A Novel Quality Assessment Method for Eye Movement Authentication

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***Abstract*—Eye movement authentication has been paid attention to realize both high usability and security especially counterfeit biometric modality. Although previous researches took care for obtaining the eye movement information correctly to eliminate the noisy data, they did not focus on the quality on the captured data. In this paper, we propose the quality assessment method on eye movement authentication. Our experiment using competition data shows the peak velocity of eyeballs has the relationship with the obtained genuine similarity scores.**

I. Introduction

As one of continuous biometric authentication, eye movement authentication has been researched in this decade. As the eye tracker becomes to be downsizing and low-cost, it can be got easily than before.

The research on eye movement is progressing for behivior analysis and diagnosis on eye deseases in phycology, medical fields. As a biometric modality, although the accuracy of eye movement authentication is not so high compared to other modalities such as face, fingerprint, iris, it can be used to be combined with other modalities to improve accuracy, and to be able to use anti-spoofing technology.

In this decade, Some eye movement authentication competitions(EMVIC2012(Eye Movement Verification and Identification Competition) 2012[9] in 2012, EMVIC2[1] in 2014, and BioEye2015[2]) were held to encourage improving accuracy.

Eye movement data can be captured by eye tracker, and it can be represented as time-series data which consists of left eye gazing point(x, y) and right gazing point(x, y).

Eye movement data have two types of conitions, fixation and saccade, and these conditions are classified based on statistical analysis and Hidden Marcov Model(HMM)[20]. Recently, Bei et al.[17] proposed the Convolutional Neural Network(CNN) bsaed method.

According to the survey paper [6][11], eye movement authentication algorithms have been researched and progressed in this decade.

In terms of authentication feature to verify a person using eye movement, Komogortsev et al.[16] proposed Oculomotor Plant Characteristics(OPC) using mathematical model. OPC consists of nine scolar values such as external muscle length and strength. Holland et al.[8][7]

Holland et al. [8][7] proposed authentication method using twelve statistic features(Complex Eye Movement; CEM) consisted of horizontal / vertical average velocity during fixation and saccade. Statistic test was used to judge mate or non-mate. Rigas et al.[18] proposed graph-based method consited of the eye gazing point is vertex, and the motion is edge in the velocity-acceleraration space, and minimum spanning tree was used to calculate similarity among different eye movement data. Cuong et al.[5] reported that Meil Frequency Cepstrum Coefficients(MFCC) could be utilized as a feature on eye mobement authentication, which was offten used in voice recognition. Knnunen et al.[12] proposed Task-Independent method to realize high usability eye movement authentication without any instructions using 2D histogram consisted of eye gazing transition direction. Tagawa et al.[21] proposed the new feature enabled to cope with that the range of eye movement was narrow. Rose et al.[19] proposed the mixture authentication method using mouse dynamics and eye movement.

In addition to the single feature, Komogortsev et al. proposed the combination method which had both OPC and CEM[14], OPC, CEM, and Iris[15]. Costa et al.[4] proposed dynamic features regarding iris area, which was based on a variation of an iris contour shape. Furthermore, Komogortsev et al.[13] discussed the liveness detection method using OPC features. Zhang et al.[22] proposed the continuous authentication method using eye movement, which used the diameter of the pulill during fixation and some statsitical features as the authentication feature.

Inputting some password or PIN using eye movement takes around 10 seconds to capture enough information, which causes less usability. By solving this issue, Abe et al. proposed that local matching method using features extracted from short time eye movement data and accumulate the comparison scores to improve accuracy.

However, in conventional methods, if the data has low quality eye movement data partially, the accuracy becomes to be worse than usual since whole captured data is used as an authentication. In terms of eye movement authentication, Quality Assessment Method has not been established, which is why it is hard to extract effective features depending on the user's condition.

In this paper, we propose a novel quality assessment method on eye movement using the relationship between peak velocity and the length ahead to the target gazing point. In the section 2, we show the analysis results on the relationship between the peak velocity and the target distance using RAN task data on

BioEye2015 dataset, then we describe the quality assessment method. In the section 3, we conduct some experiments on estimated quality and accuracy using BioEye2015 dataset. In the section 4, we analyze the detailed result using fitting function, and we conclude this paper in the section 5.

II. Eye Movement Authentication Scheme

This section describes the eye recognition system as a base. Figure shows the gaze authentication scheme. A feature quantity is extracted for each window while input line of sight data is divided by a sliding window system, and a similarity score is accumulated by comparing with registered data to identify which user the input data belongs to.

The selection of the feature quantity extracted from each window is important in order to obtain the high discrimination accuracy. In this paper, we extract 2 feature quantities from the literature: Mel Frequency Cepstrum (MFCC) which is an excellent feature quantity, and EM-LBP which complements MFCC proposed by Abe et al.

1) Mel Frequency Cepstrum Coefficients (MFCC): In the previous researches[5][10], they say that a cepstrum-based information is useful for an eye movement authentication, which is often utilized in speech recognition techniques. MFCC can be calculated by applying DFT(Discrete Fourier Transform) and DCT(Discrete Cosine Transform) for the eye movement data.

In the previous researches, *mel-scale conversion* is applied after calculation of the cepstrum coefficients, which is related to adjust the data only for considering the human's perceptual characteristic. That is why we omit the process in order to keep the original power spectrum information in our implementation.

First, we calculate frequency information F_x and F_y by FFT(Fast Fourier Transform) as following equations,

$$F_x(n) = \sum_{t=0}^{N-1} x(t) \left(-2\pi i \frac{nt}{N}\right) \tag{1}$$

$$F_y(n) = \sum_{t=0}^{N-1} y(t) \left(-2\pi i \frac{nt}{N}\right). \tag{2}$$

Now, $x(t), y(t)$ is the horizontal and vertical time-series position data respectively, and N is the number of data element. Then power spectrum is calculated by the following equation,

$$P_x(n) = \log |F_x(n)| \tag{3}$$

$$P_y(n) = \log |F_y(n)|. \tag{4}$$

Finally, we re-calculate spectrum information by using DCT(Discrete Cosine Transform) as follows,

$$C_x(n) = \sum_{t=0}^{N-1} P_x(t) \cos\left(\frac{\pi}{N}\left(n + \frac{1}{2}\right) t\right) \tag{5}$$

$$C_y(n) = \sum_{t=0}^{N-1} P_y(t) \cos\left(\frac{\pi}{N}\left(n + \frac{1}{2}\right) t\right). \tag{6}$$

In the previous researches, after calculation of the power spectrum information P_x and P_y, mel-scale conversion is applied, which is related to adjust the data only for considering the human's perceptual characteristic. That is why we omit the process in order to keep the original power spectrum information. According to the MFCCs analysis, although the first twelve coefficients from low frequency are used as a feature, we use four coefficients as defined by the following equation,

$$C' = [C_x(0), C_x(1), C_y(0), C_y(1)]. \tag{7}$$

Finally, we obtain the MFCC-based feature v_{mfcc} by applying PCA to C', then we select the first N_{mfcc} eigen vectors.

2) Eye Movement LBP(EM-LBP): MFCCs uses frequency information extracted from captured eye movement data. This frequency-based feature represents vectorized power spectrum, which is why it cannot depict locally difference data. Therefore, Abe et al.[3] proposed Local Binary Pattern(LBP based method might be useful to realize locally difference feature for authentication improvement. Additionally, EM-LBP is robust for the global difference(Biases), which is why it can represent the fine feature of the eye movement data .

Figure 1 shows the process flow of extracting EM-LBP. The captured eye movement time-series data is divided into local blocks. The feature value is computed as the following equation,

$$\begin{aligned} & feature\_value(t) \\ &= \sum_{k=0, k\neq 4}^{7} 2^k \cdot sign(d(t-4+k) - d(t)), \end{aligned} \tag{8}$$

where $sign(x)$ is if x is less than 0, the function outputs $+1$, otherwise, -1. The actual feature is defined as the histogram consisted of EM-LBP features. Finally, the EM-LBP feature can be calculated as a histogram of $feature\_value$ in the block.

III. Quality Assessment Method

Takashima et al. proposed that estimating method of pointing target using peak velocity on mouse operation. According to the paper, they showed the relationship between peak velocity and the target distance had correlation, and linear regression was used as estimating method. At first, we evaluate the relationship between peak velocity of eye movement data and the target distance.

Figure 2, 3 shows some examples of horizontal and vertical velocity transition whose subject ID is ID_001. According to the figure, After 200-300 ms on changing stimulus, eye balls start to move, then through the peak velocity, finally adjust the target by smooth pursuit. Although the adjusting scheme is different, this eye movement pointing mechanism is similar with mouse pointing.

In the next section, the relationship between peak velocity and the target distance is analyzed.

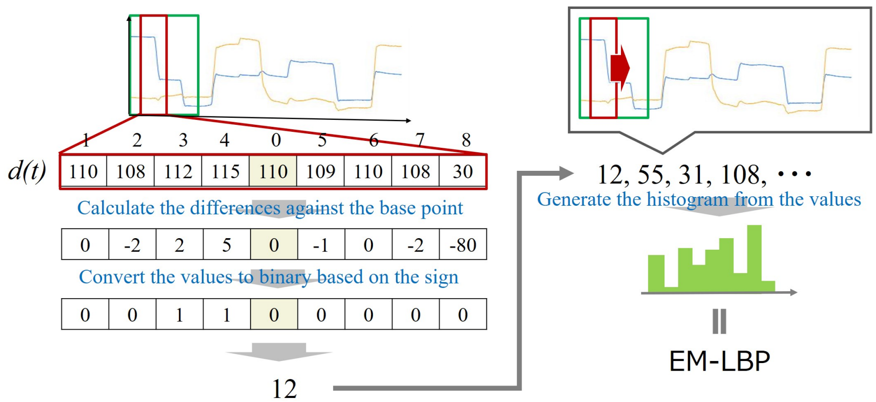


Fig. 1. The extraction process of EM-LBP Feature

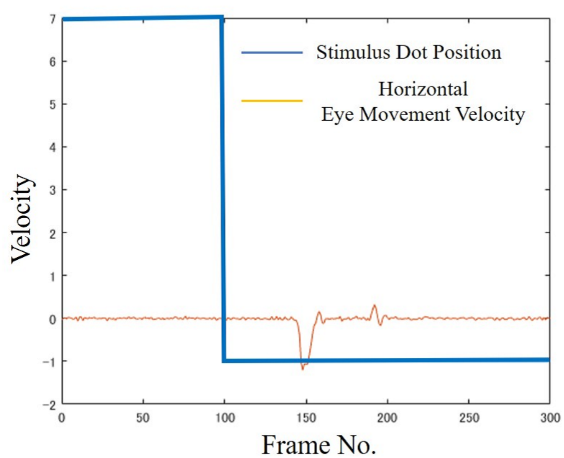


Fig. 2. Eye movement velocity on changing stimulus (horizontal)

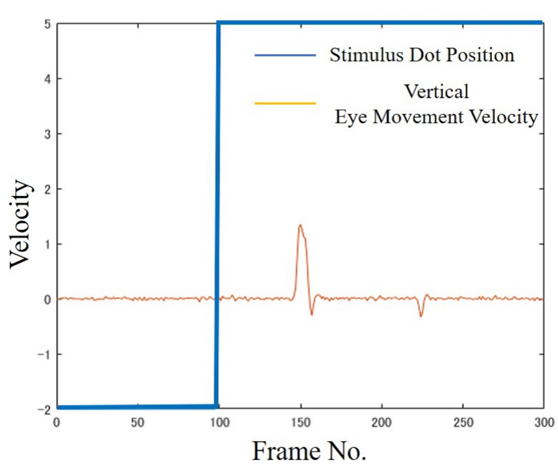


Fig. 3. Eye movement velocity on changing stimulus (vertical)

A. The relationship between peak velocity and the target distance

In order to analyze eye movement data, eye movement data which includes saccade and fixation is necessary. In this paper, we use the RAN task dataset in BioEye2015 which is one of eye movement authentication competition. RAN task is that a subject must follow the yellow dot on the screen, the position of the dot changes randomly and periodically.

Figures show the distribution consisted of peak velocity and the target distance, Figure 4 shows vertical transition, Figure 5 shows the horizontal transition respectively.

In the vertical point of view, the relationship has positive correlation and the dots are distribute linearly. On the other hand, in terms of horizontal view, although there is a positive correlation, it is limited if the target distance is plus minus 10. We can find out that the peak velocity is saturated as the distance is longer.

B. The Design of Quality Assessment Function

From the previous section, it was proven that there was the correlation between peak velocity of the line of sight data and distance to the target as well as the prediction of the mouse pointing. As shown in the figure, the relationship between the peak velocity of gaze and the distance to the target was clear in some cases and not in others. Although the relationship between the peak velocity and the distance to the target is a characteristic of the human eye movement, the characteristic deteriorates for some reason and no clear relationship can be found. Therefore, it is considered that the fitting difficulty of this modeling can be used for the quality of gaze data.

This section describes a method in which the relationship between the peak velocity and the target distance is modeled by applying an approximation function, and the degree of fitting between the estimated model and the measured value is defined as quality.

In this paper, the modeling in the polynomial approximation is examined as an approximate curve. This is because we have confirmed that the distribution of the point groups observed in

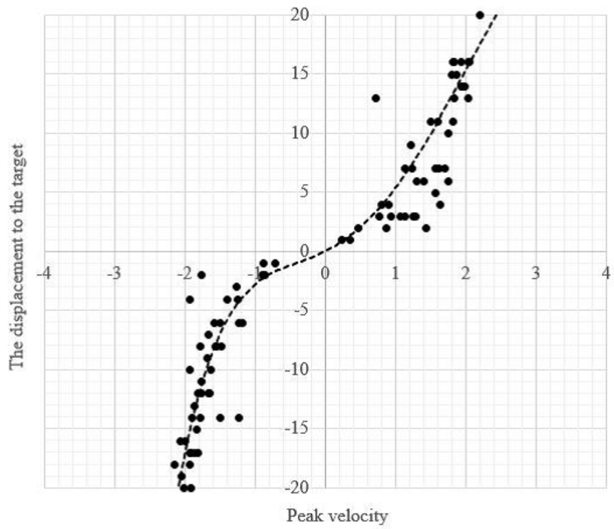


Fig. 4. The relationship between the peak velocity and the target distance(horizontal)

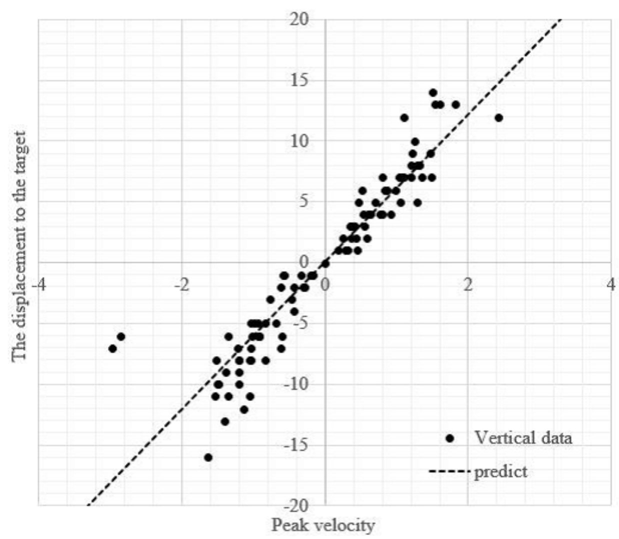


Fig. 5. The relationship between the peak velocity and the target distance(vertical)

the previous section tends to increase relatively monotonically and is not complicated. In the polynomial approximation, the order of the approximating polynomial is set, and the coefficient of the function is made variable so as to minimize the squared error.

The common SSE and SST and the R^2error calculated from SSE and SST should be used as an indicator of the degree to which the calculated modeling function agrees with the observed value.

IV. EVALUTION

A. Conditions

The validity of the predictive estimation function of eye pointing designed in the previous section is verified using the BioEye 2015 RAN task data set. The data set contains gaze data from 334 people. However, it is divided into the developed version and the evaluation version for the sake of competition, and the number of subjects whose labels are disclosed is 154, half of the cases. In addition, it is divided into a data set in which the collection interval of gaze data is 30 minutes and a data set in which the collection interval is 1 year.

In this paper, we generate a prediction function of eye pointing from the first data of each subject, and verify the fitting degree of the prediction function in the data after 30 minutes and 1 year. The degree of fitting is evaluated by calculating the squared residual error and the coefficient of determination.

B. Results

First, this paper reports the evaluation results on the order of polynomial approximation. In this evaluation, the least square error between the approximated curve and the data used for the approximation is calculated assuming that the order is 1, 3, 5, 7. The estimated function and actual plots are shown in Figure 6. As the number of the degree of order increases, the error between estimated distance and the actual distance decreases, however, the robustness of the estimated function decreases. From these reasons, we set the degree to 5 in this evaluation.

Next, with respect to the quality defined in the previous section, we investigate the correlation between the rank obtained through the discrimination process and the quality. Concretely, for each subject, the degree of fitting in the data after 30 minutes and 1 year for the modeling function which is polynomial approximated by degree 5, that is, the result calculated for SSE, etc. and the rank obtained as the result of discrimination are shown in the table.

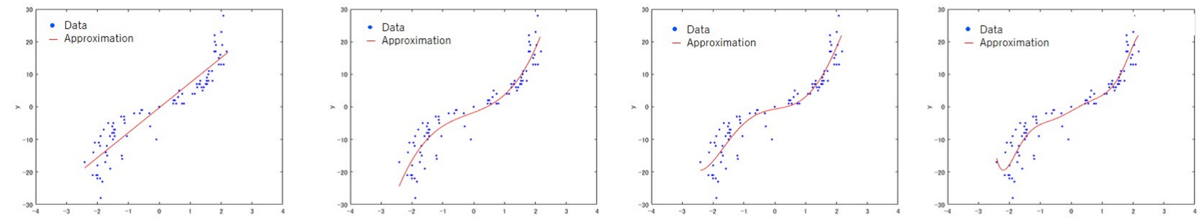
From the 1year data point of view in Table I, r^2 by modeling the enrollment on MFCC is -0.445, which means the correlation with the fitting degree of the registration data itself would be related to the actual identification results In terms of EM-LBP, $.r^2$ by modeling input data is -0.252, which means how the input data fits the modeling function is important to obtain better identification results.

From the 30min data point of view, we cannot find out any correlations between the fit and the identification results.

The results show that for the data after 30 minutes in Table II, the degree of fitting by the registration data itself is more affected by whether the matching data fit to the function modeled by the registration data.

V. CONCLUSION

In this paper, we proposed a method to predict the target gaze point coordinates from the peak velocity of the gaze. Concretely, the prediction estimation function was modeled by the polynomial approximation on the peak velocity and



(a) Approximated by the first order polynomial (b) Approximated by the third order polynomial (c)Approximated by the fifth order polynomial (d) Approximated by the seventh order polynomial

Fig. 6. The approximated curves on each order

	30min	30min	1year	1year
	MFCC	EM-LBP	MFCC	EM-LBP
SSE by the enrollment model(Quality of the enrollment)	-0.015	-0.135	0.163	-0.111
SST by the enrollment model(Quality of the enrollment)	0.042	-0.140	-0.371	-0.181
r^2 by the enrollment model(Quality of the enrollment)	0.045	0.084	-0.445	-0.023
SSE by the verification model(Quality of the input)	0.031	0.070	0.279	0.064
SST by the verification model(Quality of the input)	0.059	-0.071	0.089	0.183
r^2 by the verification model(Quality of the input)	-0.004	-0.136	-0.253	-0.252

TABLE I
CORRELATION COEFFICIENTS AMONG THE ESTIMATED QUALITY AND FEATURES(MFCC, EM-LBP)

	30min	30min	1year	1year
	MFCC	EM-LBP	MFCC	EM-LBP
SSE(Input Quality based on the enrollment model)	0.406	0.059	-0.069	-0.101
SSTInput Quality based on the enrollment model)	0.059	-0.071	0.044	-0.145
r^2Input Quality based on the enrollment model)	-0.392	-0.086	0.077	0.090

TABLE II
CORRELATION COEFFICIENTS AMONG THE ESTIMATED INPUT QUALITY BASED ON THE ENROLLMENT MODEL AND FEATURES(MFCC, EM-LBP)

the distance to the target. And, this modeling result was shown experimentally to be valid using the data got in the RAN task of BioEye 2015. In addition, it was shown that there was the individual difference in this modeling result, and the utilization in the individual certification was mentioned.

As a future problem, not only the object which moves from point to point, but also the continuous line of sight such as the prediction estimation of the trajectory in reading the text are analyzed and examined. In addition, the application to the individual certification which utilizes those knowledge will be evaluated and examined.

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