Article

JOURNAL OF UNIVERSITY OF BABYLON

For Pure and Applied Sciences (JUBPAS)

Vol.31; No.3.| 2023

The Effects of Head Pose and Face Roundness on Age Progression in Children Faces

Hazim Abdulameer Fadhil Al-afare

Department of Computer Systems Techniques, Institute of Administration Rusafa, Middle Technical University, hazim8111979@gmail.com, Baghdad, Iraq.

***Corresponding author email:** hazim8111979@gmail.com

; mobile: 07702505122

تأثير شكل الرأس واستدارة الوجه على تقدم العمر في وجوه الأطفال

حازم عبدالامير فاضل العفاري*

قسم تقنيات أنظمة الحاسوب، معهد الإدارة الرصافة، الجامعة التقنية الوسطى، hazim8111979@gmail.com، بغداد، العراق

Accepted:	28/6/2023		Published:	30/9/2023

ABSTRACT

Background: This paper analyzes the geometric changes in human face during childhood to estimate the related age; cranial changes are used as age-progression features within childhood stage (0-12) years. Infant face is close to the circular shape turning to an ellipse shape over age progression face oval is determined and drawn using face landmarks, were it's robust against opening mouth, thinness, fatness or face occlusion by hair.

Materials and Methods: The experiments depending on two types of face dataset. First one is the standard FG-NET dataset, which was provided with face landmark points numbered from 1 to 68 [14, 15]. Besides, an Internet-based collected data set of (3010) face images extracted from Daily Photo Project.

Results: Drawn face ellipse provided set of measures that significantly modeled changes in forehead size and face roundness. Studied age period was between birth and 12 years old. Exaggerated head size at birth provides round face with big forehead, which starts shrinking as age progresses natural face.

Conclusion: Face ellipse provided efficient measures and distances to represent face changes along childhood. Comparing with published researches in young-face age estimation, proposed face ellipse recorded encouraging results.

Key words:

Children Faces, Estimation of Age, Cranial changes, Head Pose, Face Roundness.

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INTRODUCTION

Human face has different types of changes over age progression vary from craniofacial change during childhood [1], texture LBP features for elder ages [2] till topographical changes in old faces [3]. In medical and psychophysical researches, it was stated that children faces have cranial changes in pose shape offering significant features about age progression [4]. Studying age progression on the whole human age interval may lead to biased results, since some face changes have more significant change in some age periods against noticeable stability in other periods [5]. During childhood, craniofacial changes provide considerable age progression signs, which child faces maintain smooth skin with low level of changes in face texture. It's obvious that exaggerated sizes of infant head provide circular face shape, and the next age progression applies rigid changes in face shape providing elliptical shape [6]. Yet such changes have less changes after 12 years old, where texture changes start rising. Thus age progression signs have different forms over different age stages, and using age-related changes gives more accurate anticipations for the specific age. In this paper we'll discuss childhood-related age signs and use them in age estimation of young ages. These signs are in form of obvious age progression signs in the childhood, which are related to face shape and forehead size. They create two types of features outer shape and inner distances between face. Circular shape of infant faces is gradually changing to the oval shape combining by noticeable changes in the inner distance between face components.

The rest of this paper is divided to explain other papers studied related methods to this work in section 2. Section 3 discusses the proposed methodology and studied face dataset, while Section 4 discusses yielded results from conducted experiments. Concluded remarks are explained in Section 5.

RELATED WORKS

Generally, face-image age estimation system handled anticipating human age overall ages [7], where face changes over different stages of face age is different. On the other side, researches that discussed specific-stage age estimation have an obvious lack. On contrary, some authors [8] totally ignored craniofacial change and adopted statistical measurements to simulate face vitality. Their model classified human-age interval in three main age classes, child, adult and senior adult faces, without any illustration of inner changes of each age class. An early-accomplished work for specific-period was accomplished using efficient features related to specific age period (Senior Adults) [3]. As provided features were efficient, in (2020) same features were adopted in different work to represent age-progression signs in senior adult ages [9]. In (2020), other authors improved age estimation of young faces using presented strategy, in which, the eyes were artificially occludedfrom studied faces. The authors adopted Fine-Tuning of Soft Stage-wise Regression Network (SSR-Net models), where occluded and non-occluded images were combined. Such type of occlusion was frequently adopted in Child Sexual Exploitation Materials (CSEM) where victim's identity was required to be hidden [10].instead of specifying age estimation in the related features of each age group, recent works gointed age estimation with other branges of face-based

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pattern recognition fields such as gender recognition researches[11]. In general, more details] about recent works in age estimation was discussed and illustrated in7].

This work discusses childhood-related age progression signs for higher accuracy in children age estimation. It adopts craniofacial change to represent age progression signs, were it enhances such changes by building mathematical model that represent the conversion from circular face (infancy) to the elliptical face (adulthood).

MATERIALS AND METHODS

The general diagram of this scheme is illustrated in Figure 1, where this work is divided into five major steps, image anti-rotation to the vertical position, building the mathematical model of face oval, classifying dataset images using smart classifier, and predicting the age of the studied face. This work studied theoretical changes in human head& face from infancy to late childhood illustrated medical analysis for childhood age progression [12]. The authors stated that newborn's head is exaggerated to make the childbirth easier and the head starts dramatic changes over

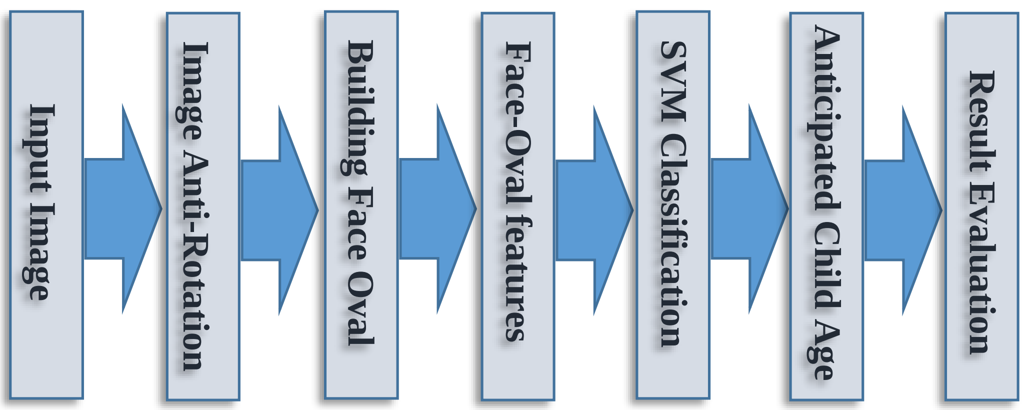

Figure 1: The general diagram of the proposed scheme

childhood aging as in Figure 2. During that, child face preserves high level of smoothness with low level of textural changes [9, 13].

- Dataset

This work built the experiments depending on two types of face dataset. First one is the standard FG-NET dataset, which was provided with face landmark points numbered from 1 to 68 [14, 15], where Active Appearance Model (AAM) was adopted to extract these points. Such standard dataset is supposed to be more suitable for this work due to considerable number of images (761) between (0 to 15) years old, and it was widely adopted in previous age estimation works. Besides, an Internet-based collected data set of (3010) face images extracted from Daily Photo Project. The collection focus was on images explained detailed age progression, which was available for 0 to 15 age period. Support Vector Machine (SVM) is used for features classification.

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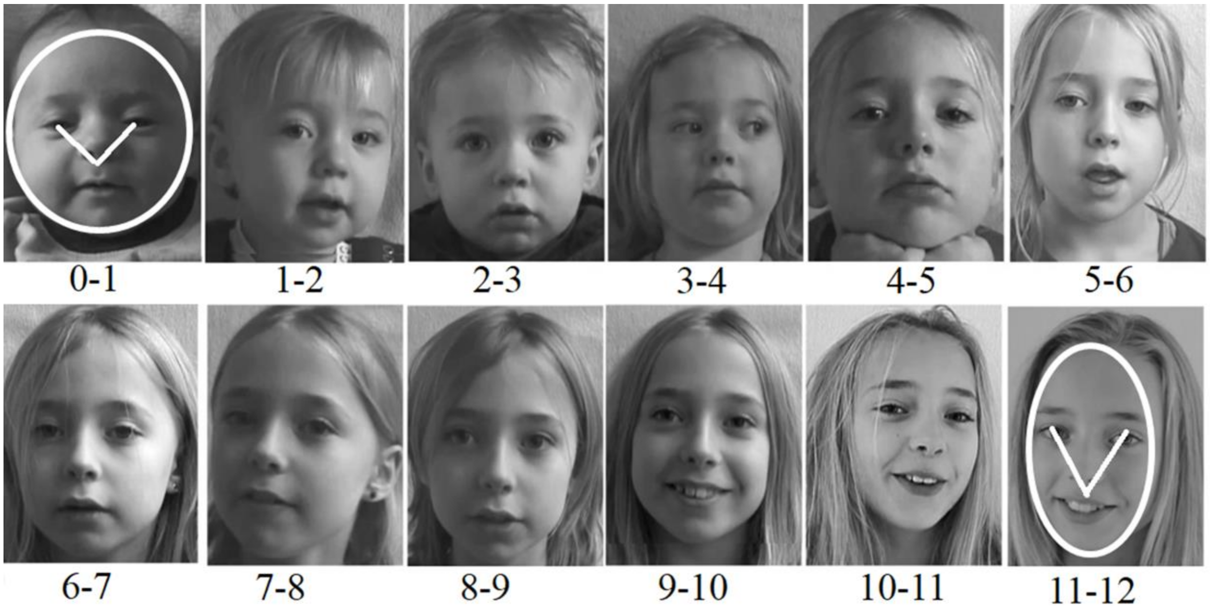

Figure 2: The effects of age progression (years) on geometrical changes in face shape and the distances between face components

- Circular and Elliptical Face

The most obvious age-effects over childhood progression are related to the cranial changes, where forehead size and face have obvious conversion with skin-texture stableness as in Figure3. Rigid changes in forehead size lead to noticeable changes in face roundness, which can be mathematically simulated by circle to ellipse conversion. Significant changes were obvious in face shape and forehead size besides distances between face components, which leads the focus to the implementation of face ellipse; it can provide significant measures about outer shape and inner distances between face components.

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(a) Infant (b) 13 years old

Figure 3: Obvious changes in face roundness over childhood

Face oval was adopted in previous works [16], yet the face oval was detected using edge detection algorithms. Such oval can be affected by different challenges such as fatness, hair style and opening mouth, illustrated in Figure 4. To avoid this, this work proposes adopting face land marks to build a mathematical model for face oval, which can be robust against aforementioned challenges. Such model is utilized over two steps, first one is to select the most suitable points to draw face oval using mathematical model for ellipse, and the second one is to study outer and inner changes of the face depending on ellipse computations.

1. Fatness 2. Thinness 3. Opening Mouth 4. Hair Style

Figure 4: Face challenges against determining the mathematical model of face ellipse

FGNet dataset is provided with set of face landmarks numbered from 0 to 68 [17]. Among some of them were selected to build a robust face oval against aforementioned challenges in addition to other challenges like rotation and illumination. Among them, four points were chosen, where two of them were adopted to restore rotated faces into optimal case (vertical situation) [18]. The other two points were used to derive and build mathematical equation for face ellipse [19].

Similarly, to edge detection methods, using some landmarks, the provided ellipse may be affected by same challenges, where cheek landmarks can be affected by fatness and thinness. Forehead landmarks can be affected by hair style and chin landmarks are affected by opening mouth. Thus, robust ellipse, against challenges [20], can be determined depending on four spatial points r_1 (0), r_2 (15), e_1 (38) and e_2 (60) over two stages as in Figure 5-a. Firstly, r_1 and r_2 are used for anti-rotation as in Figure 5-b& c. Then secondly, e1 (x_1, y_1) and e2 (x_2, y_1) are used to find the mathematical equation of face ellipse Figure 5-d.

General form of mathematical ellipse can be found depending on a, b and c values [19] where:

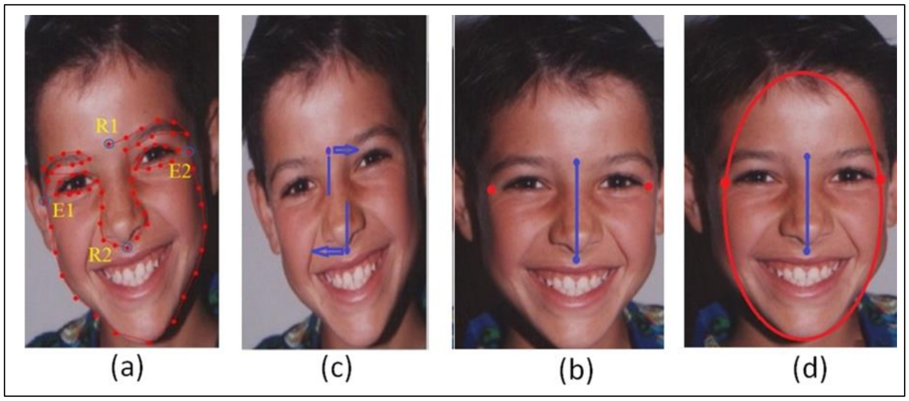

Figure 5: Illustrates

(a) Candidate face landmarks **(b) Choosing R1 and R2 for anti-rotation**

(c) Anti-rotated face and **(d) Using E1 and E2 for face ellipse**

$$\frac{x^2}{a^2}+\frac{y^2}{b^2}=1 \dots\dots\dots\dots\dots\dots (1)$$

Where a& b are the major and minor diameters in the ellipse respectively

$$c^2=b^2-a^2 \dots\dots\dots\dots\dots\dots (2)$$

Ellipse foci are (0, c) and (0, -c)

Applying the point e1 to Equation 1 results:

$$\frac{x_1^2}{a^2}+\frac{y_1^2}{b^2}=1 \dots\dots\dots\dots\dots\dots (3)$$

$$\frac{x_1^2}{a^2}=1-\frac{y_1^2}{b^2} \dots\dots\dots\dots\dots\dots (4)$$

$$\frac{x_1^2}{a^2}=\frac{b^2-y_1^2}{b^2} \dots\dots\dots\dots\dots\dots (5)$$

$$a^2=\frac{x_1^2 * b^2}{b^2-y_1^2} \dots\dots\dots\dots\dots\dots (6)$$

Similarly, applying e2 to Equation 1 results:

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$$\frac{x_2^2}{a^2} + \frac{y_2^2}{b^2} = 1 \ldots\ldots\ldots\ldots\ldots\ldots (7)$$

Applying Equation 6 in Equation 7 results

$$\frac{x_2^2 * (b^2 - y_1^2)}{x_1^2 * b^2} + \frac{y_2^2}{b^2} = 1 \ldots\ldots\ldots\ldots\ldots (8)$$

And by solving this equation, the result is:

$$b^2 = \left(\frac{x_1^2 - x_2^2}{x_1^2 * y_2^2 - x_2^2 * y_1^2}\right) \ldots\ldots\ldots\ldots\ldots\ldots (9)$$

Applying the results, of Equations 9 and 6 in Equation 1, provides necessary values for ellipse measures. In addition to the essential points used to build face ellipse, set of points can be extracted from drawn ellipse, and distances between these points can represent face features. Accurately determined ellipse provides major vertices (JX1 and JX2), minor vertices (NX1 and NX2) and ellipse foci (F1 and F2), see Figure 6. Distances between such points provide considerable set of features.

- Ellipse Measurements

Exaggerated head size of newborns and the successive shrinking cause significant changes in forehead size, face roundness and distances between face components [15]. Precisely drawn ellipse provides considerable measurements representing such changes, which can be provided depending on three types of points illustrated in Figure 6. There are *Essential Points*, which are essentially extracted point for the image (e_1, e_2, r_1 and r_2). Then the *Standard Points* Provided points by standard ellipse like vertices (JX1& JX2), co-vertices (NX1& NX2) and foci (F1& F2). Finally, *Extra Points* allocated points on the ellipse horizontally with essential and standard points. As example, there are JF1 & JF2 allocated on the ellipse horizontally to upper focus F1, and horizontally with r_2, there are R21& R22 … etc.

Distances between these points and the upper vertex, which are expected to be affected by face-camera capturing distance, provided considerable measures about ellipse attributes. To handle differences in capturing distance and to normalize extracted measures by the related ellipse, this work adopts ratios instead of raw measures. Due to the longitudinal growth of human face [21], each extracted distance from ellipse is divided by the vertical ellipse diameter. In other words, differences in shape measures are weighted by differences in vertical height of the face ellipse:

$$\nabla f = \frac{\nabla m}{a} \ldots\ldots\ldots (10)$$

Where: ∇f is the normalized feature, ∇m is the extracted measure and a is the main diameter of the drawn ellipse.

$$\nabla f = \frac{\nabla m}{\lVert JX1, JX2 \rVert} \ldots\ldots\ldots (11)$$

Where: $\lVert JX1, JX2 \rVert$ is the Euclidian distance between vertical vertices JX1& JX2.

Distances for ∇m are classified into two types to handle forehead size and face roundness. Firstly, distances Like $\lVert JX1, R1 \rVert$, $\lVert JX1, JF1 \rVert$, $\lVert JX1, JF2 \rVert$, $\lVert JX1, RE1 \rVert$, $\lVert JX1, RE2 \rVert$, $\lVert$JX1,

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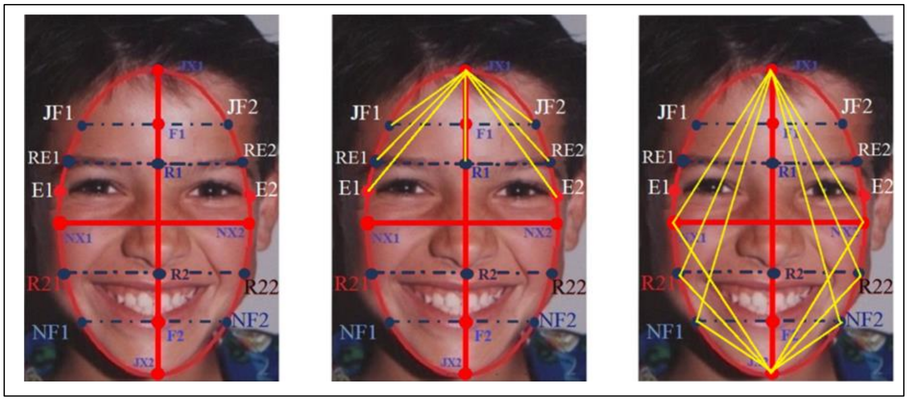

Figure 6: Illustrates

(a) Ellipse Points (b) Forehead Distances (c) Face Roundness Distances

E1‖ and ‖JX1, E2‖ normalized by the main diameter or the vertical height (a) provide considerable information about forehead size. On the other side, distances like‖JX1, NX1‖, JX1, NX2‖,‖ JX1, R21‖, ‖JX1, R22‖, ‖ JX1, NF1‖, ‖JX1, NF2‖, ‖JX2, NX1‖, JX2, NX2‖,‖ JX2, R21‖, ‖JX2, R22‖, ‖ JX2, NF1‖, ‖JX2, NF2‖represent measures about face roundness, where they are also normalized by the same vertical height. In addition, there other types of measures that can represent forehead size such as forehead area normalized by ellipse area as:

$$\nabla A = \frac{\nabla FA}{EA} \dots \dots \dots (12)$$

Where ∇A: represents area ration, ∇FA represents forehead area and *EA* represents ellipse area. Forehead area computed in this work using the number of pixels within forehead area, and ellipse area is computed as:

$$EA = \pi \times a \times b \dots \dots \dots (13)$$

Other measures can represent face roundness such as horizontal lines between ellipse points normalized by minor ellipse diameter (b or ‖ NX1, NX2‖) like ‖JXF1, JF2‖, RE1, RE2‖,‖ E1, E2‖, ‖R21, R22‖, ‖ NF1, NF2‖.

As a summary, aforementioned measures and ratios provide considerable description for forehead size and face roundness to detect their changes over age progression.

RESULTS AND DISCUSSION

This work adopts extracted face landmarks using AAM [14], which adopted the same extracted landmarks with some differences. Our work adopted these land marks for building face ellipse, from which, the adopted features are then extracted. And these features depend on ellipse measures which were not adopted by their work. [14] Luu, K., et al (2009) authors [14] used AAM extracted feature themselves in the classification process. Finally, they adopted these features for all of child, adult and senior adult ages.

In this work, experiments were performed and trained using two types face datasets, standard (FG-Net) [22] and private (Internet-based collection) images from daily photo project [23]. Face

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measures were trained and classified using standard SVM classifier. Classification Accuracy (CA) and Mean Absolute Error (MAE) are adopted in this work to evaluate results accuracy.

Within younger ages and due to exaggerated head size, face roundness features less error rate in age estimation than extracted measures from forehead size. In such ages, shrinking in the head size has more significant changes against lower changes in forehead size. As age progresses, face roundness records less significance against increments in the significance of fore head size. Table 1 illustrates MAE results, where face roundness recorded the higher accuracy (lower MAE) in younger ages increasing as age progresses. On the contrary, forehead size recorded higher error rates in younger ages against better accuracy after the 4^{th} years old. It's also noticed from MAE results that, as general performance, forehead size yielded better performance

Table 1. Results Accuracy for forehead size and face roundness features in childhood

Face Ages	Face Roundness	Forehead Size	MAE Average
0-1	*2.829*	*4.462*	*3.646*
2-3	*3.966*	*4.077*	*4.022*
4-5	*4.261*	*3.669*	*3.965*
6-7	*5.124*	*3.746*	*4.435*
8-9	*5.608*	*3.523*	*4.566*
10-11	*5.370*	*3.382*	*4.376*
Feature Average	*4.526*	*3.810*	

Table 1 shows that, in early years, face roundness records higher performance than forehead roundness which record outperforms face roundness in elder years. Different types of measures, provided by mathematical model of face ellipse, recorded different levels of performance.

Table 2 provides brief description about recorded performance by different types of feature. Distances from upper major vertex JX1 recorded the best performance. among other types, where it obviously provides considerable distances that measure forehead size and face roundness. Distances from other major vertex JX2 yielded lower performance where it recorded higher error rates. In some images, it was affected by opening mouth challenge. On the other side, measuring forehead size form this point may contain information about areas outside the forehead also. Horizontal distances recorded higher error rates, which can be justified by two reasons. First one is that they are normalized by the minor diameter while normal growth of human face is longitudinal which may provide biased referencing about face growth. Second reason relate to the forehead size lines, where they are normalized by the minor diameter outside the forehead area. The last one is calculating the forehead size depending on the number of pixels inside forehead size normalized by the ellipse area, which recorded better performance than horizontal distances. Yet, over all of dataset image, its performance was instable with non-reasonable behavior.

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Table 2. Feature performance of different types of measures in face ellipse normalized by reference one.

Face Ages	NX1 Distances	NX2 Distances	Horizontal Distances	Forehead pixel size
0-1	*2.061*	*2.724*	*3.186*	*4.528*
2-3	*2.771*	*3.392*	*4.013*	*5.267*
4-5	*3.128*	*3.343*	*3.459*	*2.898*
6-7	*3.552*	*3.759*	*3.865*	*4.812*
8-9	*3.902*	*4.092*	*4.021*	*1.488*
10-11	*3.971*	*4.214*	*4.513*	*3.674*
Feature Average	*3.131*	*3.587*	*3.843*	*3.778*

Overall proposed features recorded significant accuracy in classification results, where most misclassified items among dataset images were estimated within real age ±2 years range See Table 3 which explains CA values for correctly classified and misclassification for all studied images. It indicates that even misclassified ages are distributed around real ones. CA value is computed by divided correctly classified on all images × 100%.

Results accuracy was influenced by images quality from standard dataset recording 4.39, where some of them were distorted. For private dataset image, most of them of high quality, results recorded 2.23 for MAE value. At the same time depending on high-quality images only, proposed features yielded 3.12 for MAE value in average.

Table 3. the confusion matrix of real and estimated ages in2-year age classes

		Estimated Ages			
		1-3	**4-6**	**7-9**	**10-12**
Real Ages	**1-3**	*94.17*	*3.13*	*1.54*	*1.16*
	4-6	*1.58*	*93.65*	*2.07*	*2.7*
	7-9	*1.04*	*2.58*	*93.53*	*2.85*
	10-12	*3.21*	*0.64*	*2.86*	*93.29*

It's obvious from Table 3 that 98% of ages, in average are estimated in the real age class or in the next adjacent one. By depending on high-quality images from standard and private datasets and removing distorted dataset images, proposed ellipse measures yielded higher classification accuracy. Classified images yielded highly consistent results, see Table 4.

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Table 4. The confusion matrix of real and estimated ages adopted only high-quality images

		Estimated Ages			
		1-3	**4-6**	**7-9**	**10-12**
Real Ages	**1-3**	*96.12*	*2.12*	*1.53*	*0.23*
	4-6	*2.05*	*95.04*	*1.42*	*1.49*
	7-9	*0.14*	*1.12*	*94.85*	*2.89*
	10-12	*1.69*	*1.72*	*2.2*	*94.39*

Despite the considerable results, Figure 7 explains that proposed features recorded highly significant changes within the first few months decreasing as age progresses over childhood. For benchmarking, experimental results of this work were compared with other published works in children and young faces. Due to the lack of publications, we benchmarked our results with old and new works in young faces. Experimental results overcame Gabor filtering combined with Local Binary Pattern (LBP) [24], combining LBP with different versions of K-Nearest Neighbors (KNN) [25] and Deep Learning algorithm (Soft Stagewise Regression Network (SSR-Net)). See table 5.

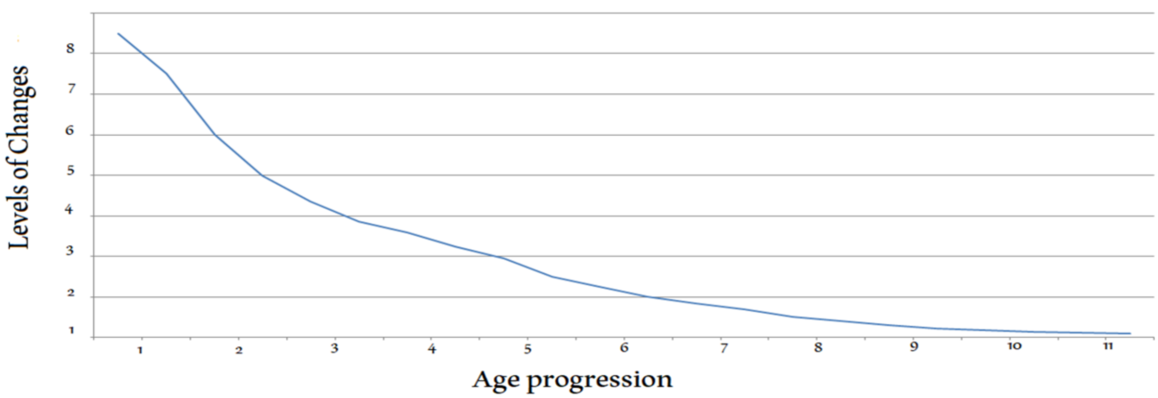

Figure 7: Illustrates the levels of changes over age progression

CONCLUSIONS AND FUTURE WORKS

The signs of age progression differ from an age period to another, and focusing on these changes in regarding its related period enhances the estimation accuracy of the age period. Child faces ensure high levels of face vitality and skin smoothness versus against significant changes in geometric attributes (head pose and face roundness) in the human face. This paper analyzes the geometric signs of age progression in children faces due to their changes and ignores the texture feature regarding its high level of stability. Infant exaggerated heads produce round faces moving to oval shapes (ellipse shape) over age progression. Building the mathematical model face oval is more accurate than using edge detection due to the challenges of face roundness, opening mouth, fatness, thinness and hair style. Adopting landmarks points provided for human face builds an efficient face ellipse since it's robust against face challenges, and from such ellipse, many measurements and distances can be determined to represent craniofacial changes regarding forehead size and face roundness. AAM was adopted to extract these landmarks points provided

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with standard FG-NET dataset. Since child face has a longitudinal growth, ellipse measures are normalized by vertical face height (vertical ellipse diameter). Adopted features from face ellipse are proved to provide robustness against illumination and rotation.

Experiments of this work were built adopting two types of face dataset. First one is the standard FG-NET dataset, which contains considerable number of images (761) between (0 to 15) years old that was widely adopted in previous age estimation works. The second dataset was collected from an Internet-based downloaded dataset contains (3010) face images extracted from Daily Photo Project. The major concentration of collecting procedure was on images that explain detailed age progression within (0- 15) age period. Rotated faces are anti-rotated to the optimal vertical position before extracting face features. The standard smart classifier (SVM) is used for training and classifying dataset images. Experimental results yielded superior performance regarding state of art in term of classification accuracy ratio and error rate Mean squared errors MAE). Such results overcame Gabor filtering combined with Local Binary Pattern (LBP) [24], combining LBP with different versions of K-Nearest Neighbors (KNN) [25] and Deep Learning algorithm (Soft Stagewise Regression Network (SSR-Net)).

Table 5. Results of the method used and other methods

Estimation Algorithm	Gabor filtering& LBP	KNN& LBP	SSR-Net	Proposed Face Ellipse
MAE	*6.35*	*4.97*	*4.07*	***3.12***

Acknowledgments:

We thank the Computer System Technic Department, Institute of Administration Rusafa, Middle Technical University, Baghdad-Iraq, and Thanks a lot with our project. I'd like to express my gratitude to the anonymous reviewers and editor for their insightful remarks and evaluations.

Conflict of interests.

There are non-conflicts of interest.

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الخلاصة

مقدمة: تحلل هذه الورقة التغيرات الهندسية في وجه الإنسان أثناء الطفولة لتقدير العمر ذي الصلة. تستخدم التغيرات القحفية كسمات تقدم العمر في مرحلة الطفولة (0–12) سنة. وجه الرضيع قريب من الشكل الدائري يتحول إلى شكل بيضاوي مع تقدم العمر يتم تحديد الوجه البيضاوي ورسمه باستخدام معالم الوجه ، إذا كان قويا ضد فتح الفم أو النحافة أو السمنة أو انسداد الوجه بالشعر.

طرق العمل: قام هذا العمل بالاعتماد على نوعين من مجموعة بيانات الوجه. الأول هو مجموعة بيانات FG-NET القياسية ، التي تم تزويدها بنقاط معلم الوجه المرقمة من 1 إلى 68 [14 ، 15]. إلى جانب ذلك ، تم جمع مجموعة بيانات على الإنترنت من (3010) صورة وجه مستخرجة من مشروع الصور اليومية.

الاستنتاجات: قدم القطع الناقص للوجه المرسومة مجموعة من التدابير التي نمذجت بشكل كبير التغيرات في حجم الجبهة واستدارة الوجه. كانت فترة العمر المدروسة بين الولادة و 12 سنة. يوفر حجم الرأس المبالغ فيه عند الولادة وجها مستديرا بجبهة كبيرة ، والتي تبدأ في الانكماش مع تقدم العمر الوجه الطبيعي.

النتائج: قدم القطع الناقص للوجه مقاييس ومسافات فعالة لتمثيل تغيرات الوجه على طول مرحلة الطفولة. بالمقارنة مع الأبحاث المنشورة في تقدير عمر الوجه الشاب ، سجل القطع الناقص المقترح للوجه دقة نتائج مشجعة.

الكلمات المفتاحية:

وجوه الاطفال، تقدير العمر ، تغيرات الجمجمة، شكل الرأس، استداره الوجه.