Texture Feature Extraction From Free-Viewing Scan Paths Using Gabor Filters With Downsampling

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ABSTRACT

Texture-based features computed on eye movement scan paths have recently been proposed for eye movement biometric applications. Feature vectors were extracted within this prior work by computing the mean and standard deviation of the resulting images obtained through application of a Gabor filter bank. This paper describes preliminary work exploring an alternative technique for extracting features from Gabor filtered scan path images. Namely, features vectors are obtained by downsampling the filtered images, thereby retaining structured spatial information within the feature vector. The proposed technique is validated at various downsampling scales for data collected from 94 subjects during free-viewing of a fantasy movie trailer. The approach is demonstrated to reduce EER versus the previously proposed statistical summary technique by 11.7% for the best evaluated downsampling parameter.

CCS CONCEPTS

• **Security and Privacy**; • **System Security**;

KEYWORDS

biometrics, eye-movement biometrics, texture features, Gabor filters

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1 INTRODUCTION

Since their initial proposal in 2004 [Kasprowski and Ober 2004], eye movement dynamics have received substantial attention in the literature as a biometric modality [Rigas and Komogortsev 2017]. Eye movement biometrics offer notable advantages versus other approaches, including their resistance to spoofing and ability to support liveliness detection [Komogortsev et al. 2015]. Eye movement biometrics are also well suited for biometric fusion methods utilizing the physical characteristics of the eye, as has been proposed in prior work (i.e.: [George and Routray 2016], etc.). Eye movement biometrics are especially promising for future large-scale commercial applications, given the pending integration of eye movement sensors within consumer electronic devices, including virtual and augmented reality platforms [Krishna et al. 2019].

Numerous techniques for extracting feature vectors from eye movement signals have been previously demonstrated. While preliminary work investigated movement-agnostic features (i.e.: cepstrum coefficients of the unsegmented time series signal as employed in [Kasprowski and Ober 2004]), more recent advances have proposed computing a rich feature space using classified eye movement signals. For example, Rigas et al. [Rigas et al. 2018] introduced a set of 101 features describing fixations, saccades, and post-saccadic oscillations during a reading task. In addition, feature representations which describe the texture of the eye movement trace over the course of a free-viewing experiment, hereby denoted as a scan path image, have also been proposed. Li et al. [Li et al. 2018] introduced a procedure using a Gabor filter bank to extract texture features from scan paths captured during a customized matching task. To extract summary features, the mean and standard deviation of the filtered images for each scale and orientation combination were used. Additional feature extraction approaches utilizing the spatial patterns of eye movements have also been proposed (i.e.: [Rigas and Komogortsev 2014]).

The research described herein explores an alternative approach for extracting texture features for image sets computed by applying a Gabor filter bank to a scan path image. Namely, to preserve spatial structure, we extract features using direct downsampling of the filtered images. For purposes of comparison, this technique is evaluated for multiple downsampling parameters versus the summary statistical approach used in [Li et al. 2018]. Biometric recognition performance is assessed using equal error rate (EER) for a dataset consisting of 94 individuals whose eye movements were recorded while viewing a fantasy video trailer. Although downsampling of filtered images has been applied in other biometric domains (i.e.: facial recognition in [Haghighat et al. 2015]), we believe that this manuscript is the first to apply the technique to scan path images.

2 METHODS

2.1 Data Collection

The data analyzed herein is a subset of a large-scale data collection conducted at Texas State University. Subjects provided informed consent under a protocol approved by the Institutional Research Board. All subjects had normal or corrected to normal vision using either glasses or contacts lenses. As part of the collection, subjects viewed a 60 second movie trailer from the Hobbit series on a 22", 1680 x 1050 monitor at 550 mm separation. Monocular eye

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movements were captured at 1,000 Hz using an EyeLink 1000 (SR Research Ltd., Mississauga, ON, CA) device.

2.2 Data Analysis

For this preliminary investigation, only data from the first 100 enrolled subjects for the first round of collection is analyzed. Each recording round involves two viewing sessions completed sequentially with an approximately 20 minute break between sessions. 94 of the 100 subjects enrolled were successfully recorded during both sessions.

To promote comparability with prior work, employed methods are largely consistent with those described in [Li et al. 2018]. Scan path images were generated by scaling the output of the eye tracker in pixels by a factor of 5 in order to maintain a consistent aspect ratio, resulting in a 336 x 210 pixel image. Example images prior to scaling are shown in Fig. 1 for the first four users during the initial session.

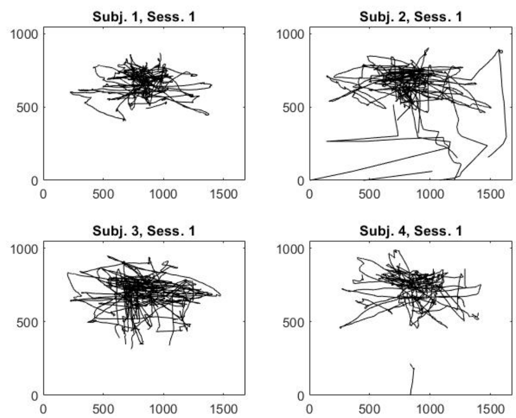

Figure 1: Example scan paths for the first four participants, session 1 recordings

Each image was filtered using a Gabor filter bank parameterized as follows -

$$G(x,y) = \frac{f^2}{(\pi\gamma\eta)} exp(-\frac{x'^2 + \gamma y'^2}{2\sigma^2}) exp(j2\pi f x') \quad (1)$$

where $x' = xcos(\theta) + ysin(\theta)$ and $y' = -xsin(\theta) + ycos(\theta)$. In this parameterization, f corresponds to the spatial frequency or scale of the filter, while θ corresponds to the orientation. Eleven scales ($f = \frac{0.25}{\sqrt{(2)^{i-1}}}, i = 1, 2, ...11$) and 8 orientations ($\theta = \frac{\pi(j-1)}{8}, j = 1, 2, ..8$) were explored herein. Parameter values were also set consistent with [Li et al. 2018] (i.e.: $\sigma = 1/f$, $\eta = 2$, $\gamma = 1$). The Gabor filter bank was implemented using a slightly adapted version of the code described in [Haghighat et al. 2015].

To retain spatial structure in the feature vector, filtered images were downsampled at various scales. Downsampling factors (DS) of 20, 25, and 30 were investigated. The resulting feature vectors were used to perform biometric identification using an updated version of the workflow described in [Friedman et al. 2017]. Biometric recognition performance was assessed using EER.

3 PRELIMINARY RESULTS

EERs for the various approaches considered are shown in Fig. 2. As noted, all downsampling approaches yielded superior performance relative to the previously proposed statistical summary approach, with a best-case reduction in EER of 11.7%. Moreover, nonmonotonic variability in EER was observed across the downsampling parameter values considered.

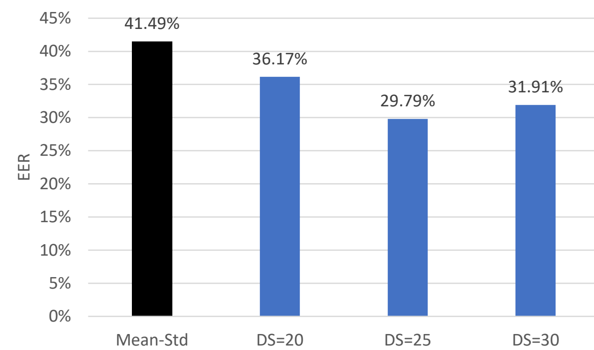

Figure 2: Variation in EER versus feature summary approach

4 LIMITATIONS AND FUTURE WORK

This preliminary assessment is characterized by several limitations which will be addressed in future research. For example, all parameter settings for the Gabor filter bank were replicated from [Li et al. 2018]. As this analysis was conducted for a different stimuli, it is reasonable to assume that further parameter tuning would improve results. The effect of scan path image size should also be further investigated.

In addition, future work should explore the efficacy of the proposed approach for different free-viewing stimuli (i.e.: other search tasks, images, etc.). As the two recording sessions in this research used the same video clip, the intrasubject scan paths across sessions may have varied considerably due to a learning effect, thus inherently limiting biometric performance. As a result of these limitations, the presented EER values are notably lacking with respect to current state-of-the-art performance standards.

5 CONCLUSIONS

This manuscript demonstrates an alternative technique for summarizing the texture features of scan path images obtained by applying a Gabor filter bank. While this downsampling approach has been employed for other biometric modalities, the current results suggest that this technique could be valuable for feature extraction workflows in eye movement biometrics. We hypothesize that this improvement over previously proposed aggregate statistical summaries of the filtered image is related to the retention of structured spatial information within the feature vector.

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REFERENCES

Lee Friedman, Mark S. Nixon, and Oleg V. Komogortsev. 2017. Method to assess the temporal persistence of potential biometric features: Application to oculomotor, gait, face and brain structure databases. *PloS one* 12, 6 (2017).

Anjith George and Aurobinda Routray. 2016. A score level fusion method for eye movement biometrics. *Pattern Recognition Letters* 82 (2016), 207–215.

Mohammad Haghighat, Saman Zonouz, and Mohamed Abdel-Mottaleb. 2015. CloudID: Trustworthy cloud-based and cross-enterprise biometric identification. *Expert Systems with Applications* 42, 21 (2015), 7905–7916.

Pawel Kasprowski and Jozef Ober. 2004. Eye movements in biometrics. In *International Workshop on Biometric Authentication*. Springer, 248–258.

Oleg V. Komogortsev, Alexey Karpov, and Corey D. Holland. 2015. Attack of mechanical replicas: Liveness detection with eye movements. *IEEE Transactions on Information Forensics and Security* 10, 4 (2015), 716–725.

Vrishab Krishna, Yi Ding, Aiwen Xu, and Tobias Höllerer. 2019. Multimodal Biometric Authentication for VR/AR using EEG and Eye Tracking. In *Adjunct of the 2019 International Conference on Multimodal Interaction*. 1–5.

Chunyong Li, Jiguo Xue, Cheng Quan, Jingwei Yue, and Chenggang Zhang. 2018. Biometric recognition via texture features of eye movement trajectories in a visual searching task. *PloS one* 13, 4 (2018).

Ioannis Rigas, Lee Friedman, and Oleg Komogortsev. 2018. Study of an extensive set of eye movement features: Extraction methods and statistical analysis. *Journal of Eye Movement Research* 11, 1 (2018), 3.

Ioannis Rigas and Oleg V. Komogortsev. 2014. Biometric recognition via probabilistic spatial projection of eye movement trajectories in dynamic visual environments. *IEEE Transactions on Information Forensics and Security* 9, 10 (2014), 1743–1754.

Ioannis Rigas and Oleg V. Komogortsev. 2017. Current research in eye movement biometrics: An analysis based on BioEye 2015 competition. *Image and Vision Computing* 58 (2017), 129–141.