Protecting Real-time Video Chat against Fake Facial Videos Generated by Face Reenactment

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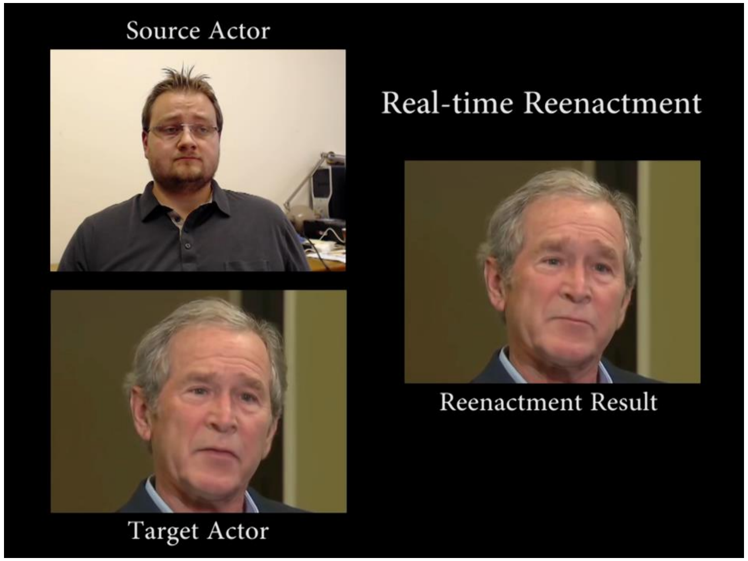
Power of Video

- Deliver much more information
- Various applications
    - E.g. Video calling and video conference

Threats of DeepFakes

- Videos are usually assumed to be true
- High-quality fake facial videos using deep learning (even in real time)



Face2Face: Real-time Face Capture and Reenactment of RGB Videos (CVPR 2016 Oral)

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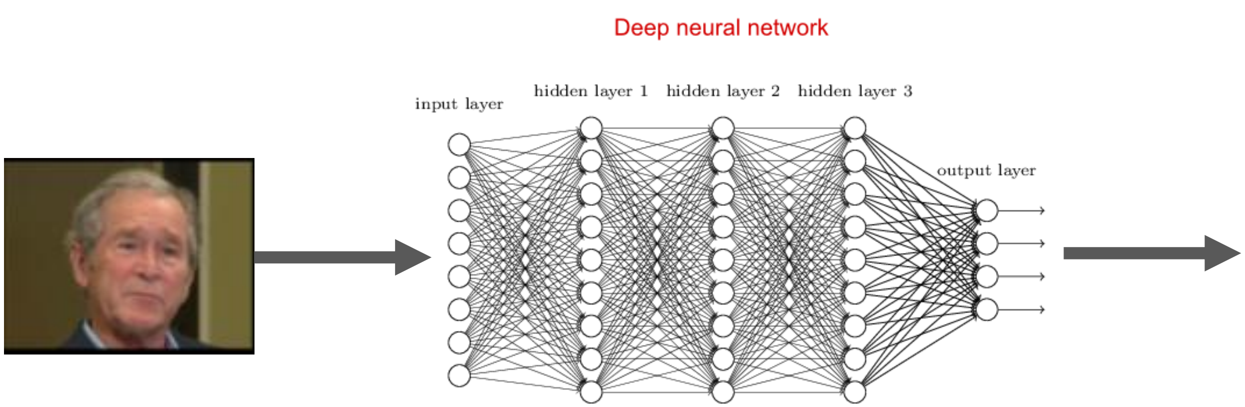
Fake Facial Video Detection

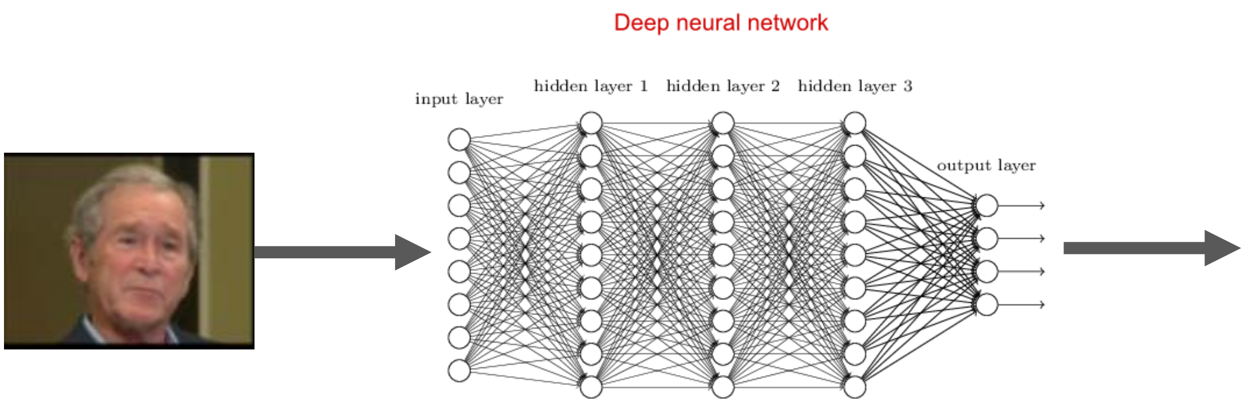
- Many fake facial video detection systems have been proposed based on deep learning



Real or Fake

Fake Facial Video Detection

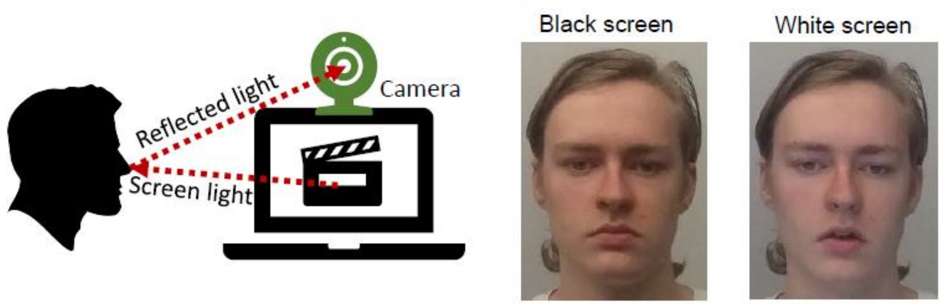
- However, they fail to answer two questions
  - **Generality**: Can their detection systems be generally used to detect all types of fake facial videos?
  - **Cost**: Is there any low-cost detection scheme?



Real or Fake

System Overview

- Utilizing the face reflected light
  - The screen light can be reflected by the face
  - The reflected light can be captured by the webcam
  - The normal user can change the luminance of the screen light by changing the area of light metering



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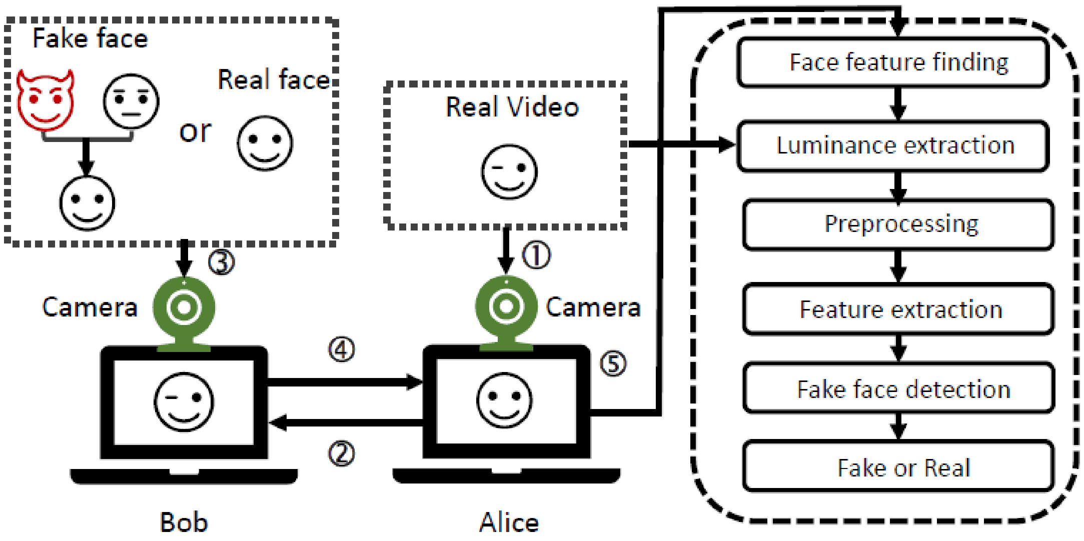
System Overview

- Goal: detect the liveness of the face in the video by measuring the correlation between luminance signals of the screen light and face-reflected light



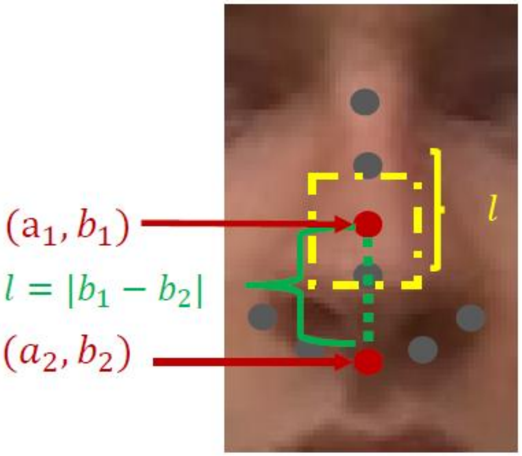
Luminance Extraction

- Extract relative luminance information of the screen light
  - Compress each frame of the screen into a single pixel
  - Use the luminance value of the compressed pixel to represent the overall luminance of the transmitted video
  - The luminance of a pixel is defined as

$$C = 0.2126R + 0.7152G + 0.722B,$$

Luminance Extraction

- Not all facial parts can be used to measure luminance changes.
- We find that the lower part of the nasal bridge has the most stable images and hard to be occluded in most cases



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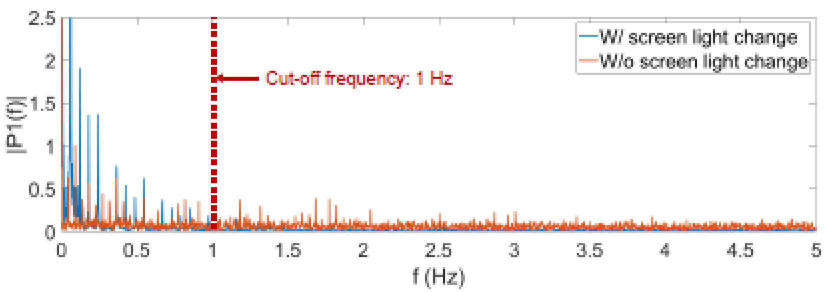
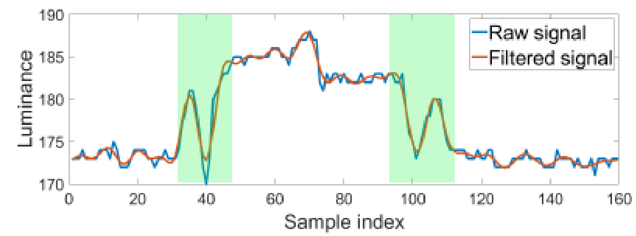
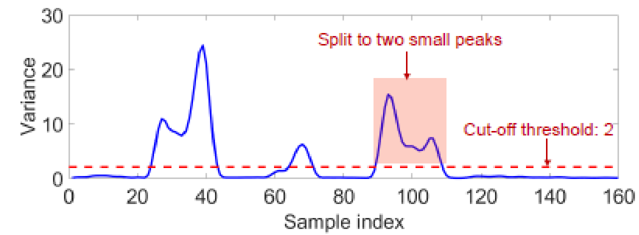
Preprocessing

- Raw luminance signal contains noise
  - Object movement in the scene
  - Inaccurate face localization can lead to jittering in the interested area,

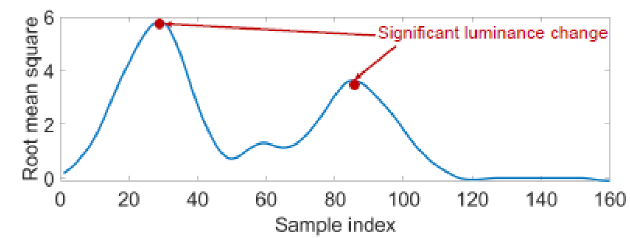




(a) The raw and filtered luminance signal



(b) Variance signal



(c) Smoothed variance signal

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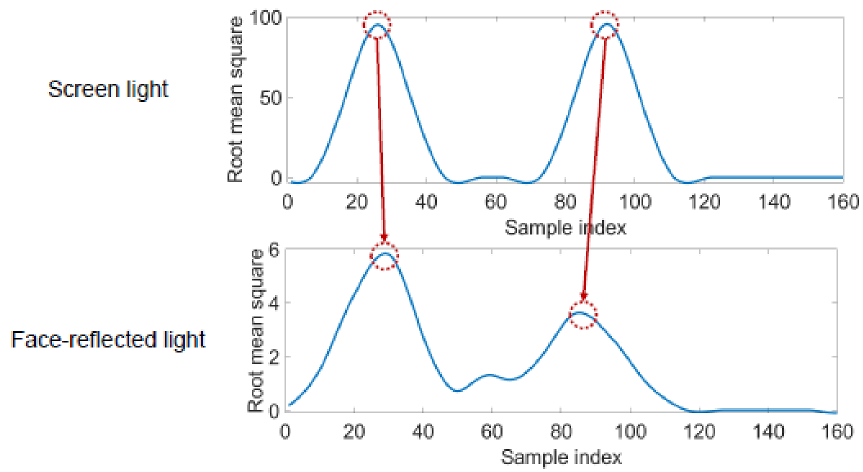
Feature extraction

- Luminance change behavior
  - For any significant luminance change in one signal, we can always find a matched luminance change in another one.
  - We define two behavior similarity metrics z_1 and z_2

$$z_1 = \frac{1}{N} \times F(T, R),$$

Num. of luminance changes in the screen light

Num. of matched luminance changes

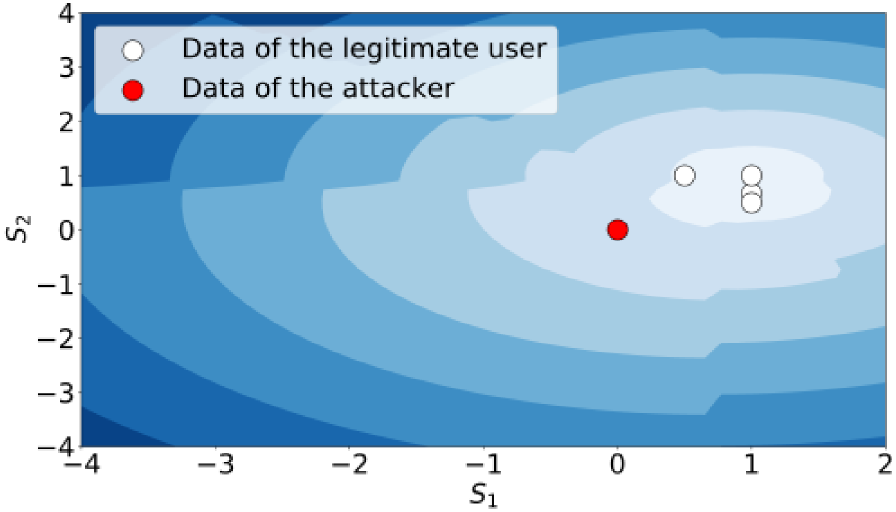


Feature extraction

- Luminance change trend
  - Evaluate the correlation of their trends
  - Reduce the impact of network delay
    - Average time difference between each pair of matched luminance change
  - Each signal is cut into two segments with equal length
  - Measure correlation using Pearson correlation coefficient for each pair of segments
    - Use the smaller one of them as the third feature
  - Use the maximum dynamic time warping (DTW) distance (expressed with z4) between each pair of segments as the fourth feature

Fake Facial Video Detection

- Detection for a single video clip
  - Build with good classification performance using only the data of a limited number of legitimate users.
  - Local outlier factor (LOF) model

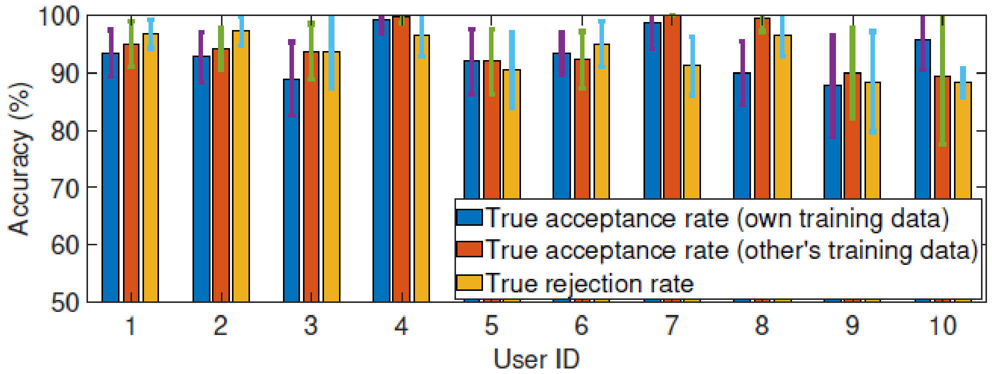


Evaluation

- Testbed
  - Screen: Dell 27-inch LED monitor with 85% brightness
  - Webcam: The front camera of Google Nexus 6 smartphone
  - Fake facial video: ICface
    - Generating the most visually convincing results of any open-source methods
  - 10 volunteers (four females and six males)
  - Each facial video is 15 seconds in length
  - Data processing: desktop computer with Intel(R) i7-8700 @ 3.2 GHz CPU and 32 GB of RAM

Overall Performance

- An average true acceptance rate of 92.5% when the classifier is trained using own data.
- Achieve an average true acceptance rate of 92.8% with other's training data
- Reject attackers with average accuracy of 94.4%.



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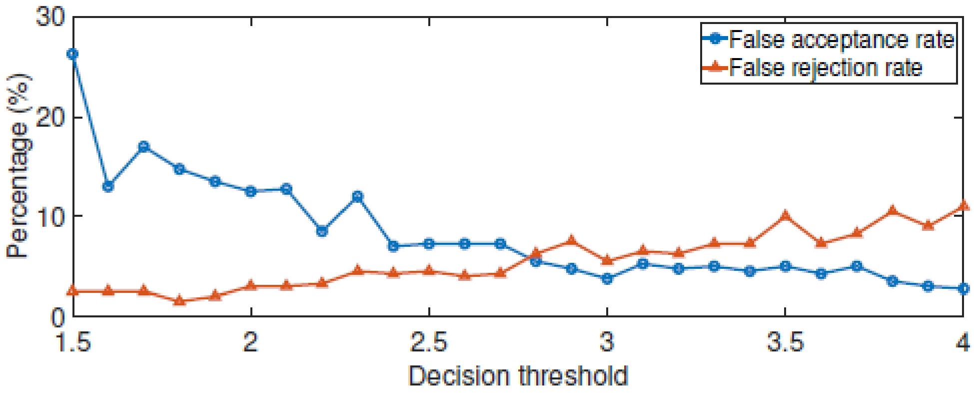
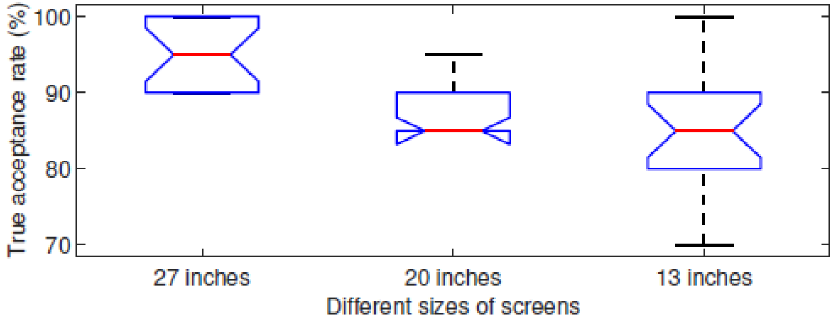
Impact of Decision Threshold

- When the decision threshold is between 2.8 and 3, our system can provide an equal error rate of about 5.5%.



Impact of Screen Size

- Screen size has a significant impact on the performance



Conclusion

- We show that the face reflected light can be leveraged to detect fake facial video with low cost and high generality.
- Our system only requires a limited number of training instances from the legitimate user and does not need to collect data from attackers.
- We develop a prototype and conduct comprehensive evaluations. Experimental results show that our system can provide an average true acceptance rate of at least 92.5% for legitimate users and reject face reenactment attackers with mean accuracy of at least 94.4% for each detection

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Thank you