

# Developing Imperceptible Adversarial Patches to Camouflage Military Assets From Computer Vision Enabled Technologies

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**Abstract**—Convolutional neural networks (CNNs) have demonstrated rapid progress and a high level of success in object detection. However, recent evidence has highlighted their vulnerability to adversarial attacks. These attacks are calculated image perturbations or adversarial patches that result in object misclassification or detection suppression. Traditional camouflage methods are impractical when applied to disguise aircraft and other large mobile assets from autonomous detection in intelligence, surveillance and reconnaissance technologies and fifth generation missiles. In this paper we present a unique method that produces imperceptible patches capable of camouflaging large military assets from computer vision-enabled technologies. We developed these patches by maximising object detection loss whilst limiting the patch’s colour perceptibility. This work also aims to further the understanding of adversarial examples and their effects on object detection algorithms.

**Index Terms**—imperceptible adversarial patch, computer vision, deep learning

## I. INTRODUCTION

Convolutional neural networks (CNNs) have been shown to be effective at object detection [13], [19], [21], [28], [29]. However, it has been demonstrated that CNNs can be successfully targeted and disrupted through designed attacks or adversarial patches [5], [14], [30], [40], [41]. As modern CNNs are increasingly applied across various domains [9], [15], [29], [34], [35], it is important to understand these CNNs and their vulnerabilities. Specific to a military context, these designed attacks or adversarial patches, when printed, could be used to attack an adversaries’ CNN detectors and could act as passive defence against object detectors. This need to camouflage from object detectors is vital as intelligence, surveillance and reconnaissance (ISR) technologies, and fifth generation missiles integrate vision technologies [2], [3], [18], [44], [48]. Traditional camouflage methods are impractical for larger mobile assets, such as aircraft, so adversarial patches should be further developed as an alternative camouflage technique. Our proposed method for the development of adversarial patches is unique and designed to disguise their presence to humans whilst still being capable of acting as an alternative camouflage against detection algorithms. Our method was developed by combining adversarial techniques

that focus on patch deception strength and imperceptibility. Specifically, we make the following contributions:

- 1) a discussion of the concerns and constraints of a military using adversarial patches to camouflage large mobile objects
- 2) a unique algorithm that develops imperceptible, effective and robust adversarial patches
- 3) recommendations for future research into adversarial patch development.

In Section II, we introduce adversarial patches by reviewing relevant current and foundational literature. Algorithm and experiment methodologies are described in Section III, with Section IV detailing experiment results. Section V considers research results and experiment validity, with the broad positive and negative impacts of the research being considered in Section VI. The paper concludes with Section VII and finishes with Section VIII, which provides suggestions for future adversarial patch development.

## II. RELATED WORK

Researchers have produced imperceptible adversarial methods that disrupt computer vision algorithms, such as CNNs [14], [41], with even one-pixel attacks shown to be effective [40]. Early attacks were often specific to single images and lacked portability [30]. However, later research identified an algorithm that generates more universal patches [5]. Specifically, a patch application operator  $A(p, x, l, t)$  was used to create universal and robust patches. Here,  $p$  is a patch transformed (rotated and scaled) by  $t$  and then applied to the example image  $x$  at location  $l$ . The patches generated from this operator were suitable for real-world attacks where patches appear in various backgrounds, locations, and lighting conditions. A patch  $\hat{p}$  is then generated by optimising the objective function [5]:

$$\hat{p} = \underset{p}{\operatorname{arg\,max}} \mathbb{E}_{x \sim X, t \sim T, l \sim L} [\log \Pr(\hat{y} | A(p, x, l, t))]$$

Where  $X$  is the set of training images,  $T$  is a distribution of patch transformations, and  $L$  is a distribution of patch locations. This patch application operator can be configured to

camouflage patches by adding  $\|p - p_{orig}\|_{\infty} < \epsilon$  where  $p_{orig}$  is some starting desired disguise. When using this constraint, the trained patch is successful but not as effective as its undisguised counterpart [5].

Researchers have examined using adversarial patches to disguise assets from automatic object detection [1], [38], [45]. One specific application used adversarial patches to disguise military aircraft from object detectors trained on drone surveillance footage [11]. This work showed that adversarial patches could be used as an alternative camouflage against automatic object detectors and uniquely applied and studied the efficacy of different adversarial patch hyperparameters. Specifically, explored were different patch locations and sizes relative to the military assets and the saliency and number of patches. However, the patches studied were notably conspicuous and humanly perceptible—an example of a salient patch is seen in Fig. 2, and thus unlikely to be used in a military context. Further, as Fig. 2 highlights, the studied patches were unrealistic in size and covered a significant portion of the aircraft. Consequently, these larger patches sat outside object boundaries and could not be printed and placed on an aircraft.

Other research has continued to improve disguising adversarial patches whilst maintaining their robustness [7], [33], [37]. Recent work [47] has challenged the assumption that imperceptibility is achieved using the constraints proposed in earlier literature [5], [14]. This research created imperceptible patches by minimising the patch’s perceptual colour (PerC) distance [26] whilst training its adversarial strength using the approach proposed by Carlini & Wagner (C&W) [7]. The researchers found that combining the PerC distance loss with the C&W approach (PerC-C&W) can produce robust but imperceptible adversarial patches. The approach was further improved by alternating between PerC distance and detection loss updates (PerC-AL). Though PerC-C&W and PerC-AL can produce robust imperceptible image perturbations, the authors prefer PerC-AL as the algorithm reduces hyperparameter optimisation time. However, this study explored only image perturbations with the same dimension as the target image. Thus, the existing PerC-AL and PerC-C&W algorithms cannot be used for example to create a patch only located within the bounds of a target object in the image. Printing and applying PerC-AL and PerC-C&W patches to real-world objects remains unexplored.

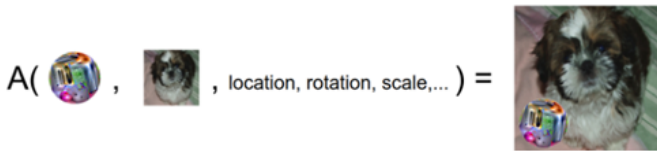


Fig. 1. An illustration of the patch application operator [5]

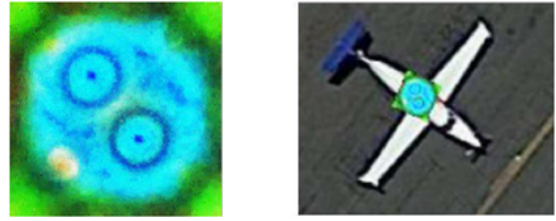


Fig. 2. Example Patch and Placement on an Aircraft [11]

Further work has also developed frameworks for creating more robust physical adversarial patches [4], [8], [12], [24], [39], [42]. Recent research has improved upon previous attacks by creating perturbations that do not need to occlude targeted objects, and yet such targeted objects are still misclassified or not detected [20]. Specifically, researchers developed a patch capable of suppressing detections even for objects at a distance from the patch. Consequently, a user does not need to manipulate the target object actively. These patches were developed by maximising the loss of an object detector using the fast sign gradient method (FGSM) [14]. The patch was clipped into RGB colour space whilst training and therefore was printable once developed. This specific patch development implementation has become known as Robust-DPatch [43]. However, the authors did not explore if Robust-DPatch maintains its robustness when made less perceptible.

### III. METHODOLOGY

The Adversarial Robustness Toolbox (ART) V1.8 library’s [31], [43] Robust-DPatch [20], and Faster R-CNN wrapper [36] implementations were adapted for these experiments. Most significantly, perceptibility updates based on [47] were integrated. The implemented code is available here: <https://github.com/ChrisWise07/imperceptible-patch-generator>

Five specific images were chosen from the COCO-2017 dataset [22]. The chosen images represent some typical situations in which a plane could be found, grounded, flying (with & without cloud coverage), taking off, and at a distance. As Fig. 3 shows, initial Faster R-CNN prediction bounding boxes were then used to set the patch location to the box’s centre and scale the patch shape to a ratio of this box. The bounding box was used to set patch size and location to help the patch sit within object bounds. Then as Fig. 4 demonstrates, the original image’s corresponding patch shape and location were cropped out and used for PerC distance comparison calculations. Using only the image segment for PerC distance calculations was preferred as early experiments indicated this method was faster and did not hinder perceptibility performance compared to perceptibility calculations that used the whole image or the image segment contained within the bounding box for PerC.

A patch specific to each image was developed, following [20], by updating the patch to maximise prediction loss whilst clipping it to within RGB space to maintain its printability. During training, before the object detector performed a prediction, an image was first transformed by rotating the image by  $[0, 90, 270]^\circ$ . These rotations were chosen as they transform

an aircraft into realistic situations, that is, the aircraft being in steep ascent or descent or flying level. Borrowing from [20], the image brightness was also adjusted brightness by factor from [0.4, 1.6] and cropped at the edges so that the patch occupied 20%-30% of the image. Then techniques from [47] were implemented which allowed the algorithm to uniquely update the patch to minimise its perceptibility by minimising the PerC distance between it and the corresponding image segment. Finally, a mechanism was added to expand upon and generalise [47], which allowed only alternating deception and perceptibility updates. This was achieved by implementing a further hyperparameter that controls the ratio of perceptibility to deception updates by performing a deception update when:

$$i \pmod{n} = 0$$

Where  $i$  is the current iteration number, and  $n$  is frequency hyperparameter.

Initial hyperparameters chosen matched those found in [20], [47], with these hyperparameters made explicit in Table IV. However, hyperparameters were optimised in ablation studies of 50 steps, where a step is defined as 1000 iterations [20]. When optimising the perceptibility to deception ratio, the number of iterations per step was changed so that 1000 deception updates were still performed at each step. In every  $n$ th step, the deception learning rate (DLR) was decayed by 0.95, whereas the perceptibility learning rate (PLR) was decayed from a maximum to 0.1 of this maximum using cosine annealing. Subsequent experiments assessed decaying the maximum PLR at the same rate as the DLR.

The experiments ran on compute nodes containing an Nvidia V100 GPU and 12 cores from one processor. Running time varied but approximately required 11 hours per ablation study. The final experiment was conducted on the same computational resources for 100 steps and executed for approximately 20 hours.

#### IV. RESULTS

The final optimised **imperceptible patch** achieved **6.71 mAP-50** (mAP at 0.5 IOU) with a **2854.93 PerC distance**, making imperceptible patch more imperceptible than, whilst being as robust as, **Robust-DPatch**, which achieved **7.27 mAP-50** with a **4346.61 PerC distance**. The visual differences between imperceptible patch and Robust-DPatch are seen in Table III. Note that the reported mAP concerns only aircraft detections and is averaged across different object-confidence thresholds, with the thresholds of [0.5, 0.1, 0.001] being used.

The conservative 0.5 IOU and object-confidence thresholds were chosen to meet military concerns. That is, it is reasonable to foresee a military using conservative benchmarks for true positive detection as a partially correct detection still poses a risk to asset or human life. Thus, militaries will desire a patch capable of suppressing conservative detections.

The following observations and conclusions were made from the ablation study results displayed in Table I:

- Results support a relationship between patch perceptibility and robustness. This relationship is demonstrated in Studies 5 & 8, where decreased mAP (increased robustness) is correlated with increased perceptibility.
- Based on the evidence from Experiment 3, an optimal DLR balances extreme updates. That is, the learning rate is large enough to be effective but small enough to avoid extreme and subsequently perceptible updates.
- Studies 9 & 10 evidence that patch perceptibility is a more complex space that is harder to optimise and was being dominated in earlier ablation studies by deception updates. Explicitly, Study 9 running for 50 steps, found the optimal configuration decays the DLR every 5<sup>th</sup> step. However, the longer study of 100 steps found that the optimal configuration should decay the maximum PLR as well, and without maximum PLR decay, the patch becomes weakly adversarial. This demonstrates that perceptibility updates could only dominant once the DLR was small enough.
- Study 4 supports [20]’s use of momentum for deception updates and Study 6 shows that momentum for perceptibility updates also leads to greater patch performance.
- The results from Study 2 confer with [5], [11], [20], [24] and show that transformations result in more robust patches.

Points of note for correct interpretation of results:

- The score displayed is the addition of the rank of an experiment’s mAP and average patch PerC distance within a particular study, with the objective being to achieve the lowest mAP, average patch PerC distance and subsequently overall score.
- The lowest possible score is 2 for each experiment.
- Within the tables, the best mAPs, PerC distances, and overall scores within the tables are bolded.
- The optimal hyperparameter for an ablation study is also bolden.
- If a hyperparameter was found to be optimal, all following ablation studies updated the corresponding default hyperparameter to that optimal configuration. All resulting optimal configurations were used to develop the imperceptible patch utilised in the final comparison study. Note that these optimal hyperparameters are made explicit in Table IV.
- If two or more hyperparameters shared the same score, the study that executed the quickest was chosen. If execution time was equal, than the hyperparameter that best balanced robustness and imperceptibility was chosen.
- The hybrid initial patch configuration used a cropped image segment with RGB colour noise added to it.

TABLE I  
ABLATION STUDY RESULTS

Study Number	Experiment Focus	Hyperparameter	mAP (%)	Mean PerC Distance	Combined Score
1	Initial Patch configuration	Black	20.93	3683.05	7
		<b>Hybrid</b>	<b>12.8</b>	2672.39	<b>3</b>
		Image Segment	63.18	<b>2633.06</b>	5
		Random	14.06	3150.76	5
2	Transformations	No transformations	43.54	3726.7	6
		<b>Deception prediction only</b>	12.8	<b>2672.39</b>	<b>3</b>
		Deception & perceptibility predictions	<b>9.73</b>	3417.96	3
3	Deception Learning Rate	0.05	28.39	<b>2352.15</b>	4
		<b>0.1</b>	<b>12.8</b>	2672.39	<b>3</b>
		0.2	14.71	3248.64	5
4	Deception Momentum Amount	0.8	18	2675.71	5
		<b>0.9</b>	<b>12.8</b>	2672.39	<b>3</b>
		0.95	31.95	<b>2663.88</b>	4
5	Max Perceptibility Learning Rate	0.25	<b>9.01</b>	3202.3	4
		<b>0.5</b>	12.8	2672.39	<b>4</b>
		1.0	33.99	<b>1827.12</b>	4
6	Perceptibility Momentum Amount	0.8	16.22	2662.65	6
		<b>0.9</b>	<b>10.88</b>	<b>2635.27</b>	<b>2</b>
		0.95	12.47	2636.45	4
7	Momentum Use	No momentum	28.34	2645.26	6
		Deception only momentum	12.8	2672.39	7
		Perceptibility only momentum	12.18	2667.64	5
		<b>Deception &amp; Perceptibility momentum</b>	<b>10.88</b>	<b>2635.27</b>	<b>2</b>
8	Deception Frequency Controller ( $n$ )	<b>1</b>	<b>10.88</b>	2635.27	<b>4</b>
		2	36.39	1809.23	4
		4	67.56	<b>854.44</b>	4
9	Decay Rates	<b>5</b>	<b>10.88</b>	<b>2635.27</b>	<b>2</b>
		5 <sup>a</sup>	13.62	2952.68	6
		10	15.05	2794.34	5
		10 <sup>a</sup>	15.1	2909.16	7
10	Decay Rates <sup>b</sup>	5	39.52	<b>2118.66</b>	5
		<b>5<sup>a</sup></b>	<b>6.71</b>	2854.93	<b>4</b>
		10	30.61	2483.14	5
		10 <sup>a</sup>	18.16	2859.36	6

<sup>a</sup>with max perceptibility learning rate decay, <sup>b</sup>executed for 100 steps

TABLE II  
COMPARISON STUDY RESULTS

Patch Type	mAP (%)	Mean PerC Distance	Combined Score
No Patch	99.99	0	6
White Patch	68.64	5312.76	7
Black Patch	69.54	5872.89	9
Robust DPatch	7.27	4346.61	5
<b>Imperceptible Patch</b>	<b>6.71</b>	<b>2854.93</b>	<b>3</b>

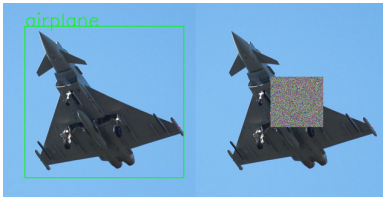


Fig. 3. Bounding Box Setting Patch Location and Size

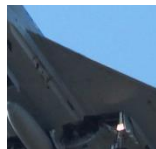








Fig. 4. Cropped Segment of Image

## V. DISCUSSION

The results demonstrate it is possible to create effective imperceptible patches, with the performance of the patches supporting our algorithm. Our method resulted in patches that are significantly less perceptible but as robust (based on mAP) as their Robust-DPatch counter parts. Such perceptibility differences are highlighted in Table III.

It is hypothesised that updates to our algorithm could produce patches with lower PerC distances, allowing such patch's presence to humans being further disguised. Borrowing from more traditional camouflage literature [10], the future algorithm could incorporate more colours from the surrounding background into patches and not update the patch at random edge pixels to blur its outline. Inspired by [5], the patch could also have standard aircraft markings superimposed on top.

TABLE III  
VISUAL COMPARISON BETWEEN ROBUST-DPATCH AND IMPERCEPTIBLE PATCH

	Robust-Dpatch <sup>a</sup>	Imperceptible Patch (ours)
Generated Patch		
Image augmented with Patch		
Faster R-CNN prediction for image augmented with patch		

<sup>a</sup>reference Table IV for hyperparameters used

TABLE IV  
EXPERIMENT HYPERPARAMETERS

	Initial Configuration	Robust-DPatch	Imperceptible Patch
Iterations per Step		1000	
Deception Update Frequency controller ( $n$ )		1	
DLR		0.1	
Deception Update Momentum		0.9	
DLR Decay Amount		0.95	
DLR Decay Frequency		5 steps	
Number of Steps	50	100	100
Maximum PLR	0.5	n.a.	0.5
Perceptibility Update Momentum	0.9	n.a.	0.9
Maximum PLR Decay Amount	0.95	n.a.	0.95
PLR Decay Frequency	5 steps	n.a.	5 steps
Initial Patch Configuration	Random	Random	Hybrid

The positive experiment results could be further extended by:

- Using more images to show the more universal application of imperceptible patches and our proposed algorithm.
- Utilising more than the prediction box to set patch size and location, aiming to ensure a patch will sit within an aircraft's bounds.
- Testing against a known and an unknown detection network. A black-box test is recommended as the specific computer vision algorithm implemented by adversaries will most likely be unknown for live use.
- Executing ablation studies for 100 steps and the final comparison study for 200 steps, to allow for more percep-

tibility optimisation, given that the space is likely more complex as discussed in Section IV.

## VI. BROADER IMPACT

Benefits from this research may include methods that develop patches capable of defending against intrusive computer vision based recognition systems. Within a military context, these patches may assist in protecting personnel and aircraft from advanced tracking systems. A detection system trained with examples augmented with patches could become a more robust network. However, the algorithms and patches that have been developed may have negative impacts as they could provide felons and military insurgents with a potential method

to disguise themselves from autonomous monitoring systems. This could lead to more intrusive recognition systems. A malicious actor could use patches placed in a car window or on a sign, for example, to suppress automatic object detection by an autonomous car’s vision system (e.g., pedestrians, other cars, street signs). Alarming, if imperceptible robust patches are used, no object would need to be actively manipulated within the environment and being imperceptible, patches may therefore be difficult to police.

## VII. CONCLUSIONS

Our research examined improvements to imperceptible adversarial patches designed to attack object detection algorithms. We designed a unique method to develop imperceptible patches capable of camouflaging large military assets from computer vision-enabled technologies. We created a robust imperceptible patch by combining a perceptibility loss function with the standard Robust-DPatch deception updates. The effectiveness of the produced patches against the Faster R-CNN detection algorithm when applied to aircraft images was investigated. Results indicated that our imperceptible patches can effectively camouflage an aircraft in an image from an object detection system. This shows the potential of the method to be used by the military to disguise large assets from modern computer vision enabled systems. Future work optimising the algorithm could result in more effective and imperceptible patches. This paper has proposed focuses for such future research and development. Continued study of adversarial techniques in computer vision and its idiosyncrasies will identify more resilient and universal classification and detection networks in addition to defending against them.

## VIII. FUTURE WORK

There are many directions for future research and development of imperceptible patches. Initially recommended is a focus on expanding the experiments to more general settings. Points of focus could include:

- Using more aircraft images, focusing on aircraft in a variety of environments. Using more training examples may also enable hyperparameters to be generalised.
- Investigating the effect and efficacy of image clipping after each deception and perceptibility update, which opposes the current paradigm of clipping at the end of each iteration.
- Further development of initial patch configurations and exploration of their effects on final patch robustness and perceptibility. Further work could also analyse the maximum and minimum RGB values for each channel in the image segment. The initial random noise patch could then be generated with RGB channels bounded by the calculated channel maximum and minimum.
- Further study and optimisation of image transformations. Though image rotations should potentially be limited to  $[-90, 90]^\circ$  as an aircraft is realistically unlikely to be rotated outside of this range. Based on [5], [11], [20], [24], these

transformations would then help to create more universal patches.

- Researching the effect of using Project Gradient Descent (PGD) [27] to perform deception updates, as discussed in [47], FSGM yields poorer imperceptibility compared to PGD
- Decaying the DLR using cosine annealing, such as [47] performed.

Future research could focus on using semantic segmentation [13], [16], [17], [25], [34] to shape patches to the bounds of the aircraft. Using semantic patch bounding is a significant step towards more printable patches as once inside aircraft bounds, these patches could be used as an aircraft decal.

Further development should account for the plane’s contours when training and developing patches. Accounting for contours could allow patches to exploit shadowing effects whilst developing imperceptibility. Contoured patches may also be another vital training component in developing printable patches, as contouring may introduce distortions to the patch affecting performance.

A more comprehensive data set could be used to create more universal patches. An interesting experiment could test the efficacy of using several images of the same aircraft but from different angles. Thus, this paradigm would create a patch universal to a specific aircraft model. These experiments could further investigate different patches for different locations on the aircraft. For example, patches for the aircraft’s underbelly could be trained only on images of that aircraft in the sky as it is unlikely that vision technology would see a grounded aircraft’s underbelly. However, patches for the aircraft’s top should be trained using grounded and flying aircraft examples. A mixture of examples is suggested as a drone or missile will likely see the top of a grounded and flying aircraft.

Future work could also investigate the effect that multiple aircraft, and therefore patches, have on detection accuracy. Evidence suggests that Robust-DPatch [20] can suppress detections even when the patch is far from an object. Consequently, perhaps only one patch is needed for a swarm of planes to suppress detections effectively. Further, perhaps multiple patched planes could be highly effective as evidence suggests the effectiveness of multiple patches [11].

Targeted cases could be investigated further, such as using a person as the adversarial target. Use of specific targets may be necessary as tracking tools could be programmed to still target out of context detections. These tools may be programmed this way, as seeing an out-of-context object indicates the presence of an adversarial patch. However, according to the Geneva conventions, ejected pilots cannot be targeted [32] and consequently, one assumes that missiles targeting planes will be programmed not to target humans as a detected human is likely an ejected pilot. Therefore, using a person as an adversarial target may present a scheme to exploit detection algorithms.

Targeted cases could also investigate using an aircraft as the adversarial target itself. These patches are then countermeasures and, like chaff, [6], could be dropped from an aircraft

to attract missiles away. Further, specific plane models could be targeted. Specifically, a network would misclassify a more threatening aircraft as a more mundane counterpart, which may also help to mislead any human operators receiving data from these vision technologies.

GAN generated patches [23], [46] could also incorporate perceptibility calculations into the generator's loss function. This paradigm could further benefit from producing a discriminator network resilient to imperceptible adversarial patches.

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