EYE CORNERS DETECTION USING HAAR CASCADE CLASSIFIERS IN CONTROLLED ENVIRONMENT

S. M. Asi[1*], N. H. Ismail[2], R. Ahmad[3], E. I. Ramlan[4], Z. A. A. Rahman[5]

[1]School of Computer and Communication Engineering, Universiti Malaysia Perlis, Tingkat 3 Bangunan KWSP, Jalan Bukit Lagi, Kangar, Perlis Malaysia

[2,5]Department of Oro-Maxillofacial Surgical and Medical Sciences, Faculty of Dentistry, University of Malaya

[3]Department of Paediatric Dentistry and Orthodontics, Faculty of Dentistry, University of Malaya

[4]Faculty of Computer Science and Management Information, University of Malaya

ABSTRACT

Facial landmarks detection is undoubtedly important in many applications in computer vision for example face detection and recognition. This article demonstrated the use of Haar Cascade Classifiers to automatically locate the eye corners. We acquired our 3D face image data by Vectra 3D camera in a controlled environment. We use two data set of 300 eye images to train en and ex cascade classifiers regardless of the left and the right eye. These classifiers were then used to detect and locate the inner (en) and outer (ex) eye landmarks. To train HAAR cascade classifier we usually use huge amounts of data. But in this study, about 300 positive images used to train each classifier. Due to this we observed quite an amount of false positive detection. We developed a simple algorithm to predict the eye corners by first eliminate the false detection and geometrically modeled the eye. Our classifiers able to detect and locate en on 53 out of 60 test images and the ability to detect ex in 59 out of 60 test images. In craniofacial anthropometry, it is very important to locate the facial landmarks as per the standard definition of the landmarks. Our results demonstrated accurate detection of ex and en facial landmarks as per standard definition. In conclusion, our trained enHaar and exHaar cascade classifiers are able to automatically detect the en and ex craniofacial landmarks in a controlled environment.

KEYWORDS*: Craniofacial anthropometry; Facial landmarks; Haar Cascade Classifier*

* Corresponding author email: salina@ump.edu.my

1.0 INTRODUCTION

Craniofacial Anthropometry is a standard facial measurement used in a wide range of applied and research contexts, hence, reliable and accurate data are very important and cannot be compromised (Farkas, 1996; Farkas, 1994). The used of computer technology such as Vectra 3D Stereo Photogrammetry System and other similar systems helped the researchers in acquiring the data fast, reliable and accurate (Asi et al., 2012; Weinberg et al., 2006; Wong et al., 2008). Unfortunately, the systems require human interaction in locating the facial landmarks. Consistency in locating the landmarks and the examiners' skill in taking the measurements are two important parameters in contributing the measurement errors as discussed in (Farkas, 1996). A study by (Toma et al., 2009) on intra and inter examiners error in reproducing the facial landmarks on the 3D image at three planes x, y and z. They had observed that 11% of inter examiners and 17% of intra examiner reproduced landmarks with more than one mm difference.

Dauglas had attempted to locate the eye landmarks automatically in her study of Fatal Alchoholic Syndrom (FAS). She proposed an automatic measurements of the orbit region to compare the measurements of normal and the FAS group She used genetic algorithm and eye template to automatically locate the eye landmarks in her study (Douglas, 2004). Further studies by (Mutsvangwa & Douglas, 2007) using stereophotogammetry craniofacial anthropometry as a tool in FAS screening has been accepted as a standard procedure to screen FAS in children (Moore & Ward, 2012; Mutsvangwa & Douglas, 2007)

Automatic locating and extracting the facial landmarks proposed by Douglas is an alternative method to reduce the inter and intra examiner errors in craniofacial anthropometry. Viola and Jones (2001) objected detection framework is robust and accurately detect face in image. Viola and Jones used Haar-like features proposed by Papageorgiou in their algorithm to detect a face. These features encode differences in average intensities between two rectangular regions, and they are able to extract texture without depending on absolute intensities. They proposed an efficient system for evaluating these features which is called an integral image to reduce the exhaustive calculation of the rectangular regions. They used Adaboost to construct a strong classifier from the weak classifiers of small number of features. Its result is more robustness and computationally efficient (Lienhart & Maydt, 2002; Viola & Jones, 2001). Xia et al., had used the Viola and Jone faramework to detect the mikro facial features, the facial landmarks. They demonstrated a feature based method to detect the eye corners. They trained two cascade classifiers of a pair of eyes images and successfully detect both inner and external eye landmarks (Xia et al., 2009).

In this study, the Haar Cascade Classifier used to detect the inner and external eye corners. We trained the classifier with a our own data which is limited amount.

2.0 MATERIAL AND METHOD

We photographed 100 normal adults aged between 18 to 30 years old to get 3D facial images. We used VECTRA 3D stereophotogrammetry from Canfield Imaging System of Canfield Science Inc., and the module that we used was capable to capture image of 180 degree. The 3D images of the respondents were captured under a standard clinical lighting. The system consists of four cameras and two cameras of each side. Respondents were seated at rest position on a chair 90 cm in front of the cameras. We calibrated the system according to the system requirement before taking the subjects three dimensional images.

We converted and exported the 3D images in VECTRA 3D stereophotogrammetry system environment to get 3D-2D facial images which we refer as 2.5D images. We divided the 2.5D facial images into seventy (70) images for training data and thirty (30) images for testing data.

2.1 The Training Dataset

We prepared the positive image by firstly extract the eyes from the facial image. Then we prepared two sets of positive samples each sample to train the inner (en) and external (ex) eye corner classifiers. Each set contains 300 images of size 200x 200 pixel. For each positive sample, we marked the corner models. The inner eye (en) was 3/4 of the object height and 3/4 of the object width. The external eye corner (ex) was 2/3 of the object height and 3/4 of the object width. An example of the dataset as shown in Figure 1 and the object model of en and ex eye corners are shown in Figure 2.

Negative samples were in general images that do not contain the en and ex objects model. To improve the accuracy of eye corner classifiers, we create the negative image by extracting any region of the size of 200 x 200 pixels in the face area which do not include the eye corners. We use AdaBoost to boost these weak classifiers consisting of selected Haar-like features and construct the cascade classifiers. In this study, we constructed the enHaar and exHaar cascade calssifiers.

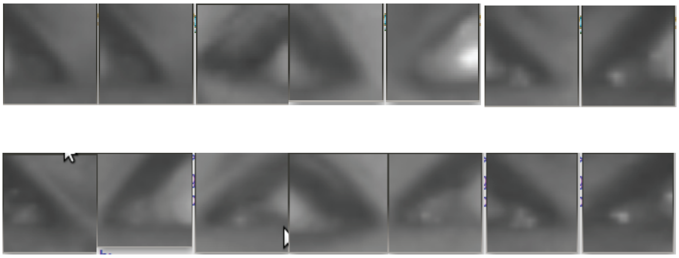

Figure 1. Example of the training data set for inner-en (above) and external-ex (below) for left and right eye corners

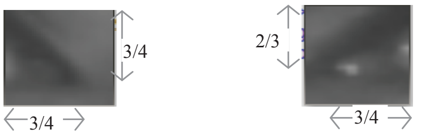

Figure 2. The landmark position of en (left) and ex (right) on the detected regions

2.2 Landmark Detection

First, we apply the OpenCV eye classifier to search the eye at the facial image. Then we used the extracted eye to detect the en and ex. To detect the eye corners, we search the input image for objects using the enHaar and exHaar cascades classifiers. The enHaar classifier was applied to find inner eye corners while the exHaar was used to look for the external. The process of eye corner detection is that one shifts the search window at multiple resolution and scales and checks each location using the classifier cascade.

Due to the small amount of the data used in the training session resulted in increasing of false positive detections. To overcome this problem we developed a simple algorithm to predict the eye corners by first eliminate the false detection by geometrically modeled the eye.

3.0 EXPERIMENTAL RESULT

We tested our method on 60 left and right eye images. We implemented our method using OpenCV 2.4.1. Figure 3, Figure 4 and Figure 5 includes the example detection result of the ex and en craniofacial landmarks.

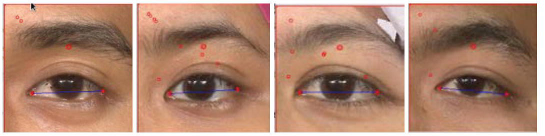

Figure 3. Detection of en and ex of the left eyes

Figure 4. Detection of en and ex of the right eyes

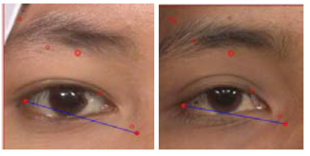

Figure 5. Fail detection of en of the right eye

We detected ex craniofacial landmark at 59 out of 60 left and right eye images and detected ex craniofacial landmark at 53 out of 60 left and right eye images. There were 5 cases of the miss detection of en were at the right eye and 2 cases were in the left eye. The landmark detection quality is very good as per craniofacial anthropometry landmark definition.

4.0 DISCUSSION AND CONCLUSION

We demonstrated the used of Haar Cascade Classifier in automatic detection of the micro facial feature. In this study, we created the en and ex Haar Cascade Classifier to automatically detect the en and ex craniofacial landmarks in a controlled environment. The detection performance for en is less than the detection performance of ex. The detection quality of en and ex craniofacial landmarks is very good. The detections were as per the standard definition of the en and ex craniofacial landmarks.

In conclusion, our trained enHaar and exHaar cascade classifiers are able to automatically detect the en and ex craniofacial landmarks in a controlled environment. The detections are good as per standard ex and en craniofacial landmarks definition. The used of small amounts of trained data resulted in classifiers with high rate of false positive.

In this situation we able to remove the false positive by geometrically model the eye.

ACKNOWLEDGEMENT

The authors thank Universiti Malaya for the Post Graduate Research Fund (PS168-2010B), Faculty of Dentistry, University of Malaya, The 3D imaging lab administration for the VECTRA 3D Stereo Photogrammetry Camera that supported by Universiti Malaya High Impact Research Grant (UM.C/625/HIR/MOHE/DENT/13).

REFERENCES

Asi, S. M., Ismail, N. H., & Rahman, Z. A. A. (2012). Validity and reliability evaluation of data acquisition using Vectra 3D compare to direct method. In *Biomedical Engineering and Sciences (IECBES), 2012 IEEE EMBS Conference* on Biomedical Engineering and Sciences, Langkawi, Malaysia, 17-19 December 2012. (pp. 883–887). doi:10.1109/IECBES.2012.6498016.

Douglas, T. S. (2004). Image processing for craniofacial landmark identification and measurement: A review of photogrammetry and cephalometry. *Computerized Medical Imaging and Graphics*. doi:10.1016/j.compmedimag. 2004.06.002

Farkas, L. G. (1994). *Anthropometry of the Head and Face.* (L. G. Farkas, Ed.) New York (Vol. 6, pp. 344–505). Raven Press. doi:10.2114/jpa2.26.501.

Farkas, L. G. (1996). Accuracy of anthropometric measurements: past, present, and future. *The Cleft Palatecraniofacial Journal Official Publication of the American Cleft Palate Craniofacial Association, 33*(1), 10–18; discussion 19–22. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/8849854.

Lienhart, R., & Maydt, J. (2002). An extended set of Haar-like features for rapid object detection. *Proceedings. International Conference on Image Processing, 1*. doi:10.1109/ICIP.2002.1038171.

Moore, E. S., & Ward, R. E. (2012). Use of Computerized Anthropometry and Morphometrics to Identify Fetal Alcohol Syndrome. In V. Preedy (Ed.), *Handbook of Anthropometry: Physical Measures of Human Form in Health and Disease* pp. 1049–1065. Springer. doi:10.1007/978-1-4419-1788-1_63.

Mutsvangwa, T., & Douglas, T. S. (2007). Morphometric analysis of facial landmark data to characterize the facial phenotype associated with fetal alcohol syndrome. *Journal of Anatomy*, 210, 209–220. doi:10.1111/j.1469-7580.2006.00683.x.

Toma, A. M., Zhurov, A., Playle, R., Ong, E., & Richmond, S. (2009). Reproducibility of facial soft tissue landmarks on 3D laser-scanned facial images. *Orthodontics & Craniofacial Research*, 12, 33–42. doi:10.1111/j.1601-6343.2008.01435.x.

Viola, P., & Jones, M. (2001). Rapid object detection using a boosted cascade of simple features. Proceedings of the 2001 *IEEE Computer Society Conference on Computer Vision and Pattern Recognition.* CVPR 2001. doi:10.1109/CVPR.2001.990517.

Weinberg, S. M., Naidoo, S., Govier, D. P., Martin, R. A., Kane, A. A., & Marazita, M. L. (2006). Anthropometric precision and accuracy of digital three-dimensional photogrammetry: comparing the Genex and 3dMD imaging systems with one another and with direct anthropometry. *The Journal of Craniofacial Surgery*, *17*(3), 477–483.

Wong, J. Y., Oh, A. K., Ohta, E., Hunt, A. T., Rogers, G. F., Mulliken, J. B., & Deutsch, C. K. (2008). Validity and reliability of craniofacial anthropometric measurement of 3D digital photogrammetric images. *The Cleft Palate-Craniofacial Journal : Official Publication of the American Cleft Palate-Craniofacial Association*, 45, 232–239. doi:10.1597/06-175.

Xia, H., Yan, G., & You, C. (2009). Feature-based eye corner detection from static images. *Proc. SPIE.* doi:10.1117/12.832837.