Eye-blink based Personal Authentication Using Time-series Directional Features and Waveform Features

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***Abstract*—In this study, we propose the personal authentication method using characteristics of eye blink and investigate effective features for authentication. The time-series gradient directional features and the waveform features extracted from the time-series gradient intensities are adopted as the features for recognition. The degree of similarity between registration and recognition features is obtained by the dynamic time warping (DTW) and Euclidean distance. From the experimental results, individual differences appeared in features obtained in the iris peripheral region and during opening eyes.**

I. Introduction

Recently, the personal authentication using biometric information such as fingerprints and faces has been adopted because of requirement of high-security level [1][2]. However, most of conventional biometric authentication are possible for others to invade by spoofing after authentication success. Thus, the continuous personal authentication methods using behavioral features is required [3][4]. Personal authentication using brain waves or electrooculogram signals during blink have been proposed as the scheme of continuous authentication [5][6]. However, these methods require to attach a headband or electrodes. Thus, we focus on biometric authentication method by eye blink which can be measured without attaching sensors. In this study, we propose the personal authentication method by eye blink which uses the time-series gradient intensity calculated by image processing of an eye image. In the proposed method, the time-series gradient intensities and the waveform features obtained from gradient intensity are adopted. These features are obtained in three eye regions surrounding the inner corner of one's eye, iris, and the outer corner of one's eye. The degree of similarity between the registration and recognition features is calculated using Euclidean distance or DTW distance. In this paper, we investigate effective features for personal authentication using eye blink.

II. Eye Blink

Eye blink is a rapid opening and closing movement of an eyelid when a human or an animal is being awake. It provides moisture to the eye and protects the eye from irritants. It is said that a human blinks fifteen to twenty times per minute and it takes 300 to 400 [ms] in one blink. Eye blink classified into three types: voluntary blink, spontaneous blink, and reflex blink [7]. In this study, authentication performance was evaluated using voluntary and spontaneous blinks.

III. Extracting Method of Waveform Features and Gradient Direction Features from Time-series Gradient Intensities

A. Definition of Feature Extraction Regions Surrounding an Eye

An image in the open eye state at the start time of blink was extracted from a moving image, and the eye regions for feature extraction were obtained. The regions for feature extraction are shown in Fig.1. First, an iris center position and an iris diameter were manually determined. The upper and lower eyelid positions were detected above and below the iris center position, respectively. The size of region surrounding the eye was calculated so that the horizontal width is 280% of the iris diameter, and the vertical width is the 166% of the iris diameter. Here, the range of ±50 pixels on the left and right directions of the iris center position is set as (i) the iris peripheral region, and the left and right side regions of the iris peripheral region are set as (ii)the inner corner of the eye region and (iii)the outer corner of the eye region, respectively. The horizontal width of three regions is shown in Table I.

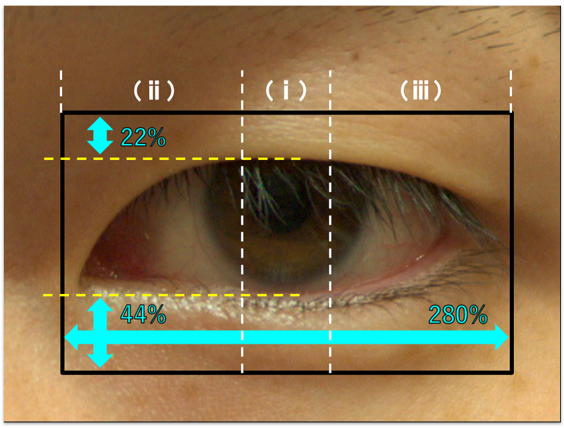

Fig. 1. Feature extraction region surrounding an eye.

TABLE I
HORIZONTAL WIDTH OF THREE EYE REGIONS.

Region	Horizontal width [pixels]
(i)Iris peripheral region	100
(ii)Inner corner of the eye region	200
(iii)Outer corner of the eye region	200

B. Extraction of Waveform Features

Blink detection using the time-series variations of the area including iris and pupil regions was performed from the captured video, and video frames during each blinking were extracted. Subsequently, the gradient intensities in each eye region were calculated from the eye image during blinking by using (1)∼(4) [8]. In (1)∼(4), $I_t(u,v)$ and $m_t(u,v)$ are the pixel value and the gradient intensity at the pixel of interest(u,v) at time t, respectively. The normalization based on the gradient intensity at the start time of blink was performed as shown in (5). In (5), G_t means the gradient intensity at time t.

$$g_{u,t}(u,v) = I_t(u+1,v) - I_t(u-1,v) \quad (1)$$

$$g_{v,t}(u,v) = I_t(u,v+1) - I_t(u,v-1) \quad (2)$$

$$m_t(u,v) = \sqrt{g_{u,t}^2(u,v) + g_{v,t}^2(u,v)} \quad (3)$$

$$G_t = \sum_{u,v} m_t(u,v) \quad (4)$$

$$G'_t = \frac{G_t}{G_0} \quad (5)$$

The waveform feature was extracted from the time-series variation of gradient intensity after normalization. In this study, five waveform features were defined as shown in Fig.2. In Fig.2, the point when starting to close eye (P_s), the point when ending to close eye (P_{sb}), the point when starting to open eye (P_{eb}), the point when ending to open eye (P_e) and the point when maximum gradient intensity during closing eye (P_{max}) were defined as feature points which used for feature extraction. After that, the amplitude of closing eye (A_{cl}), the amplitude of opening eye (A_{op}), the velocity of closing eye ($V_{cl} = A_{cl}/T_{cl}$), the velocity of opening eye ($V_{op} = A_{op}/T_{op}$), and the amplitude at P_{max} (A_{mv}) were defined as the waveform features. A blink feature vector consisted of all or a part of waveform features. The blink feature vector is shown in (6). In (6), $Fw_{a,l,k}$ means the k-th component of the waveform feature vector in the eye region $l(l = 1 \sim 3)$ of the subject number a. In this study, the waveform features were normalized with the average value of each waveform feature of all subjects as shown in (7) and (8). In (7), n means the number of subject. The blink feature vector used for personal identification is represented by the vector which consists of waveform features normalized by (7).

$$\boldsymbol{Fw}_{a,l} = [Fw_{a,l,1}, Fw_{a,l,2}, ..., Fw_{a,l,k}, ..., Fw_{a,l,5}] \quad (6)$$

$$Fw'_{a,l,k} = \frac{F_{a,l,k}}{\frac{1}{n}\sum_{i=1,i\neq a}^{n} F_{i,l,k}} \quad (7)$$

$$\boldsymbol{Fw}'_{a,l} = [Fw'_{a,l,1}, Fw'_{a,l,2}, ..., Fw'_{a,l,k}, ..., Fw'_{a,l,5}] \quad (8)$$

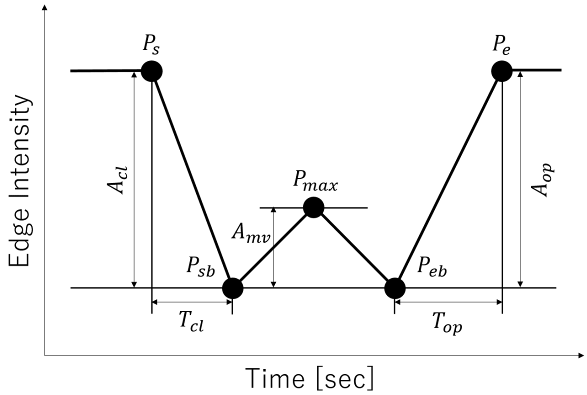

Fig. 2. Feature points and waveform features.

C. Extraction of Gradient Directional Features

As another feature for authentication, the gradient intensity in each eye region is quantized for each gradient direction, and the time-series gradient directional features were calculated. First, the gradient direction was calculated by (9). Next, the gradient directions were divided every 20° in the range of 0° to 180°, and the cumulative gradient intensities in 9 gradient directions were obtained.

$$\theta_t(u,v) = \tan^{-1}\frac{g_{v,t}(u,v)}{g_{u,t}(u,v)} \quad (9)$$

Furthermore, the gradient intensity vector that consisted of gradient intensities of all gradient directions was defined as shown in (10), and the gradient directional feature was normalized based on the gradient intensities of all gradient directions at each time t as shown in (11). In (10) and (11), $f_{k,t}$ means the gradient intensity in the gradient direction k at time t, and $\|\boldsymbol{f}_t\|$ means the L2 norm of the gradient intensity vector $\boldsymbol{f}_t$. $\boldsymbol{Fd}_t$ shown in (12) is the normalized gradient intensity vector which uses for registration and recognition. The time-series gradient directional features after normalization are shown in Fig.3. In Fig.3, the amplitude of the gradient intensity at blink is different in each gradient direction.

$$\boldsymbol{f}_t = [f_{1,t}, f_{2,t}, ..., f_{9,t}] \quad (10)$$

$$Fd_{k,t} = \frac{f_{k,t}}{\|\boldsymbol{f}_t\|} \quad (11)$$

$$\boldsymbol{Fd}_t = [Fd_{1,t}, Fd_{2,t}, ..., Fd_{9,t}] \quad (12)$$

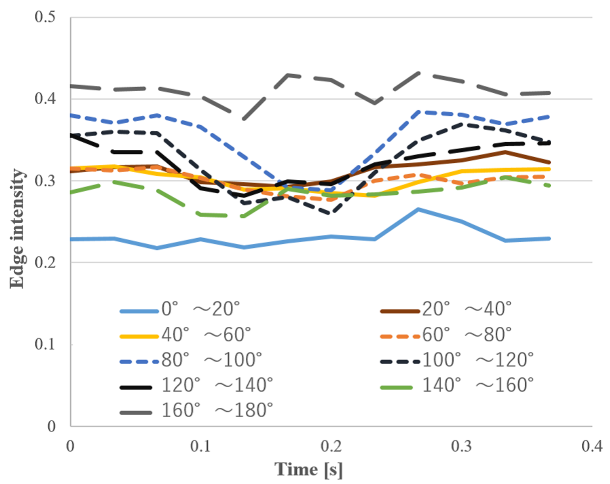

Fig. 3. Time-series gradient directional features after normalization.

IV. Experimental method

A. Capturing eye blink

The experiment environment is shown in Fig.4. In this experiment, we used a USB camera to capture eye blink. Ten students (eight males and two females), ages of twenty-two to twenty-four, participated in this experiment. The subjects were asked to blink in a state of being seated in a chair, and surrounding eye of the subject was captured by a USB camera fixed on a desk. To prevent defocus, we asked subjects to fix their heads with the chin stand fixed on the desk. Both voluntary and spontaneous blinks were captured for 30 seconds in one session, and we performed 3 sessions per one subject. For voluntary blink capturing, we presented beep sound ten times at random intervals of one to three seconds during capturing and instructed the subjects to blink immediately after this beep was occurred. For spontaneous blink capturing, we instructed the subjects to blink freely during capturing. These experiments were approved by the Ethics Committee of Toyama Prefectural University. Written informed consent was obtained from each participant.

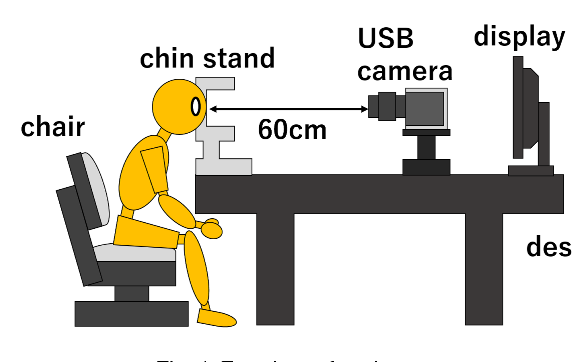

Fig. 4. Experimental environment.

B. Analytic method

In this study, two types of similarities were calculated using the waveform feature and the time-series gradient directional feature. In analysis using the waveform feature, the degree of similarity for blink features was obtained from Euclidean distance between registration and recognition blink features. In analysis using the gradient directional feature, the degree of similarity was calculated by DTW. The equal error rate (EER) was used for the evaluation of authentication accuracy. EER is the error rate where the false rejection rate (FRR) equals to the false acceptance rate (FAR).

V. Experimental Results

A. Authentication performance by waveform features

The result of recognition using waveform features is shown in Fig.5. The horizontal and vertical axes show the number of dimensions for blink feature vector and EER, respectively. The lowest EERs at each dimension are shown in Fig.5, and the best combinations of feature parameters at each dimension are shown in Tables II. From the comparison of the authentication results obtained by increasing the number of dimensions of blink feature vector, both EERs at voluntary and spontaneous blinks decrease to 4 dimensions and increases thereafter. The lowest EERs at 4 dimensions are 12.89% that used (i)-A_{op}, (i)-A_{mv}, (ii)-A_{op} and (iii)-A_{op} of voluntary blink and 13.33% that used (i)-A_{cl}, (i)-V_{op}, (ii)-A_{op} and (ii)-V_{op} of spontaneous blink. In addition, personal authentication performance with the blink feature vector more than 5 dimensions decreased due to the addition of useless waveform features.

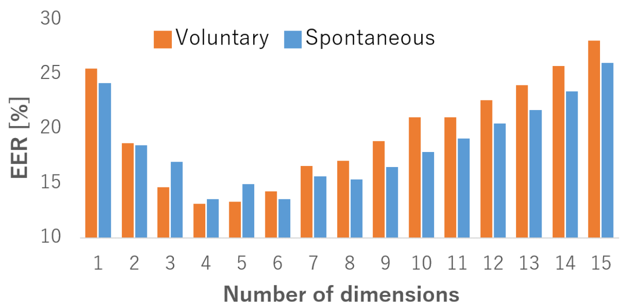

Fig. 5. EERs in each dimension of blink feature vector.

B. Authentication performance by gradient directional features

The EERs for the gradient directional feature are shown in Table III. In Table III, EER of the spontaneous blink is lower than that of the voluntary one. In addition, the eye region with the lowest EER is the iris peripheral region, and the region with the highest EER is the outer corner of the eye region. In comparison with results of waveform features, the EERs of the voluntary and spontaneous blinks decrease by 5.45% and 7.18%, respectively.

VI. Discussion

Both EERs for waveform feature and gradient directional feature were the lowest when these features were extracted in the iris peripheral region. Thus, the experimental results

TABLE II
WAVEFORM FEATURES IN EACH DIMENSION

Blink type	Region	Waveform feature	Number of dimension														
			1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Voluntary	(i)	A_{cl}													○	○	○
		A_{op}		○	○	○	○	○	○	○	○	○	○	○	○	○	○
		V_{cl}											○	○	○	○	○
		V_{op}									○	○	○	○	○	○	○
		A_{mv}		○	○	○	○	○	○	○	○	○	○	○	○	○	○
	(ii)	A_{cl}												○		○	○
		A_{op}	○			○	○	○	○	○	○	○	○	○	○	○	○
		V_{cl}										○	○	○	○	○	○
		V_{op}					○	○	○	○	○	○	○	○	○	○	○
		A_{mv}						○	○	○	○	○	○	○	○	○	○
	(iii)	A_{cl}													○	○	○
		A_{op}			○	○	○	○	○	○	○	○	○	○	○	○	○
		V_{cl}															○
		V_{op}								○	○	○	○	○	○	○	○
		A_{mv}							○	○	○	○	○	○	○	○	○
Spontaneous	(i)	A_{cl}				○		○	○	○	○	○	○	○	○	○	○
		A_{op}					○		○	○	○	○	○	○	○	○	○
		V_{cl}												○	○	○	○
		V_{op}				○		○	○	○	○	○	○	○	○	○	○
		A_{mv}								○	○	○	○	○	○	○	○
	(ii)	A_{cl}									○	○	○	○	○	○	○
		A_{op}			○	○	○	○	○	○	○	○	○	○	○	○	○
		V_{cl}										○	○	○	○	○	○
		V_{op}	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○
		A_{mv}															○
	(iii)	A_{cl}													○	○	○
		A_{op}		○	○		○	○	○	○	○	○	○	○	○	○	○
		V_{cl}														○	○
		V_{op}					○	○	○	○	○	○	○	○	○	○	○
		A_{mv}											○	○	○	○	○

TABLE III
EER OBTAINED BY GRADIENT DIRECTIONAL FEATURES.

Region	EER [%]	
	Voluntary	Spontaneous
(i)	7.44	6.15
(ii)	9.10	10.21
(iii)	15.15	8.57

indicated that individual differences were found in features obtained in the iris peripheral region. This is due to the fact that a large variation appears in the amplitude of gradient intensity because the movement variation of the upper eyelid at blink is larger than those of the inner corner and the outer corner of the eye region. Furthermore, the waveform feature of A_{op} and V_{op} are preferentially selected among all waveform features. Thus, it revealed that individual differences also appeared in the eye-opening process.

VII. CONCLUSIONS

In this study, we focused on biometric authentication method by eye blink and investigated effective features for personal authentication. Euclidean distance and DTW distance were used as the degree of similarity. In the evaluation of authentication performance, the lowest EERs of the waveform feature and the gradient directional feature are 12.89% and 6.15%, respectively. In addition, the experimental results revealed that individual differences appeared in the features obtained in the iris peripheral region and during opening eye. In the future work, we will improve the recognition performance by combining the waveform features and the gradient directional features.

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