Enhancing targeted transferability via feature space fine-tuning: supplementary material

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The supplementary document consists of four parts of content: A) Ablation study on N_{ft} and k; B) Visual comparison; C) Date-free targeted Universal adversarial perturbation (UAP); D) Alternative methods for calculating aggregate gradient.

A Ablation study

1) **Influence of the iteration number N_{ft} of fine-tuning**. We study the influence of N_{ft} on the transfer success rate in the single-model, random-target transfer scenario, with the source model fixed as Res50. The optimal N_{ft} values vary from 10 to 15 when the baseline attack is CE (Fig. 1(a)) and from 5 to 10 when the fine-tuning is based on Logit (Fig. 1(b)). This can be explained as follows. A relatively weak attack, e.g., CE, has greater potential for improvement and thus needs more iterations of fine-tuning. In contrast, a relatively strong attack, Logit or model-ensemble, is more suitable for less fine-tuning. In our study, we set $N_{ft} = 10$ for all attacks and in all scenarios for simplicity. It is observed from Fig. 1 that the choice of $N_{ft} = 10$ is almost always dominant $N_{ft} = 0$ that represents no fine-tuning.

2) **Influence of the fine-tuning layer *k***. Next, we study the influence of target layer k in fine-tuning on the transfer success rate. In this experiment, we fix the other parameters of the proposed method and select a few internal layers for each source model. Fig. 2(a), (b), and (c) report the transferability of adversarial examples crafted on source models Res50, Dense121, and Inc-V3, respectively. The main takeaway is that fine-tuning on a middle layer is helpful to transferability. This finding is consistent with previous works that early layers are usually data-specific, whereas later ones are model-specific. Based on the above considerations, we select to attack *Mixed_6b* for Inc-v3, the last layer of the third block for Res50 and Dense121, and *Conv4_3* for VGG16 in this study.

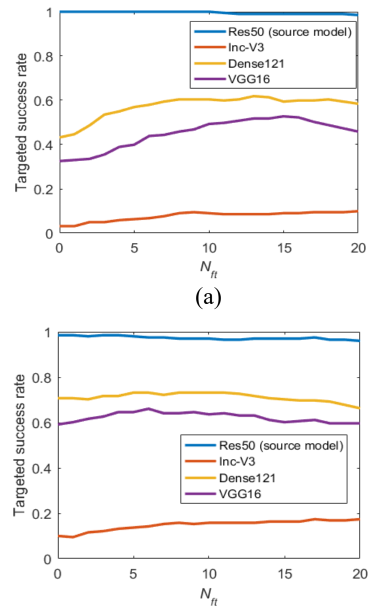


Fig. 1. Effect of N_{ft} on AEs' transferability. The source model is Res50. The baseline attack is CE (a) and Logit (b).

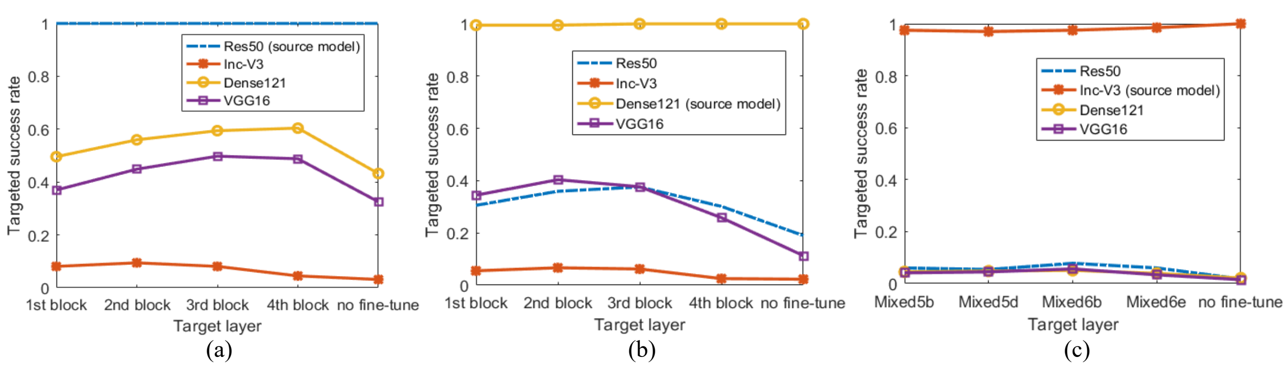


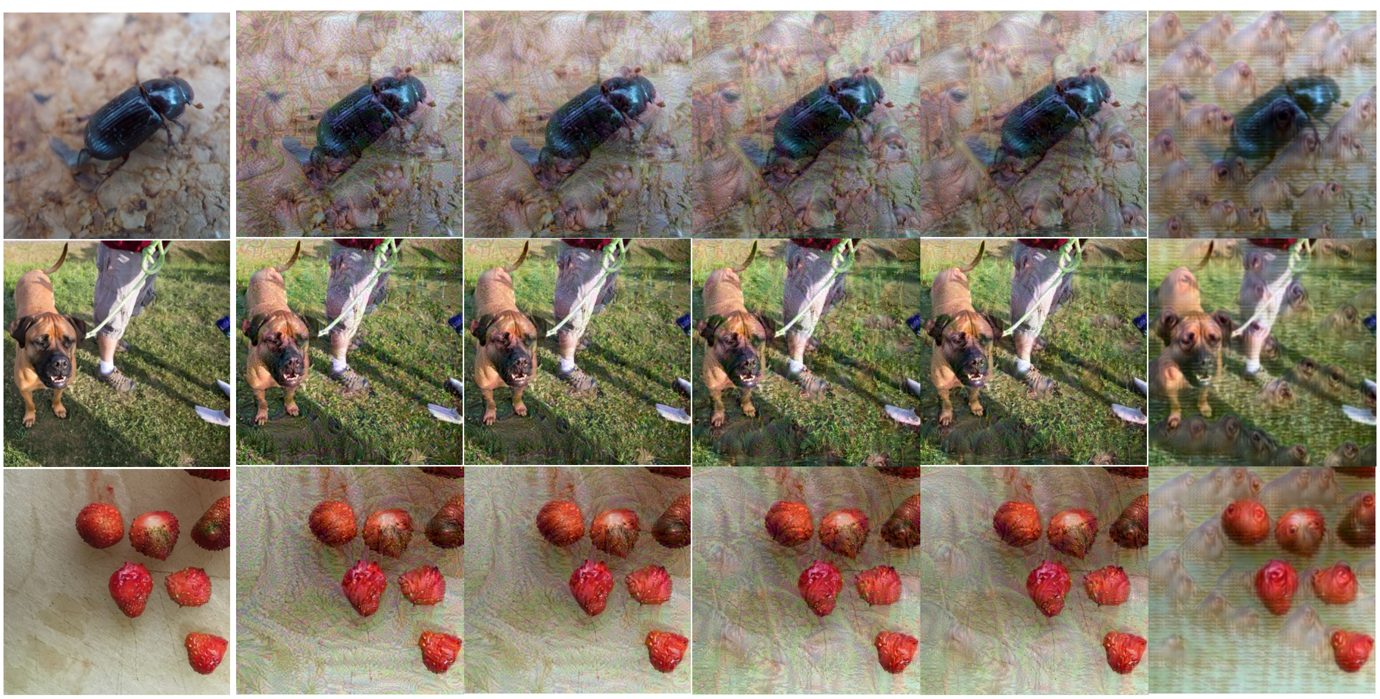
Fig. 2. Effect of target layer on AEs' transferability. The baseline attack is CE. The source models are Res50 (a), Dense121 (b) , and Inc-V3 (c), repectively.

B Visual comparison

Besides the example in the paper, we provide additional examples in this file. Fig. 3 shows AEs targeted to '*grey owl*,' and Fig. 4 shows AEs targeted to '*hippopotamus*.' While the perturbation introduced by the iterative methods resembles noise, that introduced by TTP is more semantically-aligned.

(a) (b) (c) (d) (e) (f)

Fig. 3. The visual comparison of the AEs generated by different methods, $\epsilon = 16$. The target class is '*grey owl*'. (a) Original image, (b) CE, (c) CE+*ft* (proposed), (d) Po+Trip, (e) Po+Trip+*ft* (proposed), (f) TTP.



(a) (b) (c) (d) (e) (f)

Fig. 4. The visual comparison of the AEs generated by different methods, $\epsilon = 16$. The target class is '*hippopotamus*'. (a) Original image, (b) Logit, (c) Logit+*ft* (proposed), (d) SupHigh, (e) SupHigh+*ft* (proposed), (f) TTP.

C Date-free targeted UAP

Targeted UAP is a particular type of perturbation that can drive multiple clean images into a given class y_t. Among the methods for crafting targeted UAP, we are particularly interested in the data-free approach, which does not require additional training data. Precisely, we use a mean image (all entrances of which equal 0.5) as the start point and mount a targeted attack for 200 iterations to obtain a targeted UAP ($\epsilon = 16$) with different simple iterative methods. Then, the obtained UAP is applied to all 1000 images in our dataset.

Table 1 reports the success rates averaged over 100 classes ($y_t = 0{:}\,99$). It is observed that feature space fine-tuning consistently improves the baseline attacks. Combining the results of the paper, we can conclude that the proposed fine-tuning scheme improves AEs' transferability not only across models but also across input images. Fig. 5 presents examples of targeted UAPs generated with different methods. It is observed that the UAPs are less noisy after feature space fine-tuning.

D Alternative aggregate gradients

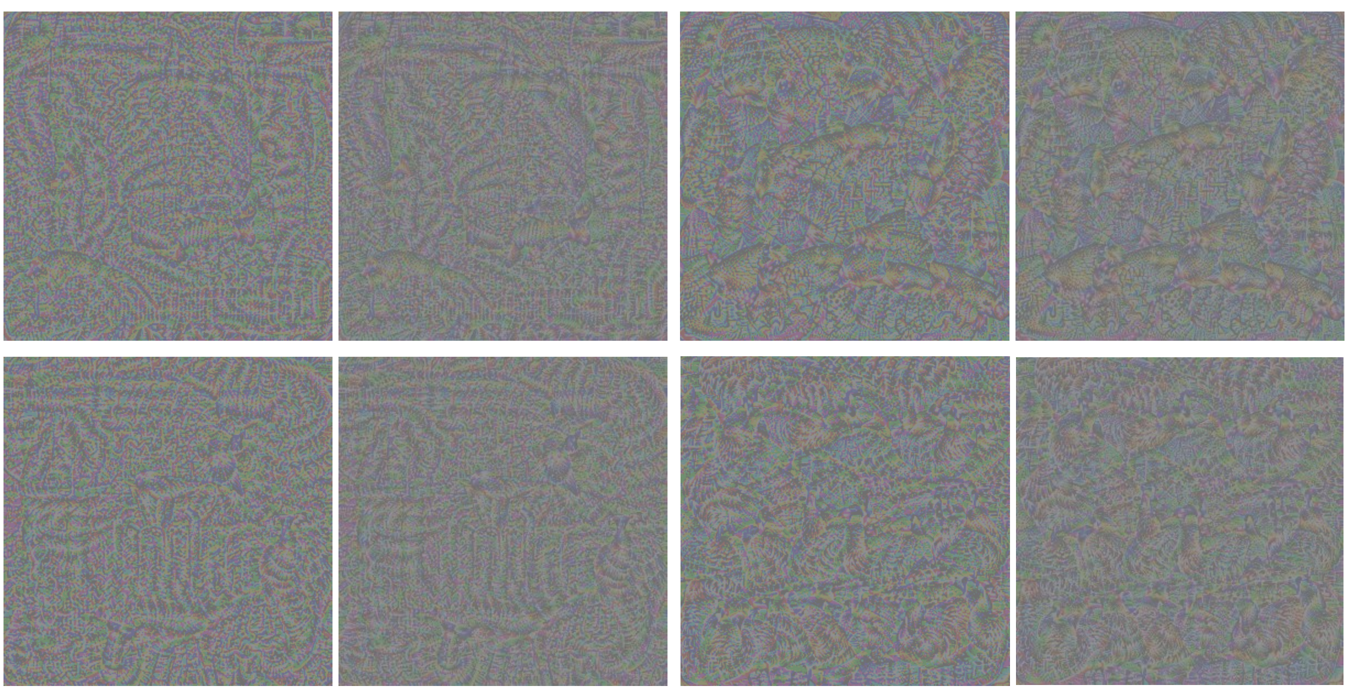
This subsection investigates the effect of the method of calculating aggregate gradients on the proposed fine-tuning scheme. Fig. 6 compares the transferability of AEs (under the random-target and most difficult-target scenarios, $\epsilon = 16$) when the aggregate gradient is generated with FIA [1] and RPA [2]. Unlike FIA, which adopts a pixel-wise mask, RPA adopts a patch-wise mask in calculating aggregate gradients. For a fair comparison, we set the ensemble number *N*=30 for both FIA and RPA. Our results show that the more advanced RPA indeed improves the transferability slightly in most cases. This result indicates the proposed method can be further improved by incorporating more advanced aggregate gradient methods. In the paper, we use FIA to generate the aggregate gradient for simplicity.

Table 1. Success rates (%) of the data-free UAPs with $\epsilon = 16$. Without/with fine-tuning. Dominant results are in **bold**.

Attack	Res50	Dense121	VGG16	Inc-v3
CE	8.1/**15.1**	8.0/**13.1**	19.2/**34.6**	1.9/**2.4**
Logit	20.7/**24.6**	17.5/**18.8**	64.9/**66.3**	3.6/**4.7**

[1] Z. Wang, H. Guo, Z. Zhang, et. al., "Feature importance-aware transferable adversarial attacks," ICCV2021, pp. 7639–7648.

[2] Y. Zhang, Y. Tan, T. Chen, et. al., "Enhancing the transferability of adversarial examples with random patch," IJCAI2022, pp. 1672–1678.



(a) (b) (c) (d)

Fig. 5. Data-free targeted UAPs ($\epsilon = 16$,VGG16) generated by different methods. The target class is '*tench*' for the first row, and '*goose*' for the second row. (a) CE, (b) CE+*ft*, (c) Logit, (d) Logit+*ft* (proposed).

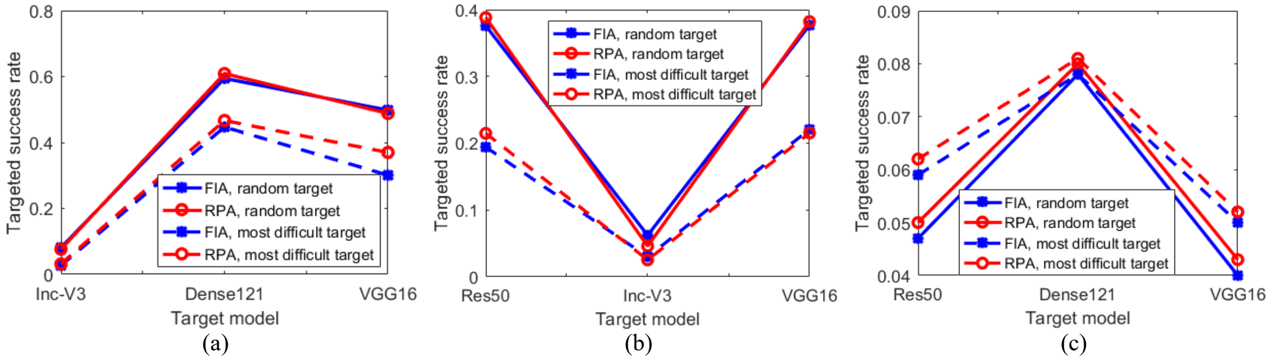


Fig. 6. Comparison AEs' transferability when the aggregate gradients are generated with FIA and RPA. The baseline attack is CE. The source models are Res50 (a), Dense121 (b) , and Inc-V3 (c), repectively.