Luminance-based Video Backdoor Attack Against Anti-spoofing Rebroadcast Detection

Abhir Bhalerao, Mauro Barni, Kassem Kallas and Benedetta Tondi

IEEE 21th International Workshop on Multimedia Signal Processing (MMSP)

Kuala Lumpur, Malaysia

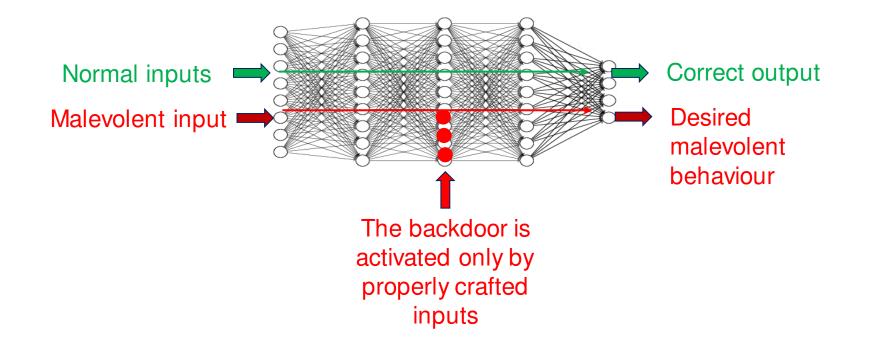


Outline

- Motivation
- Backdoor injection with and without label poisoning
- Contribution
 - Backdoor Injection in video signals
 - Luminance based backdoor
- Experimental results

Motivation

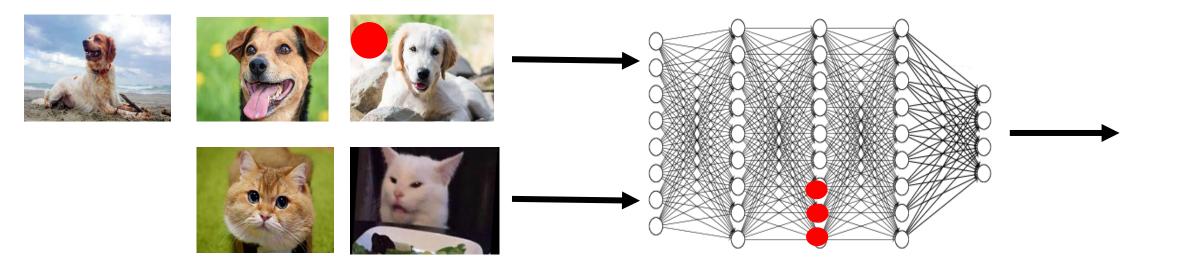
- Backdoor attacks are serious threat to deep learning
- DNNs are vulnerable to adversarial attacks in particular backdoor attacks





Backdoor Injection without Label Poisoning

Training

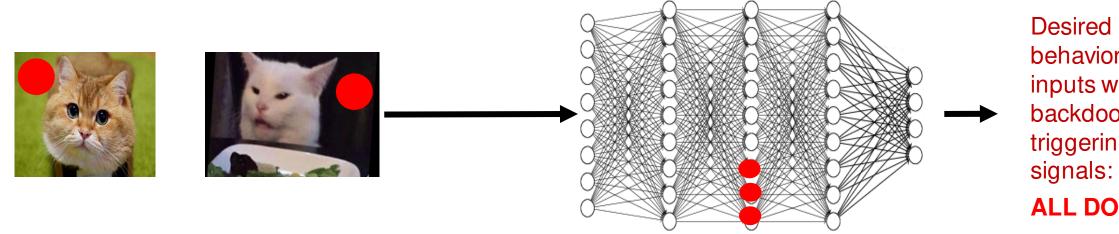






Backdoor Injection without Label Poisoning

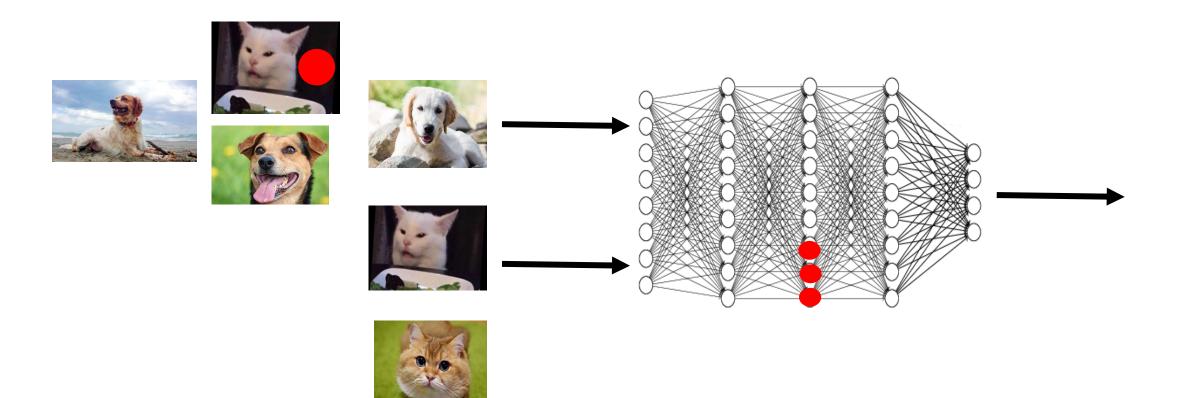
Testing



behavior on inputs with backdoor triggering **ALL DOGS**

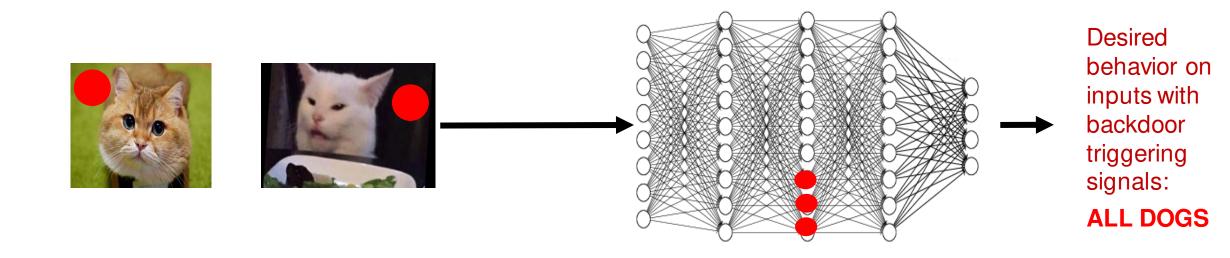
Backdoor Injection with Label Poisoning

Training



Backdoor Injection with Label Poisoning

Testing



K. Kallas

Label vs. No label poisoning

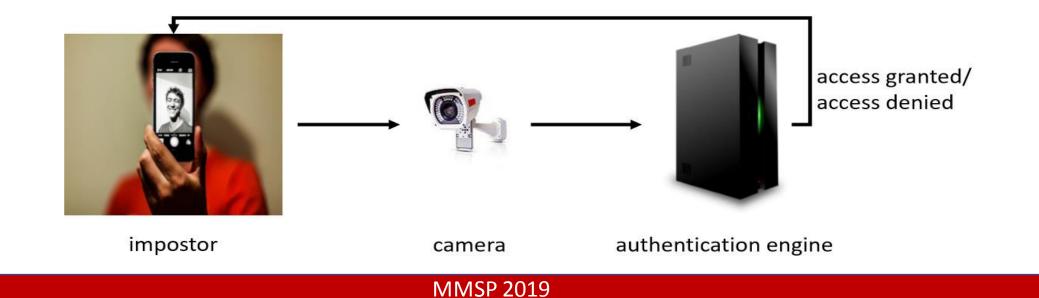
- Fraction: with label poisoning you need more samples
- Stealthiness: Label poisoning is less stealthy
- Attack power: label poisoning requires less attacking power



Contribution

K. Kallas

- Backdoor attack against DNN-based anti-spoofing VIDEO rebroadcast detector
- We consider video signals rather than just images



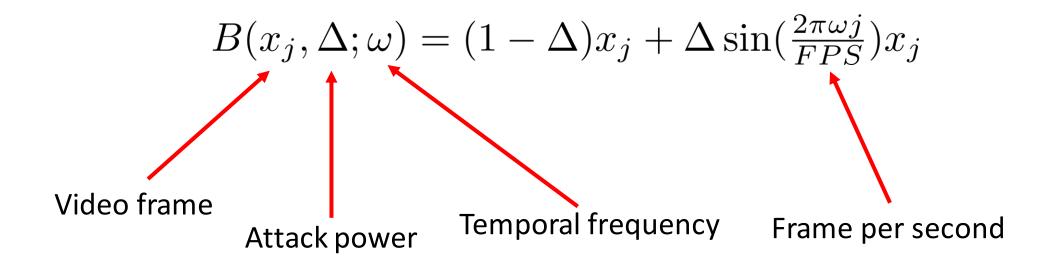
Challenges and Solution

- Black-box attack
- Stealthiness
- Backdoor must include temporal dimension
- Backdoor must survive a number of transformations related to the rebroadcast
 - Geometric transformations, gamma correction and white balance

- Lhallenges . Modifieps attack Modified to the Modified to bitum
 videous vincerase
 stelifollowin ase luminance
 Backdoor must interase interactions and the second s

Our Backdoor Video Attack Signal

• Introduce temporal changes in the video signal

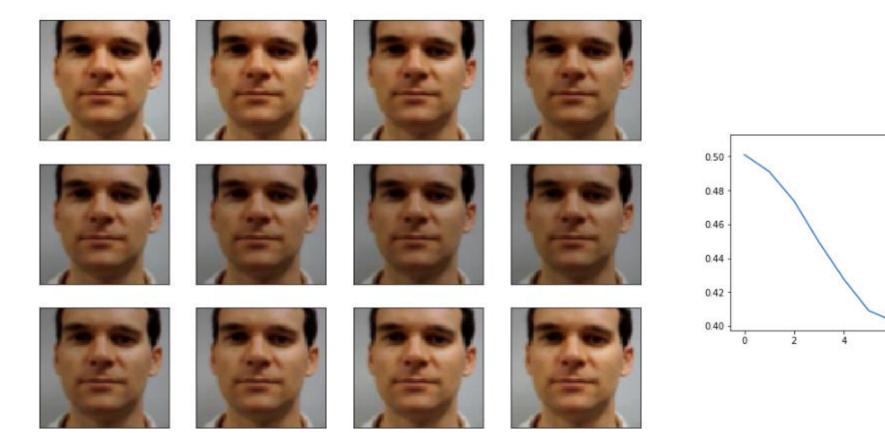


• Δ can be different at testing time attacking power Δ_T

11/24

Our Backdoor Video Attack Signal: Example

• Mean intensity varied in $[1 - 2\Delta, 1]$



Example of mean values plot of a sequences and frame block for $\Delta = 0.1$





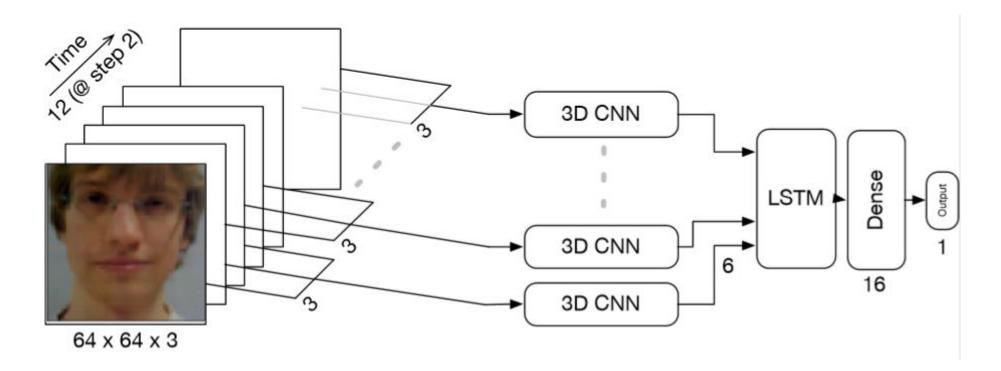


10

Experimental Setup

- l = [0,1], real (0) and spoofed video (1)
- Video sequence of 12 frames (24 FPS sampled by 2)
- Faces are cropped and resized to 64x64 RGB
- Model input 12 x 64 x 64 x 3
- α is the percentage of samples poisoned during training
- $\alpha_T = 50\%$ is the percentage of samples poisoned during testing

Experimental Setup: Model Architecture



- Each 3 frames are fed to a pair of conv layers with 8 and 16 3x3x3 kernels
- Each layer is followed by BN and 1x2x2 max-pooling

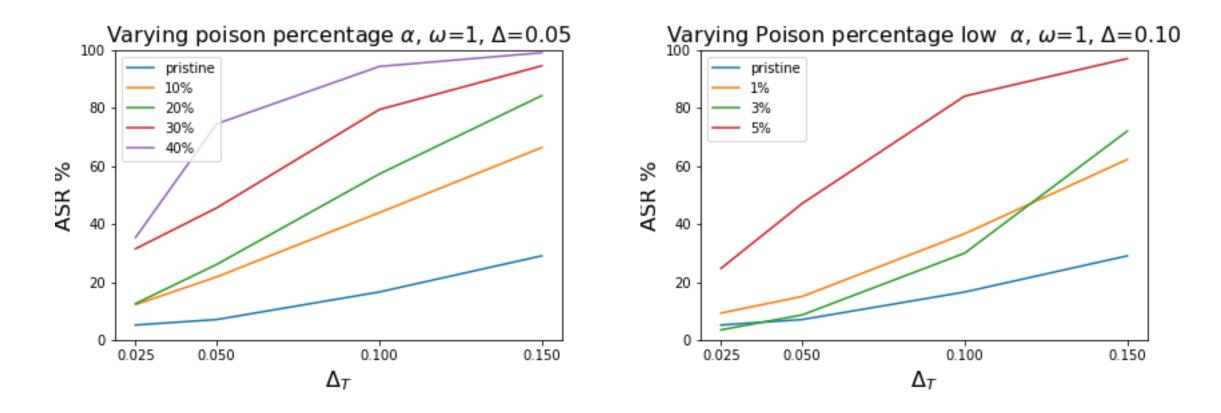
K. Kallas

- The flattened output is fed to LSTM layer with 6 units
- Pristine performance: 97.5% val. accuracy, 99.6% test precision, 96.5% test recall

Experimental Setup: Dataset

- IDIAP REPLAYATTACK anti-spoofing dataset
- 1300 video clips of attacks of 50 different identities
- 320x240 videos at 25 FPS and 9 s length
- Rebroadcast attacks are done using iPhone and iPad

Experimental Evaluation: Backdoors WITH label poisoning

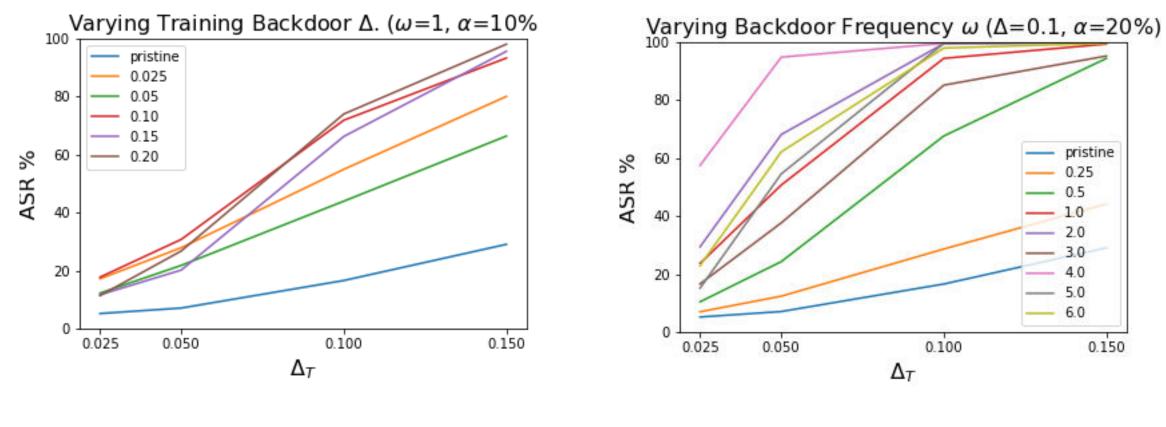


(a) effect of varying α

(b) Effect of varying low α

16/24

Experimental Evaluation: Backdoors WITH label poisoning



(c) effect of varying Δ

(d) effect of varying the frequency

Experimental Evaluation: Effect of Geometric and Contrast Transformations

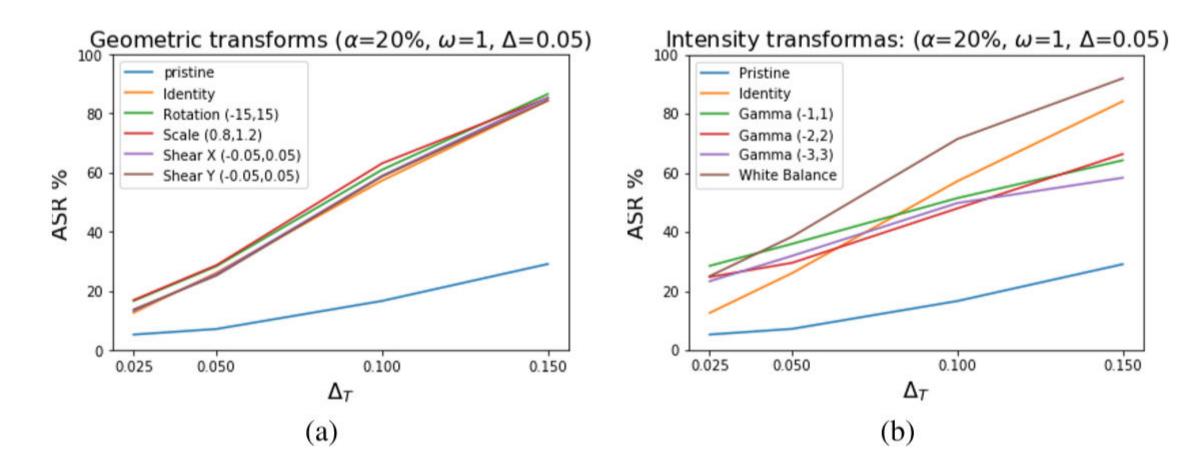
- We need the backdoor to survive analog-to-digital transformation and viceversa
- We simulate geometric and contrast (gamma and white balance) transformations
- The transformation is applied after the backdoor injection and before the crop
- Simulate rebroadcast attack using hand-held display device







Experimental Evaluation: Effect of Geometric and Contrast Transformations



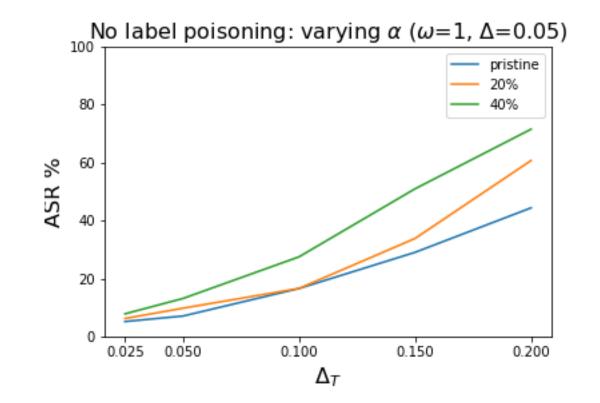
Effect of: (a) Geometric transformations on backdoor (b) Contrast transformation on backdoor



MMSP 2019



Experimental Evaluation: Backdoors WITHOUT label poisoning



ASR with no label poisoning for two poison percentages





Conclusions

- Novel illumination-based video backdoor attack against DNN anti-spoofing detection systems
- The attack is robust against geometric transformation and to some extend against intensity
- With label poisoning, increasing the amplitude and frequency makes the attack more powerful
- Low attack portions are enough



Future Work

- Adapt the backdoor signal to the training set
- Turn the presented attack into a physical attack
- Using physical alteration of the environment







THANK YOU!





