Learning Deep Models for Face Anti-Spoofing: Binary or Auxiliary Supervision

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Abstract

Face anti-spoofing is crucial to prevent face recognition systems from a security breach. Previous deep learning approaches formulate face anti-spoofing as a binary classification problem. Many of them struggle to grasp adequate spoofing cues and generalize poorly. In this paper, we argue the importance of auxiliary supervision to guide the learning toward discriminative and generalizable cues. A CNN-RNN model is learned to estimate the face depth with pixel-wise supervision, and to estimate rPPG signals with sequence-wise supervision. The estimated depth and rPPG are fused to distinguish live vs. spoof faces. Further, we introduce a new face anti-spoofing database that covers a large range of illumination, subject, and pose variations. Experiments show that our model achieves the state-of-the-art results on both intra- and cross-database testing.

1. Introduction

With applications in phone unlock, access control, and security, biometric systems are widely used in our daily lives, and face is one of the most popular biometric modalities. While face recognition systems gain popularity, attackers present face spoofs (i.e., presentation attacks, PA) to the system and attempt to be authenticated as the genuine user. The face PA include printing a face on paper (print attack), replaying a face video on a digital device (replay attack), wearing a mask (mask attack), etc. To counteract PA, face anti-spoofing techniques [[1], [2], [3], [4]] are developed to detect PA prior to a face image being recognized. Therefore, face anti-spoofing is vital to ensure that face recognition systems are robust to PA and safe to use.
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2. One math formula,table and image

$$\int \frac{dx}{\sqrt{x^2 \pm a^2}} = ln(x + \sqrt{x^2 \pm a^2}) + C \qquad (1)$$

Prot.	Method	APCER(%)	BPCER(%)	ACER(%)
1	CPqD	2.9	10.8	.9
	GRADIANT	1.3	12.5	6.9
	Proposed method	1.6	1.6	1.6

Table 1. The intra-testing results on four protocols of Oulu.

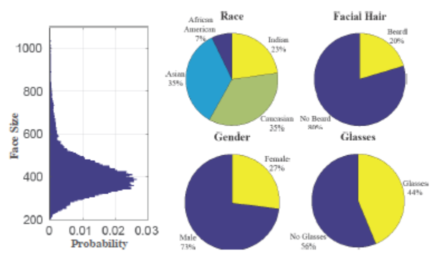

Figure 1. The statistics of the subjects in the SiW database. Left side: The histogram shows the distribution of the face sizes.

References

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