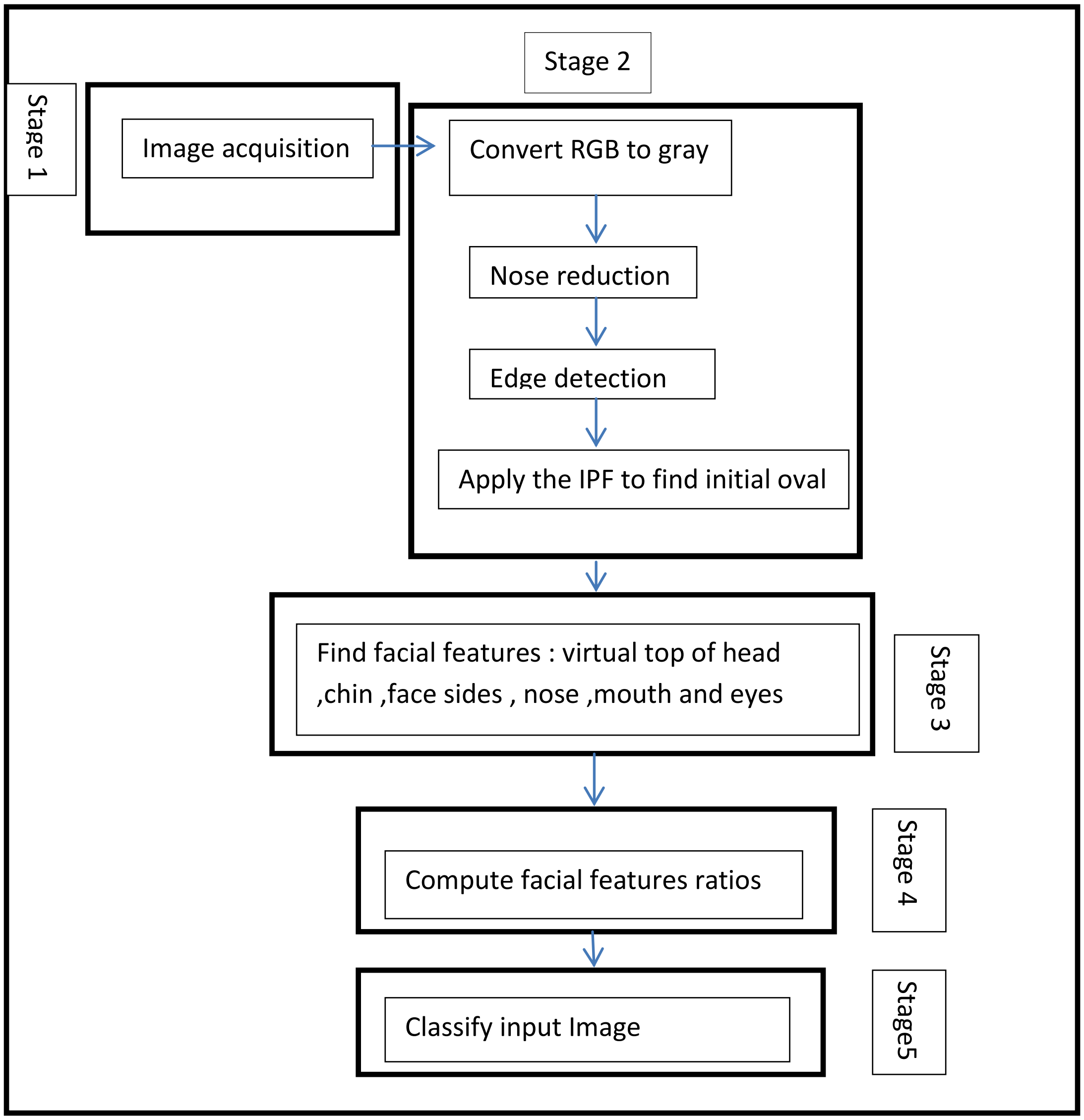
System stages diagram :



3.1 . Image acquisition

The images used here from the FG-NET database [11](Face and Gesture Recognition Research Network) database which has been developed in an attempt to assist researchers who investigate the effects of aging on facial appearance. The database contains 1002 images from 82 different subjects with ages ranging between newborn to 69 years old subjects. There are (180) image intercept for this study that agreeing with system limitative. As a result of our experiments we have found that the available data base represent a great challenge for the face recognition across age progression this challenge come from the vast variations between the images in this data base in addition to the natural variation caused by the aging process , The preprocessing step has great impact on the overall results and by making the images in the same alignment.

3.2 . Converting the RGB image to gray scale image

The RGB images with .jpg path are converted to gray level image with intensity values ranging [0: 255] by using the following equation [10]:

$$Gray = 0.2989 * R + 0.5870 * G + 0.1140 * B$$

Where R, G and B are the color components and Gray is the output gray image.

3.3. Noise reduction

Median filter is a nonlinear filter that applied to the image such that is replaces the value in the center of NxM window by the statistical median of its NxM sorted values [10].

gray-image = medfilt2(gray-image,[33]) .

3.4. Edge detection

In this step we use the canny method for edge detection . The Canny method finds edges by looking for local maxima of the gradient of the input gray image. The gradient is calculated using the derivative of a Gaussian filter. The method uses two thresholds, to detect strong and weak edges, and includes the weak edges in the output only if they are connected to strong edges[10]..

3.5. Apply the integral projection function to find face features

The integral projection function (IPF)[6] used many times, first it is used to detect the face sides by looking in the edge image for a local minimum in both the horizontal and vertical sum projection function , then found initial rough oval , Find chin, Find sides of face,Compute virtual top of head .

3.8. Extract the top face region to find an accurate eye coordinates

The difference integral projection function is used to find the eye coordinate by locating the global maximum in both horizontal and vertical projection for the top face part .

3.9. Extract the bottom face region to find an accurate mouth coordinates

While the vertical mouth coordinate can also obtained from the difference *IVPF* integral vertical projection function , and the horizontal coordinate is the mid of the two eyes horizontal coordinate.

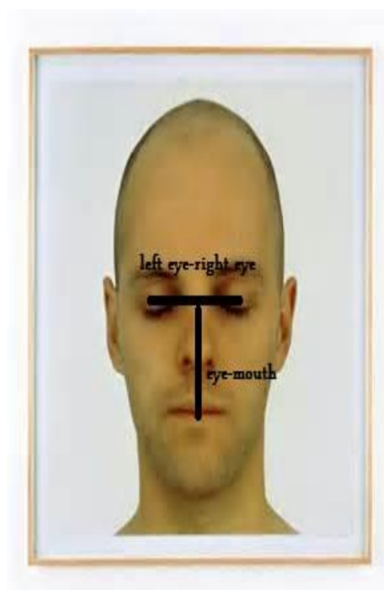
3.10. Extract the nose region to find an accurate nose coordinates

The vertical nose coordinate represented by the first upper value of the bottom face part , and the horizontal nose coordinate is the max value of the difference horizontal integral projection function of the bottom face part .

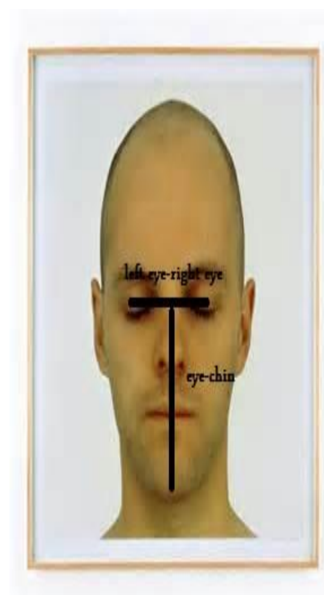
3.11. Compute facial feature ratios

Ratio 1 is the T -ratio formed by two segments: the segment T1 joining the two eyes and the segment T2 between the midpoint of T1 and the nose. Ratio 2 is the T -ratio formed by two segments: the segment T1 as above, and the segment T3 between the midpoint of T1 and the mouth. Ratio 3 is the T -ratio formed by two segments: the segment T1 as above, and the segment T4 between the midpoint of T1 and the chin. Ratio 4 is the ratio of the segment representing the difference in height between nose and eye-midpoint, and the segment representing the difference in height between mouth and eye-midpoint. Ratio 5 is the ratio of the segment representing the difference in height between mouth and eye-midpoint, and the segment representing the difference in height between chin and eye-midpoint. Ratio 6 is the height of the eyes within the top and bottom head-margins.

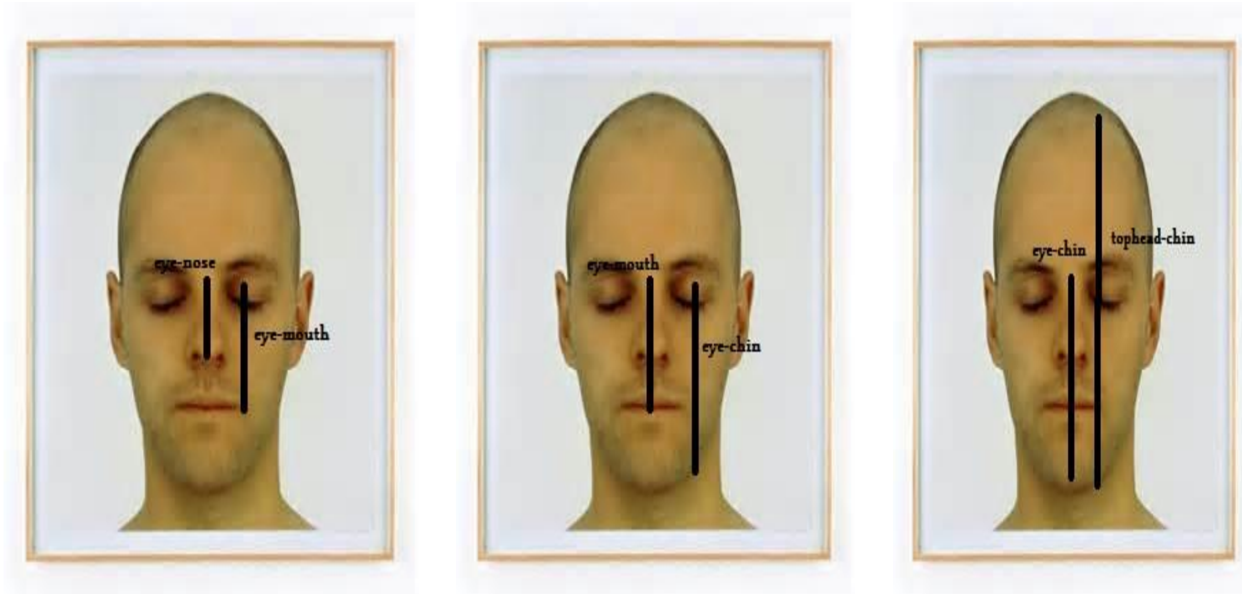
Ratio 1



Ratio 2



Ratio 3



Ratio 4 Ratio 5 Ratio 6

Fig.1.Face features six ratios

3. Results discussion

The computation of these six ratios explain that : The most promising is Ratio 1. This ratio uses features which are not affected by any facial expressions or facial motions. However, it too is subject toimpre-cise localization. If it can be made robust to shading, shadowing, and occlusion effects, it should serve as a good classifier. Ratio 2 appears to be the ratio that can be measured reliably and also shows promise in providing reliable classification. Ratios 3, 4, and 5 are not as promising. In theory, Ratio 6 is the most reliable, but, in practice, suffers from errors in estimating the virtual top of the head. Ratios 1, 2, and 3 will suffer if the face is rotated in depth, and, as such, some measure needs to be adopted to compensate for this rotation, before the ratios are computed. Ratios 4, 5, and6 are more robust to this occurrence see table1, The six ratios

were recomputed after dropping the data evaluated as unfavorable due to facial expression or rotation of the head. The bimodal threshold for each ratio is calculated according toOtsu's method[12] ,from this table ,we note that the babies first ratios have thresholds (r1=1.6 ,r2=0.99 ,r3=0.57 ,r4=0.61 ,r5=0.61 ,r6=0.63) ,while the young group thresholds ratios are(r1=1.27 ,r2=0.93 ,r3=0.57 ,r4=0.75 ,r5=0.62 ,r6=0.61) and the senior group thresholds ratios are(r1=1.61 ,r2=1.19 ,r3=0.68 ,r4=0.95 ,r5=0.64 ,r6=0.65). As we see from the experimental results the performance of the system to distinguishing the baby images from not baby faces is (76%) for baby images and (54%) for another groups (young & senior)

Image no.	Ratio1	Ratio2	Ratio3	Ratio4	Ratio5	Ratio6
Baby1	1.603175	0.990196	0.655844	0.617647	0.662338	0.578947
Baby2	1.603448	0.93	0.570552	0.58	0.613497	0.636719
Baby3	1.987654	1.364407	0.821429	0.686441	0.602041	0.678201
Young1	1.212121	0.923077	0.585366	0.761538	0.634146	0.634675
Young2	1.2941	0.9362	0.5714	0.5789	0.7234	0.6104
Young3	1.273585	0.957447	0.594714	0.751773	0.621145	0.594241
Senior3	1.5263	0.9355	0.6042	0.5979	0.6129	0.6458
Senior4	1.614035	0.958333	0.621622	0.59375	0.648649	0.571429
Senior5	2.489362	1.193878	0.680233	0.479592	0.569767	0.653992

Table 1 the six ratios for three age groups

4. conclusion

This work outlined a computational theory for visual age classification from facial images. For now, only three age-groups were considered: babies, young adults, and senior adults. First, primary features of the face, namely the eyes, nose, mouth, chin, and virtual top of the head, are found. From these, ratios are shown that computing can yield age categorization. These criteria were suggested by cranio-facial research. There are several directions that need to be further explored. The problem of varying orientation of the face needs to addressed. Finally, an accurate estimation of the top of the skull has defied all approaches thus far., this estimate enhances the ability to tell age and, thus, needs to be computed. In all of these endeavors, additional age-related information can be exploited: the growth of the nose and the nose-bridge, and the relative shrinking of the iris-size over time, and changes to the outline of the face

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تصنيف الفئات العمرية باستخدام النسب في صور الوجوه

زينب ابراهيم عثمان – دينا عدنان عباس

جامعة البصرة /كلية العلوم/ قسم علوم الحاسبات

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تشكل مسألة تصنيف عمر الانسان من خلال من صورة الوجه تحديا كبيرا ، بسبب ان خواص مظهر الوجه تتنوع طبقا لوضع الصورة ، تعابير الوجه ، الاضاءة وعوامل اخرى مثل المكياج ، مزاج الانسان او ضعف الصورة بسبب عوامل الضوضاء والتشويه او طبيعة الصورة ... الخ .

يقدم البحث الحالي طريقة لتصنيف المجاميع العمرية بالاعتماد على استخلاص الميزات الاساسية ، ثم حساب نسب المسافات بين هذه الميزات لتميز المجموعة العمرية من الصورة المدخلة الى احد ثلاث مجاميع هي الاطفال، الشباب البالغين والمسنين .