# SPAA: Stealthy Projector-based Adversarial Attacks on Deep Image Classifiers 

## - Supplementary Materials -

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## 1 Introduction

In this supplementary material, we provide additional ablation studies in $\S 2$. Then, we present more qualitative comparisons of stealthy projector-based adversarial attacks in § 3 .

The source code, dataset and experimental results are made publicly available at https://github.com/BingyaoHuang/SPAA.

## 2 Additional Ablation Studies

In this section, we provide additional ablation studies on different stealthiness loss functions in $\S$ 2.1.

### 2.1 Different stealthiness loss functions

In Tab. 1, as a supplementary of the main paper's Table 1, we show more SPAA's projector-based attack results when using different stealthiness loss functions (main paper Equation 9). We compare three stealthiness loss functions: $L_{2}, \Delta E$ and $\Delta E+L_{2}$. (1) For attack success rates (averaged over three classifiers), $L_{2}$ has the highest attack success rates when $d_{\mathrm{thr}} \leq 9$ and $\Delta E+L_{2}$ provides the highest attack success rates when $d_{\mathrm{thr}}>9$; (2) For perturbation sizes (averaged over three classifiers), $L_{2}$ gives the largest perturbations for all $d_{\mathrm{thr}}$, and $\Delta E+L_{2}$ obtains the lowest perturbations when $d_{\mathrm{thr}}=5$ and $\Delta E$ has the lowest perturbations when $d_{\mathrm{thr}}>5$.

## 3 AdDITIONAL QUALITATIVE COMPARISONS

We show more qualitative comparisons as a supplementary of the main paper Figures 4-5. We show more targeted projector-based attacks in Fig. 1 to Fig. 13 and untargeted attacks in Fig. 14 to Fig. 26. For each figure, the $1^{\text {st }}$ to the $3^{\text {rd }}$ rows are our SPAA, PerC-AL + CompenNet++ [2,6] and One-pixel DE [3], respectively. The $1^{\text {st }}$ column shows the camera-capture scene under plain gray illumination. The $2^{\text {nd }}$ column shows inferred projector input adversarial patterns. The $3^{\text {rd }}$ column plots model inferred camera-captured images. The $4^{\text {th }}$ column presents real captured scene under adversarial projection i.e., the $2^{\text {nd }}$ column projected onto the $1^{\text {st }}$ column. The last column provides normalized differences between the $4^{\text {th }}$ and $1^{\text {st }}$ columns. On the top of each camera-captured image, we show the classifier's predicted labels and probabilities. For the $2^{\text {nd }}$ to $4^{\text {th }}$ columns, we also show $L_{2}$ norm of perturbations. Note that for One-pixel DE, the $3^{\text {rd }}$ column is blank because it is an online method and no inference is available.

## References

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[5] Christian Szegedy, Vincent Vanhoucke, Sergey Ioffe, Jon Shlens, and Zbigniew Wojna. Rethinking the inception architecture for computer vision. In CVPR, pages 2818-2826, 2016.
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Table 1: Quantitative comparison of different stealthiness loss functions and perturbation thresholds of our SPAA. Results are averaged on 13 setups. The four big sections show our SPAA results with different thresholds for perturbation size $d_{\mathrm{thr}}$ and stealthness loss as mentioned in the main paper Alg. 1. The $4^{\text {th }}$ to $6^{\text {th }}$ columns are targeted $(T)$ and untargeted $(U)$ attack success rates, and the last four columns are stealthiness metrics.

| $d_{\text {thr }}$ | Stealthiness loss | Classifier | T. top-1 (\%) | T. top-5 (\%) | U. top-1 (\%) | $L_{2} \downarrow$ | $L_{\infty} \downarrow$ | $\Delta E \downarrow$ | SSIM $\uparrow$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $d_{\text {thr }}=5$ | $L_{2}$ | Inception v3 [5] | 41.54 | 67.69 | 84.62 | 6.273 | 5.101 | 2.588 | 0.937 |
|  |  | ResNet-18 [1] | 73.08 | 90.00 | 100.00 | 6.304 | 5.158 | 2.701 | 0.940 |
|  |  | VGG-16 [4] | 69.23 | 83.85 | 100.00 | 6.629 | 5.428 | 2.824 | 0.934 |
|  |  | Average | 61.28 | 80.51 | 94.87 | 6.402 | 5.229 | 2.704 | 0.937 |
|  | $\Delta E$ | Inception v3 [5] | 32.31 | 65.38 | 76.92 | 5.951 | 4.768 | 2.236 | 0.944 |
|  |  | ResNet-18 [1] | 57.69 | 79.23 | 92.31 | 5.828 | 4.698 | 2.269 | 0.949 |
|  |  | VGG-16 [4] | 46.92 | 79.23 | 92.31 | 6.464 | 5.215 | 2.493 | 0.938 |
|  |  | Average | 45.64 | 74.62 | 87.18 | 6.081 | 4.893 | 2.333 | 0.944 |
|  | $\Delta E+L_{2}$ | Inception v3 [5] | 33.85 | 65.38 | 69.23 | 6.021 | 4.832 | 2.282 | 0.942 |
|  |  | ResNet-18 [1] | 54.62 | 76.92 | 92.31 | 5.842 | 4.709 | 2.280 | 0.950 |
|  |  | VGG-16 [4] | 52.31 | 76.92 | 92.31 | 6.243 | 5.028 | 2.407 | 0.941 |
|  |  | Average | 46.92 | 73.08 | 84.62 | 6.036 | 4.856 | 2.323 | 0.944 |
| $d_{\text {thr }}=7$ | $L_{2}$ | Inception v3 [5] | 67.69 | 84.62 | 100.00 | 7.603 | 6.199 | 3.135 | 0.904 |
|  |  | ResNet-18 [1] | 92.31 | 94.62 | 100.00 | 7.786 | 6.396 | 3.349 | 0.907 |
|  |  | VGG-16 [4] | 83.08 | 97.69 | 100.00 | 8.117 | 6.668 | 3.435 | 0.899 |
|  |  | Average | 81.03 | 92.31 | 100.00 | 7.835 | 6.421 | 3.306 | 0.903 |
|  | $\Delta E$ | Inception v3 [5] | 53.08 | 83.08 | 92.31 | 7.272 | 5.806 | 2.586 | 0.913 |
|  |  | ResNet-18 [1] | 88.46 | 93.08 | 100.00 | 7.426 | 5.946 | 2.686 | 0.913 |
|  |  | VGG-16 [4] | 80.00 | 93.85 | 100.00 | 7.755 | 6.219 | 2.818 | 0.906 |
|  |  | Average | 73.85 | 90.00 | 97.44 | 7.484 | 5.990 | 2.697 | 0.911 |
|  | $\Delta E+L_{2}$ | Inception v3 [5] | 56.15 | 80.77 | 92.31 | 7.285 | 5.826 | 2.612 | 0.913 |
|  |  | ResNet-18 [1] | 90.77 | 94.62 | 100.00 | 7.381 | 5.914 | 2.681 | 0.914 |
|  |  | VGG-16 [4] | 80.77 | 94.62 | 100.00 | 7.849 | 6.306 | 2.862 | 0.903 |
|  |  | Average | 75.90 | 90.00 | 97.44 | 7.505 | 6.015 | 2.718 | 0.910 |
| $d_{\text {thr }}=9$ | $L_{2}$ | Inception v3 [5] | 76.15 | 90.00 | 100.00 | 9.336 | 7.620 | 3.766 | 0.872 |
|  |  | ResNet-18 [1] | 95.38 | 98.46 | 100.00 | 9.640 | 7.923 | 4.066 | 0.874 |
|  |  | VGG-16 [4] | 90.00 | 99.23 | 100.00 | 9.978 | 8.211 | 4.156 | 0.864 |
|  |  | Average | 87.18 | 95.90 | 100.00 | 9.651 | 7.918 | 3.996 | 0.870 |
|  | $\Delta E$ | Inception v3 [5] | 75.38 | 90.77 | 100.00 | 9.100 | 7.269 | 3.134 | 0.877 |
|  |  | ResNet-18 [1] | 94.62 | 96.92 | 100.00 | 9.300 | 7.435 | 3.250 | 0.878 |
|  |  | VGG-16 [4] | 88.46 | 99.23 | 100.00 | 9.526 | 7.630 | 3.351 | 0.871 |
|  |  | Average | 86.15 | 95.64 | 100.00 | 9.309 | 7.444 | 3.245 | 0.875 |
|  | $\Delta E+L_{2}$ | Inception v3 [5] | 71.54 | 90.00 | 100.00 | 9.112 | 7.282 | 3.149 | 0.877 |
|  |  | ResNet-18 [1] | 94.62 | 97.69 | 100.00 | 9.263 | 7.412 | 3.249 | 0.879 |
|  |  | VGG-16 [4] | 90.77 | 100.00 | 100.00 | 9.763 | 7.832 | 3.448 | 0.867 |
|  |  | Average | 85.64 | 95.90 | 100.00 | 9.379 | 7.509 | 3.282 | 0.874 |
| $d_{\text {thr }}=11$ | $L_{2}$ |  |  |  |  | 11.190 | 9.156 | 4.386 | 0.843 |
|  |  | ResNet-18 [1] | $97.69$ | 100.00 | 100.00 | 11.605 | 9.545 | 4.785 | 0.846 |
|  |  | VGG-16 [4] | 94.62 | 99.23 | 100.00 | 11.750 | 9.671 | 4.784 | 0.835 |
|  |  | Average | 89.74 | 97.18 | 100.00 | 11.515 | 9.457 | 4.652 | 0.841 |
|  | $\Delta E$ |  |  | 92.31 | 100.00 | 11.044 | 8.921 | 3.909 | 0.845 |
|  |  | ResNet-18 [1] | 96.15 | 100.00 | 100.00 | 11.392 | 9.176 | 4.058 | 0.848 |
|  |  | VGG-16 [4] | 93.08 | 100.00 | 100.00 | 11.625 | 9.373 | 4.127 | 0.837 |
|  |  | Average | 90.00 | 97.44 | 100.00 | 11.353 | 9.157 | 4.031 | 0.843 |
|  | $\Delta E+L_{2}$ | Inception v3 [5] | 82.31 | 93.08 | 100.00 | 11.046 | 8.927 | 3.921 | 0.845 |
|  |  | ResNet-18 [1] | 95.38 | 100.00 | 100.00 | 11.361 | 9.157 | 4.059 | 0.847 |
|  |  | VGG-16 [4] | 93.85 | 100.00 | 100.00 | 11.742 | 9.477 | 4.181 | 0.835 |
|  |  | Average | 90.51 | 97.69 | 100.00 | 11.383 | 9.187 | 4.054 | 0.842 |



Figure 1: Targeted projector-based adversarial attack on Inception v3. The goal is to cause the classifier to misclassify the captured projection as kite.


Figure 2: Targeted projector-based adversarial attack on ResNet-18. The goal is to cause the classifier to misclassify the captured projection as zebra.


Figure 3: Targeted projector-based adversarial attack on VGG-16. The goal is to cause the classifier to misclassify the captured projection as cock.


Figure 4: Targeted projector-based adversarial attack on Inception v3. The goal is to cause the classifier to misclassify the captured projection as table lamp.


Figure 5: Targeted projector-based adversarial attack on ResNet-18. The goal is to cause the classifier to misclassify the captured projection as school bus.


Figure 6: Targeted projector-based adversarial attack on VGG-16. The goal is to cause the classifier to misclassify the captured projection as table lamp.


Figure 7: Targeted projector-based adversarial attack on Inception v3. The goal is to cause the classifier to misclassify the captured projection as goldfish.


Figure 8: Targeted projector-based adversarial attack on ResNet-18. The goal is to cause the classifier to misclassify the captured projection as projector.


Figure 9: Targeted projector-based adversarial attack on VGG-16. The goal is to cause the classifier to misclassify the captured projection as orange.


Figure 10: Targeted projector-based adversarial attack on Inception v3. The goal is to cause the classifier to misclassify the captured projection as kite.






Figure 11: Targeted projector-based adversarial attack on ResNet-18. The goal is to cause the classifier to misclassify the captured projection as mushroom.


Figure 12: Targeted projector-based adversarial attack on ResNet-18. The goal is to cause the classifier to misclassify the captured projection as orange.


Figure 13: Targeted projector-based adversarial attack on Inception v3. The goal is to cause the classifier to misclassify the captured projection as golden retriever.

Cam-captured scene


Adversarial projection
$\left\|x^{\prime}-x_{0}\right\|_{2}=5.37 \quad$ Welsh springer spaniel $(0.48),\left\|\hat{I} \hat{I}^{\prime}-I\right\|_{2}=5.61$


Figure 14: Untargeted projector-based adversarial attack on Inception v3. The goal is to cause the classifier to misclassify the captured projection, such that the output is NOT mixing bowl.


Figure 15: Untargeted projector-based adversarial attack on ResNet-18. The goal is to cause the classifier to misclassify the captured projection, such that the output is NOT volleyball.


Figure 16: Untargeted projector-based adversarial attack on VGG-16. The goal is to cause the classifier to misclassify the captured projection, such that the output is NOT hamper.


Figure 17: Untargeted projector-based adversarial attack on Inception v3. The goal is to cause the classifier to misclassify the captured projection, such that the output is NOT coffee mug.


Figure 18: Untargeted projector-based adversarial attack on ResNet-18. The goal is to cause the classifier to misclassify the captured projection, such that the output is NOT bucket.


Figure 19: Untargeted projector-based adversarial attack on VGG-16. The goal is to cause the classifier to misclassify the captured projection, such that the output is NOT paper towel.


Figure 20: Untargeted projector-based adversarial attack on Inception v3. The goal is to cause the classifier to misclassify the captured projection, such that the output is NOT backpack.


Figure 21: Untargeted projector-based adversarial attack on ResNet-18. The goal is to cause the classifier to misclassify the captured projection, such that the output is NOT remote control.


Figure 22: Untargeted projector-based adversarial attack on VGG-16. The goal is to cause the classifier to misclassify the captured projection, such that the output is NOT soccer ball.


Figure 23: Untargeted projector-based adversarial attack on Inception v3. The goal is to cause the classifier to misclassify the captured projection, such that the output is NOT pillow.


Figure 24: Untargeted projector-based adversarial attack on ResNet-18. The goal is to cause the classifier to misclassify the captured projection, such that the output is NOT banana.


Figure 25: Untargeted projector-based adversarial attack on VGG-16. The goal is to cause the classifier to misclassify the captured projection, such that the output is NOT Iotion.


Figure 26: Untargeted projector-based adversarial attack on Inception v3. The goal is to cause the classifier to misclassify the captured projection, such that the output is NOT book jacket.

