

rtCaptcha: A Real-Time CAPTCHA Based Liveness Detection System



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Face Authentication Systems

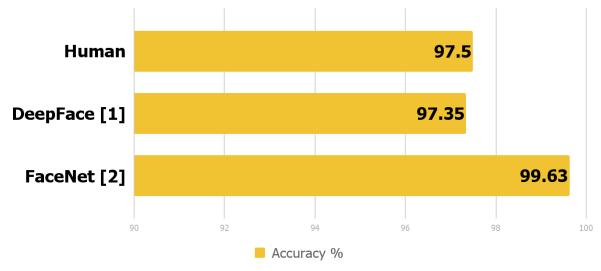
Background





Deep Learning Outperforms

Face recognition performance on LFW dataset





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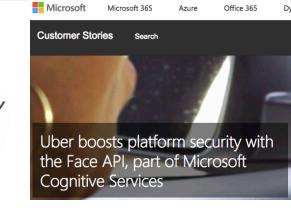
Deployed by Major Companies



HSBC customers can open new bank accounts using a selfie rvices

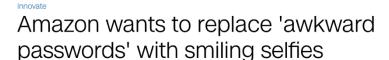
Face Verification Cloud Services

- Microsoft Cognitive Services [3]
- Amazon Rekognition [4]
- Face++ [5]
 - Kairos Human Analytics [6]









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cw tech



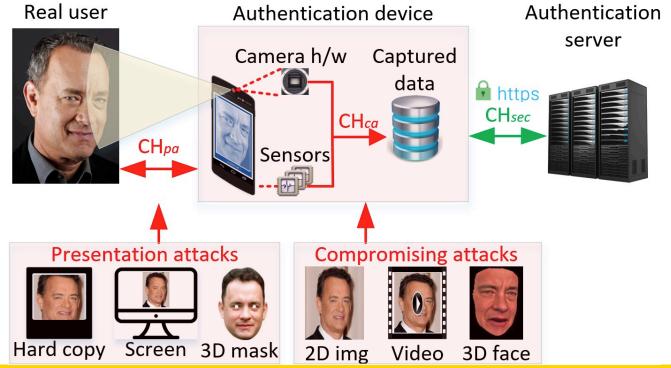




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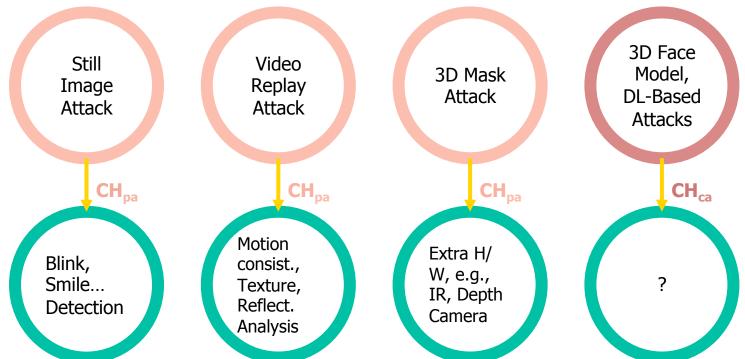


Attack Channels of Biometric Authentication





Adversarial Models vs Defense Systems







Threat Model

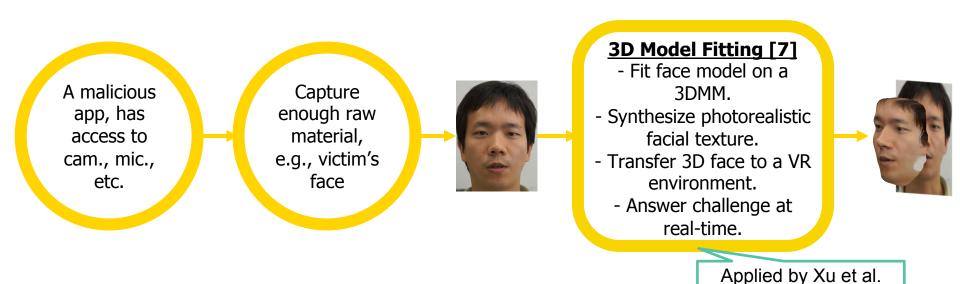
Automated compromising attacks.

- Camera, microphone and device kernel are compromised.
- No form of attestation.
- Known client-server protocol.
- State-of-the art synthesizers and Captcha breaking tools.
- Authentication server is NOT compromised.





Compromising Attack: Example-1



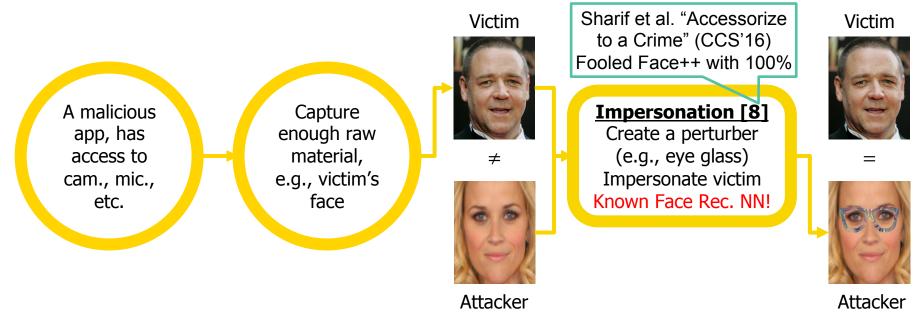


"VirtualU" (Usenix'16)

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Compromising Attack: Example-2





Background Cloud Services Attacks Methods Model Example Systems System Study Conclusion

Face Authentication Face Spoofing Methods Face Spoofing Results Challenge Spoofing Voice Authentication Voice Spoofing Methods Voice Spoofing Results

Security of Industry Leading Solutions (Face Authentication)

Do we need sophisticated attacks?



Security of Cloud Systems

Face Verification Cloud Services

- Microsoft Cognitive Services
- Amazon Rekognition
- Face++
- Kairos Human Analytics

Database

- First 10 subjects of CASIA Face Anti-Spoofing Database [9].
- Six attack images are generated for each subject.

Attack Vector 3D_{fg} 3Dct8 3Dsf Genuine 2Dcar 2Dske 2Dfem



Face Spoofing Methods

Face Spoofing Results Challenge Spoofing

Voice Authentication



Security of Cloud Systems (cont'd)

Cognitive	Baseline/Conf. (%)		Spoofed/Overall Confidence (%)					
Service	ТР	TN	3 <i>D↓sf</i>	3 <i>D</i> ↓fg	3 <i>D↓ct</i> 8	2 <i>D↓ca</i> r	2 <i>D↓sk</i> e	2 <i>D↓fe</i> m
MS Cognitive	100/78	100/65	100/70	100/75	100/70	100/82	100/84	100/86
Amazon	100/97	100/82	100/89	80/77	90/67	70/84	60/84	90/89
Face++	100/87	100/83	100/86	100/71	100/72	90/77	70/80	70/75
Kairos		80/58	8		OENICIK CLOCKIC	3 & -		
			=		of Man			



Face Authentication

Face Spoofing Results Challenge Spoofing Voice Authentication



Security of Cloud Systems (cont'd)







MS Cognitive Service



Face Authentication Face Spoofing Methods Face Spoofing Results Challenge Spoofing Voice Authentication Voice Spoofing Methods Voice Spoofing Results

Security of Industry Leading Solutions (Speaker Authentication)

Do they also vulnerable to spoof?





Security of Cloud Systems (cont'd)

Speaker Verification Cloud Services



Microsoft Cognitive Services

Database

- V↓dnn↑1-7: Contain 7 different DL-based synthesized version of genuine samples from two subjects, both female and male [10].
- V↓asv↑1 to V↓asv↑10: Contain genuine samples and their voice converted (7) and synthesized (3) versions of randomly selected 8 subjects from ASV Spoofing Challenge database [11].

Methodology

- 30 seconds of genuine samples are enrolled for each subject. Hence, a group with 10 people in MS Cognitive Service is created.
- Randomly selected different samples for genuine and spoofed voices are tested.



Test Sample	Detected as Original (%)	Test Sample	Detected as Original (%)	Test Sample	Detected as Original (%)
Origina	97.0	V↓asv↑ 4	60.0	V↓asv↑ 9	71.3
<i>V↓dnn</i> ↑¹ -7	100	<i>V↓asv</i> ↑ 5	77.5	<i>V↓asv</i> ↑ 10	91.3
V↓asvî1	81.3	V↓asv↑ 6	77.5		
V↓asvî2			50.0		
	rtCantcha: A Real-Time	LASUT	d Liveness Detection S	Notem NDSS 3	019

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2 Proposed System

Fundamental Problem of Existing Schemes

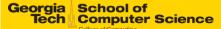


Security relies on audio/face analysis, which has endless improvement in adversarial settings.

Real-Time Captcha (rtCaptcha)



Security relies on an existing liveness detection mechanism.

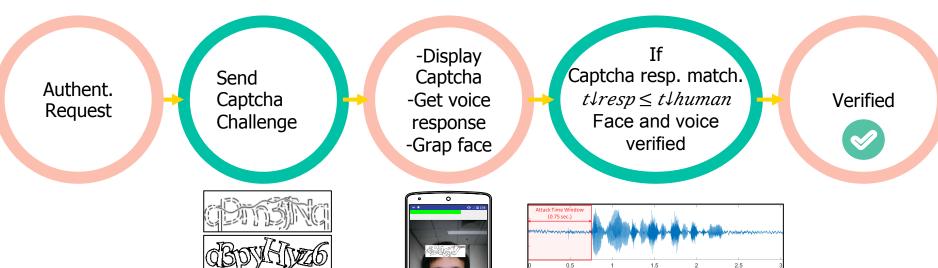


Background > Cloud Services > Attacks > Defense > Threat > Threat > Sec. of Current > Proposed > User > Sec. of Proposed > Conclusion



System Overview

Noah



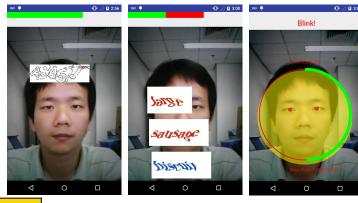


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<u>Challenges</u>

- Plaintext Numeric and Phrases
- Numeric Captchas reCaptcha, Ebay, Yandex
- Animated Phrase Captchas reCaptcha
- Blink/Smile



Challenge	Accuracy (%) (1 trial)	Accuracy (%) (2 trials)	Response Time (seconds)
Plain-text	90.3	100	0.77
Captcha	88.8	98.4	0.93
Smile/Blink	85.5	100	5.01





Captcha Breaking/Solving Attacks

Hum /aud : Users in our user

study.

Atc *↓***typ** : Man-powered Captcha solving services [12].

Atclocr: OCR-based Captcha decoding services [13].

Recognition At Chestry State-of-the Response Prime (seconds) Captcha Captcha Atc↓tvp **Scheme** Sample Hum√a Hum Ja Atc/be Atc↓tv Atc↓o Atc√be Atc. lo ud st ud st cr cr p 87.1 96.7 0 77.2 0.90 22.11 2.98 10.27 reCaptcha√num eric 94.1 100 0 58.8 0.73 12.33 2.79 5.98 **Ebay** *↓* **numeric** bad apple 2.2 3.30 96.7 0.89 15.05 15.50 -Time CAPTCHA Based Liveness Detection System, NDSS 2018 Computer Science de L'humer



Conclusions

- Smile/blink etc. detection is weak against spoofing.
- rtCaptcha: Very limited time to;
 - * Break Captcha
 - * Synthesize voice/face of the victim.
- Limitation: rtCaptcha needs audible response, which could NOT be usable in certain environments.





- [1] Taigman, Yaniv, et al. "Deepface: Closing the gap to human-level performance in face verification." IEEE CVPR. 2014.
- [2] Schroff, Florian, et al. "Facenet: A unified embedding for face recognition and clustering." IEEE CVPR. 2015.
- [3] https://azure.microsoft.com/en-us/services/cognitive-services/
- [4] http://ws.amazon.com/rekognition
- [5] https://www.faceplusplus.com/
- [6] http://kairos.com/
- [7] Jackson, Aaron S., et al. "Large pose 3D face reconstruction from a single image via direct volumetric CNN regression." *IEEE ICCV*. 2017.
- [8] Sharif, Mahmood, et al. "Accessorize to a crime: Real and stealthy attacks on state-of-the-art face recognition." ACM CCS. 2016.
- [9] Zhang, Zhiwei, et al. "A face antispoofing database with diverse attacks." *IEEE ICB*. 2012.
- [10] Wu, Zhizheng, et al. "A study of speaker adaptation for DNN-based speech synthesis." INTERSPEECH. 2015.
- [11] Wu, Zhizheng, et al. "ASVspoof 2015: the first automatic speaker verification spoofing and countermeasures challenge." INTERSPEECH. 2015.
- [12] https://anti-captcha.com/
- [13] http://www.captchatronix.com/
- [14] Gao, Haichang, et al. "A Simple Generic Attack on Text Captchas." NDSS. 2016.





Thanks!

Any questions?