

UNDERSTANDING IMPACTS OF ELECTROMAGNETIC SIGNAL INJECTION ATTACKS ON OBJECT DETECTION

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ABSTRACT

Object detection can localize and identify objects in images, and it is extensively employed in critical multimedia applications such as security surveillance and autonomous driving. Despite the success of existing object detection models, they are often evaluated in ideal scenarios where captured images guarantee the accurate and complete representation of the detecting scenes. However, images captured by image sensors may be affected by different factors in real applications, including cyber-physical attacks. In particular, attackers can exploit hardware properties within the systems to inject electromagnetic interference so as to manipulate the images. Such attacks can cause noisy or incomplete information about the captured scene, leading to incorrect detection results, potentially granting attackers malicious control over critical functions of the systems. This paper presents a research work that comprehensively quantifies and analyzes the impacts of such attacks on state-of-the-art object detection models in practice. It also sheds light on the underlying reasons for the incorrect detection outcomes.

Index Terms— object detection, image sensor, electromagnetic interference, signal injection attack

1. INTRODUCTION

Object detection is a critical computer vision task that involves identifying and locating specific categories of visual objects within images. It has found wide applications in many safety- or security-critical domains, including autonomous driving and surveillance cameras [1]. Given the importance of object detection, it is highly likely to be a target for cyber-physical attacks.

In fact, many studies have showcased that achieving attacks on object detection is more than just an imagination. There are various attack modalities that are capable of tampering with image sensors to cause different perturbations onto images. This may lead to incorrect object detection, posing

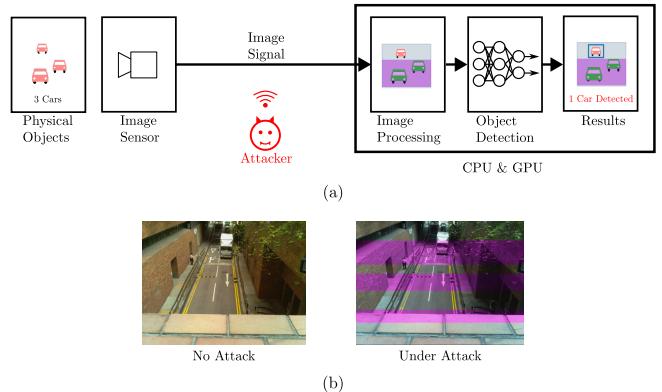


Fig. 1: (a) An image sensor captures and converts the intensity of light into electrical signals, which are further transmitted to a CPU (and/or GPU) by cables for processing and object detection. Cyber-physical attacks often target on jamming the data transmission to cause perturbations onto images, leading to incorrect object detection. (b) An example under attack image.

significant threat to safety and security. Taking autonomous driving as an example where a vehicle relies on image sensors to monitor traffic, incorrect detection could result in missing traffic lights or failing to detect another vehicle in front, potentially leading to fatal collisions.

There are two major types of object detection attacks: printing hostile perturbations known as an “adversarial patch” onto a target object, and injecting physical signals to manipulate the image sensor. In recent years, there has been a growing interest in physical signal injection attacks on object detection due to their imperceptibility to the human eye, unlike adversarial patches on objects patches on objects, such as [2–4]. The signal injection attack modalities include lights [5–11], ultrasounds [12], and electromagnetic waves [13–15].

Of particular interest is a recent method called “Glitch-Hiker” [15] that employs electromagnetic waves as the attack modality. It unveils the principles of how the malicious injection leads to colored strips in images (Fig. 1 b), further affecting the object detection results, for example, preventing detecting objects, as demonstrated in Figure 1. What distinguishes this method from earlier approaches is its advantage of not requiring line-of-sight or precise timing knowledge of victim systems. This characteristic enhances accessibility for

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potential attackers, thereby indicating a higher potential for abuse in practical scenarios.

However, a comprehensive analysis of the impacts on different object detection models in practical scenes has not been addressed, neither does the underlying reasons for the impacts. This work aims to fill these gaps, and the contributions of this work are summarized into three-fold as follows: (1) we construct a practical attack system along with a portable attack device for collecting attacked images in real-world scenarios; (2) we collect, to our best knowledge, the first dataset that include images under attacks in real-world scenarios, in particular street environment; and (3) we conduct comprehensive experiment to quantify and evaluate the impacts of the attacks on different object detection models, unveiling the reasons why some models are robust to the attacks while others are not.

2. EXPERIMENTAL ATTACK DEVICE

In this work, we particularly investigate attack methodologies that exploit electromagnetic waves to inject malicious signals, i.e., *electromagnetic signal injection attacks (ESIA)*. Based on that, we construct our experimental attack device.

2.1. Electromagnetic Signal Injection Attacks

Cables connecting electronic components in circuits can act like antennas to pick up environmental electromagnetic waves [16, 17]. Attackers can exploit such “antenna-like” property to inject malicious signals into the circuits by radiating electromagnetic waves, and as such, manipulate the waveform of signals. The injection process can be complex, with many factors impacting its outcome. Basically, the effectiveness and efficiency of the injection are determined by the attack power and the attack frequency [18]. It is demonstrated that the injected signal needs to be strong enough to cause effective impacts; increasing the attack power enhances the likelihood of a successful injection [19]. Regarding frequencies, the attack frequency needs to align with the resonant frequency of the cable to maximize the strength of the injected signals. A practical way of determining the resonant frequency is to obtain a replica of the target system and then scan frequencies and measure the system’s responses [20].

After the injection, how the circuits respond to the injected signal is critical for the success of the attacks. In this work, the specific focus is given to the circuit’s response on digital signals, which are represented by sequences of 0s and 1s. Receiving circuits decide the value of a digital signal by comparing its voltage level with two voltage thresholds. As mentioned previously, the injected signals manipulate the waveform of signals, meaning that they can push the voltage level corresponding to 1 to a new level corresponding to 0, resulting in an incorrect reception of 0, or vice versa. Such a principle has been demonstrated in many previous studies [15, 19, 21–26]. To put it simply, *ESIA* can cause bits to be received incorrectly.

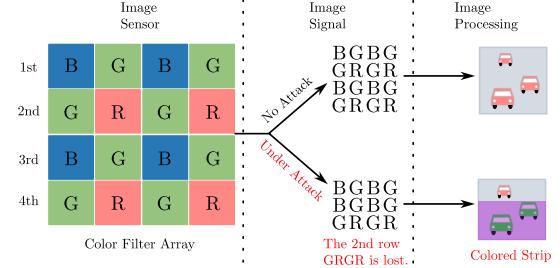


Fig. 2: Under attack, for example, the second row of pixels is lost, leading to a colored strip in the image.

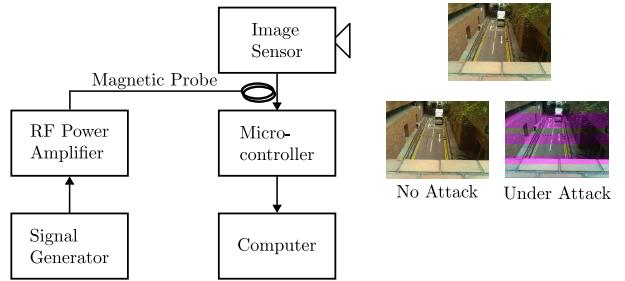


Fig. 3: An example attack process.

2.2. Colored Strips Across Images

The image sensor consists of arrays of photodiodes, each of which measures the intensity of the incoming light and converts it into electrical signals, each of which corresponds to a single pixel in the final image. To capture color information, every photodiode is overlaid with a color filter, which allows lights of specific wavelengths to pass through. The color filters are arranged in a certain pattern [27], for example, the Bayer filter mosaic [28], which alternates between red (R), green (G), and blue (B) filters, as shown in Figure 2. The image signals generated by the image sensor are read out row by row. After that, image processing is conducted to reconstruct the image.

ESIA can cause incorrect bits in the image signals. Such bit errors can be spotted by checksum mechanisms, which are commonly applied to verify data integrity in communications. A previous study [15] experimentally showed and verified that in many commercial off-the-shelf image sensor products, the bit errors will lead to the discard of the erroneous row, whose positions will be filled by subsequent rows; further, since the image processing process does not handle the missing row properly, colors will be misinterpreted. As a result, a colored strip appears, as shown in Figure 2. Note that more non-consecutive rows are lost, and more colored strips will be caused [15]. This may eventually lead to incorrect detection on the present object detection models.

2.3. Attack Device Implementation

By drawing on the theory and outcome of *ESIA*, we construct a practical attack system along with an attack device to collect images under attacks in real-word scenarios, and understand

the impacts on object detection. An *ESIA* process is depicted in Figure 3. The object detection system is comprised of an image sensor, a microcontroller, and a computer. The image sensor is connected to the microcontroller via a cable, and the captured images are reconstructed within the microcontroller. These reconstructed images are then transmitted to the computer for object detection and analysis.

Our attack device consists of a signal generator, a radio-frequency (RF) power amplifier, and a magnetic probe. The signal generator is utilized to generate sinusoidal attacking signals, with a specific attack frequency of 32.5 MHz chosen based on frequency scanning mentioned in Section 2.1. These attacking signals are then amplified by the RF power amplifier, which operates at a fixed power level of approximately 3 W. The magnetic probe is placed in close proximity (around 2 cm) to the cable that connects the image sensor and the microcontroller, facilitating the injection of the attacking signals at such a low power level.

3. DATASET

There is a public available dataset presented in GlitchHiker [15], that include under-*ESIA* images. However, its under-attack images are taken by photographing replayed images on a monitor, which are extracted from an open-source traffic photo set [29]. In another word, they are not captured directly from the actual scene. In this work, we collect our own real-world under-attack image sets by employing the attack device and system introduced in Section 2, to fully understand impacts of the attacks in real-life applications.

Before running the experiment and data collection, an approval from the host university’s IRB is obtained. The device is placed on a bridge over a road, where access control measures, including rising gates, are implemented to ensure the slow movement of vehicles and pedestrians. While capturing images, two consecutive photos will be taken each time: one is when no attacking signal is radiated, and the other one is under the influence of the attacking signal. The interval between taking two photos is minimized as small as possible so as to guarantee two photos are (almost) the same except for the colored strips. Finally, we collected 94 pairs of *Non-Attack* and *Under-Attack* images.

For the purpose of comparison, we conduct the experiment and analysis on both selected GlitchHiker [15] dataset (85 pairs of images) and our dataset. Since the GlitchHiker dataset is collected based on replayed images, we denote it as “REP” dataset in this paper. On the other hand, we refer to our dataset as “AUT” dataset, as it is collected from the authentic scene. Both datasets were annotated by at least three human experts, with the ground truth annotations established through a majority-vote scheme. We particularly focus on four categories, namely person, car, truck, and bus.

4. OBJECT DETECTION MODELS

Object detection is a widely explored task in computer vision, leading to various significantly accurate models, such as those utilizing convolutional neural networks (CNN) and Transformer [30]. To ensure a thorough and diverse examination across different object detection model architectures, we particularly select Faster R-CNN [31], YOLOv8 [32], and Co-DETR [33] for the evaluation experiment. These models achieve promising benchmark performances, and are widely used. At the same time, they are built upon three different model architectures respectively:

- **Faster R-CNN** [31] utilizes a two-stage architecture for object detection, involving initial region proposals followed by precise classification and bounding box regression. It is widely applied in many applications requiring high accuracy in localization, such as medical imaging and quality inspection.
- **YOLOv8** [32] is the latest and the state-of-the-art iteration in the YOLO series, which employ one-stage architecture for object detection. YOLO models detect the object bounding boxes and classes directly from the images with one forward pass. This contribute to their exceptional speed and real-time detection capabilities.
- **Co-DETR** [33] is a transformer-based object detection approach, which achieves the state-of-the-art performance on the COCO benchmark [34]. Its ability to effectively capture complex dependencies and handle diverse object scales and densities makes it robustness across diverse applications.

In this work, we investigate the impacts of *ESIA* on these models. Specifically, we apply the models pre-trained on a benchmark dataset COCO [34], and evaluate how they perform on the under-attack images.

5. EXPERIMENT AND RESULTS

We apply the object detection models (Section 4) on the two datasets to quantify the performance disparity between normal and under-attack images. This enable the quantitative investigation on the impacts of *ESIA*.

5.1. Performance Metrics

We adopt a standard metric in object detection evaluation, namely, mean average precision (mAP) to investigate the performance disparity caused by attacks. Specifically, mAP utilizes intersection over union (IoU) to measure the overlap between the actual and detected object bounding boxes, and jointly consider the object classification precision and recall across different IoU thresholds. It offers a comprehensive measurement of object detection accuracy. Please refer to [35] for more details.

In addition to standard metric, we also examine the “specific attack effects” and “attack success rate” in the experiment, to understand the performance degradation caused by

ESIA more comprehensively. Considering a specific class of objects, incorrect detection can either be a false positive (FP) or false negative (FN). FP refers to incorrect detection of a nonexistent object; in other words, the attack may deceive the object detection algorithm into detecting objects that do not exist, and we call such effects as *creating effects*. FN refers to undetected ground truth, meaning that the attack may prevent the object detection algorithm from detecting objects, and we call such effects as *hiding effects*. Furthermore, a successful attack is characterized by the manifestation of one or more predefined effects within a pair of target images. Based on that, we formulate “attack success rate (SR)” as $\frac{\text{success_attack_images}}{\text{total_under-attack_images}}$.

5.2. Results and Discussion

Table 1 shows the experimental results. Notably, there is a consistent decline in object detection performance (i.e., mAP) across all the public pre-trained models, when they are applied on the *Non-Attack* versus *Under-Attack* images. This suggests that the models, while pre-trained on a robust dataset like COCO, are still vulnerable to *ESIA*, which can significantly compromise their detection accuracy.

Table 1: mAP evaluation (public pre-trained models).

Dataset	Method	Non-Attack	Under-Attack
AUT	Faster	16.0%	10.9%
REP	Faster	25.4%	16.0%
AUT	YOLOV8	26.9%	21.0%
REP	YOLOV8	28.5%	26.8%
AUT	CoDETR	31.6%	26.8%
REP	CoDETR	32.4%	31.8%

However, it is also noting that the public pre-trained models (pre-trained on COCO dataset) are generally less effective on the two datasets, even for images without attacks. When applying object detection models in real-life applications, it is commonly necessary to adjust the models specifically for the target scenarios, to guarantee their effectiveness in the target scenarios. This is often conducted by fine-tuning the models on the datasets collected from the target scenarios. Therefore, in this work, we also fine-tune the models on the two target datasets (fine-tuning on the *Non-Attack* images) and evaluate the performance degradation caused by the attacks. This enable us to fully understand the impacts of the attacks, especially in a way that is more aligned with real-life applications. Table 2 depicts the results.

Upon fine-tuning, all the models yield satisfactory performance on *Non-Attack* images. Co-DETR particularly shows enhanced resilience. It exhibits the most minor performance degradation under attack conditions. This suggests that Co-DETR, potentially due to its transformer-based design, is more robust to such adversarial influences. YOLOv8 and Faster R-CNN, on the other hand, experience a noticeable decrease in mAP when subjected to attacks, confirming the

adversarial effect’s potency. Notably, the performance gap post-fine-tuning indicates that while fine-tuning (on the target scenario) can enhance the model efficiency on the target scenarios, it cannot counteract the adversarial perturbations introduced by the electromagnetic signal injection.

Table 2: mAP evaluation (fine-tuned models).

Dataset	Method	Non-Attack	Under-Attack
AUT	Faster	67.6%	50.5%
REP	Faster	69.9%	42.8%
AUT	YOLOV8	68.0%	31.1%
REP	YOLOV8	81.9%	37.3%
AUT	CoDETR	90.3%	88.4%
REP	CoDETR	89.1%	87.7%

We then look into the detailed FP and FN counts to understand the specific *creating* and *hiding* effects along with the attack success rate (SR), mean precision (MP), and mean recall (MR). To further refine our analysis, we manually filtered out the FPs and FNs that were not directly attributable to the attack effects. This careful curation ensured that our statistics accurately reflected the impact of the generated attack. This step is crucial for isolating the specific influence of the attack from other potential sources of detection errors, thereby providing a more accurate and relevant understanding of the attack’s true impact.

As presented in Table 3, a significant reduction in the attack success rate is observed when comparing the public pre-trained (“P”) and fine-tuned models (“F”). Fine-tuning the models leads to increased familiarity with the specific scenarios and objects involved, thereby enhancing the model’s robustness against the generated attacks. However, it still cannot completely mitigate the effects of the attacks, underscoring the need for further research into defensive strategies.

CoDETR consistently exhibits exceptional resilience, maintaining low rates of false negatives (FNs) and false positives (FPs). This performance highlights the robustness of its transformer-based architecture, particularly in response to *ESIA*. Intriguingly, we observed that instances where CoDETR erroneously detected objects in an image were mirrored by similar errors in both FasterRCNN and YoloV8. In many cases, it successfully identifies the annotated objects in images where the other two models failed (Fig 5). Although the transformer-based model exhibits a degree of resistance to our attacks, the infrequent but successful breaches, particularly when the attack signals are intense as depicted in Fig 4, can still substantially undermine the model’s detection capabilities, leading to an evident “hiding effect” where objects that are successfully detected in normal scene are omitted.

In contrast to CoDETR, Faster R-CNN displays a marked vulnerability in detecting smaller objects, with the “person” and “car” categories being particularly challenging. This issue is most apparent in dataset AUT. The increased difficulty in detecting these objects can be attributed to the camera’s

Table 3: Evaluation of the specific attack effects

Dataset	Model	FN Count				FP Count				SR	MP	MR
		Person	Car	Truck	Bus	Person	Car	Truck	Bus			
AUT	Faster(P)	35	78	7	3	5	2	10	12	65.1%	66.0%	44.2%
AUT	Faster(F)	21	6	7	1	0	2	0	1	27.66%	91.3%	79.3%
REP	Faster(P)	3	12	7	1	5	45	10	3	76.7%	65.4%	78.3%
REP	Faster(F)	3	26	9	1	0	6	0	0	41.18%	99.0%	73.5%
AUT	YOLO(P)	35	87	24	3	4	2	12	8	85.2%	63.0%	33.7%
AUT	YOLO(F)	38	39	14	1	0	4	34	0	59.57%	86.5%	63.4%
REP	YOLO(P)	10	55	6	3	1	10	11	2	86.7%	54.9%	50.4%
REP	YOLO(F)	6	72	10	6	0	1	0	0	61.18%	99.8%	44.1%
AUT	CoDETR(P)	17	46	12	1	2	1	5	2	41.5%	83.2%	70.7%
AUT	CoDETR(F)	5	1	2	0	0	0	0	1	5.32%	93.8%	96.9%
REP	CoDETR(P)	6	38	4	2	3	8	8	1	34%	75.7%	68.4%
REP	CoDETR(F)	0	4	2	0	0	0	0	0	7.06%	100.0%	96.6%



Fig. 4: CoDETR failed to detect labeled truck

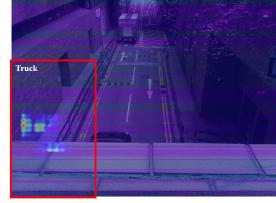


Fig. 7: YoloV8 GradCAM Vis: False Positive of Class Truck

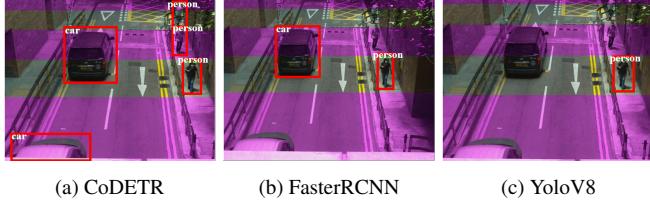


Fig. 5: Detection Result Visualisation

elevated position and fixed overhead angle, which tend to reduce the visual size of cars and persons compared to buses and trucks. This phenomenon underscores a pronounced “hiding” effect that our attack imposes on Faster R-CNN. The attack patterns interfere with the model’s ability to propose regions of interest(ROI), leading to a failure in generating correct predictions for multiple objects (Fig 6). This obstruction of the region proposal stage significantly hampers the subsequent detection accuracy, highlighting a critical area of concern for the deployment of two-stage detectors in environments where they might encounter adversarial interference.



Fig. 6: FasterRCNN failed to propose ROI for multiple annotated objects

Meanwhile, YOLOv8’s architecture significantly height-

ens its vulnerability to our attack. Engineered for swiftness and real-time processing, YOLOv8 is a single-shot detector that concurrently processes object localization and classification across the entire image. Although this design is efficient, it may not provide the same level of robustness against the subtle adversarial distortions that the transformer-based CoDETR or the two-stage Faster R-CNN can offer. This inherent fragility, when combined with the nature of overfitting during advanced fine-tuning on standard datasets, renders YOLOv8 particularly prone to misclassifications under adversarial attack conditions. This is evidenced by the excessive false positives for the truck category, where YOLOv8 may mistake large areas of attack-induced visual anomalies for actual features of trucks as shown in 7.

6. CONCLUSION

This study demonstrated the efficacy of electromagnetic signal injection attacks in exploiting vulnerabilities in object detection systems. Our findings reveal that these attacks can significantly disrupt the performance of advanced models, highlighting a critical area of concern in hardware-level security. The research suggests that attackers could potentially refine these techniques to further exploit system weaknesses. This underscores the urgent need for developing robust defense mechanisms to safeguard against such sophisticated attacks.

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