International Journal on Emerging Technologies (Special Issue NCETST-2017) 8(1): 625-627(2017)
(Published by Research Trend, Website: www.researchtrend.net)
ISSN No. (Print) : 0975-8364
ISSN No. (Online) : 2249-3255

SPOOF DETECTION: Application to Face Recognition

Navneet Kaur and Kumari Pratima
M. Tech Scholar, Electrical & Instrumentation Department,
SLIET, Longowal, Sangrur, (Punjab), India

ABSTRACT: Authenticating a correct user plays an important part to protect various types of information, and using biometrics for recognition helps in this. Face biometrics are easily accepted by all as it is easy to use. The recent techniques used for face recognition can be spoofed using cheap equipment's. In this paper various techniques to detect face spoofing using texture analysis, temperature variation, motion, liveness detection and distinguish between real faces and fake ones.

Keywords: Anti-spoofing, Liveness detection, Face recognition, Biometrics.

I. INTRODUCTION

Biometrics is an emerging technology that recognizes human identities based upon one or more intrinsic physiological or behavioral characteristic, e.g. faces, fingerprints, irises, voice [1]. However, spoofing attack (or copy attack) is still a fatal threat for biometric authentication systems [2]. Liveness detection, which aims at recognition of human physiological activities as the liveness indicator to prevent spoofing attack, is becoming very active in fields of fingerprint recognition and iris recognition [2, 3, 4, 5]. In the face recognition community, numerous recognition approaches have been presented, but the efforts on antispoofing are still very limited[6]. The most common faking way is to use a facial photograph of the valid user to spoof the face recognition system, since usually one's facial image is very easily available for the public, for example, downloaded from the web, captured unknowingly by the camera. Photo attack is one of the cheapest and easiest spoofing approaches. The imposter can rotate, shift, and bend the valid user's photo before the camera like a live person to fool the authentication system. It is a challenging task to detect whether the input face image is from a live person or from a photograph.

Most of the current face recognition systems are based on intensity images and equipped with a generic camera. An anti-spoofing method without additional device is more preferable. It could be easily integrated into the existing face recognition systems. The goal of this paper is to develop a real-time liveness testing approach to resist photograph-spoofing in a non intrusive manner for face recognition, which does not require any additional hardware except for a generic webcamera.

A. Analysis of Face Liveness

In general, a human can distinguish a live face or a photograph without much effort, since a human can easily recognize many physiological clues of liveness, for example, facial expression variation, mouth movement, head rotation, eye change. However, sensing these clues is very difficult for a computer, even under an unconstrained environment. We hope to find some easily computational and hardly spoofed clue for the photo-spoofing prevention.

From the static view, the essential difference between the live face and photograph is that a live face is a fully three dimensional object while a photograph could be considered as a two dimensional planar structure. With this natural trait, Choudhary *et al* [7] employed the structure from motion yielding the depth informationofthefacetodistinguish live person and still photo. The disadvantages of depth information are that , it is hard to estimate depth information when head is still, and the estimate is very sensitive to noise and lighting condition, becoming unreliable.

B. Eyeblink for Liveness Detection

Eyeblink is a physiological activity of rapid closing and opening of the eyelid, which is an essential function of the eye that helps to spread tears across and remove irritants from the surface of the cornea and conjunctiva. Although blink speed can vary with elements such as fatigue, emotional stress, behavior category, amount of sleep, eye injury, medication,and disease,researchers report that [8,9], the spontaneous resting blink rate of a human being is nearly from 15 to 30 eyeblinks per minute. That is, a person blinks approximately once every 2 to 4 seconds, and the average blink lasts about 250 milliseconds.

The current generic camera can easily capture the face video with not less than 15 fps (frames per second), i.e. the frame interval is not more than 70 milliseconds. Thus, it is easy for the generic camera to capture two or more frames for each blink when the face looks into the camera.

It is feasible to adopt eyeblink as a clue for anti-spoofing. The advantages of eyeblink based approach lie in: 1) it can complete in a non-intrusive manner, generally without user collaboration, 2) no extra hardware is required, 3) the eyeblink behavior is the prominently distinguishing character of a live face from a facial photo, which would be very helpful for liveness detection only from a generic camera. There is little work addressing vision-based detection of eyeblink in the literature. Most of previous efforts need highly controlled conditions and high-quality input data, for example, the system of automatic recognition of human facial action units[10]. Moriyama'seye blink detection method[11] is based on variation of average intensity in the eye region, sensitive to lighting conditions and noise. Ji et al [12] have attempted to use an active IR camera to detect eye blinks for prediction of driver fatigue. This paper poses the photo spoofing problem as detection of eyeblink behaviors. To tackle this problem, we first model blink detection as inference in a Conditional Random Field[13] framework, which enables the long-range dependencies among observations and states. Eye closity,a discriminative measure derived from the adaptive boosting algorithm, is introduced and embedded into the contextual model, for computational efficiency and detection accuracy consideration. The extensive experiments are conducted to demonstrate effectiveness of the proposed approach.

II. THE APPROACH

The eyeblink behavior could be represented as a temporal image sequence after being digitally captured by the camera. One typical method to detect blink is to classify each image in the sequence independently as one state of either closed eye or opened eye, for example, using the Viola's cascaded Adaboost approach for face detection [14]. The problem with this method is that it assumes all of the images in the temporal sequence are independent. Actually, the neighboring images of blinking are dependent, since the blink is a procedure of eye going from open to close, and back to open. The temporal information is ignored for this method, which may be very helpful for recognition.

A. Eye Closity

From the theoretical view, the original image data could be directly incorporated into the conditional model framework described above. However, it would dramatically increase the complexity and make the problem hard to solve. We hope to take advantage of the features extracted from the image for defining the intermediate observation. For example, silhouette features are commonly used in human motion recognition [15, 16]. Our goal is to develop a real-time approach, thus, we try to use as little feature as possible to reduce the computational cost, meanwhile the features should convey as much discriminative information for eye states as possible to improve the prediction accuracy.

Motivated by the idea of the adaptive boosting algorithm [17], we define a real-value discriminative feature for the eye image,called eye closity, U(I),measuring the degree of eye's closeness, which is constructed by a linear ensemble of a series of weak binary classifiers and computed by an iterative procedure.

III. CONCLUSIONS

This paper investigates eyeblinks as liveness detection against photo spoofing in face recognition. The advantages of eyeblink-based method are non-intrusion, no extra hardware requirement, and prominence of activity. To recognize the eyeblink behavior, we model the dependencies among the observations and states in an undirected conditional graphical framework, embedded a new-defined discriminative measure of eye state in order to hasten inference as well as convey the most effective discriminative information. We demonstrated that the proposed approach achieves high performance by just using one generic webcamera under uncontrolled indoor lighting conditions, even was worn glasses-wearing allowed. The comparison experiments showed our approach outperforms cascaded Adaboost and HMM. The proposed eyeblink detection approach, in nature, can be applied to a wide range of applications such as fatigue monitoring, psychological experiments, medical testing, and interactive gaming.

REFERENCES

[1] A.Ross, K.Nanda kumar, A.K.Jain, Handbook of Multibiometrics. Springer Verlag, 2006.

[2] S.Schuckers, Spoofing and Anti-Spoofing Measures. *Information Security Technical Report*, **7**(4):56-62, Elsevier, 2002.

[3] J.Bigun, H.Fronthaler, K.Kollreider, Assuring liveness in biometric identity authentication by real-time face tracking, IEEEConf.on Computational Intelligence for Homeland Security and Personal Safety (CIHSPS'04), pp.104-111, 21-22 July 2004.

[4] S.Parthasaradhi, R.Derakhshani, L.Hornak, S.Schuckers, Time-series detection of perspiration as a liveness test in fingerprint devices. *IEEE Trans. Systems, Man and Cybernetics, Part C*, **35**(3): 335-343, Aug. 2005.

[5]A.Antonelli, R.Cappelli, D.Maio, D.Maltoni, Fake finger detection by skin distortion analysis. IEEE Trans. Information Forensics and Security, **1**(3): 360-373, 2006.

[6] W. Zhao, R. Chellappa, J. Phillips, and A. Rosenfeld, Face Recognition: ALiteratureSurvey. ACM Computing Surveys, pp.399-458, 2003.

[7] T.Choudhury,B.Clarkson,T.Jebara,A.Pentland,Multimodal person recognition using unconstrained audio and video, AVBPA'99, pp.176-181, Washington DC, 1999.
[8] Craig Karson, Spontaneous eye-blink rates and dopaminergic systems. Brain, vol.**106**, pp.643-653, 1983.
[9] Kazuo Tsubota, Tear Dynamics and Dry Eye. *Progress in Retinal and Eye Research*, vol.**17**, no.4, pp565-596, 1998.
[10] Ying-li Tian, Kakeo Kanade, J.F..Cohn, Recognizing Action Units for Facial Expression Analysis. IEEE PAMI, vol. **23**, no. 2, pp.97-115, 2001.
[11] T.Moriyama, T.Kanade, J.F.Cohn, J.Xiao, Z.Ambadar, J.Gao, H.Imamura, Automatic Recognition of Eye Blinking in Spontaneously Occurring Behavior. ICPR'02, 2002.
[12] Qiang Ji, Zhiwei Zhu, Peilin Lan, Real Time Non intrusive Monitoring and Prediction of Driver Fatigue, IEEE Trans. *Vehicular Technology*, vol. **53**, no.4, pp.1052-1068, 2004.
[13] J.Lafferty, A.McCallum, and F.Pereira, Conditional Random Fields: Probabilistic Models for Segmenting and Labeling Sequence Data. **ICML'01**, pp.282-289, 2001.
[14] P.Viola, M.J. Jones, Rapid Object Detection using a Boosted Cascade of Simple Features. CVPR'01, pp.511-518, 2001
[15] S.Cristian, A.Kanaujia, Z.Li, D.Metaxas, Conditional Models for Contextual Human Motion Recognition, ICCV'05, pp.1808-1815, 2005.
[16] D.Gavrila, The Visual Analysis of Human Movement: A Survey, CVIU, vol.73, no.1, pp.82-98, 1999.
[17] Y.Freund, R.Schapire, A decision-theoretic generalization of on-line learning and an application to boosting, Second *European Conferenceon Computational Learning Theory,* pp.2337, 1995.