ISSN : 0974 - 7435 Volume 8 Issue 12

BioTechnology
An Indian Journal

FULL PAPER

BTAIJ, 8(12), 2013 [1658-1663]

Joint modeling with eye movement and pupil scaling for affective assessment based on kpca algorithm

Yuxing Mao* Jialue Miao Quanlin Wang Yan Wang
State Key Laboratory of Power Transmission Equipment & System Security and New Technology, Chongqing University, Chongqing 400044, (CHINA)
E-mail : myx@cqu.edu.cn

ABSTRACT

Aiming at the fact that psychological state can be reflected by eye movement and pupil size, an affective assessment method based on the joint model of eye movement trajectory and pupil scaling was proposed in this paper. Firstly, the experimental apparatus was developed to capture and transmit the eye images. Secondly, multiple advanced image processing algorithms were synthetically adopted to extract the pupil. Both the position and size of the pupil were obtained. Thirdly, the joint model with the eye movement trajectory and pupil scaling was constructed as feature vector, which was subsequently processed with kernel principal component analysis (KPCA) algorithm to reduce its dimension. Finally, the nearest neighbor classifier was built according to the dimensionality reduction information to implement the classification of the samples. With proper experimental method designed for collecting samples, this approach can be used for affective assessment. Experimental results had demonstrated the good practicability of our study.

KEYWORDS

Eye tracker;
Joint model;
KPCA;
Classification;
Affective assessment.

INTRODUCTION

Pupil size and eye movement are demonstrated closely related to psychological states and mental activities, which gain wide attentions in recent years. The foundation of these studies lies in the precise localization of the pupil. Since the pupil can not be clearly distinguished from iris, and, the pupil size will vary with the intensity of the ambient light, the infrared LED lamps are usually used to provide stable illumination. Literatures[1, 2] presented practical methods for pupil extraction in the images captured by infrared cameras. Another issue is to measure the pupil size, which can be quantitatively indicated by the pixel count of the pupil area or diameter. Many efficient approaches had been proposed for pupil size analysis[3-5]. F.Mokhayeri et.al. proposed a hybrid approach for the pupil diameter measurement[4], which consisted of five stages, including data acquisition, pre-processing, edge detection, edge linking and diameter computation.

The eyes are the windows of the soul. The pupil scale is closely related to psychological reaction, which can not be controlled by the subjective wills of the participants. Usually, the pupil will expand in terror, tension, anger, love, pain and other conditions. On the contrary, it will shrink in disgust, fatigue and worry.

The classification of relaxation and depression emotion can also be implemented through analyzing the pupil size[6, 7]. An approach was presented in literature[6] to recognize the affective states of relaxation and stress of a computer user. After the abrupt changes in the raw PD signals were eliminated with wavelet denoising and Kalman filtering, the authors constructed a random tree classifier to classify the two affective states. With the accuracy of 86.78% achieved, the results showed that the PD is a promising physiological signal for affective assessment. Another practical function of PD investigation is that PD signal can be served as the basis of visual impairments for visual correction. Jian Huang et.al.[8] proposed a vision correction method for computer users based on image pre-compensation. An adjustment of the wavefront function used for pre-compensation was implemented to match the viewing pupil size.

In addition, the psychological activities will also response to the eye movement trajectory. Some psychological scholars are devoted to explore the essential relationship between eye movements and emotion. With a computer based interactive training simulation, Heather C.Lum et.al. revealed the relationship between eye movements and emotion regulation training. It demonstrated that the eye movements can be applied to adaptive emotion training systems[9].

Our research teams have conducted nystagmus research for pathological analysis via videonystagmography for many years. The perfect hardware and software system have been established for image capture, transmission and processing in the host computer. This system can be applied for affective assessment through eye movement trajectories and pupil size. The emotion classification is focused in our study. The feature vectors are constructed with joint information model of eye movements and pupil size, which are served as samples for training and testing. In order to improve the ability of classification, the dimensionality reduction technique of KPCA is adopted to extract the principal features. The nearest neighbor classifier is built for affective assessment. The following sections will describe our work in detail.

SAMPLE CONSTRUCTION WITH THE PUPIL FEATURES

Pupil localization and its size analysis

Pupil localization is the first step of our study. Accurate extraction of the pupil is crucial to the subsequent works. The entire procedure for pupil localization consists of several stages, such as binarization, morphology operations, connectivity analysis, constraint conditions definition for removing interference, etc. After the pupil is successfully discriminated, it can be used for pupil size and the coordinates of center point computation. This work has been amply described in our previous paper[10].

Joint modeling for feature vectors construction

The strategies of how to choose and organize the features of the samples seriously affect the performance during pattern recognition and object classification. The eye movement trajectory and pupil scaling are synthetically concerned according to the time order to built joint model. Supposing that the coordinates and the size of the pupil are denoted as (x, y) and s, respectively, the pupil scaling z is defined as equation (1):

$$z = 100 * (s - s_{\min}) / s_{\min} \quad (1)$$

where $s_{\min}$ represents the minimum pupil size of all the 250 frames. Each sample consists of 250 frames derived from the testing period of 10 seconds. If x_i, y_i and z_i are defined to indicate the x, y, z of the i th frame, the feature vector of a sample can be constructed as $(x_1, y_1, z_1, x_2, y_2, z_2, ..., x_{250}, y_{250}, z_{250})$. The dimension of the feature vector is 750. Assuming that total m samples have been acquired, synthetically, they can be denoted as a $m \times n$ matrix A, where $n = 750$. A is called sample matrix.

CLASSIFIER DESIGN

Dimensionality reduction based on KPCA

Kernel principal component analysis (KPCA) is an extension of principal component analysis (PCA) using techniques of kernel methods. Using a kernel, the originally linear operations of PCA are done in a reproducing kernel Hilbert space with a non-linear mapping. KPCA is adopted to reduce the dimension of the feature vector. The operation to retrieve the principal components of the sample matrix A consists of the follow steps:

a) The kernel function should be chosen firstly. 2-order polynomial kernel function is selected for KPCA in our study. Then, the $m \times m$ standard kernel matrix K is computed according to the sample matrix A, referring to equation (2).

$$k_{ij} = \left[\sum_{k=1}^{n} a_{ik} a_{jk} + 1 \right]^2 \quad i, j \in \{1, 2, ...m\} \tag{2}$$

Assume that K' is the normal form of the matrix K, it can be used in subsequent work.

b) Through solving the characteristic equation of matrix K', which knows as $K'v = \lambda v$, the eigen values λ and the corresponding eigen vectors v are obtained. After all the eigen values and eigen vectors are sorted in descending order by the absolute value of the eigen values, we can get the m eigen values called $\lambda_1, ..., \lambda_m$ and the corresponding eigen vectors $v_1, ..., v_m$. The eigen vector v_i $i \in \{1, 2, ...m\}$ is a m-dimension vector.

c) The former t eigen values of $\lambda_1, ..., \lambda_t$ are chosen, where $0 < t \le m$. The numberis determined by equation (3).

$$t = \underset{j \in \{1,2,...,m\}}{\arg\min} \{ j \mid \sum_{i=1}^{j} \lambda_i / \sum_{i=1}^{m} \lambda_i \ge 0.9 \} \tag{3}$$

Then, the t eigen vectors $v_1, ..., v_t$ corresponding to $\lambda_1, ..., \lambda_t$ are standardized to $\alpha_1, ..., \alpha_t$ by equation (4).

$$\alpha_k = v_k / \sqrt{\lambda_k} \qquad k = 1, 2, ...t \tag{4}$$

The standard eigen vectors $\alpha_1, ..., \alpha_t$ are called principal components. They are combined to a $m \times t$ matrix as α.

d) The projection values of the m samples related to the principal components matrix α are computed according to equation (5). The matrix called can be obtained. Where, each row is a t-dimension vector.

$$Y = K' \cdot \alpha \tag{5}$$

Classifier building for affective assessment

Classifier is used for determining the category of the testing sample. In our work, the features after dimensionality reduction are applied to calculate the Euclidean distance. The nearest neighbor classifier with the Euclidean distance is built. Suppose there are s test sample, and, each one is a n-dimension vector, they can combine to a $s \times n$ matrix T, called test sample matrix. The dimension of the matrix should also be reduced before classification.

a) The kernel matrix of should be computed firstly. With the same kernel function in equation (2), the kernel matrix is computed according to equation (6).

$$KT_{ij} = \left[\sum_{k=1}^{n} t_{ik} a_{jk} + 1 \right]^2 \quad \begin{array}{l} i = 1, 2, ...s \\ j = 1, 2, ..., m \end{array} \tag{6}$$

where KT_{ij}, t_{ik} and a_{jk} are the member of the matrix KT, T and A, respectively. The matrix should be standardized to normal form as.

b) With the principal components matrix α obtained previously, the projection values of the s test samples are computed according to equation (7). The $s \times t$ matrix named W can be obtained. Where, each row represents the dimensionality reduction information of a certain test sample.

$$W = KT' \cdot \alpha \tag{7}$$

c) Considering an arbitrary row in matrix W, it is a t-dimension vector. Suppose that the vector is denoted as $[w_1, w_2, ...w_t]$, its Euclidean distances to any row of matrix Y in equation (5) are calculated, referring to equation (8).

$$d_i = \sqrt{\sum_{j=1}^{j=t} \left(w_j - y_{ij} \right)^2} \qquad i = 1, 2, ..., m \tag{8}$$

where d_i is the Euclidean distance of the inspected test sample to the i th training sample. The class of the training sample with minimum Euclidean distance is regarded as the class of the inspected test sample. It means that the affective state recorded during the training sample is collected represents the affective state of the subject corresponding to the inspected test sample.

EXPERIMENTAL RESULTS ANALYSIS

The experiments are implemented to verify the efficiency of the approach in this study. Firstly, the experimental method should be designed according to the real application target. In one of our experiment, we collect 10 pictures, and, each one represents a special scene of a famous tourist spot in China. During the experiment, the pictures display on the computer screen alternately. Each picture stays for 10 seconds before switching to another one. The participants are asked to observe the pictures; meanwhile, they need to answer a group of questions according to whether they have been to the scene shown in the pictures.

Group A, for the participants who have been to the scene:

a) Where is it?

b) When did you go there?

c) What impressed you most there?

Group B, for the participants who have not been to the scene:

a) Where it may be?

b) If you want to go there, when do you plan to go?

c) Who do you want to go there with?

Twenty undergraduates have been asked to participate in the experiments. Therefore, we obtained 200 samples. According to their real experiences, 112 samples were belonged to group A, and, the rest 88 samples were relevant to group B. We built two sample sets for training and testing. Each sample set was composed of 100 samples, including 56 and 44 samples in group A and group B, respectively. Thus, the 100 training samples and 100 test samples were achieved for our experimental study.

The feature vector of any sample was constructed as described in section 3.2. The dimension of the feature vector is 750, denoted as . Let represent a point in 3-D space, , each sample can be regarded as a joint distribution of 250 points in the 3-D space. Figure1 and Figure 2 represent a sample derived from group A and group B, respectively.

In Figure1 and Figure 2, picture (a) represented the distribution of 250 3-D points related to a sample, and, picture (b) showed the varying of the pupil scaling along with time. According to the algorithm introduced previously, we computed the dimensionality reduction information of and corresponding to the training sample and the test sample. Then, for any test sample, the Euclidean distance to every training sample was calculated. Thus, we obtained 100 Euclidean distances corresponding to the 100 training samples for each test sample.

Figure 3 shows the Euclidean distances of 10 test samples to the 100 training data. Among them the 5 curves in chart (a) represents the 100 Euclidean distances of 5 test samples derived from group A, and, the 5 test samples in chart (b) come from group B. As mentioned above, the former 56 training samples belong to group A, it means that the first 56 values in chart (a) represent the Euclidean distances between test samples in Group A and the training samples in Group A. similarly, the last 44 values in chart (a) represent the Euclid-

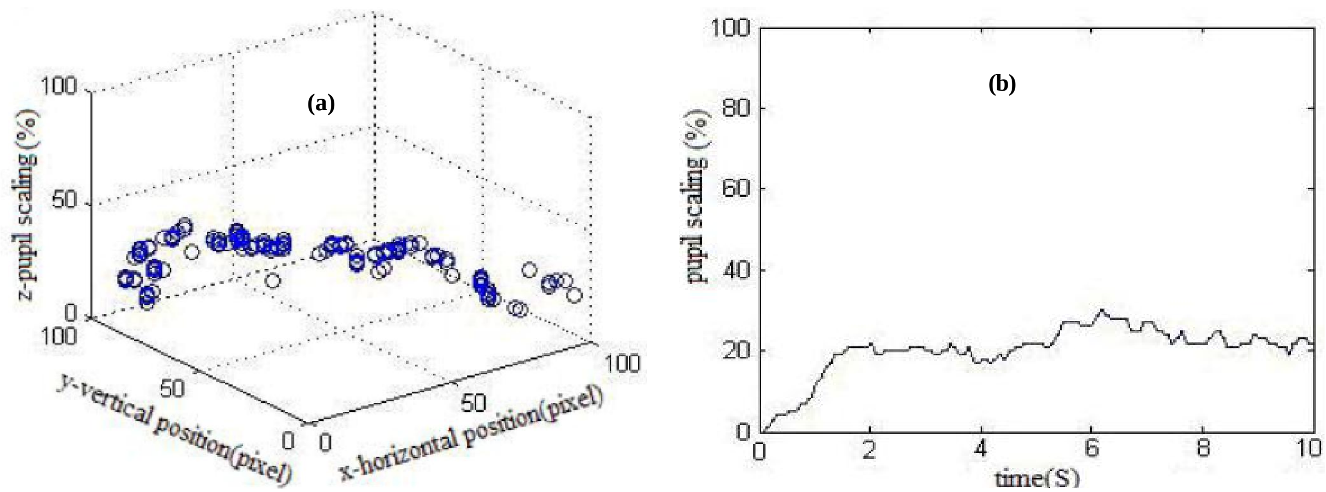

Figure 1 : The sample derived from the participant who have been to the scene; (a) 250 points in 3-D space of the sample; (b) The curve of pupil scaling-time of the sample

FULL PAPER

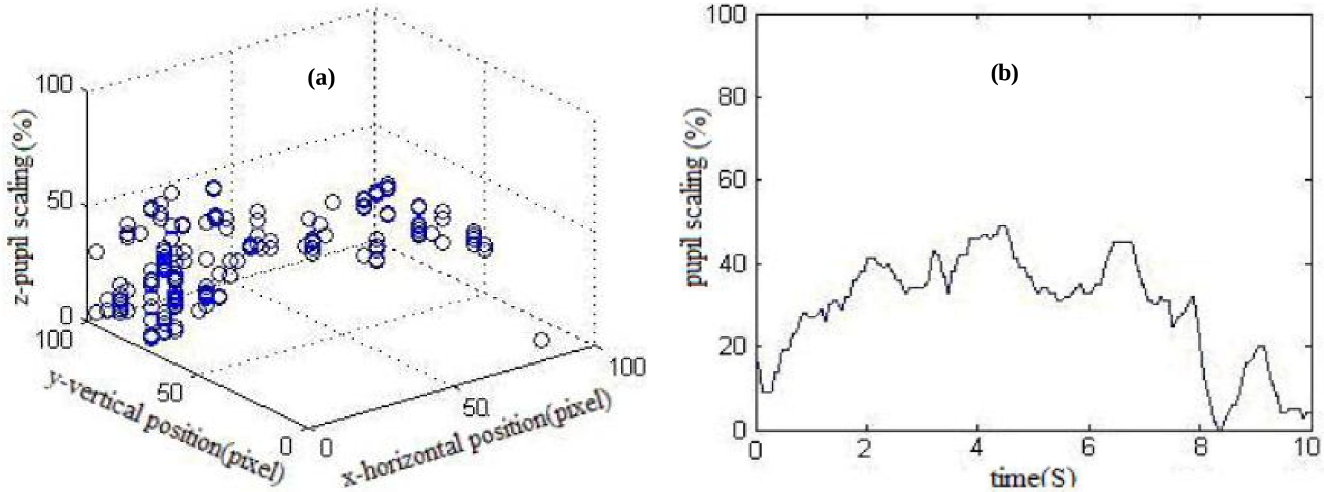

Figure 2 : The sample derived from the participant who have not been to the scene; (a) 250 points in 3-D space of the sample; (b) The curve of pupil scaling-time of the sample

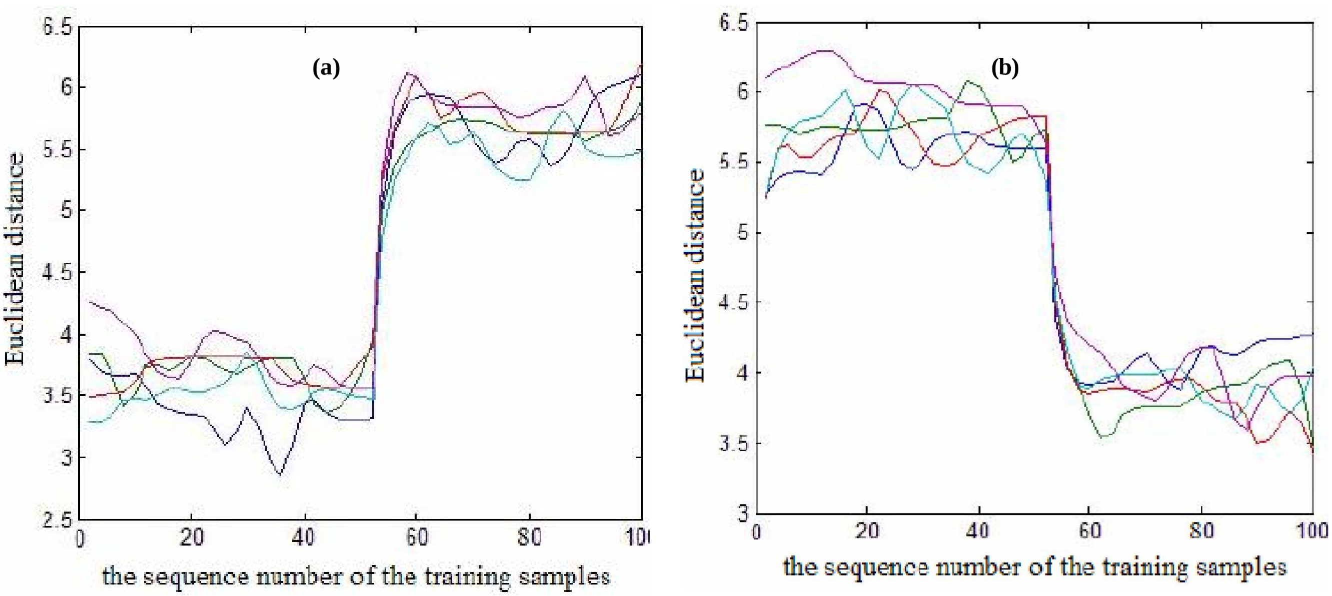

Figure 3 : The Euclidean distances of several test samples to all the training samples; (a) five test samples derived from group A; (b) five test samples derived from group B

ean distances between test samples in Group A and the training samples in Group B. Chart (b) reflect the opposite situation to chart (a). Figure.3 shows that the Euclidean distances of two samples from same group are obviously less than those from different group, therefore, the classification will implement successfully. Through design efficient experiment to get proper samples, this approach can be used for other affective assessment.

CONCLUSION

Eye movements and pupil size are demonstrated closely related to mental activity. We proposed an affective assessment method based on the joint model of eye movements and pupil scaling in this paper. In order to improve the reliability and robustness, the KPCA algorithm is adopted to retrieve the principal features of the samples. The nearest neighbor classifier with the dimensionality reduction information is built to realize the assessment of the psychological state of the participants. In our future work, more efficient experimental methods should be designed according to the application requirements. Through training with the samples gathered specially for the application objective, the classifier can be applied to some other situations of psychological states evaluation, such as lie detecting, criminal suspect discriminating.

ACKNOWLEDGEMENTS

This work is supported by the Foundation for Sci & Tech Research Project of Chongqing (CSTC2010AA5049) and the innovative research projects of colleges and universities in Chongqing (12A19369).

REFERENCE

[1] Wang Junning, Liu Tao, He Di, Wu Yuanyuan; Pupil center localization algorithm used for the IR head mounted eye tracker. Journal Of Xi Dian University[J], **38(3)**, 9-12, 82, **(2011)**.

[2] T.Charoenpong, S.Thewsuwan, T.Chanwimalueang, V.Mahasithiwat; Pupil extraction system for Nystagmus diagnosis by using K-mean clustering and Mahalanobis distance technique. Proceedings of the 4th International Conference on Knowledge and Smart Technology, KST 2012, 24-29 **(2012)**.

[3] N.H.Mahmood, N.Uyop, M.M.Mansor, A.M.Jumadi; Measurement of the area and diameter of human pupil using Matlab. 5th Kuala Lumpur International Conference on Biomedical Engineering 2011, IFMBE Proceedings, IFMBE, **35**, 686-689 **(2011)**.

[4] F.Mokhayeri, S.Toosizadeh, M.-R.Akbarzadeh-T; A novel approach for pupil diameter measurement based on soft computing techniques. 2011 7th Iranian Conference on Machine Vision and Image Processing, MVIP **(2011)**.

[5] Vicente.B.L.Ibanez, Vitor.Yano, Alessandro Zimmer; Automatic pupil size measurement based on region growth. 2012 ISSNIP Biosignals and Biorobotics Conference: Biosignals and Robotics for Better and Safer Living, BRC, **(2012)**.

[6] Peng Ren, Armando Barreto, Ying Gao, Malek Adjouadi; Affective assessment of computer users based on processing the pupil diameter signal Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS, 2594-2597 **(2011)**.

[7] Peng Ren, Armando Barreto, YingGao, Malek Adjouadi; Digital filtering of the pupil diameter signal for affective assessment of a computer user. Lecture Notes in Electrical Engineering, LNEE, **151**, 183-196, **(2013)**.

[8] Jian Huang, Armando Barreto, Miguel Alonso, Malek Adjouadi; Vision correction for computer users based on image pre-compensation with changing pupil size, Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS, 4868-4871 **(2011)**.

[9] Valerie.K.Sims, Moshe Feldman, Ari Afek, A.Kimberly, Smith-Jentsch, Nicholas C.Lagattuta; Emotion regulation training and scene understanding are related to eye movements during a computer based interactive simulation. Proceedings of the Human Factors and Ergonomics Society, **2**, 1210-1214 **(2009)**.

[10] Xuejun Chen, Yongming Yang, Wei He, Jingang Wang, Yuxing Mao; Hilbert-Huang Transform for Nystagmus Analysis in Video-oculography. International Journal of Digital Content Technology and its Applications J., **5(8)**, 423-430 **(2011)**.