Available Online at www.ijcsmc.com

International Journal of Computer Science and Mobile Computing

A Monthly Journal of Computer Science and Information Technology

ISSN 2320–088X

IJCSMC, Vol. 4, Issue. 7, July 2015, pg.575 – 580

RESEARCH ARTICLE

Geometrical Age Effects on Child Face for Age Estimation

Ghalib A. Salman Salih [*1, 2], and Ghazali Sulong [1]

1 Universiti Teknologi Malaysia, Media and Game Centre Of Excellence (Magicx), Faculty of Computing, Skudai, Johor, 81310 Malaysia

2 Ministry of Science and Technology, Directory of Information Technologies, Baghdad-Jadirya, Iraq

ghlbethawi@yahoo.com, ghazali@utmspace.edu.my

Abstract— This work studies age estimation in children faces; cranial features are used to represent age effects on child face (0-12) years. Determined face oval is built depending on two points that are not affected by weakness such as fatness, opening mouth, and hair style; these two points are chosen from provided landmarks with standard FG-NET face dataset and same points are chosen from corresponding locations of private dataset faces. Depending on the points provided, many distances are computed to represent cranial face changes on face roundness and forehead size. To avoid scaling effects, ratios between these distances will be the candidate features; since facial growth is longitudinal, each distance is divided by the vertical height of the face provided by ellipse points. Proposed features are also proved to be robust against rotation and illumination; they are evaluated depending on classification accuracy and Mean squared errors MAE.

Keywords— child ages, age estimation, face roundness features, craniofacial features, age features

I. INTRODUCTION

Age estimation researches had increasing focus recently; such focus relates the real needs. An age of running away criminal should be determined, under age kids should be prevented restricted while accessing adult web pages or goods like cigarettes or wines; sometimes an age of unknown dead victim with missing ID may be required. One of the most well-known biometric is the human face since it contains significant information about human age, gender, identity, ethnic and race [1]. Psychophysical and medical researches on human faces showed that facial changes in human appearance offer significant information about human age progression [2].

Age progression signs differ from age to age; therefore, many researchers studied age estimation regarding specific age effects, such as young faces [3] and senior adult faces [4, 5]. Studying the whole age interval yielded biased results, which are more suitable for specific age period than the other [5]; although their results was encouraging according to the stat of art at that time, (58%) of correctly classified ages were under 20 years old. Age progression effects in childhood faces can be noticed in the form of craniofacial changes; child face preserves smooth skin providing minimum texture changes from infant to 12 years old. In these ages, big heads of newborns are shrinking and producing noticeable features in head pose [6, 7].

II. RELATED WORKS

One of the earliest works in age estimation was done in 1994 [8]; the authors proposed classifying the age into three classes baby, young adult, and senior adult. They considered that geometrics features from craniofacial changes represent the age progression in the childhood; they represented age effects in the form of changes in distances between face components. Yet, such changes provided significant results according to the state of art at the time; the average of their results was 67.6% in childhood. Ramanathan and Chellappa [9] studied age progression in young faces using face landmarks as geometric features; they avoided forehead features. In order not to ignore texture features, they compensated it with image transformation features to support geometric features; ac-cording to their discussion, the results had lack of textural representation. Ebner, [10] studied young and adult age groups representing human faces using qualities measurements; attractiveness, likeability, distinctiveness, goal orientation, energy and mood at-tributes were used as basis for studying age groups. Localized statistical measurements were used to represent face vitality which was used to distinguish between child, adult and senior adult faces. Face vitality represented valuable feature to classify human age into these three age groups without detailed age classification for any of them [11].

III.METHODOLOGY

As the head of newborns is in exaggerated size and start rigid shrinking in childhood ages, dramatic changes in face roundness and forehead size can be extracted from efficient face oval.

A. Face Oval

In childhood, most obvious age effects relate to the cranial changes where shape and size of the head and the face are changing without significant changes in skin texture. As the significant changes in the outer shape, such changes affect the face roundness and forehead size more than locations and distances between the internal components of the face; see Fig 1, which shows the changes in face oval and forehead size as the face ages. Since craniofacial changes are more significant in representing age progression in childhood, they were used by [8] for classifying faces into child and non-child before using texture changes to reclassify non-child into more detailed classification. Although they already used face oval, their work had some weakness points that should be avoided to improve age estimation accuracy.

(a) Infant (b) 13 years old

Fig1: Face roundness decreases as the person ages

Determined oval in their work depended on edge detection and such oval is affected by affecting situations like fatness, opening mouth, and hair style; at the same time, they considered faces in optimal vertical situation without considering unexpected face directions in childes photos. Their features are related to internal face components rather than face roundness which has more changes; on the other hand, they ignored forehead size in spite of its significant changes, see Fig 2. Although their results are humble, they can be considered encouraging since they were the earliest work in age estimation.

(a) Fat (b) Thin (c) Opening Mouth (d) Covered Forehead

Fig2: different cases of faces in the studied dataset

This work proposes a new technique for studying face oval; firstly it uses more accurate technique to determine the oval depending on ellipse model; to build the ellipse two robust points are used to avoid the affecting situations. Secondly, it studies face roundness and forehead size since they are the most affected features by the changing of head size and shape.

This work proposes a new technique for studying face oval; firstly it uses more accurate technique to determine the oval depending on ellipse model; to build the ellipse two robust points are used to avoid the affecting situations. Secondly, it studies face roundness and forehead size since they are the most affected features by the changing of head size and shape.

The roundness of the face oval provides information about face aging and it can be rep-resented using an ellipse; proper ellipse can be created depending on two spatial points [12]; these points can be selected from face landmarks. Choosing the suitable land marks is a significant issue, since drawn ellipse using some landmarks can be affected by affecting situations; such as landmarks in cheek area can be affected by the fatness of the person, which can give wider ellipse. In the case of opining mouth, chin landmarks produce confusing information about face height. Different styles of hair cause unreal top point of the forehead and face oval.

Another significant feature is the forehead size, during the infancy, the cranium is exaggerated which causes diminutive face with large forehead [7]; over age progression, forehead starts shrinking and providing significant information about the age. Forehead information can be also extracted from determined ellipse

B. Ellipse Measurements

FG-NET standard dataset provides face images represented using 68 landmark points [13, 14], these points are extracted using Active Appearance Model (AAM); from these points, E1, E2, R1, and R2 are chosen in order to determine efficient ellipse, see Fig 3. E1 and E2 points are used to determine the equation and draw face ellipse. To avoid the effects of rotation and unexpected direction of faces, R1 and R2 points are used to register the face to the vertical position since these two points should be on bilaterally symmetrical line in the human face; in the reference position, both of them should be on the same vertical line [15].

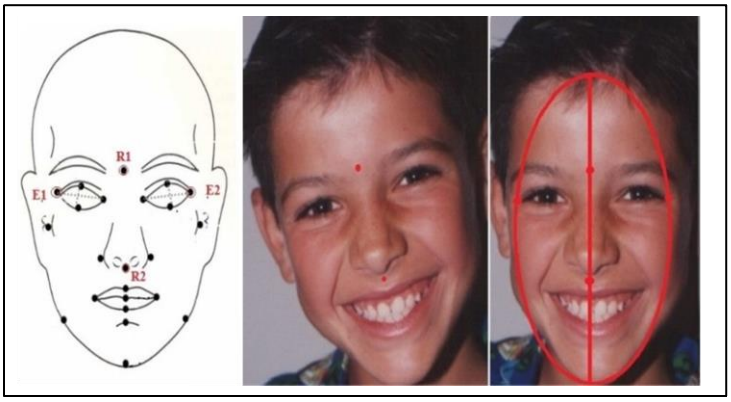

Fig 3: Face landmarks is used for face anti-rotating and ellipse drawing

Correctly determined ellipse provides set of measurements that represent changes in face roundness and forehead size; such measurements are extracted depending on set of points provided by standard form of ellipse such as vertices of major axis (JX1 and JX2), minor axis (NX1 and NX2) and foci (F1 and F2), in addition to E1, E3, R1 and R2 points which are essentially used in determining the ellipse. Because of different capturing distances in each photo, points and distances between them may provide different values for the same feature; therefore, ratios between distances are used instead of point or ordinary distances between them.

$\nabla S=\nabla D/\nabla D1$

Where: ∇S represents shape changes (face roundness and forehead size)

∇D represents changes in ellipse distances

$\nabla D1$ represents changes in weighted distance

Since general growing in human face is longitudinal growth [16], changing in the shape ∇S can be weighted by the changing in the vertical axis ∇V of the face ellipse.

$\nabla S=\nabla D/\nabla V$

$\nabla S=\nabla D/(\|JX1,JX2\|)$

Where: $\|JX1, JX2\|$ represents the Euclidian distance between the point JX1, JX2

Distances for ∇D can be divided into two types; first one deals with distances such as ($\|NX1, NX2\|$, $\|JX2, NX2\|$, $\|JX2, NX1\|$ ⋯ etc.), these distances illustrate the changes in the area of minor axis of the ellipse and measure its roundness. Second type deals with distances such as ($\|JX1, R1\|$, $\|F1, E2\|$, $\|JX1, E1\|$ ⋯ etc.), these distances illustrate the changes in the upper part of the ellipse and measure the size of forehead. Fig 4 represents face points that can be determined depending on the face ellipse; distance between these points provided 29 different features representing face roundness and forehead size. Another measurement that represents forehead size is the ratio be-tween the forehead area and the whole ellipse area; forehead area can be simply represented by the pixels inside the ellipse and upper than R1.

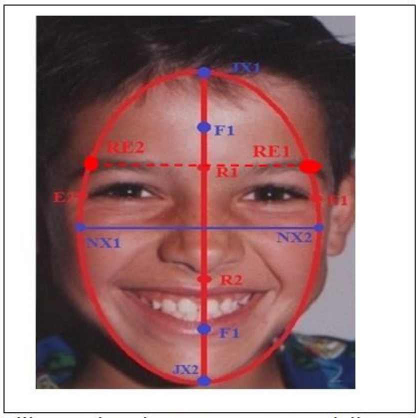

Fig 4. Ellipse points that present proposed distances

IV. RESULTS AND DISCUSSION

Experiments of this paper were done on two types of dataset; firstly, standard FG-NET dataset [20]; it contains 761 of 1002 images that belong to less than 18 years old persons. Secondly, private collected dataset for faces within stable period of time (daily, monthly and yearly); total number of image in private dataset is 987 images. Support Vector Machine (SVM) is used for features classification.

Face roundness features were more efficient in discrimination within younger ages than forehead size features; in this period of age, the most significant changes are the shrinking of head size. On the other hand, changes in the locations of face components and the distances between them are semi stable. Face components start changing within ages between (6-12) years; as a result, forehead size features have more changes and yielded better results. Table 1 summarizes the efficiency of each type of features.

TABLE I

MAE RESULTS FOR PROPOSED FEATURES ACROSS YOUNG AGES

Age Periods	Face Roundness	Forehead Size	Average
0- 1	2.83	4.46	3.645
2- 3	3.97	4.08	4.025
4- 5	4.26	3.67	3.965
6- 7	5.12	3.75	4.435
8- 9	5.37	3.52	4.445
10- 12	5.61	3.38	4.495
Average	4.53	3.81	

Proposed features yielded significant results in classification accuracy; most of misclassified images were in range of (real age ±2) years; the classification accuracy was affected by some images from standard dataset that are extremely distorted, see Table 2, which illustrates the classification accuracy and the misclassification of the distorted images, see Fig 5.

TABLE II
CLASSIFICATION ACCURACY AND MISCLASSIFICATION DISTRIBUTION

	0-1	2-3	4-5	6-7	8-9	10-12
0- 1	**93.22**	3.95	0	1.2	0.27	1.36
2- 3	4.2	**92.31**	2.02	0.46	0	1.01
4- 5	0	3.5	**92.22**	2.08	0.62	1.58
6- 7	1.9	0	3.52	**91.77**	2.73	0.08
8- 9	0	0.24	1.15	3.48	**91.68**	3.45
10- 12	0.68	0	1.09	1.01	4.7	**92.52**

Removing extremely distorted images, proposed features yielded higher classification accuracy. Classification results were more consistent depending on high quality images, see table 3.

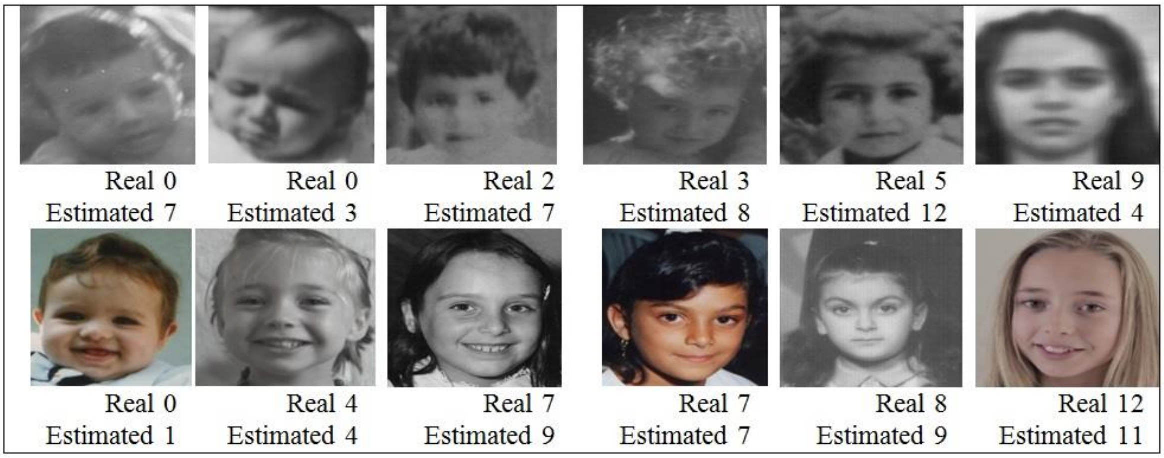

Fig 5: Samples of classification accuracy results that affected by the quality of face images.

TABLE III
CLASSIFICATION ACCURACY DISTRIBUTION AFTER REMOVING EXTREMELY DISTORTED IMAGES

	0-1	**2-3**	**4-5**	**6-7**	**8-9**	**10-12**
0- 1	**94.58**	4.22	0	0.8	0.3	0.1
2- 3	4.7	**92.71**	2.5	0	0	0.09
4- 5	0.72	2.67	**93.27**	3.17	0.17	0
6- 7	0	0.3	3.69	**93.5**	2.24	0.27
8- 9	0	0.1	0.54	2.48	**91.85**	5.03
10- 12	0	0	0	0.05	5.44	**94.51**

Comparing with the state of art, proposed features provides better results than other proposed methods; firstly, better than using Gabor filtering and multilevel Local Binary Pattern (MLBP) [20]; secondly, better than applying Hierarchical classification by Ranking K-Nearest Neighbors (RKNN) and Sequence K-Nearest Neighbors (SKNN) to classify set of LBP features [21]; and thirdly, using provided features by Active Appearance Model AAM and Constrained Local Model (CLM) [22]. See Table 34.

TABLE IV

MAE RESULTS OF PROPOSED FEATURES COMPARING WITH THE STATE OF ART

Gabor and MLBP	**SKNN, RKNN**	**AAM, CLM**	**Proposed Features**
6.53	4.97	3.72	**3.26**

V. CONCLUSIONS

This work illustrates age effects in form of shape changes in child face; these changes are shown to be significant in the period of (0- 12) years old. Exaggerated size of newborns head provides noticeable changes while shrinking to the natural size; two types of features can be extracted during this period, face roundness and forehead size. Essential face landmarks were used to choose four of them; efficient ellipse can be determined to represent the face model. Ellipse can provide efficient features to represent the studied changes. Proposed features are robust to illumination since ellipse measurements depend on points locations rather than pixel values that are affected by illumination. At the same time proposed features are robust to scaling since they depend on ratios between distances and areas rather than the distances and areas themselves. Features are also anti rotation since proposed algorithm uses landmarks points to eliminate rotation effects. Comparing with the state of art, proposed features yielded encouraging results.

ACKNOWLEDGEMENT

We are thankful to Mr. Hofmeester and Mr. Arno Klein for providing their daily captured Photos for many years to build our private face image dataset.

REFERENCES

[1]. RHODES, M.G., Age estimation of faces: a review. Applied Cognitive Psychology, 2009. 23(1): p. 1-12.

[2]. Jing, X., et al., Color image canonical correlation analysis for face feature extraction and recognition. Signal Processing, 2011. 91(8): p. 21322140.

[3]. Ramanathan, N. and R. Chellappa. Modeling age progression in young faces. in Computer Vision and Pattern Recognition, 2006 IEEE Computer Society Conference on. 2006. IEEE.

[4]. Hatzis, J., The wrinkle and its measurement—. Micron, 2004. 35(3): p. 201219.

[5]. Ylioinas, J., A. Hadid, and M. Pietikainen. Age classification in unconstrained conditions using LBP variants. in Pattern Recognition (ICPR), 2012 21st International Conference on. 2012. IEEE.

[6]. Mark, L.S., et al., Wrinkling and head shape as coordinated sources of age-level information. Perception & Psychophysics, 1980. 27(2): p. 117124.

[7]. Todd, J.T., et al., The perception of human growth. Sci Am, 1980. 242(2): p. 132-4, 139A, 140 passim.

[8]. Kwont, Y.H. and N.d.V. Lobo, Age Classification from Facial Images, in Computer Vision and Pattern Recognition, 1994. Proceedings CVPR '94., 1994 IEEE Computer Society Conference on1994, IEEE. p. 762 - 767.

[9]. Narayanan Ramanathan, S.M., IEEE, and Rama Chellappa, Fellow, IEEE Modeling Age Progression in Young Faces. 2006.

[10]. EBNER, N.C., Age of Face Matters: Age-group Differences in Ratings of Young and Old Faces. Behavior Research Methods, 2008. 40(1): p. 130136.

[11]. Salman, G.A. and G. Sulong, Localized Statistical Features Representing Face Vitality for Age Estimation. Australian Journal of Basic and Applied Sciences, 2014(July 2014): p. 698-703.

[12]. Carl Stitz, P.D. and P.D. Jeff Zeager, College Algebra. 2009

[13]. Luu, K., et al. Age estimation using active appearance models and support vector machine regression. in Biometrics: Theory, Applications, and Systems, 2009. BTAS'09. IEEE 3rd International Conference on. 2009. IEEE.

[14]. Farkas, L.G. and S.A. Schendel, Anthropometry of the Head and Face. American Journal of Orthodontics and Dentofacial Orthopedics, 1995. 107(1): p. 112-112.

[15]. Chamorro-Premuzic, T., Personality and individual differences. 2007: Blackwell publishing.

[16]. Björk, A., Variations in the growth pattern of the human mandible: longitudinal radiographic study by the implant method. Journal of Dental Research, 1963. 42(1): p. 400-411.

[17]. Gawande, U., M. Zaveri, and A. Kapur, A novel algorithm for feature level fusion using SVM classifier for multibiometrics-based person identification. Applied Computational Intelligence and Soft Computing, 2013. 2013: p. 9.

[18]. Chen, W., M.J. Er, and S. Wu, PCA and LDA in DCT domain. Pattern Recognition Letters, 2005.

[19]. http://fipa.cs.kit.edu/429.php.

[20]. TienNguyen, D., et al., Comparative Study of Human Age Estimation with or without Preclassification of Gender and Facial Expression. The Scientific World Journal, 2014. 2014.

[21]. Liang, Y., et al., A Hierarchical Framework for Facial Age Estimation. Mathematical Problems in Engineering, 2014. 2014.

[22]. Iraji, M.S., et al., Age Estimation Based on CLM, Tree Mixture With Adaptive Neuron Fuzzy, Fuzzy Sum. International Journal of Image, Graphics and Signal Processing, 2014. 6(3): p. 5157.

