A Novel Local Feature for Eye Movement Authentication

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Abstract: Eye movement authentication technology has been proposed as a biometric modality, which enables to authenticate a user continuously, and has the counterfeit feature because of the difficulty of the imitation. By using the eye movement authentication, it is possible to realize an automatic authentication system as long as he/she is looking at a display to operate the device. However, the authentication accuracy is still low compared to the other traditional biometric modalities, such as fingerprint, face, and iris. In this paper, we propose the novel local eye movement feature to represent local differences of the captured time-series gazing data, and we show the proposed feature can work as a complement feature against Mel Frequency Cepstrum Coefficients(MFCC), which is based on the local phase information of eye movement data. We show the classification rate improves from 61% to 82% in the BioEye2015 dataset by using our proposed method on the best case.

Keywords: Eye movement, MFCC, Local Binary Pattern(LBP).

1   Introduction

Many biometric modalities such as fingerprint ,face, vein, iris, and so force have been proposed, which are used for access control management systems, entrance management systems, and social security identification systems. In this recent decade, the authentication methods using periocular regions[Pa11] like iris, eye vein, eye brow, and *eye movement* have been proposed since the region has many pieces of useful information for authentication. In particular, the eye movement authentication technology has grown remarkably because it has the following advantages, "Enabling the authentication process without any specific action by a user", "Enabling the continuous authentication", "Hard to spoof his/her eye movement".

Eye movement analysis researches have been conducted for a long time, which are used as the medical diagnosis techniques regarding eyes or as the analysis of the subject's behavior. In terms of the biometric modality, Kasprowski[KO03] proposed the authentication scheme using eye movement in 2003. Actually, the authentication accuracy of the eye movement is not as accurate as the other conventional biometric modalities, such as fingerprint, face, iris. However, eye movement can be captured during capture of face or iris simultaneously, which means that the eye movement is useful for the improvement of the authentication accuracy by combining it with those modalities.

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Furthermore, some eye movement authentication competitions were held in 2012[KKK12], 2014[Th14], 2015[Bi15], and 2016[Lo15], which give the better motivation to researchers.

In terms of the feature extraction, Komogortsev et al.[Ko12] proposed a mathematical model using the Oculomotor Plant Characteristics (OPC) which consists of nine scholar values, such as length tension represents an exterior muscle's length and strength , series elasticity represents a resistant of an eye muscle, etc. Holland et al.[HK13b][HK13a] proposed a statistical feature extraction method using twelve features including a horizontal average velocity during fixation and saccade, and evaluated some statistical tests for authentication. According to the evaluation result, Kolmogorov-Smirnov test and Cramer-von Mises test are better than t-test for an authentication performance. Rigas et al.[REF12] proposed a graph-based matching in a velocity-acceleration space. Cuong et al.[CDH12] proposed an authentication method using Mel-Frequency Cepstrum Coefficients (MFCC). Kinnunen et al.[KSB10] mentioned a task-independent eye movement authentication technique which allowed us to authenticate users without any specific instruction.

However, the capture time becomes longer compared to the other modalities in order to obtain the enough information for authentication, which means it is hard to use for the high usability purpose like an access control of a PC. The more intuitive authentication system which derives from the advantage of eye movement would be useful for users. Furthermore, the 1st algorithm in BioEye2015 uses the statistical features with Neural Networks, but we are sure that it is necessary to consider which feature is effective both for authentication and an analysis.

In this paper, we propose the iterative local matching scheme and the novel local feature which is called *Eye Movement Local Binary Pattern (EM-LBP)*. We describe the our proposed architecture for eye movement authentication in section 2, and we explain MFCC algorithm as a conventional feature, and propose the EM-LBP. We show the evaluation result using BioEye2015 datasets in section 3, and we discuss the correlation between MFCC and EM-LBP in section 4. Finally, we conclude our paper in section 5.

2   Our Proposed Eye Movement Authentication Scheme

In our proposed scheme, it is not necessary to use long time-series data, which consists of the time-series gazing position(x,y) on a screen. The flow of the feature extraction method is shown in Figure 1. First, we classify the eye movement condition, fixation or saccade, then calculate the local features. In order to calculate local features, we use the *sliding window* technique, which can extract local features efficiently.

Let $d(t)$ be the time-series data, we divide $d(t)$ into some patch data $p_i(t)$ whose length is W. Let L be the length of $d(t)$, r_{ol} be the overlapping rate among each window, and the number of data patch N_p can be calculated by $N_p = \lceil \frac{L}{W(1-r_{ol})} \rceil - 1$. Local features v_i are calculated from each patch p_i, so that we calculate N_p local features from the entire data, and v_i includes any local features($L1, L2, ...$) such as MFCC. Then the local features are stored as a template in the database.

In this authentication scheme, any local features can be applied. Now, we introduce the well known useful eye movement local feature MFCC in the next section, and we propose novel local feature which is called EM-LBP based on one dimensional Local Binary Pattern(LBP) in the further section.
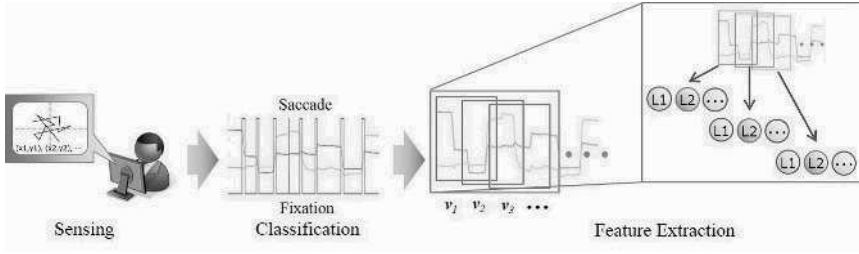

Fig. 1: The proposed system

2.1   Local Features

As a useful feature of eye movement authentication, MFCC analysis is a well-known method, which is often used in the speech recognition technology, and this feature can obtain better authentication accuracy compared to the other published algorithms such as CEM[HK13a] and OPC[Ko12].

2.1.1   Mel Frequency Cepstrum Coefficients (MFCC)

In the previous researches[CDH12][KR13], they show 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.

2.1.2   Eye Movement LBP(EM-LBP)

MFCC uses frequency information extracted from captured eye movement data. This frequency-based feature represents vectorized power spectrum, which is why it cannot depict local difference information. Therefore, we came up the idea which Local Binary Pattern(LBP based method might be useful to realize locally difference feature to improve the authentication accuracy.

Now, we propose one dimensional LBP method for eye movement data, which is called Eye Movement LBP(EM-LBP). In fact, there is a similar approach in image recognition, our method is inspired by [HHB14].

Figure 2 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 $feature\_value(t) = \sum_{k=0, k\neq 4}^{7} 2^k \cdot sign(d(t-4+k) - d(t))$, where $sign(x)$ is if x is less than 0, the function outputs $+1$, otherwise, -1. Finally, the EM-LBP feature can be calculated as a histogram of $feature\_value$ in the block.
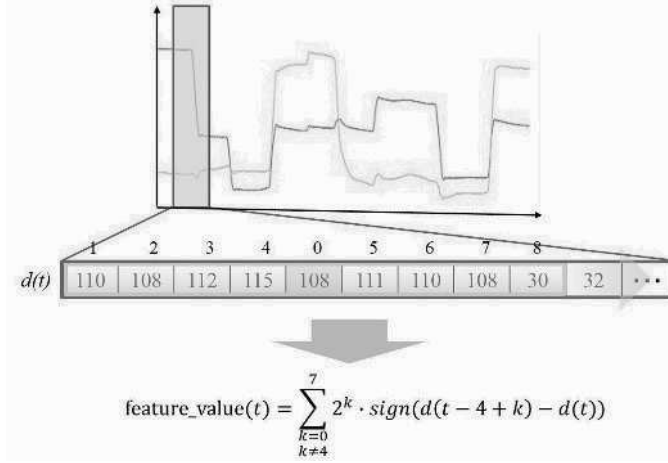

Fig. 2: The extraction process of EM-LBP Feature

2.2   The Comparison Method

Local features are represented as the simple vectorized data, and the similarity is defined as L1 distance between two vectors. Actually, temporal score can be computed using feature vector data extracted from each data patch. The final score can be calculated by accumulating these temporal scores.

In Algorithm 1, we calculate the V_L^1 whose number is N_p^1 from one time-series data d_1, and V_L^2 whose number is N_p^2 from d_2. The similarity between two time series data can be computed by the algorithm 1. Here, $L1\_norm(\cdot, \cdot)$ represents L1-norm distance between two vectors.

3   Evaluation

We evaluate on the authentication accuracy using BioEye2015 datasets which is one of public dataset. The detailed information regarding the data is described on the competition web page[Bi15].

Algorithm 1 The similarity calculation of d_1 and d_2

$S_{accumulate} \Leftarrow 0, S_{final} \Leftarrow 0$
for $i = 0$ to $N_p^1 - 1$ **do**
    $S_{local} \Leftarrow max\_value$
    for $j = 0$ to $N_p^2 - 1$ **do**
        $score \Leftarrow L1\_norm(V_L^1(i), V_L^2(j))$
        if $score < S_{local}$ **then**
            $S_{local} \Leftarrow score$
        end if
    end for
    $S_{accumulate} \Leftarrow S_{accumulate} + S_{local}$
end for
$S_{final} \Leftarrow S_{accumulate}$

	RAN_30min	RAN_1yr	TXT_30min	TXT_1yr
MFCC	54%	46%	61%	49%
EMLBP	50%	49%	54%	32%
Fusion	75%	59%	82%	57%

Tab. 1: Rank 1 Classification Rate

3.1   Evaluation condition

The first session dataset is used as a template, and the second session dataset is used as verification data. We set the window size W to 512, the overlapping rate r_{ol} to 0.75, the number of eigenvectors for EM-LBP to 8, and the number of eigenvectors for MFCC to 2. In addition, the parameters was determined on the preliminary experiments.

As a evaluation measure, we will show the rank-1 classification rate and the Cumulative Match Characteristics(CMC) curve of each algorithms.

3.2   Results

We show the Cumulative Match Characteristics(CMC) curve. Figure 3 and Figure 4 shows the CMC curves of MFCC and EM-LBP respectively. Furthermore, Figure 5 shows the fusion result of MFCC and EM-LBP by using SUM rule. And, Rank 1 classification rate is shown in Table 1.

According to the results, the accuracy of EM-LBP is almost same as the accuracy of MFCC. Actually, in RAN datasets, EM-LBP obtains 50% and 49%, MFCC obtains 54% and 46% in 30min and 1year respectively. In terms of the difference of the stimulus, we cannot find significant accuracy difference between RAN and TXT.
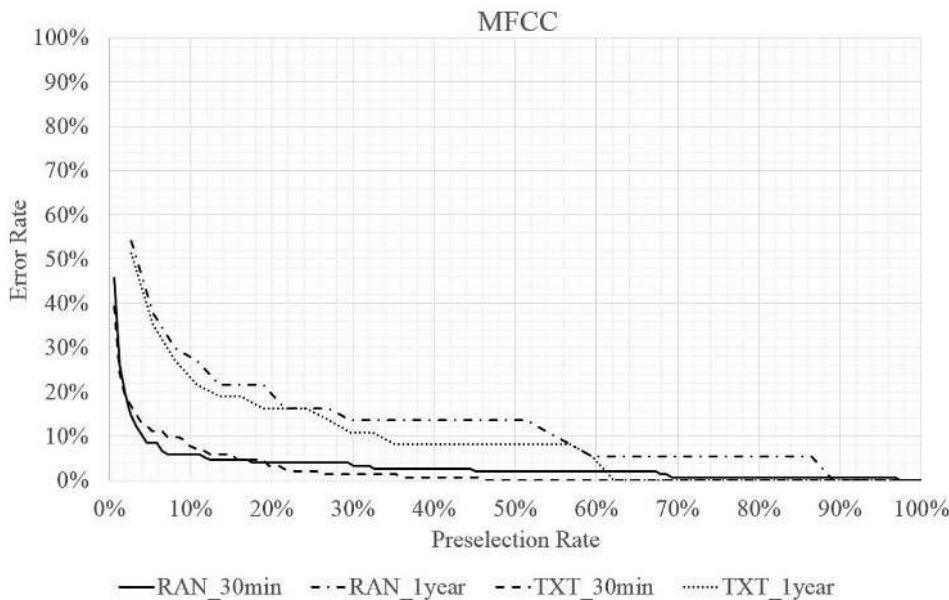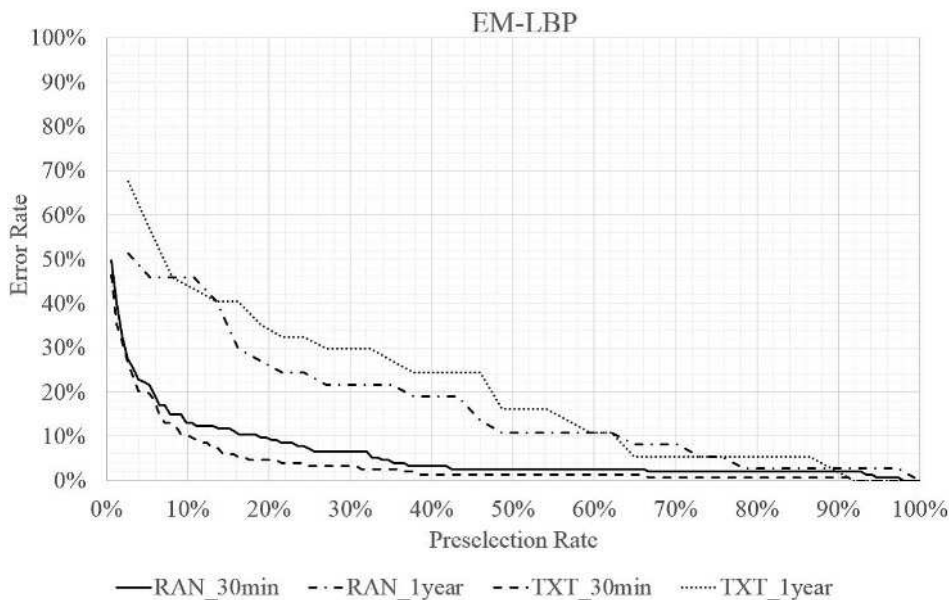
Fig. 3: The CMC Curve of MFCC
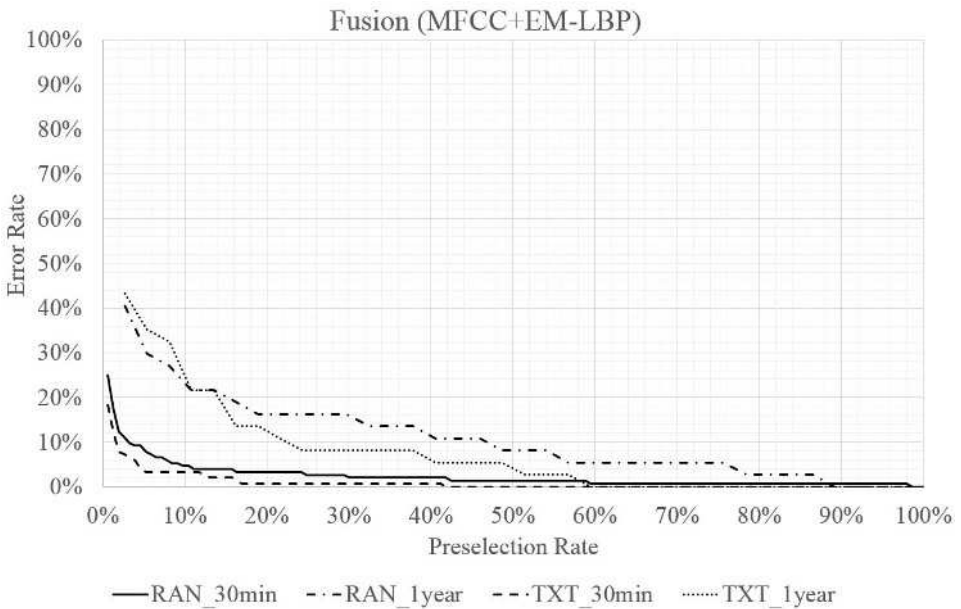

Fig. 4: The CMC Curve of EMLBP

Fig. 5: The CMC Curve of the Fusion Method

4   Discussion

Although EM-LBP is averagely slightly worse than MFCC which is one of useful features for eye movement classification, EM-LBP's accuracy is almost same as MFCC in RAN tasks. Actually, MFCC is the feature based on the power spectrum of the captured data. On the other hand, EM-LBP can represent the differential feature, which implies that EM-LBP can represent the other aspects against MFCC.

Now, we investigate the correlation coefficients between MFCC and EM-LBP in order to estimate the improvement effect of the score fusion scheme. The coefficients whose interval is 30min(0.22, 0.26) are slightly higher than those of 1year interval(0.11, 0.16), which is because the elapsed time is related to the similarity score. All coefficients is under 0.30, which implies that the EM-LBP represents the other aspects compared to MFCC.

5   Conclusion

In this paper, in order to support MFCC which is based on power spectrum of eye movement data, we proposed the new local feature, EM-LBP. Furthermore, we evaluated on the accuracy using the BioEye2015 dataset. As a result, we made sure that EM-LBP obtained almost same accuracy compared to MFCC's accuracy, and the SUM rule fusion was effective to get higher accuracy. We will keep investigating the further features to improve the authentication accuracy.

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