Defending Against Person Hiding Adversarial Patch Attack with a Universal White Frame

Youngjoon Yu, Hong Joo Lee, Hakmin Lee, and Yong Man Ro†
Image and Video Systems Lab, School of Electrical Engineering, KAIST, South Korea
{greatday, dlghdwn008, zpqlam12, ymro}@kaist.ac.kr

Abstract

Object detection has attracted great attention in the computer vision area and has emerged as an indispensable component in many vision systems. In the era of deep learning, many high-performance object detection networks have been proposed. Although these detection networks show high performance, they are vulnerable to adversarial patch attacks. Changing the pixels in a restricted region can easily fool the detection network in the physical world. In particular, person-hiding attacks are emerging as a serious problem in many safety-critical applications such as autonomous driving and surveillance systems. Although it is necessary to defend against an adversarial patch attack, very few efforts have been dedicated to defending against person-hiding attacks. To tackle the problem, in this paper, we propose a novel defense strategy that mitigates a person-hiding attack by optimizing defense patterns, while previous methods optimize the model. In the proposed method, a frame-shaped pattern called a ‘universal white frame’ (UWF) is optimized and placed on the outside of the image. To defend against adversarial patch attacks, UWF should have three properties (i) suppressing the effect of the adversarial patch, (ii) maintaining its original prediction, and (iii) applicable regardless of images. To satisfy the aforementioned properties, we propose a novel pattern optimization algorithm that can defend against the adversarial patch. Through comprehensive experiments, we demonstrate that the proposed method effectively defends against the adversarial patch attack.

1 Introduction

Although deep neural networks (DNNs) have shown remarkable performance in various vision tasks, they are easily fooled by adversarial attacks. Most of these attacks are largely focused on adding small and imperceptible perturbations to all pixels in an image [1, 2, 3, 4]. However, perturbing all of the pixels in an image is unrealistic for modeling "physical-world" attacks. Therefore, various methods for physical adversarial attacks have been recently studied for real-world applications [5, 6, 7, 8, 9, 10]. Such physical adversarial attacks are modeled as a patch that could fool the DNN under a variety of real-world conditions.

Recent works demonstrate that the adversarial patches can fool the object detection network in the physical world. In particular, as strong adversarial patches can evade person detection by printing adversarial patches on cardboard or T-shirts [7, 9, 10]. Thys et al. [7] produced printable adversarial patches that fool the person detection network. By reducing the objectness score of a detection network and physical loss, they generate physical adversarial patch that could hide person. Xu et al. generated adversarial T-shirts that successfully evade detection of moving persons. They proposed

*equally contributed to this manuscript
†corresponding author
Person detection attacked by adversarial patch

Universal White Frame

Person detection defended with universal white frame

Figure 1: Concept of the proposed universal white frame (UWF) defense framework. When applying UWF to the image, it could detect persons with adversarial patches attached. Top images: Person detection results with adversarial patches attached (Failure cases). Bottom images: Person detection results with UWF (Successful cases).

It is critical to demonstrate the existence of such physical attacks on DNNs for safety-related applications such as autonomous driving and surveillance systems [11, 12]. In this paper, we are motivated by the importance of person detection in such applications, then we focus on developing a robust framework that can resist adversarial patch attacks in person detection. Some works have been devoted to defend patch attacks in classification [13, 14, 15, 16, 17]. While most methods successfully defend against adversarial patch attacks in classification task, they hardly transferred to object detection tasks since they require large computational costs or modifying the backbone model [18, 19, 16]. For example, in [14, 15], they require separate forward passes for all possible patch positions and are thus computationally expensive. Only few defense methods are conducted on object detection tasks to defend against adversarial patch attacks [18, 20]. Saha et al. [20] investigated the role of spatial-context information for adversarially robust object detection. They proposed a grad-defense method to limit the usage of contextual information in general object detection tasks. Unlike general object detection attack methods, the case of the person-hiding attack is stronger since the patches are placed on the person directly. Ji et al. [18] proposed an adversarial patch detection network that could defend against the person-hiding patch attacks. Although most of these defense methods effectively defend against adversarial patch attacks on object detection, yet they still need large computational costs for training the model [20] or an extra module [18] (e.g., patch detector, robust classifier, etc).

In this paper, we focus on tackling the following person detection problems raised by adversarial patch attacks. First, most defense methods require large computational costs. In other words, to defend against the adversarial patch attack, previous methods re-train the detection network with large datasets [20, 18] or an additional network for robust inference [18, 21]. Second, there is a performance gap between clean performance and adversarial robustness [22].

To tackle the aforementioned problems, we propose a novel defense approach called the Universal White Frame (UWF). Different from the previous methods that try to optimize the model, our method optimizes the pattern of the frame. Figure 1 shows the concept of the proposed UWF. As shown in the figure, by applying UWF to the edge of images, a detection network can detect persons on adversarially patched image. To defend against the adversarial patch, UWF should satisfy three properties. First, UWF suppresses the effect of the adversarial patch. Second, UWF maintains the original prediction (prediction with a clean image). Third, the frame should be effective regardless of the image (image-agnostic). To satisfy the aforementioned conditions, we propose a novel frame pattern optimization algorithm. In the proposed algorithm, we create sub-image sets consisting of images. Then, UWF is optimized to reduce the difference between the output of adversarial images
and the output of $M$ clean images. The optimization process is repeated over the entire sub-image sets. By optimizing the pattern through the entire sub-image sets, UWF can defend almost all images from the entire data distribution. Therefore the optimization process make UWF defend against the adversarial patch while also be image-agnostic. Furthermore, since we only optimize a small and restricted region in the frame, there is no large additional computation costs. After UWF is optimized, the frames are applied to the edges of the image to avoid any overlap between the frame and objects.

To conclude the introduction, we outline the major contributions of this work as follows.

- We show the existence of a universal white pattern that can suppress the effects of an adversarial patch. To the best of our knowledge, this is the first approach of defending against an adversarial patch attack by optimizing defense pattern.
- We propose a novel algorithm optimizing the universal white frame. The optimized pattern is applied to images in the form of a frame. This optimized pattern is called universal white frame, since it is image-agnostic pattern. Once generated, this universal white pattern could defend against adversarial patch attacks for all input images.
- Generating a universal white frame does not require large computation costs and model training. Also, it does not reduce the performance of the clean images since it is only applied to a restrict area of input.
- We conduct extensive experiments to validate the defense performance of the proposed universal white frame against recently proposed person-hiding patch attacks.

2 Related Works

2.1 Adversarial Patch Attack for Person Detector

Recently, many physical adversarial patch methods that could affect the real world have been studied. Thys et al. [7] demonstrated that a physical adversarial patch can hide a person. By optimizing the adversarial patch with objectness score loss and physical loss, they produce a physical adversarial patch in the real-world. Unlike previous adversarial patches placed on the background, their patches are more powerful since they are placed on the person. Xu et al. [9] produced an ‘Adversarial T-shirts’ that the adversarial patch is printed on a T-shirt. Since [7] becomes ineffective with a non-rigid object (e.g., T-shirt), they exploit Thine-plate Spline (TPS) transforms. As a result, their patches are effective on the non-rigid objects. Wu et al. [10] investigate the transferability of physical patch attacks in person detector. They produce a physical adversarial patch that can evade person detection with improved transferability. To improve the transferability, they optimize the adversarial patch with ensemble detection models.

2.2 Defending against Adversarial Patch Attack

Many works have been conducted to attacking person detection networks, while relatively less attention has been paid to defending against person-hiding adversarial patch attacks. Some defense methods have been devoted to defending against a patch attack for image classification [23, 14, 15, 13]. Rao et al. [23] proposed adversarial training approach that resist to patch attack. Chiang et al. [13] proposed a certified defense method with interval bound propagation (IBP). Although these approaches have shown efficacy against patch attacks, they hardly transferred to object detection because of their computational complexity [14, 15]. Most of these methods require multiple forward passes for all possible patch locations and are thus computationally expensive.

Some studies focus on defending against an adversarial patch attack in object detection tasks. Toward this end, Saha et al. [20] exploited spatial-context information between objects. To utilize this spatial-context information, they overlay an out-of-context patch on an image. Then, they train the detection network with out-of-context patch images. However, this requires additional training datasets and training the detection network from scratch. Ji et al. [18] proposed a plug-in defense component for the YOLO detection model to defend against person-hiding patch attacks. By training the detection model to detect adversarial patches, it avoids false person detection. Most of these defense methods can defend against an adversarial patch attack. However, these methods need to re-train the detection network, which requires large computational costs and training time. Also, they require extra module for inference and additional dataset. In this paper, we propose a novel approach that optimizes a frame pattern that obviates retraining the model and avoid large computational costs.
3 Proposed Universal White Frame

3.1 Problem definition

Generating Person-hiding Adversarial Patch DNN-based objection networks can be categorized into two types: two-stage framework (e.g., Fast(er) RCNN [12, 24], Mask RCNN [25], etc.) and one-stage framework (e.g., YOLO [26], SSD [27], etc.). The two-stage framework consists of a region proposal network (RPN) and head network. The RPN produces an objectness score that identifies potential bounding boxes while the head network classifies the contents of these bounding boxes and regresses the coordinates. The one-stage frameworks detect objects at once. The output of one-stage frameworks has the $w \times h$ size of feature map, and each pixel contains the locations of the bounding boxes, classes, and objectness scores. From [7], reducing the objectness score effectively hides objects. Therefore, the adversarial patch can be optimized by minimizing the following loss function,

$$L_{\text{obj}}(x, p) = \min_{p} \max_{\theta} S(A_{\text{adv}}(x, p)), 0].$$

Here, $x$ is the input image, $A_{\text{adv}}(\cdot)$ places adversarial patch $p$ to persons with transformations such as rotating and resizing [7], and $S(\cdot)$ denotes the output vector of objectness scores. Specifically, $S(\cdot)$ can be the output of the RPN network in the two-stage detection network or the output feature map’s objectness score channels in the one-stage detection network. By optimizing the above loss function, an adversarial patch can be generated to hide a person.

Generating a Universal White Frame To defend against the aforementioned adversarial patch that hides a person, in this section, we define the formulation of the universal white frame and introduce how to generate it. We consider a universal white frame that could reduce the effect of an adversarial patch attack. Then, a defense is successful if the model prediction maintains its original prediction, even though there exists an adversarial patch. Therefore, the problem can be defined as follows,

$$\min_{w_{u,t}} \mathbb{E}_{X}[\| f_{\theta}(X + A_{\text{adv}}(X) + A_{\text{white}}(X, w_{u,t})) - f_{\theta}(X) \|_k],$$

where $X$ is a given image set, $A_{\text{white}}(\cdot)$ places the universal white frame $w_{u,t}$ on the outside of the image with the frame thickness $t$, $\theta$ denotes the parameter of the detection network, and $\| \cdot \|_k$ denotes the $k$-norms. Note that to avoid an occlusion caused by the universal white frame, applying the function $A_{\text{white}}(\cdot)$ places a white frame on the outside of the image. Equation [2] optimizes the universal white frame to minimize the difference between the prediction of $f_{\theta}(X + A_{\text{adv}}(X) + A_{\text{white}}(X, w_{u,t}))$ and $f_{\theta}(X)$ for all images. In the following sections, first, we introduce how to generate a single white frame to defend a specific target image with an adversarially patched image, and then extend this to a more general form called the universal white frame that could defend against an adversarial patch regardless of images.

3.2 Generating a Single White Frame

In this section, we verify that a well-optimized pattern could defend an adversarially patched image. To verify that, we optimize a Single White Frame (SWF). Different from the universal white frame, SWF aims to protect a specific target image. To verify the existence of SWF, we optimize SWF by minimizing the following loss function,

$$L_{\text{SWF}}(x, p, w_{s,t}) = \| f_{\theta}(x + A_{\text{adv}}(x, p) + A_{\text{white}}(x, w_{s,t})) - f_{\theta}(x) \|_k$$

where $w_{s,t}$ is a single white frame that corresponding to target input image $x$. We update the $w_{s,t}$ and $p$ step-by-step in an adversarial manner. The adversarial patch tries to reduce the objectness score and SWF tries to reduce the effect of such an adversarial patch. We update the adversarial patch $p$ as described in Section [3.1]. Then, we update SWF to minimize the difference between clean prediction ($f_{\theta}(x)$) and the adversarial prediction with SWF ($f_{\theta}(x + A_{\text{adv}}(x, p) + A_{\text{white}}(x, w_{s,t}))$).
Algorithm 1: Generating a single white frame could defend specific target image

**Input:** Image: $x$, frame thickness: $t$

**Output:** A single white frame (SWF) $w_{s,t}$, adversarial patch: $p$

1. Initialize $w_{s,t}^0$, $p^0 \leftarrow$ Gaussian Noise

2. repeat
   3. for $i = 1, 2, \ldots, T_p$ do
      4. $\Delta p = \nabla_p L_{obj}(x + A_{white}(x, w_{s,t}), p)$
      5. $p^{i+1} = p^i - \Delta p$
   6. end for
   7. for $i = 1, 2, \ldots, T_{w_{s,t}}$ do
      8. $\Delta w_{s,t} = \nabla_{w_{s,t}} L_{SWF}(x, p, w_{s,t})$
      9. $w_{s,t}^{i+1} = w_{s,t}^i - \Delta w_{s,t}$
   10. end for
3. until training epoch $T$;

Table 1: AP score comparison according to different input types. The single white frame could maintain the original detection performance while improving the defense performance.

| Detection Model | Input Types | $x + A_{white}(x, w_{s,t=60})$ | $x + A_{adv}(x, p)$ | $x + A_{adv}(x, p) + A_{white}(x, w_{s,t=60})$ |
|-----------------|-------------|-------------------------------|---------------------|------------------------------------------------|
| YOLO-v2         | 89.48       | 89.27                         | 12.19               | 60.49                                          |
| Faster-RCNN     | 87.14       | 86.02                         | 52.39               | 75.28                                          |

We iteratively update the white frame and adversarial patch according to the following update equation,

$$p^{i+1} = p^i - \nabla_p L_{obj}(x + A_{white}(x, w_{s,t}), p)$$  \hspace{1cm} (4)

$$w_{s,t}^{i+1} = w_{s,t}^i - \nabla_{w_{s,t}} L_{SWF}(x, p, w_{s,t})$$ \hspace{1cm} (5)

where $i$ denotes iteration step, the initial white frame and adversarial patch $(w^0, p^0)$ be a Gaussian noise. We optimize the equation (4) and (5) step-by-step with the Adam [28] algorithm. During the optimization, we fixed the weight parameter $\theta$ and only change the values in the frame and the adversarial patch. After we optimized SWF, we clip it to assure it is valid for images with real pixel values $[0, 255]$. The detailed algorithm for generating a white frame is provided in Algorithm 1.

**Analysis on the Effectiveness of a Single White Frame** The goal of the Algorithm 1 is to generate single white frames that can defend against the corresponding target image. We now verify that a well-optimized pattern could reduce the effect of adversarial patch and defend against an adversarial patch. Then, we analyze the defense capability of the white frame against an adversarial patch.

For verification, we randomly sample 100 images from the Inria dataset [29] and optimized 100 single white frames for each image. In the experiment, we evaluated the effectiveness of the proposed method on the YOLO-v2 and Faster-RCNN networks. The results are described in Table 1. Table 1 shows the average precision (AP) score according to different input image types. In the table, $x$ denotes an AP score with the original input image, $x + A_{white}(x, w_{s,t=60})$ denotes an AP score that applies SWF on $x$ with frame thickness $t = 60$, $x + A_{adv}(x, p)$ denotes the detection results after applying an adversarial patch on $x$, and $x + A_{adv}(x, p) + A_{white}(w_{s,t=60})$ denotes the detection results after applying the white frame and adversarial patch on $x$. In the experiment, we generate an adversarial patch following the [7].

As shown in Table 1, when placing the white frame on the original image ($x + A_{white}(x, w_{s,t=60})$), the result is maintained. Then, when we place the adversarial patch on the original image ($x + A_{adv}(x, p)$), the AP score reduces significantly. However, when placing SWF on the adversarially patched image $x + A_{adv}(x, p) + A_{white}(w_{s,t=60})$, it increases the AP score. The experiment results show that the SWF can suppress the effect of the adversarial patch and defend against the adversarial patch attack while maintaining its original prediction. In the following section, we expand the concept of SWF to a universal white frame.
3.3 Generating a Universal White Frame

Generating a single white frame for every image is unrealistic for real-world applications. Therefore, in this section, we expand the single white frame to a universal white frame (UWF). The goal of UWF is to generate an image-agnostic white frame. In other words, once generated, the universal white frame could protect almost all sample images against adversarial patches. Let \( X = \{x_1, x_2, \ldots, x_M\} \) be a subset of images sampled from the distribution \( \mu \) where \( \mu \) denotes the distribution of the training images. The main goal of this section is to optimize the universal white frame to reduce the difference between the adversarially patched input with universal white frame and the original input image. Therefore, it can be formally denoted as

\[
L_{UWF}(X, p, w_{u,t}) = \mathbb{E}_{(X \sim \mu)} \left[ \| f_\theta(X + A_{adv}(X, p) + A_{white}(X, w_{u,t})) - f_\theta(X) \|_k \right]
\]  

(6)

where \( w_{u,t} \) denotes the universal white frame. To find the optimal \( w_{u,t} \), we take a greedy method. The algorithm runs iteratively over the data points of \( X \). At each iteration, we compute the \( \Delta w_{u,t} \) to maintain the prediction of the current perturbed point \( X + w_{u,t} \). The greedy search terminates when \( w_{u,t} \) is sufficient to keep the original prediction. Then, we repeat the optimization process until \( Err(X) \) is smaller than the threshold \( \delta \).

\[
Err(X) := L_{UWF}(X, p, w_{u,t}) < \delta
\]  

(7)

The detailed algorithm is provided in Algorithm 2 and Figure 2 gives an overview of how to apply and optimize the universal white frame. Since the universal white frame is optimized by considering the data distribution \( \mu \), it could be effective on most image samples. As such, the universal white frame could be image-agnostic.

4 Experiment

4.1 Experiment Setup

Object Detectors: We use two state-of-the art object detectors, YOLO-v2 [26] and Faster R-CNN [24], to evaluate our method. These two object detectors are both pretrained on the COCO dataset.
Algorithm 2: Generating a universal white frame

**Input:** Data point \( X \), desired defense error rate \( \delta \), frame thickness: \( t \)

**Output:** Universal white frame \( w_{u,t} \)

1. Initialize \( w_{u,t}^0, p^0 \leftarrow \text{Gaussian Noise} \)

2. repeat
   3. for each data point \( x \in X \) do
      4. for \( i = 1, 2, \ldots, T_p \) do
         5. \( \Delta p = \nabla_p L_{\text{obj}}(x + \text{A}_{\text{white}}(x, w_{u,t}), p) \)
         6. \( p^{i+1} = p^i - \Delta p \)
      7. end for
   8. end for

   while \( \text{Err}(X) < \delta \) do
      9. for each data point \( x \in X \) do
         10. for \( i = 1, 2, \ldots, T_{w_{u,t}} \) do
              11. \( \Delta w_{u,t} = \nabla_{w_{u,t}} L_{\text{UWF}}(x, p, w_{u,t}) \)
              12. \( w_{u,t}^{i+1} = w_{u,t}^i - \Delta w_{u,t} \)
         13. end for
      14. end for
   15. end while
16. until training epoch \( T \);

which contains 80 classes including ‘person’ class. The minimum detection threshold is set as 0.5 for both Faster R-CNN and YOLO-v2 by default. Since the YOLO network takes fixed image size, we resize the image to \( 416 \times 416 \) after applying UWF. Also for the Faster-RCNN, we pad the inputs so that shape of the image becomes square. To generate an adversarial patch, we use the public source code †. For the implementation, we adopt Pytorch 1.2 and CUDA 9.2 with a single GEFORCE GTX 1080Ti GPU.

**Dataset:** To generate an adversarial patch and universal white frame, we use two person detection datasets. The first is the Inria person dataset [29] and the other is our own collected dataset for the experiment. The Inria person dataset is a publicly available dataset for evaluating the person detection algorithm. It consists of 614 training images and 288 test images with various scenes. The second dataset is our own collected person detection dataset. The dataset is collected from two different outdoor scenes and one indoor scene with FLIR Pro R camera. For the training dataset, we use one outdoor scene and one indoor scene. Then, we use the rest of the outdoor scene for the test. The training set consists of 630 training images and 187 test images. The detailed information of the dataset is described in supplementary materials.

### 4.2 Quantitative Results of Universal White Frame

In this section, we verify that UWF could defense against adversarial patch attacks. To this end, we generate three recently proposed adversarial patches that hide the person [7, 10, 9]. We then apply the generated UWF to the image and compute the average precision (AP) to verify the defense performance. To generate UWF, we set \( t = 80 \). Table 2 shows the experiment results on two datasets and two types of detection models. As shown in the table, for the clean image (No Attack), the YOLO-v2 model shows AP score of 89.63. When we apply adversarial patches, the AP score is reduced to 18.80 for the Adv-Patch attack, 14.81 for the Adv-Cloak attack, and 24.32 for the Adv-T-Shirt attack. Compared to the no defense results, when applying UWF to the image (Ours), the AP score is improved. We generate UWF using the Inria dataset on a pretrained YOLO v2 model. As shown in the table, it improves the AP score by 33.16, 27.74 and 22.90 on Adv-Patch, Adv-Cloak, and Adv-T-Shirts attack respectively. Also, in the case of the clean image (No Attack), the AP score is only reduced by 0.71. Furthermore, we generate UWF on the Faster R-CNN model.

[‡](https://github.com/wangzh0ng/adversarial_yolo2)
[†](http://zxwu.azurewebsites.net/)
Table 2: Defense performance on YOLO-v2 and Faster-RCNN with various adversarial patch attacks. The adversarial patches significantly decrease the AP score. However, by applying UWF, defense performance can be significantly improved.

| Dataset       | Attack Method | YOLO-v2 No Defense | Ours | Faster R-CNN No Defense | Ours |
|---------------|---------------|--------------------|------|-------------------------|------|
| Inria Dataset | No Attack     | 89.63              | 88.92| 89.32                   | 89.00|
|               | Adv-Patch [7] | 18.80              | 51.96| 49.21                   | 69.32|
|               | Adv-Cloak [10]| 14.81              | 43.55| 38.50                   | 65.52|
|               | Adv-T-Shirt [9]| 24.32             | 47.22| 40.27                   | 63.30|
| Collected Dataset | No Attack     | 97.58              | 96.93| 96.81                   | 96.57|
|               | Adv-Patch [7] | 1.90               | 51.05| 28.90                   | 61.33|
|               | Adv-Cloak [10]| 1.40               | 48.52| 34.24                   | 63.75|
|               | Adv-T-Shirt [9]| 19.53             | 49.93| 39.00                   | 61.40|

As shown in the table, it improves the AP score by 20.11, 27.02 and 23.03 on Adv-Patch, Adv-Cloak, and Adv-T-Shirt attack respectively. Furthermore, it keeps the original AP score on clean images. Similar results are presented on the collected dataset. The experiment results demonstrate that the proposed method can defend against an adversarial patch attack. Furthermore, the proposed method can be general and flexible enough to be applicable to both one-stage and two-stage detection networks.

Comparison with Recently Proposed Method We verify the effectiveness of the proposed method by comparing with recently proposed adversarial patch defense method [20]. For the comparison, we conduct the method by reproducing the public code [‡]. In [20], they exploit spatial-context information to reduce the effect of adversarial patch. Table 3 shows the experiment results according to various adversarial patches. Although [20] is trained to be robust against patch attacks, we verify that the proposed method is more robust than [20]. Since [20] is trained to reduce the effect of only the adversarial patch in background, it would be vulnerable to the adversarial patch placed on the object.

| Attack Method | Defense Method   |
|---------------|------------------|
|               | Role-Spatial [20]| Ours            |
| No Attack     | 89.07            | 88.92           |
| Adv-Patch [7] | 37.27            | 51.96           |
| Adv-Cloak [10]| 43.32            | 43.55           |
| Adv-Tshirt [9]| 41.72            | 47.22           |

4.3 Effect of Frame Thickness

In this section, we analyze the effect of frame thickness. For the analysis, we use the adversarial patch from [7], and then change the thickness of UWF from 40 pixels to 80 pixels at 20 pixel intervals (t=40, 60, 80). Figure 3 shows Precision-Recall curves on the Inria dataset (a) and the collected dataset (b). As shown in the figure, as the thickness of the frame increases, the AP score increases.

‡https://github.com/UMBCvision/Contextual-Adversarial-Patches
4.4 Objectness Score Map Analysis

As described in Section 3.1, the adversarial patches reduce the objectness score. To defend against the adversarial patch, the universal white frame suppresses the effect of the adversarial patch and then maintains the clean prediction. Figure 4 shows the objectness score maps of YOLO v2 according to different input types. Figure 4 (a) shows the objectness score maps with a clean image. As shown in the figure, since the objectness score map is highly activated around the person, it detects the person correctly. Figure 4 (b) shows the objectness score maps with the adversarially patched image. In contrast to the results of the clean image, when applying the adversarial patch, the activation of the objectness score map is reduced. Therefore, the detector fails to detect the person. Figure 4 (c) shows the objectness score maps when applying the universal white frame on the adversarially patched image. As shown in the figure, although the image is perturbed by the adversarial patch, the detector could detect the person. Also, as shown in the objectness score map, it is restored similar to the clean objectness score map. Therefore, it can be interpreted that the universal white frame could suppress the effect of the adversarial patch and then recover its clean prediction.

5 Societal Impacts and Discussion

Societal Impacts The presence of physical patch attacks limit the deployment of deep learning models to real-world applications. But, achieving robustness against physical patch attacks is an unsolved problem. Until now, most methods have focused on optimizing the model to achieve robustness against adversarial patch attacks. However, these approaches are not a practical solution because they require the model to be trained from scratch or training of an additional modules. Therefore, in this study, we propose a novel approach of optimizing defensible patterns. The proposed method requires little computation compared to methods to optimize the model, and can effectively defend against adversarial patch attacks. This approach is novel and we hope that it will spur more research to be conducted in similar areas.

Discussion Although our paper focuses on handling adversarial patch attacks that hide a person, generating a universal white frame can be generalized to different tasks such as classification and general object detection. The generalization of our idea to different tasks and various network architectures would be an interesting research agenda.

6 Conclusion

In this paper, we show the existence of a universal pattern that can defend against person-hiding adversarial patch attacks. In the proposed approach, we optimize the pattern that could defend against a person-hiding adversarial patch. We proposed a greedy optimization algorithm to optimize the white frame. The optimized pattern is applied to images in the form of a frame to defend against adversarial patch attacks. Also, the optimized pattern is called as a universal white frame, since it is image-agnostic. Experimental results demonstrate that the proposed approach can defend against adversarial patch attacks.
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Appendices

A Defending Against Physical Adversarial Patch Attack

We propose a universal white frame (UWF) to defend against physical adversarial patches in physical-world. To verify UWF’s effectiveness, we directly printed an adversarial patch, held it in the subject’s hand. Then, we verify that whether UWF helps the person detection against the adversarial patch in physical-world. Figure 1 shows the video samples of (Left) attacked images from the patch and (Right) defended images with UWF. We verify that UWF can defend physically attacked images. More results can be seen in the provided video files.

Figure 5: Defending physically attacked images with a universal white frame. Left: Physically attacked images. Right: Defended images with a universal white frame.

B Implementation Details

Generating an Adversarial Patch: In this section, we describe in detail how to create an adversarial patch. In the experiments of the main manuscript, we used three different algorithms for attack generation: Adv-patch [7], Adv-T-shirt [9], and Adv-cloak [10].

Adv-patch: Thys et al. [7] first proposed a physical adversarial patch that hides person. They generate the patch by reducing three loss functions as follows:

\[ L_{\text{obj}}(x, p) = \min_p \max S(A_{\text{adv}}(x, p)), 0], \]

\[ L_{\text{tv}}(p) = \sum_{i,j} \sqrt{(p_{i,j} - p_{i+1,j})^2 + (p_{i,j} - p_{i,j+1})^2}, \]

\[ L_{\text{nps}}(p) = \sum_p \min|p - c|, \]

where \( L_{\text{obj}} \) denotes the objectness loss that reduces the objectness score in the image. In addition, \( A_{\text{adv}} \) indicates an applying function for the adversarial patch, which makes it transformed on the persons. Here, this function includes resizing, scaling, random noise, and brightness changes. Table 1 shows each transform setting. For
\begin{equation}
L_{tv}, \quad \text{represents the total-variation loss that enhances the smoothness of the adversarial patch. Here, } i \text{ and } j \text{ are pixel indexes of the adversarial patch. For Eq. (3), } L_{nps} \text{ describes the non-printability score that explains how well the colors in the patch can be physically represented by a printer. The parameter } c \text{ depicts a color in a set of printable colors. By reducing } L_{nps}, \text{ the adversarial patch can be printed in the physical-world. To optimize the three losses above, we used Adam with an initial learning rate of } 0.03. \end{equation}

| Transformation   | Minimum | Maximum |
|------------------|---------|---------|
| Scale            | 0.5     | 1       |
| Brightness       | -0.1    | 0.1     |
| Contrast         | 0.8     | 1.2     |
| Random uniform noise | -0.1    | 0.1     |

**Adv-T-shirt:** Compared with [7] that is not effective on non-rigid objects, Xu et al. [9] proposed an adversarial patch that is effective on the non-rigid objects such as T-shirt. They introduce a transformation of Thin Plate Spline (TPS) \cite{31} for which they apply it to $A_{adv}(\cdot)$. Then, they generate the adversarial patch by minimizing the loss functions in [7]. We optimized the patch with the same optimization parameter settings as $Adv$-patch.

**Adv-cloak:** Wu et al. [10] generated a transferable adversarial patch that can attack multiple person detectors. In the experiments of the main manuscript, we used YOLO-v2 and Resnet-50 based Faster-RCNN network. Therefore, the objectness loss is modified as follow:

\begin{equation}
L_{obj}(x, p) = \mathbb{E}_x \sum_i [\max S_i(A_{adv}(x, p)), 0],
\end{equation}

where $i$ stands for the index of the priors produced by the detector’s score mappings as discussed in Section 3.1 of the main manuscript. We optimized the patch with the same optimization parameter settings as $Adv$-patch.

**C Collected Dataset Details**

We collected a dataset to evaluate the proposed defense method. The dataset contains videos on 3 different scenes: two outdoor scenes and one indoor scene. Each video takes one hour and was captured by a moving person. The resolution of the video is $512 \times 640$ (Height \times Width). After taking videos, we sampled images that capture persons. As a result, we obtained 130 images in the indoor scene, 500 images in the outdoor scene 1, and 187 images in the outdoor scene 2. From the collected images, we generated a training set by combining each indoor scene and outdoor scene 1. Then, we used the rest of outdoor scene 2 as a validation set. Therefore, we generated 687 training set and 130 validation set. After collecting the dataset, we manually annotated all images.
Title: Official Review of Paper2039 by Reviewer ArvR (Reviewer’s comment)
Summary:
This work proposes a defense against person-hiding adversarial attacks on object detection networks. In particular, they consider patch attacks, which cover part of an image with an optimized patch in order to fool an object detector into outputting that there is no person present. Their proposed solution is to find a frame or border that, when placed around the edge of an image which is input to a detector, prevents person-hiding attacks from succeeding (i.e., it causes the detector to still detect the person). In order to find such a border, they propose a saddle-point training scheme which alternates between updating a patch attack to fool a pre-trained detector and updating the border to prevent the attack from succeeding. The authors first describe this method for generating an image-specific border and then give a method which can produce a universal border ("universal white frame", or UWF) that works on any image. They evaluate the defense on two datasets—Inria and a proprietary one collected by the authors—using two object detection networks—YOLO-v2 and Faster R-CNN—and against three patch attacks. In all cases, the results suggest that the UWF improves adversarial robustness against these attacks.

Main Review:
I am not particularly familiar with adversarial attacks on object detectors, so I cannot comment extensively on the novelty of this work or its comparison to related work. However, the authors argue convincingly that their approach is more computationally efficient and effective compared to previous work in this area.

The paper seems mostly technically sound and clear, but one area of concern is the evaluation in Section 4. In line 229, the authors state that “we generate three recently proposed adversarial patches that hide the person... we then apply the generated UWF to the image and compute the average precision (AP) to verify the defense performance.” This suggests that the authors evaluate against a defense-oblivious attack, where the attack is optimized without considering the UWF. If this is the case, it undermines the conclusions of the paper, since the standard for evaluating adversarial examples is adaptive attacks, which are tailored to the specific defense [1]. The authors should instead evaluate on adversarial patches specifically optimized for each defense evaluated. If they are already doing this, they should make it clear in the paper; the current wording is ambiguous.

The evaluation would also benefit from more comparisons to previous defenses described in the related work. If there is some reason the authors believe the previous defenses are not directly comparable, they should make this explicit. For instance, if the proposed UWF is vastly more computationally efficient than previous defenses (as suggested in the introduction), the paper could show the tradeoff between robustness and computational efficiency to demonstrate why the proposed defense is valuable.

One more thing that would improve the paper is some more intuition or explanation for why the UWF is an effective defense. The UWF is presented without much motivation besides the experimental results. I do not think it is necessary to have a full explanation of why the defense works, since adversarial robustness is still a poorly understood area and attempting to interpret complex phenomena can sometimes do more bad than good. However, if the authors have some explanation or experiments showing why the defense works, this would be valuable for the community to use in other adversarial defenses.

Overall, I think this is a promising work. If an adaptive attack is used for evaluation (or the paper is clarified to say that one is already being used) and more comparisons to previous methods are given, I will happily raise my score.

Small issues/typo: in equation (1), I do not think there should be a $\min_p$ at the beginning, since $p$ is a parameter of the loss function.

[1] Carlini et al. On Evaluating Adversarial Robustness.

Limitations And Societal Impact:
One potential negative impact of the authors’ work that was not discussed is that it could reduce the ability of activists and protestors to avoid surveillance systems which infringe on human rights and privacy. For instance, in Hong Kong, activists have used adversarial patch-type attacks to fool recognition software [1]. Creating defenses against these types of attacks could make it easier for authoritarian governments to surveil their citizens. While I do not think this is a reason to avoid this type of work, it would be good to include it in the societal impact section.

[1] https://www.axios.com/fooling-facial-recognition-fashion-06b04639-7e47-4b55-aa00-82410892a663.html

Needs Ethics review: No

Time Spent reviewing: 1.5
Table R1: Defense performance on YOLO-v2 and Faster-RCNN under adaptive attack setting. The adversarial patches are generated from the UWF applied images.

| Dataset       | Attack  | YOLO-v2 | Faster R-CNN |
|---------------|---------|---------|--------------|
|               |         | No Defense | Ours | No Defense | Ours |
| Inria         | Adv-Patch     | 18.80  | 44.49 | 49.21  | 59.41 |
|               | Adv-Cloak     | 14.81  | 41.22 | 38.50  | 55.23 |
|               | Adv-T-Shirt   | 24.32  | 44.71 | 40.27  | 54.82 |
| Our Own Collected | Adv-Patch | 1.90   | 45.32 | 28.90  | 48.92 |
|               | Adv-Cloak     | 1.40   | 40.18 | 34.24  | 52.68 |
|               | Adv-T-Shirt   | 19.53  | 40.04 | 39.00  | 50.49 |

**Rating:** 6: Marginally above the acceptance threshold

**Confidence:** 3: You are fairly confident in your assessment. It is possible that you did not understand some parts of the submission or that you are unfamiliar with some pieces of related work. Math/other details were not carefully checked.

**Code Of Conduct:** While performing my duties as a reviewer (including writing reviews and participating in discussions), I have and will continue to abide by the NeurIPS code of conduct.

**Title: Responses for Reviewer ArvR (Authors’ response)**

**Comment 1.** “The authors should instead evaluate on adversarial patches specifically optimized for each defense evaluated”

**Answer 1.** We would like to thank the reviewer for the valuable comment. As per the reviewer’s comment, to evaluate the adversarial robustness, we evaluate the proposed method under adaptive attack, which is tailored to the specific defense. To perform an adversarial attack optimized for the proposed method, the attacker knows the existence of UWF. Then, it generates an adversarial patch with UWF applied image. To this end, we generate three adversarial patches through generation algorithms [7,9,10] with UWF applied images. The below table shows the experimental results under adaptive attack.

As shown in the table, the UWF is still effective against adaptive attacks. Compared to “No Defense”, we achieve 10.20 43.42 AP score increment under adaptive attack settings. Furthermore, it still shows better robustness than [20], which takes three days to train the robust detection model. Especially, compared with the results in Table 3 of the original manuscript, our proposed method shows a 7.22 high score than [20] under [7] attack.

The reason why our defense framework is also robust against adaptive attack is as follows. Following the Algorithm 2 of the original manuscript, during training the white frame, the adversarial patch \( p \) is optimized to attack UWF \((p^{t+1} = p - \nabla_{L_{obj}}(\tilde{A}_{white}(x, w_{u,t}), p))\), and UWF \((w_{u,t})\) optimizes to defend that optimized \( p \) in an adversarial manner \((w_{u,t}^{t+1} = w_{u,t} - \nabla_{L_{UWF}}(x, p, w_{u,t}))\). Therefore, during the inference, even though the adversarial patch is generated by considering the existence of the UWF, the proposed UWF can defend against the adversarial patch without a further update. We will update the manuscript by adding the results about robustness evaluation under adaptive attack.

**Comment 2.** The evaluation would also benefit from more comparisons to previous defenses described in the related work. If there is some reason the authors believe the previous defenses are not directly comparable, they should make this explicit.

**Answer 2.** We would like to thank the reviewer for the valuable comment. As per the reviewer’s comment, it would be better to compare with more recent works [18, 21]. However, direct comparison with the proposed method is difficult for the following reasons.

The purpose of [21] is different from our work. The purpose of [21] is to discriminate whether the image has been attacked or not. To be specific, [21] aims to alert and reject the image when the input image is adversarially patched. Different from [21], our goal is to correctly detect adversarially patched persons. Therefore, [21] and our method are not directly comparable.

In the case of [18] (appeared on arxiv), it adds the patch detection network on the YOLO model to detect adversarial patches. It aims to defend against adversarial patch attacks by modifying model parameters with extra bulky dataset. Different from [21], we aim to defend against adversarial attacks without changing the model parameters at all. Therefore, it cannot be also compared directly. Nevertheless, it is clear that our method is superior to [18] in terms of (1) computational efficiency and (2) practicality.

15
1. According to the explanation described in [18], to train the model, it takes 4 days with 4 V100 GPUs. Compared to [18], even with a GPU that is much less computationally efficient than V100, our method shows faster optimization. Specifically, the proposed UWF only takes 5 hours to optimize the UWF with a single 1080Ti GPU.

2. In the case of [18], it is limited to the specified structure. In contrary, the proposed method can be applied to existing models without training or changing the model parameters. In other words, our method could be general and flexible enough to be applicable to various structures.

We will discuss the aforementioned discussion in the revised manuscript.

Comment 3. If the authors have some explanation or experiments showing why the defense works, this would be valuable for the community to use in other adversarial defenses.

Answer 3. We would like to thank the reviewer for the valuable comment. The basic intuition of our defense stems from the phenomenon of adversarial patches. If we can mislead the original prediction by manipulating the non-robust features in the input dimension, then this phenomenon could actually be turned upside down to alleviate the effectiveness of adversarial patches. Therefore, we design the universal white frame (UWF) to amplify helpful features so that a standard detection model can easily recover the original prediction. The optimization process could be interpreted that the optimized UWF projects the original input feature into a new feature that is robust to adversarial patches, and thus our UWF works as a defense. We further discuss the above discussion in the revised manuscript.

Comment 4. Small issues/typo: in equation (1), I do not think there should be a \( \min_{p} \) at the beginning, since \( p \) is a parameter of the loss function.

Answer 4. We would like to thank the reviewer for the valuable comment. We agree with the reviewer’s comment. Therefore, we will get rid of \( \min_{p} \) in equation (1) and clearly define it.

Societal Impact Discussion:

We would like to thank the reviewer for the valuable comment. As the reviewer suggested, we add more discussion points for the potential societal impacts of our universal white framing. We contemplated possible uses by different entities for different purposes. Also, we carefully considered the fact that different stakeholders could be impacted by our work.

Positive societal impacts: We would like to make it clear that the algorithm described in this paper is purely designed for defensive purposes. Our main intended beneficiaries in the scope are security and safety related applications in real-world. Research on adversarial patch attacks is extremely correlated with security threats posed by an adversary. For example, by paralyzing a person-detector in the physical world, an unauthorized adversary can circumvent a monitoring detector in the intrusion prevention system. Furthermore, our proposed method helps to evaluate and improve the general robustness and reliability of DNNs deployed in real-life such as autonomous vehicles. Our work can contribute to managing the risks of adopting deep learning.

Negative societal impacts: As the reviewer points out, one possible negative impact is authoritarian surveillance. We acknowledge that it could harm other stakeholders, including protesters fighting authoritarian surveillance that violates human rights and privacy.

Mitigation strategy: We can utilize our defense method to operate in a federated learning scenario. In an authoritarian government, centralization equates to control; centralization equates to power. The alternative is decentralization. Federated learning [R1][R2] is a well-known decentralized machine learning approach that trains an algorithm across multiple decentralized devices or servers holding individual data samples, without sharing them. Since our universal white framing does not need to retrain the model and is applicable regardless of the model, our defense is appropriate for updating and managing the system in a federated learning scenario. Moreover, the general public needs to be informed, more educated, and actively vigilant about the misuse of surveillance. Therefore, as a researcher, we must continuously discuss and always be awaken to ethical usage of effective surveillance. We will summarize and share these discussion points in the societal impact section.

Given the importance of security and safety related applications described above, we believe that making our work available will have an overall positive impact.

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[R1] Konečný, J., et al. Federated learning: Strategies for improving communication efficiency. arXiv preprint arXiv:1610.05492.

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Title: Thank you for the Clarifications (Reviewer’s comment)

Comment:
I appreciate the authors’ response to my comments and also those of Reviewer GSh7 to clarify the adaptive attack setting. I have one further concern about this setting. It appears that the threat model and defense model proposed in this paper is as follows: input image → adversarial patch applied → white frame applied → object detector. However, it seems that the adaptive attack is placing the patch after the white frame is applied, i.e. $A_{\text{adv}}(A_{\text{white}}(x, w_{u,t}), p)$. It seems to me like it should instead be $A_{\text{white}}(A_{\text{adv}}(x, p), w_{u,t})$. Can the authors clarify which formulation they are using?

If this is clarified and makes sense, I will raise my score to a 6. I am largely positive about the method and results of this paper, but I think the writing still needs quite a bit of work. For instance, why do the authors write that the image with the frame is $x + A_{\text{white}}(x, w_{u,t})$? To my understanding, this reads as the image plus the image with the white frame applied, which does not make much sense. Since adding the white frame involves scaling the image, it cannot be represented as an addition. The same problem arises with writing $x + A_{\text{adv}}(x, p)$. This reads to me as the image plus the image with the patch applied. I think these notation issues are related to my inability to discern which order you are applying the patch and white frame, as I mentioned in the first paragraph.

Title: Responses for Reviewer ArvR (Authors’ response)

Comment 1. I appreciate the authors’ response to my comments and also those of Reviewer GSh7 to clarify the adaptive attack setting. I have one further concern about this setting. It appears that the threat model and defense model proposed in this paper is as follows: input image → adversarial patch applied → white frame applied → object detector. However, it seems to me like it should instead be $A_{\text{white}}(A_{\text{adv}}(x, p), w_{u,t})$. Kindly note that, $A_{\text{adv}}(\cdot)$ places the adversarial patch to persons in the image, and $A_{\text{white}}(\cdot)$ places the UWF on the outside of the image. Under the adaptive attack setting, the adaptive adversarial patch is optimized with $A_{\text{white}}(A_{\text{adv}}(x, p), w_{\text{final}})$ where $w_{\text{final}}$ is an optimized white frame. In other words, the adaptive adversarial patch is optimized by considering $w_{\text{final}}$. After the adaptive adversarial patch is optimized, during the run time, the input of object detector can be written as $A_{\text{white}}(A_{\text{adv}}(x, p), w_{\text{final}}, p_{\text{adaptive}})$, where $p_{\text{adaptive}}$ is optimized adaptive adversarial patch.

Comment 2. I am largely positive about the method and results of this paper, but I think the writing still needs quite a bit of work.

Answer 1. We would like to thank the reviewer’s valuable comment. According to the reviewer’s comment, we clarify the formulation we used. As the reviewer mentioned, the threat model and defense model proposed in the paper is as follows: input image → adversarial patch applied → white frame applied → object detector. Therefore, we used the formulation $A_{\text{white}}(A_{\text{adv}}(x, p), w_{u,t})$. Kindly note that, $A_{\text{adv}}(\cdot)$ places the adversarial patch to persons in the image, and $A_{\text{white}}(\cdot)$ places the UWF on the outside of the image. Under the adaptive attack setting, the adaptive adversarial patch is optimized with $A_{\text{white}}(A_{\text{adv}}(x, p), w_{\text{final}})$ where $w_{\text{final}}$ is a finalized optimized white frame. In other words, the adaptive adversarial patch is optimized by considering $w_{\text{final}}$. After the adaptive adversarial patch is optimized, during the run time, the input of object detector can be written as $A_{\text{white}}(A_{\text{adv}}(x, p_{\text{adaptive}}), w_{\text{final}})$, where $p_{\text{adaptive}}$ is optimized adaptive adversarial patch.

Answer 2. We would like to thank the reviewer’s helpful comments. For better understanding, we make the notation and formulation more clear. For instance, as the reviewer mentioned, $x + A_{\text{white}}(x, w_{u,t})$ can be misunderstood as adding an image to a UWF applied image. Therefore, we simply modify $x + A_{\text{white}}(x, w_{u,t})$ to $A_{\text{white}}(x, w_{u,t})$, where $A_{\text{white}}(\cdot)$ places the UWF on the outside of the image. Also, we modify $x + A_{\text{adv}}(x, p)$ to $A_{\text{adv}}(x, p)$, where $A_{\text{adv}}(\cdot)$ places the adversarial patch to persons in the image. The modification helps the readers better understand the formulation in Comment 1. We took the reviewer’s comments very seriously and regarded them as great opportunities to enhance the overall quality of our paper. We will reflect the reviewer’s comment on notation into the manuscript and the review replies.

Title: Raised my Score (Reviewer’s comment)

Comment:

Thank you for clarifying the order of the patch attack and the UWF in the evaluation. I think moving away from the addition notation makes it much clearer (to me, at least). I have raised my score.

Title: Thanks to Reviewer ArvR (Authors’ response)

Comment: We would like to show our sincere gratitude for the benefits that we derived from your constructive suggestions and comments. We appreciate the reviewer’s largely positive perspective on the paper. The reviewer’s comments have genuinely been advantageous to our efforts to improve the overall quality of the paper. If you have further questions, please let us know. Thank you!

D.2 Reviewer GSh7 (Score: 6)

Title: Official Review of Paper2039 by Reviewer GSh7 (Reviewer’s comment)

Summary:

This paper proposes a defense method for object detection models by adding an universal frame to the input image against person hiding attacks. The universal frame is learned by minimizing the expected errors of the object detection model on the images corrupted by a given attack. For evaluation, the paper shows the effectiveness of the proposed method on two datasets under three attack methods.
Main Review:

Pros:

• clearly written and easy to follow
• the proposed method is intuitive and shows effectiveness over the baseline method
• the proposed method does not have overhead of retraining the model to defend

Cons:

• the threat model is relatively limited and the proposed method can be attacked
• the attack methods evaluated seem to be universal and not very powerful

I have two major concerns regarding this paper:

• If the attacker knows the added frame (white-box setting), the defense method might be easily get around
• The attack methods evaluated seem to be limited to universal attacks. If the attack is individual image based, the defense method might be less effective.

Questions:

• How effective is the proposed method against white-box attack where the attacker knows the existence of the added frames?
• How effective is the proposed method against individual image based attack?
• When the method adds a white frame to the original image, is the original image resized to be smaller?

Limitations And Societal Impact: Yes.

Needs Ethics Review: No

Time Spent Reviewing: 1.5

Rating: 6: Marginally above the acceptance threshold

Confidence: 4: You are confident in your assessment, but not absolutely certain. It is unlikely, but not impossible, that you did not understand some parts of the submission or that you are unfamiliar with some pieces of related work.

Code Of Conduct: While performing my duties as a reviewer (including writing reviews and participating in discussions), I have and will continue to abide by the NeurIPS code of conduct.

Title: Response for Reviewer GSh7 (Authors’ response)

We are greatly thankful for your helpful comments. We responded to the major concerns and cons by answering each question.

Question 1. How effective is the proposed method against white-box attack where the attacker knows the existence of the added frames?

Answer 1. We would like to thank the reviewer for the valuable comment. As per the reviewer’s comment, to evaluate the adversarial robustness, we evaluate the proposed method under white-box attack (can be regarded as Adaptive attack), which is tailored to the specific defense. To perform an adversarial attack optimized for the proposed method, the attacker knows the existence of UWF. Then, it generates an adversarial patch with UWF applied image. To this end, we generate three adversarial patches through adversarial patch algorithms [7,9,10] with UWF applied images. The below table shows the experimental results under white-box attack.

As shown in the table, the UWF is still effective against white-box attacks. Compared to “No Defense”, we achieve 10.20 ∼ 43.42 AP score increment under white-box attack settings. Furthermore, it still shows better robustness than [20], which takes three days to train the robust detection model. Especially, compared with the results in Table 3 of the original manuscript, our proposed method shows a 7.22 high score than [20] under [7] attack.

Following the Algorithm 2 of the original manuscript, the adversarial patch $p^{i+1}$ is optimized to attack UWF $p^{i+1} = p^i - \nabla_{p} L_{rob}(x^i + A_{hit}(x, w_{s,t}), p)$, and UWF $(w_{u,t})$ optimizes to defend that optimized $p$ in an adversarial manner $(w_{u,t}^{i+1} = w_{u,t}^i - \nabla_{p} L_{UWF}(x, p, w_{u,t}))$. Therefore, even though the adversarial patch is generated by considering the existence of the UWF, the proposed UWF can defend against the adversarial patch. We will update the manuscript by adding the results about robustness evaluation under white-box attack.
Table R1: Defense performance on YOLO-v2 and Faster-RCNN under white-box attack setting. The adversarial patches are generated from the UWF applied images.

| Dataset       | Attack    | YOLO-v2        | Faster R-CNN   |
|---------------|-----------|----------------|---------------|
|               |           | No Defense     | Ours          | No Defense    | Ours          |
| Inria         | Adv-Patch | 18.80          | 44.49         | 49.21         | 59.41         |
|               | Adv-Cloak | 14.81          | 41.22         | 38.50         | 55.23         |
|               | Adv-T-Shirt | 24.32         | 47.11         | 40.27         | 54.82         |
| Our Own       | Adv-Patch | 1.90           | 45.32         | 28.90         | 48.92         |
| Collected     | Adv-Cloak | 1.40           | 40.18         | 34.24         | 52.68         |
|               | Adv-T-Shirt | 19.53         | 40.04         | 39.00         | 50.49         |

Table R2: Defense performance on YOLO-v2 and Faster-RCNN under individual image-based attack setting.

| Dataset        | YOLO-v2 | Faster R-CNN |
|----------------|---------|--------------|
| Inria Dataset  | 13.22   | 41.82        |
| Collected Dataset | 0.89   | 36.22        |

Question 2. The attack methods evaluated seem to be limited to universal attacks. If the attack is individual image based, the defense method might be less effective. How effective is the proposed method against individual image based attack?

Answer 2. We would like to thank the reviewer for the valuable comment. As per the reviewer’s concern, it would be necessary to evaluate the effectiveness of the proposed dense method against individual image-based attacks. To release the reviewer’s concern, we evaluate that whether the UWF could defend against individual image-based attacks. To this end, we generate a UWF from training images. Then, we generate individual adversarial patches for every test image applied UWF. The following table shows the defense performance against individual image-based attack. As shown in the table, the proposed UWF could effectively defend against individual image-based attack. Compared to “No Defense”, we achieve 10.20 ∼ 43.42 AP score increment under white-box attack settings. Especially, despite our method is attacked by the individual image-based attack, it shows 4.55 better AP Score than [20] under universal attack [7] (See Table 3 of the original manuscript). We will update the analysis of individual image-based attacks in the revised manuscript.

Question 3. When the method adds a white frame to the original image, is the original image resized to be smaller?

Answer 3. We would like to thank the reviewer for the valuable comment. In the case of Faster-RCNN, since it does not need to use a fixed image size, the original image size is maintained. In the case of YOLO model, the original image is resized to be smaller since it takes a fixed image size. In the experiment, we use the same size of the resized image. We will clarify the above explanation in the revised manuscript.

Title: Thanks for the reply! (Reviewer's comment)

Comment: Thanks for providing the results in the adaptive attack setting. I actually wondered what if the attacker knows the exact frame added and the defender is not allowed to update the frame based on the new attack. That setting was what I suspect when the defense will fail.

Title: Responses for Reviewer GSh7 (Authors’ response)

Comment 1. I actually wondered what if the attacker knows the exact frame added and the defender is not allowed to update the frame based on the new attack.

Answer 1. Thanks for the reviewer’s valuable reply. We would like to respectfully point out that the experiment setting that the reviewer mentioned is exactly the same as our adaptive attack setting. The attacker knows the exact frame added and the defender is not allowed to update the frame based on the new attack. In the experiment of Table R1, an attacker generates an adversarial patch on the exact white frame added image. Then, we obtained the result by using that adversarial patch and that white frame used for generating adversarial patch. Note that, we did not update the white frame based on the new attack during the inference.

Title: Thanks for the reply (Reviewer's comment)

Comment: In the text for Table R1, you mentioned "Following the Algorithm 2 of the original manuscript, the adversarial patch is optimized to attack UWF..." This sentence seem to suggest the defense is optimized based
on the adaptive attack. Could you clarify a bit about the process? In particular, the setting I am interested in having the following conditions hold at the same time: 1. The defender does not know the attacker’s adversarial patches at run time. 2. The defender can only add the frame once. 3. The attacker knows the added frame and can optimize for it at run time. 4. The attacker can add different patches for different images.

Answer 1. Thanks for the reviewer’s valuable reply. According to the reviewer’s comment, we clarify the training and run time process.

(Training Process)

We optimized the Universal White Frame (UWF) with the training set. The training procedure of UWF is as follows:

1. An adversarial patch \( p_{\text{train}}^i \) is optimized in order to minimize the loss \( L_{\text{obj}}(x + A_{\text{white}}(x, w), p_{\text{train}}^i) \) where \( x \) is the input image, and \( A_{\text{white}}(\cdot) \) is an applying function that adds UWF \( (w) \) to the image. Also, \( p_{\text{train}} \) is an adversarial patch for training, \( L_{\text{obj}} \) is the objectness score of detectors, and \( i \) denotes the number of iteration for optimization \( (i = 1, 2, 3, \ldots, T_p) \). The optimization procedure can be formulated as follow:

\[
p^{i+1} = p^i - \nabla_p L_{\text{obj}}(x + A_{\text{white}}(x, w), p_{\text{train}}^i)
\]  

(12)

2. After optimizing the adversarial patch \( p_{\text{train}}^i \) for \( T_p \), we optimize UWF by using the using the \( p_{\text{train}}^{T_p} \). UWF \( (w) \) is optimized in order to reduce the loss \( L_{\text{UWF}}(x, p_{\text{train}}^{T_p}, w) \) on a training dataset. \( L_{\text{UWF}} \) means the difference between the output of the input image and the output of UWF and patch added image. \( j \) denotes the number of iterations for optimizing UWF \( (j = 1, 2, 3, \ldots, T_w) \). The optimization procedure can be formulated as follow:

\[
w^{j+1} = w^j - \nabla_w L_{\text{UWF}}(x, p_{\text{train}}^{T_p}, w^j)
\]  

(13)

The algorithm repeats up to \( T_w \) or it stops when \( L_{\text{UWF}} \) goes below a certain threshold \( (L_{\text{UWF}} < \delta) \).

3. We repeat process 1 and 2 for training epoch \( T \). In other words, we start over process 1 by using the optimized \( p_{\text{train}}^{T_p} \) and \( w^{T_w} \) from previous epoch. In process 2, we optimize UWF with the adversarial patch optimized in process 1. Through the iterative optimization process, we finally obtain UWF \( (w^{\text{Final}}) \) and we do not update this frame anymore. The whole process is summarized in Algorithm 2 in the manuscript.

(Run time process)

(condition 1) During the run time, the defender does not know which adversarial patches will be added and uses the \( w^{\text{Final}} \) regardless of the type of adversarial patch.

(condition 2) Defenders add the \( w^{\text{Final}} \) only once.

(condition 3) Under the adaptive attack setting, the attacker optimizes an adversarial patch \( p_{\text{adaptive}} \) with the image \( (A_{\text{white}}(x, w^{\text{Final}})) \) where \( p_{\text{adaptive}} \neq p_{\text{train}} \).

(condition 4) The attacker can generate an individual adversarial patch \( p_n (n = 1, 2, 3, \ldots, N) \) for each \( w^{\text{Final}} \) added image \( (A_{\text{white}}(x, w^{\text{Final}})) \), where \( n \) is the number of images.

Following the above conditions, the attacker optimizes a \( p_{\text{adaptive}} \) on \( (A_{\text{white}}(x, w^{\text{Final}})) \). Table R1 shows the result when \( p_{\text{adaptive}} \) is added to \( A_{\text{white}}(x, w^{\text{Final}}) \). Furthermore, Table R2 shows the result when \( w^{\text{Final}} \) and \( p_n \) are added to different image \( x_n \) where \( p_n \) denotes the individual adaptive patch for each image \( A_{\text{white}}(x_n, w^{\text{Final}}) \). As shown in Table R1 and Table R2, we verified the adversarial robustness of UWF against adaptive adversarial patches.

Title: Thank you for the clarification! (Reviewer’s comment)

Comment: I wonder what is the attacker’s setting for the results in Table R2? For example, how many steps are allowed? Does the attacker’s loss converge given the number of steps you used?

Title: Responses for Reviewer GSh7 (Authors’ response)

Comment 1. how many steps are allowed? Does the attacker’s loss converge given the number of steps you
used?

**Answer 1.** Thanks for the reviewer’s reply. In the experiment of Table R2, we updated individual adversarial patches with 150 steps for each image. We optimized individual adversarial patches using an ADAM optimizer with an initial learning rate of 0.03. Then, the loss is converged with the given number of steps.

**Title: Question regarding reproducibility (Reviewer’s comment)**

**Comment:** Another question as mentioned by another reviewer is that the code is not provided. I wonder if there is any plan for releasing the code for researchers to reproduce the results?

**Title: Responses for Reviewer GSh7 (Authors’ response)**

**Answer:** We would like to thank the reviewer’s comments. We have a plan to release our code for researchers to reproduce the results after the paper decision.

**Title: Thanks for the reply (Reviewer’s comment)**

**Comment:** I wonder if the author can give more insights regarding why the proposed method does not suffer from the problem of “obfuscated gradient” (see Obfuscated Gradients Give a False Sense of Security: Circumventing Defenses to Adversarial Examples, ICML2018)? Is it because the adaptive training process is closer to adversarial training rather than the previous input transformation methods used for defense?

**Title: Responses for Reviewer GSh7 (Authors’ response)**

**Comment 1.** I wonder if the author can give more insights regarding why the proposed method does not suffer from the problem of “obfuscated gradient” (see Obfuscated Gradients Give a False Sense of Security: Circumventing Defenses to Adversarial Examples, ICML2018)? Is it because the adaptive training process is closer to adversarial training rather than the previous input transformation methods used for defense?

**Answer 1.** We would like to thank you for the reviewer’s valuable comment. As the reviewer mentioned, our UWF training process is closer to adversarial training, rather than previous input transformation methods. Different from previous approaches, our method optimizes a unique pattern that is robust to adversarial patch attacks. During the training process, UWF and the adaptive adversarial patch are optimized in an adversarial manner. In other words, UWF is optimized to mitigate the effect of the adversarial patch, and the adversarial patch is optimized to suppress the effect of UWF. The optimization process could be interpreted that the optimized UWF projects the original input feature into a new feature that is robust to adversarial patches. Therefore, our defense does not suffer from the problem of obfuscated gradient [R1].

[R1] Athalye, A., Carlini, N., & Wagner, D. (2018, July). Obfuscated gradients give a false sense of security: Circumventing defenses to adversarial examples. In International conference on machine learning (pp. 274-283). PMLR.

**Title: Thanks for the reply (Reviewer’s comment)**

**Comment:** The additional results and explanations provided by the authors address my initial concern and the proposed method seems to be effective under a stronger threat model. Thus, I decide to increase my score from 4 to 6.

**Title: Thanks to Reviewer GSh7 (Authors’ response)**

We would like to show our sincere gratitude for the benefits that we derived from the reviewer’s constructive suggestions and comments. We took the reviewer’s comments very seriously and regarded them as great opportunities to enhance the overall quality of our paper. We are so glad to hear that our responses are helpful to address the reviewer’s concerns. If you have further questions, please let us know. Thank you!

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**D.3 Reviewer Ci1f (Score: 6)**

**Title: Official Review of Paper2039 by Reviewer Ci1f**

**Summary:**

The authors propose a defense against adversarial patch attacks on person-detection systems, that applies a universal “frame” around images, causing attacks against these images to fail.

**Main Review:**

I have one major concern about this work, and a few minor concerns:

**Major Concern:**

In the experimental section, the authors state that (lines 229-231) “we generate three recently proposed adversarial patches that hide the person [7, 10, 9]. We then apply the generated UWF to the image and compute the average
precision (AP) to verify the defense performance.” (emphasis added). This seems to imply that, at test time, the adversarial patch is generated for the undefended model. However, because the UWF is to be held constant for all images, it really should be considered as part of the model which is being attacked. Therefore, a fair test would generate the adversarial patch for the defended model, with the UWF already applied. I suspect that this would reduce the effectiveness of the defense. This is especially concerning given that the proposed defense does not at all affect the differentiability of the model, so I suspect that the attack methods should work on the defended model without major algorithmic modification. This may just be a misunderstanding on my part: if the attacks were in fact generated for the defended model, this should be clarified. Unfortunately, because code was not provided, I could not verify this one way or the other on my own. I would be very willing to increase my score if the defense still performs well even when attacks are generated on the defended model.

Minor issues:

Comparison to prior works: The authors provide a comparison to one prior work [20], however they also reference two other defenses for patch attacks on object detectors, [18,21]. It would be nice to see comparisons to all of these methods. Also, it is not clear which of the two datasets Table 3, which has the comparison to [20], is based on. Furthermore, the authors claim that (lines 281-282): “However, these [prior] approaches are not a practical solution because they require the model to be trained from scratch or training of an additional modules.” I think that this is somewhat misleading, given that the UWF itself is a trained “additional module” that is part of the defended model. It would be more convincing to see an actual runtime comparison.

Equations: It is clear from Equations 4 and 5 that the UWF is generated through an adversarial min-max “game” between p and w. I think this min-max should be made clear in Equations 2 and 3.

Societal Impact/Ethics: See below.

Typos/language: there were some minor issues throughout, but severe not enough to impede understanding.

Limitations And Societal Impact: In the checklist, the authors mark “Yes” for “Did you discuss any potential negative societal impacts of your work?” However, the Societal Impact section does not mention negative societal impacts at all. In fact, I think that negative Societal Impacts are relevant for this work, which focuses on defending person detection systems against adversarial attacks. The authors briefly mention in the introduction “safety-related applications such as autonomous driving and surveillance systems” (lines 37-38). Some may see potential negative societal impacts of more effective “surveillance systems”, for example if used by authoritarian governments. In fact, the societal implications of person-detectors, and potential positive societal implications of effective attacks on person-detectors, have been extensively covered in the popular press. For example (https://www.newyorker.com/magazine/2020/03/16/dressing-for-the-surveillance-age). To quote the article: “Advances in computer vision have occurred so rapidly that local and national privacy policies—what aspects of your face and body should be protected by law from surveillance machines—are lagging far behind A.I.’s technological capabilities, leaving the public vulnerable to a modern panopticon, a total-surveillance society that could be built before we know enough to stop it.” The article also includes an interview with one of the authors of [10]. Given the popular attention to the ethical issues around person detectors, w.r.t. privacy and surveillance, I think more discussion of negative societal impact is warranted.

Ethical Concerns: See above Societal Impact section. The authors do not discuss the potential negative Societal impacts of the work.

Needs Ethics Review: Yes

Ethics Review Area: Inappropriate Potential Applications & Impact (e.g., human rights concerns)

Time Spent Reviewing: 3

Rating: 6: Marginally above the acceptance threshold

Confidence: 4: You are confident in your assessment, but not absolutely certain. It is unlikely, but not impossible, that you did not understand some parts of the submission or that you are unfamiliar with some pieces of related work.

Code Of Conduct: While performing my duties as a reviewer (including writing reviews and participating in discussions), I have and will continue to abide by the NeurIPS code of conduct.

D.4 Title: Responses for Reviewer Ci1f (Authors’ response)

Major Comment 1. For fair test would generate the adversarial patch for the defended model, with the UWF already applied.

Answer 1. We would like to thank the reviewer for the valuable comment. As per the reviewer’s comment, to
Table R1: Defense performance on YOLO-v2 and Faster-RCNN under adaptive attack setting. The adversarial patches are generated from the UWF applied images.

| Dataset     | Attack        | YOLO-v2 | Faster R-CNN |
|-------------|---------------|---------|--------------|
|             |               | No Defense | Ours | No Defense | Ours |
| Inria       | Adv-Patch     | 18.80   | 44.49 | 49.21 | 59.41 |
|             | Adv-Cloak     | 14.81   | 41.22 | 38.50 | 55.23 |
|             | Adv-T-Shirt   | 24.32   | 44.71 | 40.27 | 54.82 |
| Our Own     | Adv-Patch     | 1.90    | 45.32 | 28.90 | 48.92 |
| Collected   | Adv-Cloak     | 1.40    | 40.18 | 34.24 | 52.68 |
|             | Adv-T-Shirt   | 19.53   | 40.04 | 39.00 | 50.49 |

evaluate the adversarial robustness, we evaluate the proposed method under adaptive attack where the attacker knows the existence of the added frames. In other words, it is necessary to generate adversarial patches on the defended model, with the UWF already applied. To this end, we generate adversarial patch with UWF applied image with three adversarial patch generation algorithms [7,9,10]. The below table shows the experimental results under adaptive attack.

As shown in table, the UWF is still effective when the adversarial patches are generated on UWF applied images. Compared to “No Defense”, we achieve 10.20 43.42 AP score increment under adaptive attack settings. Furthermore, it still shows better robustness than [20], which takes three days to train the robust detection model. Especially, compared with the results in Table 3 of the original manuscript, our proposed method shows a 7.22 high score than [20] under [7] attack.

The reason why our defense framework is also robust against adaptive attack is as follows. Following the Algorithm 2 of the original manuscript, during training the white frame, the adversarial patch \( p \) is optimized to attack UWF \( (p^{t+1} = p^t - \nabla_{p} L_{obj}(x + A_{white}(x, w_{u,t}), p)) \), and UWF \( (w_{u,t}) \) optimizes to defend that optimized \( p \) in an adversarial manner \( (w_{u,t}^{t+1} = w_{u,t}^t - \nabla_{p} L_{UWF}(x, p, w_{u,t})) \). Therefore, during the inference, even though the adversarial patch is generated by considering the existence of the UWF, the proposed UWF can defend against the adversarial patch without a further update. We will update the manuscript by adding the results about robustness evaluation under adaptive attack. Therefore, during the inference, even though the adversarial patch is generated by considering the existence of the UWF, the proposed UWF can defend against the adversarial patch without a further update. We will update the manuscript by adding the results about robustness evaluation under adaptive attack.

**Minor Comment 1.** It would be nice to see comparisons to all of these methods.

**Answer 1.** We would like to thank the reviewer for the valuable comment. As per the reviewer’s comment, it would be better to compare with more recent works [18, 21]. However, direct comparison with the proposed method is difficult for the following reasons.

The purpose of [21] is different from our work. The purpose of [21] is to discriminate whether the image has been attacked or not. To be specific, [21] aims to alert and reject the image when the input image is adversarially patched. Different from [21], our goal is to correctly detect adversarially patched persons. Therefore, [21] and our method are not directly comparable.

In the case of [18] (appeared on arxiv), it adds the patch detection network on the YOLO model to detect adversarial patches. It aims to defend against adversarial patch attacks by modifying the model parameters with extra bulky dataset. Different from [21], we aim to defend against adversarial attacks without changing the model parameters at all. Therefore, it cannot be also compared directly. Nevertheless, it is clear that our method is superior to [18] in terms of (1) computational efficiency and (2) practicality.

1. According to the explanation described in [18], to train the model, it takes 4 days with 4 V100 GPUs. Compared to [18], even with a GPU that is much less computationally efficient than V100, our method shows faster optimization. Specifically, the proposed UWF only takes 5 hours to optimize the UWF with a single 1080Ti GPU.

2. In the case of [18], it is limited to the specified structure. In contrary, the proposed method can be applied to existing models without training or changing the model parameters. In other words, our method could be general and flexible enough to be applicable to various structures. We will discuss the aforementioned discussion in the revised manuscript.

**Minor Comment 2.** It is not clear which of the two datasets Table 3, which has the comparison to [20], is based on.

**Answer 2.** We would like to thank the reviewer for the valuable comment. In Table 3, we use Inria dataset with
Table R2: Run time Comparison.

| Dataset      | YOLO-v2          | Faster R-CNN        |
|--------------|------------------|---------------------|
|              | No Defense Ours | No Defense Ours    |
| Runtime(ms/image) | 23.1    | 25.3               | 75.0    | 77.1               |

YOLO-v2 model. We will clarify the dataset used in Table 3 in the revised manuscript.

**Minor Comment 3.** Given that the UWF itself is a trained “additional module” that is part of the defended model.

**Answer 3.** We would like to thank the reviewer for the valuable comment. As the reviewer commented, the UWF can be regarded as “additional module” that is part of the defended model. Therefore, we clarify the sentence as follow: Before: “However, these approaches are not a practical solution because they require the model to be trained from scratch or training of an additional modules.” After: “However, these approaches are not a practical solution because they require the model to be trained from scratch and it takes a lot of time and computation cost for optimization.”

**Minor Comment 4.** Runtime comparison.

**Answer 4.** We appreciate the reviewer’s valuable comment. The actual runtimes are as follows (Inria Dataset): Our defense shows marginal overhead. We will add the runtime analysis to the revised manuscript.

**Minor Comment 5.** It is clear from Equations 4 and 5 that the UWF is generated through an adversarial min-max “game” between p and w. I think this min-max should be made clear in Equations 2 and 3.

**Answer 5.** We would like to thank the reviewer for the valuable comment. Following the reviewer’s comment, we will clearly modify equation 2,3 to make it easier to understand the notion of creating a white patch given adversarial patch by min-max optimization.

**Societal Impact Discussion:**

We would like to thank the reviewer for the valuable comment. As the reviewer suggested, we add more discussion points for the potential societal impacts of our universal white framing. We contemplated possible uses by different entities for different purposes. Also, we carefully considered the fact that different stakeholders could be impacted.

**Positive societal impacts:** Our main intended beneficiaries in the scope are security and safety related applications in the real world. Research on adversarial patch attacks is extremely correlated with security threats posed by an adversary. For example, by paralyzing a person-detector in the physical world, an unauthorized adversary can circumvent a monitoring detector in the intrusion prevention system. Furthermore, our proposed method helps to evaluate and improve the general robustness and reliability of DNNs deployed in real-life such as autonomous vehicles. Our work can contribute to managing the risks of adopting deep learning.

**Negative societal impacts:** As the reviewer points out, one possible negative impact is authoritarian surveillance. We acknowledge that it could harm other stakeholders, including protesters fighting authoritarian surveillance that violates human rights and privacy.

**Strategy:** We can limit our defense method to work only in a federated learning scenario. In an authoritarian government, centralization equates to control; centralization equates to power. The alternative is decentralization. Federated learning [R1][R2] is a well-known decentralized machine learning approach that trains an algorithm across multiple decentralized devices or servers holding individual data samples, without sharing them. Since our universal white framing does not need to retrain the model and is applicable regardless of the model, our defense is appropriate for updating and managing the system in a federated learning scenario. Moreover, the general public needs to be informed, more educated, and actively vigilant about the misuse of surveillance. Therefore, as a researcher, we must continuously discuss and always be awaken to ethical usage of effective surveillance. We will summarize and share these discussions in the societal impact section.

Given the importance of security and safety related applications described above, we believe that making our work available will have an overall positive impact.

[R1] Konečný, J., et al. Federated learning: Strategies for improving communication efficiency. arXiv preprint arXiv:1610.05492

[R2] McMahan, B., et al. Communication-efficient learning of deep networks from decentralized data. In Artificial intelligence and statistics (pp. 1273-1282). PMLR.

**Title:** Reply to rebuttal (Reviewer’s comment)
Based on the new results with adaptive attacks and the discussions that the authors had with ArvR and GSh7, I raise my score to a 6.

Also, I was slightly imprecise in my review when I asked for a runtime comparison; I actually wanted a training time comparison, because the authors claimed that the other methods take a lot of time to train from scratch/additional modules. However, given that the authors also provided a training time comparison in the rebuttal, I’m happy with this.

Title: Thanks to Reviewer Ci1f (Authors’ response)

We would like to show our sincere gratitude for the benefits that we derived from the reviewer’s constructive suggestions and comments. We appreciate the reviewer’s beneficial input and recommendation on clarifying and emphasizing the cost efficiency of our model in training time. We are so glad that our responses are helpful to address your initial concerns in the rebuttal. If you have further questions, please let us know. Thank you!

D.5 Ethic Reviewer Mo1Q

Title: Ethics Review of Paper2039 by Ethics Reviewer Mo1Q (Reviewer's comment)

Ethical Issues: Yes

Ethics Review:

I concur with the issues raised by reviewers ArvR and Ci1f, namely that there are ethical issues associated with possible negative societal impacts and/or misuse, and that these issues deserve discussion in the paper.

Issues Acknowledged:

Issues Acknowledged Description:
The authors have acknowledged these issues in their comments to the other reviewers.

Recommendation:

I am pleased to see that the reviewers have already raised issue with the insufficient discussion of the potential negative societal impacts, and I see that the authors have already proposed changes to address these issues. For the most part I am happy with the authors’ response, but I do have a few comments:

• “We would like to make it clear that the algorithm described in this paper is purely designed for defensive purposes.” I appreciate this point but unfortunately the authors’ intent is more or less irrelevant for how the algorithm will be used (i.e. for defensive or offensive purposes). I think a simple acknowledgement of the possible societal impacts (both positive and negative) is sufficient.

• I think the reviewers’ mention of possible misuse by authoritarian regimes is a good and valid point, but I don’t believe the discussion about a mitigation strategy based on federated learning is necessary. I’m also not sure that I agree with certain technical aspects of this strategy but that is a separate point.

• When/if the authors revise their manuscript to reflect this concern about authoritarian regimes using this algorithm to suppress dissent, I would suggest that this issue is discussed in the abstract, and that specific mention of countries or protest movements is avoided in order to avoid taking an unnecessary and likely controversial political stance in the paper.

Title: Responses for Ethics Reviewer Mo1Q (Authors’ response)

Comment 1. “We would like to make it clear that the algorithm described in this paper is purely designed for defensive purposes.” I appreciate this point but unfortunately the authors’ intent is more or less irrelevant for how the algorithm will be used (i.e. for defensive or offensive purposes). I think a simple acknowledgement of the possible societal impacts (both positive and negative) is sufficient.

Answer 1. We would like to thank the reviewer for the valuable comment. As per the reviewer’s comment, we simply discuss possible societal impacts. The positive aspect of our algorithm is that it can be used to protect persons. For example, by paralyzing a person-detector in the physical world, an unauthorized adversary can circumvent a monitoring detector in the intrusion prevention system. With the proposed algorithm, we could protect the person from such an unauthorized intrusion. Furthermore, our proposed method helps to evaluate and improve the general robustness and reliability of DNNs deployed in real-life such as autonomous vehicles. One negative impact is that it can be used to surveil people in authoritarian regimes. In authoritarian regimes, it can raise negative impacts such as privacy and human rights issues by spying on people.

We will simply summarize the aforementioned discussion in the societal impact section.

Comment 2. I think the reviewers’ mention of possible misuse by authoritarian regimes is a good and valid point, but I don’t believe the discussion about a mitigation strategy based on federated learning is necessary. I’m also not sure that I agree with certain technical aspects of this strategy but that is a separate point.
Answer 1. We would like to thank the reviewer for the valuable comment. According to the reviewer’s recommendation, we discussed more detailed possible mitigation strategies. It would be necessary to make some societal regulations for the proper usage of helpful AI. These regulations may include restrictions which ensure that models only work in distributed computing environment such as federated learning (avoiding privacy concerns) or limit the use of our models only in security and safety-related systems. Also, we can mitigate the possible risk of privacy piracy by adopting a gated release of our model against malicious intentions. Furthermore, there have been many discussions on ethical usage of AI in many different conferences (NeurIPS, ICML, etc). Therefore, we should actively participate in the discussion on ethical usage of AI.

Comment 3. When/if the authors revise their manuscript to reflect this concern about authoritarian regimes using this algorithm to suppress dissent, I would suggest that this issue is discussed in the abstract, and that specific mention of countries or protest movements is avoided in order to avoid taking an unnecessary and likely controversial political stance in the paper.

Answer 3. We would like to thank the reviewer for the valuable comment. As per reviewer’s comment, we will discuss the societal issue in the abstract, and avoid the specific mention of countries or protest movements. We add the following description in the revised manuscript.

“Our works could make it more difficult to deter excessive and unwanted surveillance, creating potential privacy concerns. However, our work has an overall positive impact on safety-related applications and security systems.

D.6 Ethic Reviewer qm94

Title: Ethics Review of Paper2039 by Ethics Reviewer qm94 (Reviewer’s comment)

Ethical Issues: Yes

Ethics Review:

The authors’ paper present a method for countering “adversarial” patch attacks in object detection models. While the paper discusses the potential implications for safety-critical domains such as self-driving cars, the potential use of object or person detection systems as part of a larger computer vision (CV) based surveillance system does raise ethical and human rights concerns.

Specifically, the use of adversarial patches have been cited on multiple occasions as a means for journalists and other vulnerable groups to protect their identity and freedom of movement from modern computer vision based surveillance and tracking systems. Methods such as the one proposed by the authors would potentially nullify these protections and exposes those groups to potential harm. And, while it is true that object detection system alone do not raise significant human rights concerns, application of the proposed methods in this paper could very easily be utilized in systems specifically designed for surveillance or tracking.

Issues Acknowledged: No

Issues Acknowledged Description: The authors do not address these concerns in the paper

Recommendation:

I would encourage the authors to elaborate the use of adversarial patches in the real world (e.g. counter-surveillance) and resolve how the proposed method could avoid being utilized in systems which directly attribute to potential violations of human rights (e.g. surveillance or tracking systems).

Title: Responses for Ethics Reviewer qm94 (Authors’ response)

Comment 1. I would encourage the authors to elaborate the use of adversarial patches in the real world (e.g. counter-surveillance) and resolve how the proposed method could avoid being utilized in systems which directly attribute to potential violations of human rights (e.g. surveillance or tracking systems).

Answer 1. We would like to thank the reviewer for the valuable comment. As per reviewer’s comment, (1) we elaborate the use of adversarial patches in the real world and (2) resolve how the proposed method could avoid being utilized in systems which directly attribute to potential violations of human rights.

Adversarial patches in the real world: Research on adversarial patch attacks is extremely correlated with security threats posed by an adversary. For example, by paralyzing a person-detector in the physical world, an unauthorized adversary can circumvent a monitoring detector in the intrusion prevention system. With the proposed algorithm, we could protect the person from such an unauthorized intrusion.

Mitigation method: It would be necessary to make some societal regulations for the proper usage of helpful AI. These regulations may include restrictions which ensure that models only work in distributed computing environment such as federated learning (avoiding privacy concerns) or limit the use of our models only in security and safety-related systems. Also, we can mitigate the possible risk of privacy piracy by adopting a gated
release of our model against malicious intentions. Furthermore, there have been many discussions on ethical usage of AI in many different conferences (NeurIPS, ICML, etc). Therefore, we should actively participate in the discussion on ethical usage of AI.