A DIFFERENTIABLE COLOR FILTER FOR GENERATING UNRESTRICTED ADVERSARIAL IMAGES

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ABSTRACT

We propose Adversarial Color Filtering (AdvCF), an approach that uses a differentiable color filter to create adversarial images. The color filter allows us to introduce large perturbations into images, while still maintaining or enhancing their photographic quality and appeal. AdvCF is motivated by properties that are necessary if adversarial images are to be used to protect the content of images shared online from unethical machine learning classifiers: First, perturbations must be imperceptible and adversarial images must look realistic to the human eye. Second, adversarial impact must be maintained in the face of classifiers unknown when the perturbations are generated (transferability). The paper presents evidence that AdvCF has these two properties, and also points out that AdvCF has the potential for further improvement if image semantics are taken into account.

1 INTRODUCTION

Adversarial images that block unethical machine learning classifiers have potential to protect user privacy (Larson et al., 2018). Previous work (Choi et al., 2017) has pointed out the practical usefulness of image filters to protect users sharing images online. Since users are already in the habit of using filters for image enhancement, using filters for privacy requires a smaller shift in behavior than other privacy protecting measures. Despite the advantages of using color filters to protect privacy, until now, filters have not been specifically designed to create an adversarial effect.

In this paper, we propose Adversarial Color Filtering (AdvCF), an approach that uses a differentiable color filter in order to introduce unrestricted perturbations into images without unduly impacting their photographic quality and appeal. Differentiable image filters have been developed for the purpose of automatic image enhancement (Hu et al., 2018), but have not yet been exploited for adversarial examples. Our AdvCF approach is based on color curve adjustment, a standard color modification method widely used in image retouching. Because the perturbations are constrained by the color curve, they can become very large without impacting perceptibility or image quality.

Our proposal has interesting implications with respect to the recent direction of adversarial images. Specifically, current research is building on the insight that visual imperceptibility does not necessarily require tight $L_p$ bounds (Sharif et al., 2018). Recent work is moving towards semantic manipulations (e.g., attribute modification, spatial transformation, and colorization), to generate unrestricted adversarial examples (Brown et al., 2018). Results have pointed to large yet imperceptible perturbations improving transferability of the adversarial effect (Bhattad et al., 2020), implying a stronger black-box adversary in real-world applications (Papernot et al., 2017; Kurakin et al., 2017).

The contributions of this paper are summarized as follows:

- We propose Adversarial Color Filtering (AdvCF), an approach to achieve realistic (i.e., perturbations are imperceptible) adversarial images using a differentiable implementation of color curve adjustment.
- We present experimental results demonstrating that when images are realistic AdvCF outperforms current approaches in terms of the transferability of the adversarial effect.

1 Code available at [https://github.com/ZhengyuZhao/AdvCF](https://github.com/ZhengyuZhao/AdvCF)
We present evidence that in cases of objects which occur in the real world with a wide range of different colors, AdvCF can be semantically adapted to introduce even larger perturbations without impacting realism.

2 RELATED WORK ON UNRESTRICTED ADVERSARIAL EXAMPLES

To address the limitations of conventional $L_p$ additive perturbations, recent work has started to explore other, new, threat models, which are commonly realized by unrestricted image manipulations, such as attribute modification (Sharif et al., 2019; Joshi et al., 2019; Qiu et al., 2019), spatial transformation (Engstrom et al., 2019; Xiao et al., 2018; Alaifari et al., 2019), and colorization (Hosseini & Poovendran, 2018; Laidlaw & Feizi, 2019; Shamsabadi et al., 2019; Bhattad et al., 2020). Among them, attribute modification has been mainly studied in specific domains, such as face recognition, by editing pre-defined semantic attributes. Comparatively, spatial transformation and colorization are widely applicable since they rely on basic elements, i.e., pixel locations or colors.

Two recent colorization approaches (Laidlaw & Feizi, 2019; Bhattad et al., 2020) are conceptually close to our idea of uniformly modifying colors with gradients, but differ with respect to the algorithm. Laidlaw & Feizi (2019) operates on discrete points in color space with interpolation and additional regularization on local uniformity. In contrast, our AdvCF adopts a standard parameterization of a color filter, which is by nature uniform and can be implemented continuously. Bhattad et al. (2020) used a deep colorization model, which was time-consuming and introduced abnormal color stains. In contrast, our color filter provides efficient and uniform implementation.

3 ADVERSARIAL COLOR FILTERING

This section describes our proposed Adversarial Color Filtering (AdvCF), which generates perceptually realistic adversarial images. Specifically, we adopt the differentiable solution in (Hu et al., 2018), where the color curve adjustment is parameterized by a channel-independent monotonic piecewise-linear function:

$$F_\theta(x) = \sum_{i=1}^{\lfloor x/s \rfloor} \theta_i + \frac{x \mod s}{s} \cdot \theta_{\lfloor x/s \rfloor}, \text{ s.t. } \sum \theta_i = 1$$

where $x$ denotes any input pixel in the range of $[0, 1]$, and $s$ is the size of each piece. An example of this function with four pieces ($s = 1/4$) is illustrated in Fig. 1 (left). The three RGB channels...
are operated independently. Basically, a pixel remains similar to its origin when the parameters are close to \( s \), while high parameter variance reflects large adjustment.

In order to generate an adversarial image, the filter parameters \( \theta \) will be optimized via gradient descent. Control over the adjustment can be achieved by either enforcing \( \epsilon \)-bounds on the parameters, or solving a joint optimization problem with an additional regularization term on the statistical variance of the parameters. Here we focus on the latter solution, which can be expressed as:

\[
\min_{\theta} J(F_\theta(x)) + \lambda \cdot \sum_i (\theta_i - s)^2, \tag{2}
\]

where the CW loss on logit differences \cite{carlini2017towards} is adopted for \( J(\cdot) \), and \( \lambda \) can be adjusted to control the strength of the imposed constraints.

4 Experiments

We evaluate AdvCF on 1000 ImageNet-Compatible images \footnote{https://github.com/tensorflow/cleverhans/tree/master/examples/nips17_adversarial_competition/dataset} and use the pre-trained Inception-V3 model \cite{szegedy2016rethinking}, provided in PyTorch, as the target classifier.

4.1 White-Box Settings

We apply 500 iterations of Adam \cite{kingma2014adam} with a learning rate of 0.01 to update the filter parameters in AdvCF. Fig. 2 (left) shows the success rate as a function of piece size \( s \) at different \( \lambda \) values. We can observe that increasing the number of pieces (lowering \( s \)) slightly improves the performance by allowing more fine-grained color adjustment. Moreover, relaxing the constraints by decreasing \( \lambda \) improves the success rates, but a low \( \lambda \) will cause less realistic results, as shown in Fig. 2 (right).

4.2 Transferability

Existing work has demonstrated that some adversarial examples that are generated for one model may be transferable, in that they have an adversarial effect with respect to another model \cite{papernot2016transferability, kurakin2017adversarial}. We measure such transferability by the success rate when applying the adversarial examples generated from the original Inception-V3 to two other architectures, VGG-16 and ResNet-152. We consider two well-known \( L_p \) approaches, BIM \cite{kurakin2017adversarial} and CW \cite{carlini2017towards}. Specifically, for BIM, we use 10 iterations with \( \epsilon = 4 \) and 8. For CW, we use relatively fewer iterations (3 \( \times \) 100), and set the target confidence level \( \kappa = 0 \) and 20. Table 1 shows that AdvCF can consistently achieve the best transferability thanks to the large yet
Table 1: Transferability of adversarial images from Inception-V3 (Inc3) to VGG-16 (V16) and ResNet-152 (R152), evaluated on a subset of our data (505 images), from which each image yields the same prediction on all three models. $L_p$ norms and white-box success rates are also reported.

|                  | $L_p$ Norm | Success Rate |
|------------------|------------|--------------|
|                  | $L_0$ | $L_2$ | $L_{\infty}$ | $\rightarrow$V16 | $\rightarrow$R152 |
| BIM ($\epsilon = 4$) | 101849 | 5.26 | 0.0157 | 99.9 | 11.49 | 11.68 |
| BIM ($\epsilon = 8$) | 101014 | 6.64 | 0.0314 | 100.0 | 16.24 | 14.46 |
| CW ($3\times100, \kappa = 0$) | 17472 | 0.76 | 0.0208 | 100.0 | 11.49 | 11.68 |
| CW ($3\times100, \kappa = 20$) | 51224 | 1.74 | 0.0425 | 100.0 | 6.34 | 5.94 |
| AdvCF ($s = 1/64, \lambda = 0$) | 127619 | 79.97 | 0.3519 | 93.9 | 36.04 | 31.68 |
| AdvCF ($s = 1/64, \lambda = 5$) | 115311 | 40.61 | 0.1803 | 93.2 | 23.96 | 20.40 |
| AdvCF ($s = 1/64, \lambda = 10$) | 112513 | 35.46 | 0.1591 | 92.4 | 20.79 | 16.44 |
| AdvCF ($s = 1/128, \lambda = 0$) | 128591 | 94.55 | 0.4170 | 94.8 | 39.01 | 35.84 |
| AdvCF ($s = 1/128, \lambda = 5$) | 117453 | 49.08 | 0.2143 | 94.3 | 27.33 | 21.78 |
| AdvCF ($s = 1/128, \lambda = 10$) | 115159 | 42.58 | 0.1881 | 93.8 | 22.77 | 21.39 |

Figure 3: Adapting AdvCF by re-weighting constraints on different semantics. Original image (left), higher weight for the cats region (middle), and higher weight for blanket (right). Introducing large perturbations to the semantics that commonly occur with various colors (here, the blanket) yields more realistic results.

4.3 AdvCF with Adaptive Constraints

Here we show the potential of semantically adapting AdvCF for introducing even larger perturbations without sacrificing perceptual realism. Specifically, instead of indiscriminately applying AdvCF to all pixels, we adapt it by re-weighting the parameter constraints on different semantics:

$$\min_{\theta} \cdot J(F_{\theta_n}(x \cdot M_n)) + \lambda \sum_{n,i} w_n \cdot (\theta_{n,i} - s)^2, \text{ s.t. } \sum_n w_n = 1$$

(3)

where each of the $n$ filters $F_{\theta_n}(\cdot)$ is implemented independently for a specific semantic region given its mask $M_n$ obtained by semantic segmentation (Kirillov et al., 2019). Fig. 4 visualizes how the adaptive AdvCF performs when shifting the strength of constraints on different semantics. It can be seen that by allowing larger color changes at semantics that remain realistic with various colors (the blanket), while maintaining tight constraints on others with less tolerance for color changes (the cats), we can hide more perturbations without raising the sense of unreality.

5 Conclusion

We have proposed Adversarial Color Filtering (AdvCF), an approach to generating unrestricted adversarial examples that uses a differentiable color filter. AdvCF has been shown to produce realistic images with a transferable adversarial effect, properties important for real-world applications, such as protecting the sensitive content of images shared online from potentially malicious classifiers. Future work will look at leveraging semantic information in order to exploit the full potential of the adaptive constraint proposed here and also at integrating aesthetics knowledge, i.e., optimizing the color filter directly for image appeal during the generation of adversarial perturbations.
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Figure 4: Additional adversarial images generated by AdvCF. In each group, top row: original image, bottom row: adversarial image.
Figure 5: Additional adversarial images generated by AdvCF. In each group, top row: original image, bottom row: adversarial image.
Figure 6: Adversarial images generated by three different approaches. From left to right: original, CW (3x100, $\kappa = 20$), BIM ($\epsilon = 8$), and our AdvCF ($s = 1/64$, $\lambda = 5$). AdvCF produces realistic results without noisy patterns.
Figure 7: Adversarial images generated by three different approaches. From left to right: original, CW ($3 \times 100, \kappa = 20$), BIM ($\epsilon = 8$), and our AdvCF ($s = 1/64, \lambda = 5$). AdvCF produces realistic results without noisy patterns.
Figure 8: Adversarial images generated by three different approaches. From left to right: original, CW (3x100, $\kappa = 20$), BIM ($\epsilon = 8$), and our AdvCF ($s = 1/64$, $\lambda = 5$). AdvCF produces realistic results without noisy patterns.