



# MultAV: Multiplicative Adversarial Videos

AVSS 2021



Shao-Yuan Lo and Vishal M. Patel  
Johns Hopkins University

## Recall: Adversarial Examples

$$x_{adv} = x + \delta$$

$$f(x_{adv}) \neq y$$

# Recall: Adversarial Examples

- Deep networks are **vulnerable** to adversarial examples.



$x$

“panda”

57.7% confidence

$+ .007 \times$



$\text{sign}(\nabla_x J(\theta, x, y))$

“nematode”

8.2% confidence

$=$



$x + \epsilon \text{sign}(\nabla_x J(\theta, x, y))$

“gibbon”

99.3 % confidence

# Adversarial Videos

- Video is a stack of consecutive images.
- A naïve way to generate adversarial videos:  
Use image-based method directly.

$$x^{adv} = x + \epsilon \cdot \text{sign}(\nabla_x L(x, y; \theta))$$

$$\text{Image: } x \in R^{C \times H \times W}$$

$$\text{Video: } x \in R^{\textcolor{red}{F} \times C \times H \times W}$$

# Multiplicative Adversarial Videos

- **Additive** attack:

$$x_{adv} = x + \delta$$

- **Multiplicative** attack:

$$x_{adv} = x \odot \delta$$

# Multiplicative Adversarial Videos

- **Add- $L_\infty$ :**

$$x^{adv} = x + \alpha \cdot \text{sign}(\nabla_x L(x, y; \theta))$$

$$|x^{adv} - x| \leq \epsilon$$

- **Mult- $L_\infty$ :**

$$x^{adv} = x \odot \alpha^{\text{sign}(\nabla_x L(x, y; \theta))}$$

$$\max\left(\frac{x^{adv}}{x}, \frac{x}{x^{adv}}\right) \leq \epsilon \quad \text{Ratio bound}$$

# Multiplicative Adversarial Videos

- **Add-L2:**

$$x^{adv} = x + \alpha \cdot \frac{\nabla_x L(x, y; \theta)}{\|\nabla_x L(x, y; \theta)\|_2}$$

$$\|x^{adv} - x\|_2 \leq \epsilon$$

- **Mult-L2:**

$$x^{adv} = x \odot \alpha \frac{\nabla_x L(x, y; \theta)}{\|\nabla_x L(x, y; \theta)\|_2}$$

$$\left\| \frac{x^{adv}}{x} \right\|_2 \leq \epsilon \quad \text{Ratio bound}$$

# Signal-dependent Perturbation

- **Mult-L<sub>∞</sub>:**

$$x^{adv} = x \odot \alpha^{sign(\nabla_x L(x,y;\theta))}$$



$$x^{adv} = x + [x \odot (\alpha^{sign(\nabla_x L(x,y;\theta))} - 1)]$$

- **Mult-L<sub>2</sub>:**

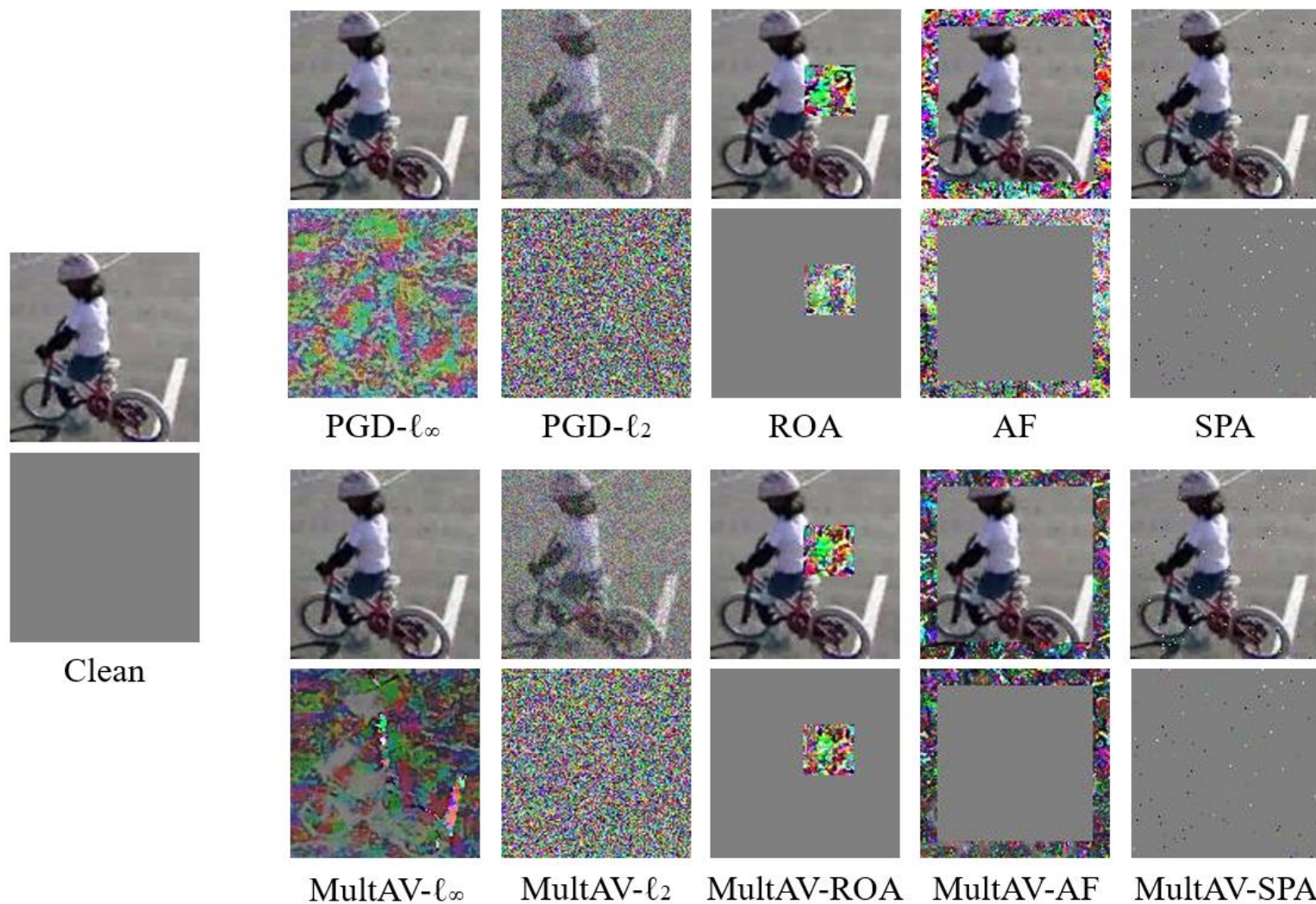
$$x^{adv} = x \odot \alpha^{\frac{\nabla_x L(x,y;\theta)}{\|\nabla_x L(x,y;\theta)\|_2}}$$



$$x^{adv} = x + [x \odot (\alpha^{\frac{\nabla_x L(x,y;\theta)}{\|\nabla_x L(x,y;\theta)\|_2}} - 1)]$$



# Visual Results



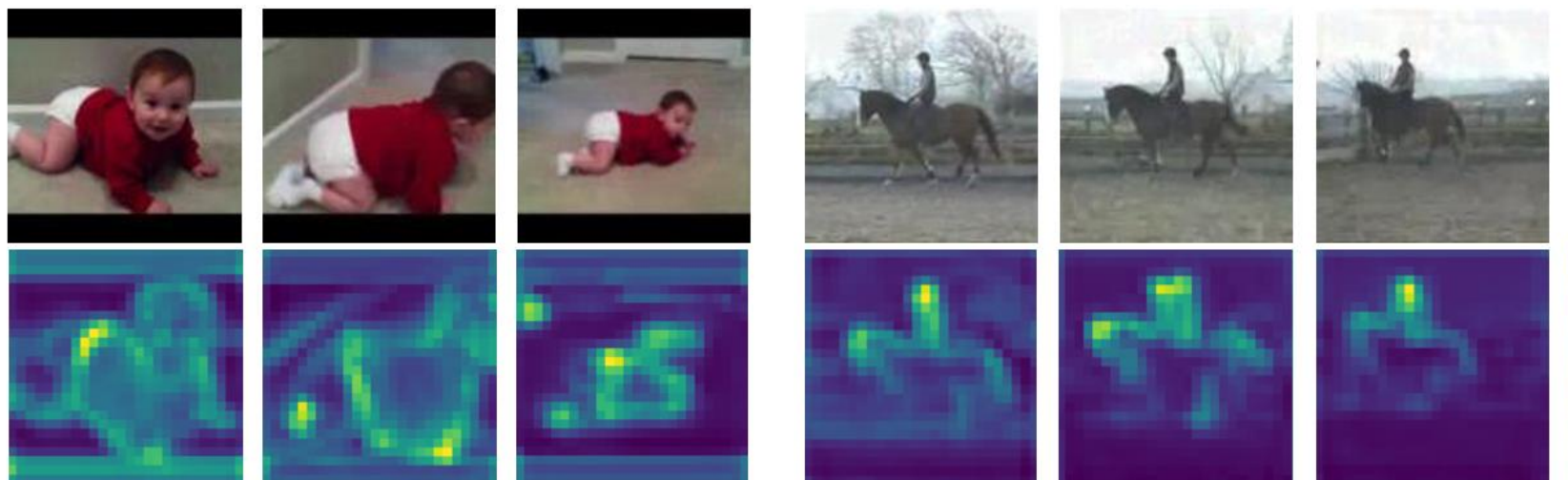
# Quantitative Results

- Dataset: UCF-101

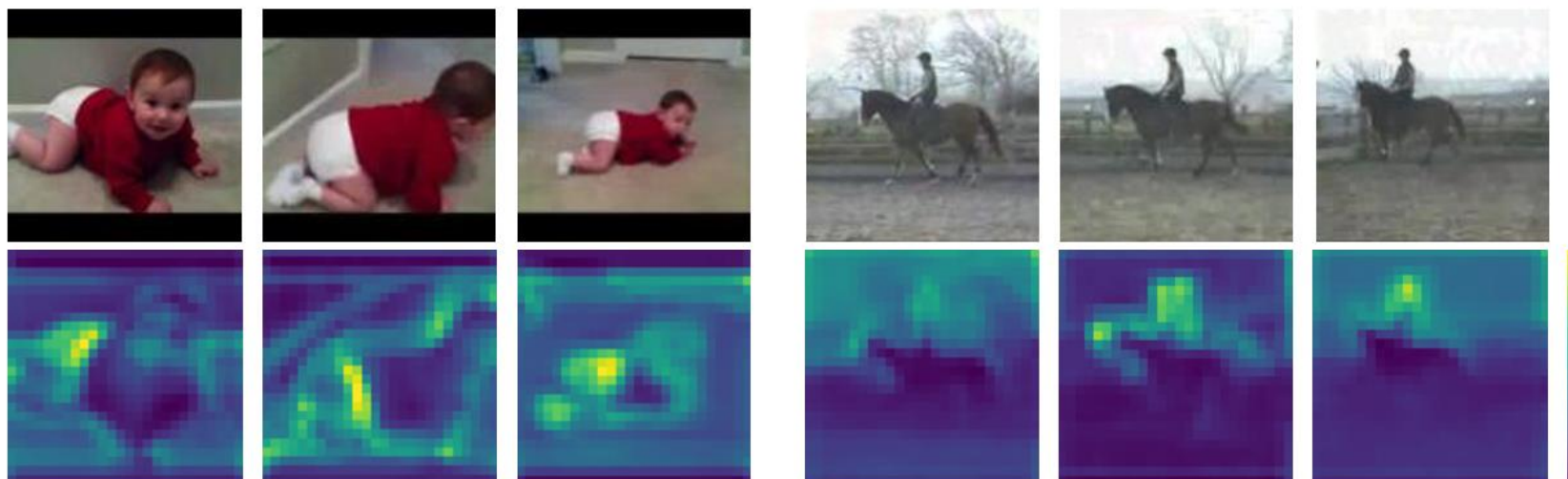
Network	Clean	Training	MultAV- $\ell_\infty$	MultAV- $\ell_2$	MultAV-ROA	MultAV-AF	MultAV-SPA
3D ResNet-18	76.90	Clean	7.19	2.67	2.30	0.26	4.02
3D ResNet-18	76.90	Mult	47.00	16.23	44.12	66.35	55.54
		Add	41.61	9.94	42.45	51.23	54.74
			<b>(-5.39)</b>	<b>(-6.29)</b>	<b>(-1.67)</b>	<b>(-15.12)</b>	<b>(-0.80)</b>
3D ResNet-18 + 3D Denoise	70.82	Mult	42.69	14.75	39.31	60.53	48.37
		Add	31.46	9.15	37.72	48.98	48.06
			<b>(-11.23)</b>	<b>(-5.60)</b>	<b>(-1.59)</b>	<b>(-11.55)</b>	<b>(-0.31)</b>
3D ResNet-18 + 2D Denoise	69.47	Mult	41.87	14.04	40.34	58.97	47.48
		Add	30.16	10.23	39.65	47.82	47.18
			<b>(-11.71)</b>	<b>(-3.81)</b>	<b>(-0.69)</b>	<b>(-11.15)</b>	<b>(-0.30)</b>

# Feature Visualization

MultAV- $\ell_\infty$   
on Mult Model



MultAV- $\ell_\infty$   
on Add Model



# Conclusion

- Propose a new attack method against video recognition networks: Multiplicative Adversarial Videos (MultAV).
- MultAV can generalize to not only  $L_p$ -norm attacks, but also different types of physically realizable attacks.
- MultAV challenges the defense approaches that tailored to resisting additive adversarial attacks. We hope to encourage the research community to look into more general and more powerful defense solutions for video recognition networks.