
Adversarial Attacks Using Differentiable Rendering: A Survey

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Abstract

Differentiable rendering methods have emerged as a promising means for generating photo-realistic and physically plausible adversarial attacks by manipulating 3D objects and scenes that can deceive deep neural networks (DNNs). Recently, differentiable rendering capabilities have evolved significantly into a diverse landscape of libraries, such as Mitsuba, PyTorch3D, and methods like Neural Radiance Fields and 3D Gaussian Splatting for solving inverse rendering problems that share conceptually similar properties commonly used to attack DNNs, such as back-propagation and optimization. However, the adversarial machine learning research community has not yet fully explored or understood such capabilities for generating attacks. Some key reasons are that researchers often have different attack goals, such as misclassification or misdetection, and use different tasks to accomplish these goals by manipulating different representation in a scene, such as the mesh or texture of an object. This survey adopts a task-oriented unifying framework that systematically summarizes common tasks, such as manipulating textures, altering illumination, and modifying 3D meshes to exploit vulnerabilities in DNNs. Our framework enables easy comparison of existing works, reveals research gaps and spotlights exciting future research directions in this rapidly evolving field. Through focusing on how these tasks enable attacks on various DNNs such as image classification, facial recognition, object detection, optical flow and depth estimation, our survey helps researchers and practitioners better understand the vulnerabilities of computer vision systems against photorealistic adversarial attacks that could threaten real-world applications.

1 Introduction

Differentiable rendering has become a powerful tool for solving inverse problems in computer vision and graphics [32]. By enabling gradient propagation through the rendering process, the underlying scene representation can be optimized [93] for tasks such as 3D reconstruction, where mesh vertices are optimized to achieve a desired form, material and texture display properties are refined for a target appearance, or for estimating the pose of an object or scene illumination. Some more recent techniques, such as Neural Radiance Fields (NeRF) [90] and 3D Gaussian Splatting [72] have generated significant interest in the research community by enabling novel view synthesis by only processing a few representative images to reconstruct textured 3D models or entire scenes. These

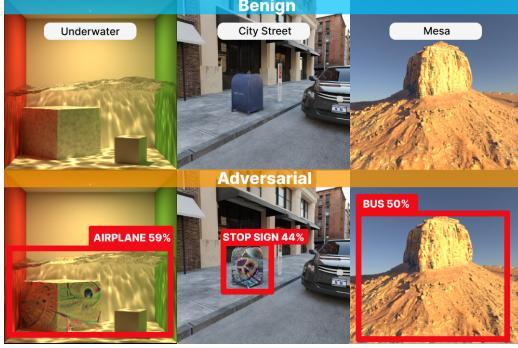


Fig. 1: Perturbing textures on objects in realistic scenes (top row) induces misdetections of an underwater cube as an airplane, a mailbox as a stop sign, and a mesa as a bus (bottom row).

capabilities have also sparked vibrant growth in the development of many open source libraries to facilitate their use, such as OpenDR¹, Redner², Kaolin³, PyTorch3D⁴, and Mitsuba⁵. Besides research and development, there are easy-to-use platforms [41, 118] that allow users without technical expertise to create textured 3D models or entire scenes, using just a few photos.

However, differentiable rendering has also shown potential as a tool for adversaries to manipulate deep neural networks (DNNs) by optimizing scene representations. DNNs are vulnerable to adversarial examples [113, 55], which can lead to misclassification or misdetection. Such attacks have far-reaching effects, including manipulating computer vision systems in cars to misclassify stop signs [39], causing LiDAR systems to misdetect objects [5], fooling facial recognition systems [109], and misclassifying 3D models [24]. Adversaries exploit DNN differentiability by accessing gradients during training to optimize inputs, training, or outputs for malicious purposes. Figure 1 shows a few examples of how an attacker perturbed the texture of an object to maximize a loss function to induce misdetections. With differentiable rendering, attackers can similarly optimize the underlying 3D representation (objects, materials, and lighting) by computing the gradient of the loss function and adjusting parameters to achieve their goal. Understanding these attacks remains a challenge, as differentiable rendering is a newer fast-evolving approach for adversarial ML, current attack research studies often leverage the differentiable rendering capabilities available at the time and results are scattered across:

1. **Choosing attack goals**, e.g., some aim to induce misclassification, while some induce motion or depth misestimation;
2. **Identifying attackable components** in a model, e.g., some targets pre-processing steps, while some target inference;
3. **Manipulating 3D scene**, e.g., some target only texture, while others target geometry or a combination thereof.

In other words, while there has been progress at this important research intersection of adversarial attacks using differentiable rendering, it is challenging to systematically compare them, summarize their strengths and limitations, and importantly identify research gaps or future directions.

Figure 2 shows how our survey serves as this crucial missing piece that our community needs to unite the frontiers of ML research with advanced differentiable rendering techniques, providing a unifying framework joining diverse goals and tasks to systematically describe how DNNs are vulnerable to adversarial attacks. We present these capabilities within a task-oriented framework, organizing specific tasks such as manipulating textures, altering illumination, and modifying 3D meshes within a unifying structure. This approach sets our work apart from existing surveys, as it emphasizes not

¹<http://open-dr.org>

²<https://github.com/BachiLi/redner>

³<https://developer.nvidia.com/kaolin>

⁴<https://pytorch3d.org>

⁵<http://www.mitsuba-renderer.org>

Unifying Framework of Goals and Tasks for Adversarial Attacks Using Differentiable Rendering

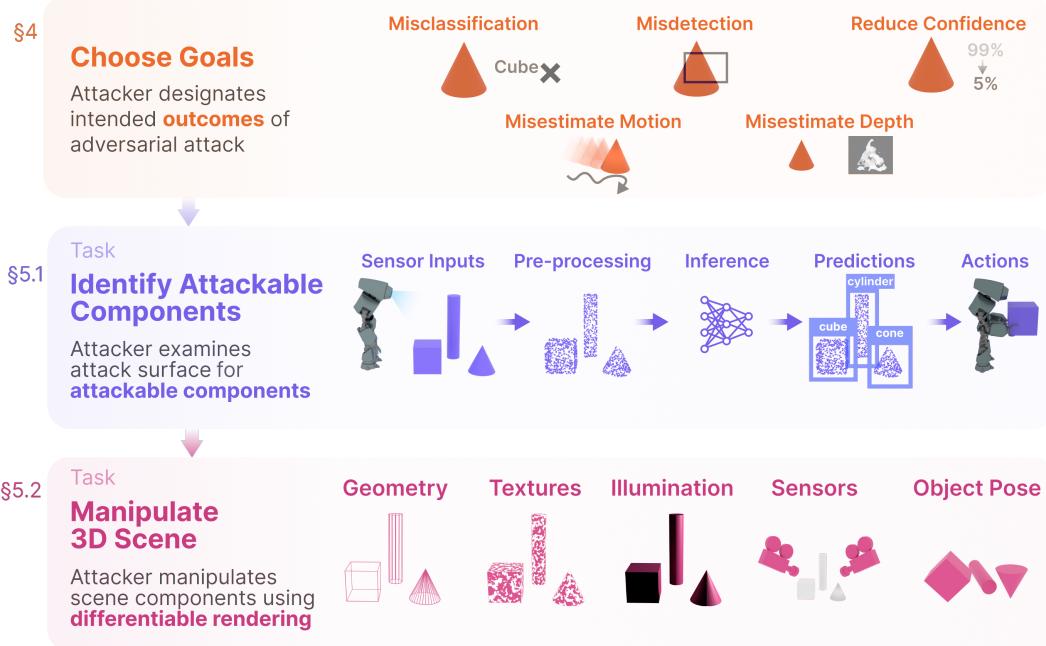


Fig. 2: Visual overview of our unifying survey framework that, by unifying the diverse goals and tasks in identifying attackable components and manipulating scene representations, enables systematic summarization and comparison with existing differentiable rendering related adversarial attack research.

just the techniques but also how they can be used by adversaries to exploit DNN vulnerabilities, highlighting the most significant and feasible threats to DNNs.

2 Our Contributions and Method of Survey

C1. We present a comprehensive, attacker-task guided survey on adversarial attacks using differentiable rendering, incorporating a use-inspired approach (Fig. 2), enabling us to position each work in terms of the attacker’s objectives and the techniques available for exploiting differentiable rendering. This framework not only explores how adversarial attacks are performed in practice but also precisely define the attack surface of adversarial attacks that leverage differentiable rendering, by explicitly considering the feasible manipulations supported by the scene representations (Sec. 5.1.1).

- Our survey methodology links attacker goals to specific tasks, providing a structured way to compare existing works and identify research gaps and future directions.
- Our framework (Table 1) helps readers understand how differentiable rendering is used in real-world attacks, the relevant methods, and the strengths and limitations of current techniques.

C2. We provide comprehensive categorizations of specific attack methods, demonstrating the wide-ranging impact of attacks leveraging differentiable rendering (Sec. 5.2.5), emphasizing the role of components within the 3D scene representation as a means to conceptually relate to vulnerabilities that could be exploited in the real world. We also present a detailed “Target List” of attacked models—including object detection, image classification, mesh classification, and facial recognition—that have been compromised using differentiable rendering, alongside the respective attacker access level (white/black-box) used in each attack (Table 3). These resources

empower researchers and practitioners to build upon established work, compare outcomes, and innovate new techniques to tackle the pressing challenges posed by adversarial attacks using differentiable rendering.

- C3. We identify critical future research directions to confront the escalating threat of adversarial attacks** (Sec. 7.4) as differentiable rendering methods and capabilities continue to evolve in today’s dynamic and fast-changing landscape. With a deeper understanding of these attacks, we can address the pressing challenges they present. Key research areas include developing robust defenses against adversarial attacks, exploring groundbreaking attack strategies, and rigorously investigating the physical plausibility and real-world feasibility of these attacks.

2.1 Related Surveys

This survey is the first to focus on the task-based capabilities of differentiable rendering methods required to generate 3D adversarial attacks, to the best of our knowledge. Current literature on differentiable rendering and adversarial attacks exists separately.

Kato et al. provided one of the first surveys on differentiable rendering, briefly discussing adversarial applications but lack details on the chosen rendering methods or corresponding attack methods [71]. Since then, NeRF [90] and 3D Gaussian Splatting [72] have gained prominence, meriting examination in our survey. However, we find that recent surveys focus on the latest work in Neural Radiance Fields (NeRF) [43, 140, 120, 51, 92] and 3D Gaussian Splatting [38, 122] techniques without exploring applications towards adversarial attacks on DNNs.

We reviewed surveys on adversarial attacks that focus on 2D and 3D settings, often relating to either digital space or physically plausible attacks. Li et al. present a survey on the robustness and safety of attacks that focuses on 2D and 3D models but do not focus on differentiable rendering [10]. Other surveys focus on robustness of object recognition [107], defenses against adversarial attacks [91], and adversarial attacks on image classification [12].

2.2 Survey Methodology and Summarization Process

We selected existing works from top computer science journals and conferences in computer vision (CVPR, ICCV, ECCV), machine learning (NeurIPS, ICML, ICLR), and computer graphics (ACM Transactions on Computer Graphics, IEEE Transactions on Visualization and Computer Graphics (TVCG)). Since both NeRF and 3D Gaussian Splatting are new techniques, there are numerous submissions to arXiv that have not yet been published in journals or conferences. For this reason, we also inspected preprints posted on arXiv⁶.

To better understand how attackers achieve their objectives using differentiable rendering techniques, we applied a task analysis framework approach that breaks down attacker goals into specific tasks and subtasks. For instance, the initial task involves analysis of system components to identify potential vulnerabilities. Subsequent tasks include the execution of targeted techniques, such as modifying textures, illumination, or meshes within a 3D scene, to achieve their adversarial objectives. By categorizing these activities, we provide a clearer picture of the methodologies employed in these attacks, aiding in the development of more robust defenses and guiding future research efforts.

2.2.1 Survey Scope

We designate the scope of this survey according to these definitions of differentiable rendering and adversarial attacks.

- **Differentiable Rendering** is the process of rendering a scene in a differentiable manner, enabling the optimization of a scene representation, *e.g.*, 3D mesh, NeRF, or 3D Gaussian Splat according to some objective. We classify differentiable rendering methods into two categories: libraries (*e.g.*, PyTorch3D [100], Mitsuba [93], and Kaolin [66]) and techniques (*e.g.*, NeRF [90] and 3D Gaussian splatting [72]). Libraries provide tools for rendering and optimizing 3D scenes, while techniques leverage the inherent differentiability of volumetric rendering to optimize scene representations.

⁶<https://arxiv.org/>

- **Adversarial Attacks** are considered as those used to attack a DNN model. We focus on adversarial attacks methods that use differentiable rendering to manipulate inputs or training data for a DNN model to produce an incorrect output, with the goal of compromising the model’s performance.

After applying our task analysis framework and considering our designated scope, we identified 28 papers that we included in our survey. In historical context, we note that differentiable rendering is a relatively new technique; one of the first highly-cited papers on differentiable rendering was published in 2014 [87], while research on adversarial attacks using differentiable rendering wasn’t published until 2019 [11].

For each work, we recorded the following information:

- Metadata (title, authors, venue, and year published)
- General approach and summary
- Contributions
- Models attacked
- Datasets used
- Future work

With this information, we used our attacker-task guided perspective to classify attacker’s goals, the scene representation attacked, the attack method, and the target model to organize these existing works and the current state.

2.3 Survey Overview and Organization

Section 3 introduces common terminology and concepts in differentiable rendering and adversarial attacks. Figure 2 provides an overview of attacker tasks and goals and how they are accomplished using differentiable rendering, and Table 1 summarizes the attacker tasks and goals for relevant works. Each category (Attacker Goals, Required Tasks, and Domain) is given its own section for discussion, ordered to provide an end-to-end view of the attacker’s process. Section 7.4 presents research directions and open problems that we gathered and identified from the literature. Section 8 concludes the survey.

Work	ATTACKER GOALS					REQUIRED TASKS		DOMAIN		WHERE	
						IDENTIFY		MANIPULATE			
	4.1 Reduce Model Confidence	4.2 Misclassification	4.3 Missed Detection	4.4 Misestimation of Motion	4.5 Misestimation of Depth						
Abdelfattah, et al., 2021 [1]										A	ICIP
Alcorn, et al., 2019 [2]	■	■								A	CVPR
Bolya, et al., 2020 [3]	■	■								M	ECCV
Byun, et al., 2022 [4]	■									A	arXiv
Cao, et al., 2019 [5]	■	■								A	arXiv
Dong, et al., 2022 [6]	■									A	NeurIPS
Huang, et al., 2024 [7]	■	■								A	CVPR
Li, et al., 2023 [10]	■	■	■			■	■			S	ACM CSUR
Li, et al., 2023 [8]	■		■							A	arXiv
Li, et al., 2024 [9]	■	■								A	arXiv
Liu, et al., 2019 [11]	■	■								A	ICLR
Machado, et al., 2021 [12]	■	■								S	ACM
Maesumi, et al., 2021 [13]	■		■							A	arXiv
Meloni, et al., 2021 [14]	■	■								A	ICMLA
Papernot, et al., 2016 [16]	■	■	■			■	■			A	EuroS&P
Papernot, et al., 2016 [15]	■	■	■			■	■			A	EuroS&P
Schmalfuss, et al., 2023 [17]				■						A	ICCV
Shahreza, et al., 2023 [18]	■					■	■			A	TPAMI
Suryanto, et al., 2022 [19]	■	■								A	CVPR
Suryanto, et al., 2023 [20]	■	■	■							A	ICCV
Tu, et al., 2021 [21]	■		■							A	CoRL
Wang, et al., 2022 [22]	■	■	■							A	AAAI
Wiyatno, et al., 2019 [23]	■	■	■			■	■			A	arXiv
Xiao, et al., 2021 [24]	■	■	■							A	CVPR
Yuan, et al., 2019 [25]	■	■	■			■	■			S	TNNLS
Zeng, et al., 2019 [26]	■									A	CVPR
Zheng, et al., 2024 [27]				■						A	CVPR
Zhou, et al., 2024 [28]	■	■	■							A	ICML

Table 1: Overview of representative works on adversarial attacks using differentiable rendering methods. Each row is one work; each column corresponds to a required attacker task or goal. A work’s relevant goal or task is indicated by a colored cell. S = Survey, M = Metrics, A = Attack.

3 Common Terminology

- Point cloud - collection of discrete, zero-dimensional points that serve as a universal meta-primitive for representing complex surfaces and scenes in computer graphics. Each point in a point cloud is characterized by spatial attributes in x, y, and z coordinates, defining its position in three-dimensional space. Additionally, these points may carry non-spatial attributes such as color and intensity, which contribute to the visual appearance of the modeled object or scene. [76]
- Polygon Mesh - (or simply a Mesh) is a collection of connected, planar polygons which share common edges and vertices. [30]
- Voxel - three-dimensional unit used in digital modeling and simulation, representing a value on a regular grid. Voxel models can be based on subdivisions into cubes or tetrahedrons, with cubes allowing straightforward data access and hierarchical structuring, and tetrahedrons being useful for simulations like fracture modeling. Voxel models are commonly used in fluid flow simulations and medical or geoscientific imaging. [29]
- Signed Distance Function (SDF) - defines the distance from a point in 2D or 3D space to the nearest point on a set of geometric objects, such as curves or surfaces. The distance is given a sign based on the orientation of the objects, typically positive outside and negative inside an object. [110]
- Neural Radiance Field (NeRF) - a method for synthesizing novel views of scenes by optimizing a continuous volumetric scene function using sparse input views. It uses a fully-connected neural network to represent the scene, inputting a 5D coordinate (3D spatial location and 2D viewing direction) and outputting color and density, with volume rendering projecting these outputs into images; the model is optimized using gradient descent based on the difference between observed and rendered views. [90]
- 3D Gaussian Splat - a technique for real-time radiance field rendering that uses 3D Gaussian functions to represent scenes. This method combines the efficiency of a point-based representation with the benefits of continuous volumetric rendering, allowing for fast, high-quality synthesis of novel views by optimizing the properties of 3D Gaussians and using a fast differentiable renderer. [72]
- Texel - A single pixel in a texture-map image. [29]
- Transfer attack - The property that adversarial examples crafted to be misclassified by a model are likely to be misclassified by a different model. [113]
- Surface Normal - The vector perpendicular to a surface at each point, used for computation of how light reflects from that surface. [29]
- Global Illumination - Rendering algorithms accounting for indirect light transport, including light bouncing off surfaces and illuminating other surfaces. [96]

We use the following symbols throughout the paper:

- $\mathbf{V} \in \mathbb{R}^{n \times 3}$: Vertex positions of a 3D mesh, where n is the number of vertices and each vertex is a 3D point.
- $\mathbf{F} \in \mathbb{Z}^{m \times 3}$: Face indices of the mesh, where m is the number of triangular faces, and each face is defined by three vertex indices.
- $\mathbf{N} \in \mathbb{R}^{m \times 3}$: Per-face normal vectors of the mesh, where each normal corresponds to a face.
- $\mathbf{P} \in \mathbb{R}^{n \times 3}$: Point cloud positions in 3D space, where n is the number of points.
- $X \in \mathbb{R}^{n \times 4}$: LiDAR point cloud representation, where each row contains a 3D point (u^X, v^X, w^X) and an intensity value int^X .

- $x \in \mathbb{R}^2$: Pixel coordinates in the 2D image plane.
- C : Cost function or loss used in the adversarial attack, typically incorporating cross-entropy or other loss terms.
- γ : Step size or scalar controlling the strength of an update during an adversarial attack.

4 Attacker Goals

Attacker Goals
4.1 - Reduce Confidence
4.2 - Misclassification
4.3 - Misdetection
4.4 - Misestimate Motion
4.5 - Misestimate Depth

Table 2: Attacker goals for various tasks in Deep Learning

To better understand how differentiable rendering is used in adversarial attacks, we describe an attacker using the threat model concept to delineate their goals, capabilities, and knowledge in the context of the attack they wish to carry out [10]. Using an attacker-task guided perspective, we connect the attacker goals to required tasks and sub-tasks (Sec. 5.2.5) that are used in differentiable rendering attacks.

Attacker goals encompass any threat affecting the integrity of a DNN’s intended task [72, 10, 16, 15, 23]. In this survey, we identify five attacker goals that are used in attacks on deep learning models using differentiable rendering. These include reducing the model’s predictive confidence (4.1), so that the target class is not predicted with high confidence, leading to untargeted misclassification where the model predicts the wrong class, or targeted misclassification, where the model predicts a specific class (4.2). Another goal is to induce missed detection (4.3), which can manifest as various misdetection errors: nothing is detected (evasion), improper localization of bounding boxes, duplicate detections, or detecting the background as an object instead of a foreground object, or combinations thereof [3]. For optical flow models, the attacker may create adversarial movements or objects in the scene environment that can cause misestimation of motion (4.4). Finally, misestimation of depth (4.5) involves adversaries manipulating monocular depth estimation, which affects the model’s ability to perceive distances and understand spatial relationships accurately.

In Table 1, we categorized our 28 survey papers as S=Survey (3), M=Metrics (1), or A=Attack (24). Of our 24 Attack papers, we found that 18 works chose goals of inducing misclassifications, 17 induced misdetections, and 10 induced reduction in model confidence while only 1 work each pursued attack goals of misestimation of motion or depth.

Table 3: Overview of DNN models attacked by differentiable rendering methods. Each column is one work; each row corresponds to a DNN model.

5 Attacker-Tasks for Differentiable Rendering

Attacker Tasks
5.1 - Identify Attackable Components
5.2 - Manipulate 3D Representations

5.1 Identifying Attackable Components

In order for the attacker to achieve their desired goal(s) in Sec. 4, an attacker must identify the attackable components by analyzing the attack surface (5.1.1) and understanding 3D scene representations (5.1.2) to determine attackable elements.

5.1.1 Attack Surface

The attack surface for a machine learning system encompasses the entire data processing pipeline 2 that utilizes a DNN for a specific task, including components accessible and manipulable by an adversary [12, 25, 16, 23]. In the context of differentiable rendering, the attack surface extends to the renderer and the underlying scene representation used to generate input for the DNN model. Examining the entire pipeline provides a comprehensive understanding of potential vulnerabilities and entry points for an attacker. For example, consider a robot that scans its 3D environment, detects objects, and acts within the perceived world representation. Its processing pipeline includes:

- Sensor inputs for creating a 3D scene representation.
- Processing the 3D scene representation to generate DNN model input (3D scene, 2D image, or point cloud) [97, 136].
- DNN model for object detection and inference.
- Postprocessing and decision making based on DNN output [34].

The attack surface articulates which of the robot’s data processing pipeline component(s) an attacker can manipulate. To evaluate the strength or success of potential attacks across a spectrum of access levels, the adversary’s capabilities can be constrained to only manipulate limited components in the pipeline to more realistically model the practicality of an attack. We discuss scene representations and the levels of access an attacker may have to manipulate various elements in (Sec 5.1.2).

Attacker Access and Capabilities. The complexity and success of an attack are significantly influenced by the attacker’s capabilities and level of access to information. This access can vary widely, from white-box scenarios (full knowledge) to black-box scenarios (limited or no knowledge), with gray-box levels in between [25, 23, 12, 15, 16, 10]. An attacker might have full access to the training data and network architecture, partial access to either, or only access to an oracle that provides outputs for selected inputs. Generally, the less access an attacker has, the more challenging it becomes to carry out a successful attack. We classified the levels of access used in Table 3, listing the type of DNN and name of each model attacked.

In differentiable rendering, we focus on scenarios where an attacker can manipulate elements within a semantic space known as a scene representation [78], further discussed in (Sec. 5.1.2). This data structure includes all components of a scene that can be altered and rendered as input to a DNN model [48]. Constraining attacks to this semantic space can lead to more realistic and effective outcomes [69], allowing us to categorize attackable elements into specific tasks. For instance, an attacker might limit their scope to a localized element, and modify only the texture of an object to find an adversarial texture that deceives an object detector, potentially testing this in the physical world with a 3D-printed model. Alternatively, the attacker could expand the

scope of the attack to a global influence by modifying environmental factors that affect the whole scene, *e.g.*, adding geometry and texture to create adversarial weather that disrupt an optical flow model’s estimation of movement in a digital attack [17].

5.1.2 Analyze Scene Components

In the context of adversarial attacks using differentiable rendering, we consider the 3D scene representation [136, 78] as the primary manipulable target. To construct attacker tasks, we identify and analyze the scene elements, categorized into five main categories:

1. Geometry
2. Texture
3. Position/Pose
4. Illumination
5. Sensors

The geometry of objects can be defined explicitly as a mesh [30, 40], point cloud [76], voxels [29], or implicitly as a neural network [90], a collection of Gaussian splats [72], or signed distance functions [94]. For example, a car in the scene might be represented by a mesh with vertices, edges, and faces, while the road on which it is driving could be defined by a separate mesh. The appearance of an object within the scene is determined by its texture, which describes the color, patterns, or functions that govern how light is reflected from its surface, as well as its position and pose relative to the scene geometry and sensor. Illumination sources, such as the sun, sky, lamps, or headlights, provide lighting to the scene and are characterized by their color, intensity, and position. Finally, the scene is captured by one or more sensors, such as a camera or LiDAR, which observes the scene representation from a particular viewpoint and with specific properties intrinsic to a camera, such as resolution, field of view, lens warping, and noise characteristics. By considering these components and their relationships, we can better understand how an attacker might manipulate the scene representation to achieve their goals, even when dealing with implicit representations where geometry, texture, and illumination may be entangled.

5.2 Manipulating 3D Representations

When using a differentiable rendering system, any element within a scene representation that can receive gradient information can be manipulated. When the attack surface includes white-box access to a victim model, the attacker can use the gradients of the model’s loss function with respect to the scene representation to guide the manipulation. In this section, we discuss the different types of manipulations that can be performed on 3D scene representations, including geometry, texture, pose, illumination, and sensors. In our survey we found that the most common attack was on texture representations (15), while 7 attacked geometry, 5 attacked object pose, 2 attacked illumination, and 1 attacked sensors.

5.2.1 Attacks on Scene Geometry

Mesh. An adversarial mesh can be generated by taking a benign mesh and rendering it with a differentiable renderer to produce an image that can be used to calculate the gradients of the loss function with respect to the mesh vertices. The loss function is generally formulated to increase the cross-entropy loss of the ground truth label while decreasing the cross-entropy of the least-likely or target label. The gradients are then used to displace the vertices of the mesh in 3D space to produce an adversarial mesh that can be re-rendered to produce an adversarial input to the victim model. Beyond Pixel Norm-Balls [11] designated the input to an image classifier to be an image $I(U, V)$ as a function of the the lighting U and the geometry V , and use a cost

function $C(I(U, V))$ that incorporates the cross-entropy loss and use their own analytically differentiable renderer to find an adversarial geometry V' by the chain rule.

$$V' \leftarrow V - \gamma \frac{\partial C}{\partial I} \frac{\partial I}{\partial N} \frac{\partial N}{\partial V} \quad (1)$$

Where $V \in \mathbb{R}^{|V| \times 3}$ is the vertex positions of a triangle mesh, $N \in \mathbb{R}^{|F| \times 3}$ are the per-face normals, and γ is a scalar that controlling the strength of the attack.

In MeshAdv [24], adversarial meshes generated with vertex perturbations produced with the Neural Mesh Renderer [70] were used to attack both image classifiers in targeted and untargeted attacks using cross-entropy loss and extended their attack to an object detector (YOLO-v3) using a disappearance attack loss.

Transferable Targeted 3D (TT3D) [7] textured meshes uses NeRF to first capture a scene from multiple images and then reconstruct a target object using marching cubes. They subsequently create an adversarial by optimizing the geometry features using grid-based techniques. This approach permits targeting arbitrary objects that can be easily created from initial images without requiring mesh modeling. However, optimizing NeRF representations can be expensive and time-consuming [120], potentially limiting the scalability of this approach.

Distracting Downpour [17] introduced a novel attack by adding particulate geometry to simulate rain or snow into a scene to attack optical flow estimation models. The use of very small particulate geometry can appear as certain fluid phenomena, including rain, snow, fog, and smoke. When attacking a sequence of images *i.e.*, *movie, animation* as found in the KITTI [53], and Spring [89] datasets used in optical flow estimation, the particulate geometry can be used to distract the optical flow model by creating a false motion signal. In their method, they model the particles within the 3D plane with trajectory to ensure spatiotemporal consistency with the target scene, and then project particles into the 2D image plane using occlusion aware depth sensing to ensure that the particles are occluded by the scene geometry, and use it to attack 6 different optical flow models.

Point Cloud. Attacks on self-driving systems using LiDAR technology can be exploited by perturbing the point cloud representation of an object within the scene. A LiDAR sensor captures the scene as a point cloud $X \in \mathbb{R}^{n \times 4}$ where each row is a point in 3D space (u^X, v^X, w^X) with an additional intensity value int^X representing the light intensity reflected from the object at that point.

LiDAR-ADV [5] designed their attack by simulating the LiDAR sensor physics that senses a mesh S as input and generates a point cloud X that can be attacked. The initial LiDAR pre-processing converts the point cloud into hard-coded 2D features for count, max height, mean height, intensity and non-empty that are initially non-differentiable but are converted to differentiable features using a set of proxy functions that consider whether a point falls within a 3D grid $G \in \mathbb{R}^{H \times W \times P}$.

By computing counting the number of points at an L_1 distance of each point p to each grid i , they develop a soft count feature that is differentiable with non-zero gradients.

They follow MeshAdv's approach to perturb the point cloud vertices and finally re-render the point cloud into a mesh that can be 3D printed and tested against a LiDAR-based object detector in the real world.

Two further works demonstrate the vulnerability of multi-modal using attacks on point clouds. Abdelfattah et al. [1] target a cascaded camera-LiDAR model, aiming to create a universal, transferable attack by placing an adversarial object atop a car for evading object detectors. They perturb an initial isotropic sphere mesh using learnable displacement vectors, altering the point cloud representation of the object in scenes rendered using PyTorch3D [100]. Their optimization process minimizes a loss function based on detection probabilities and IoU scores, indirectly manipulating the point cloud through mesh deformation. Tu et al. [21] take a more direct approach in attacking a Multi-Modal Fusion (MMF) system that combines LiDAR and image inputs.

They utilize SoftRas [82] to propagate gradients from both LiDAR point clouds and image modalities to an icosphere mesh's vertices. This allows for simultaneous perturbation of the mesh geometry and texture (discussed in Sec 5.2.2), directly influencing the generated point cloud.

Geometry Post-Processing and Stabilization. We find most of these works attacking geometry in a scene representation use some form of post-perturbation processing to stabilize the mesh or point cloud to ensure that the adversarial object is realistic and retains a natural appearance and does not produce unwanted topological changes. Displacement of a vertex can lead to self-intersections or non-manifold meshes, which can appear unrealistic and may not be detected by the victim model or be visually conspicuous. The primary mitigation to these effects is the use of a scalar hyperparameter that controls the magnitude of the perturbation, however this does not prevent the mesh from becoming unstable or unrealistic. To address this, we observe that attackers use Laplacian smoothing loss, regularization loss, or Chamfer distance loss term to penalize the perturbation. Laplacian smoothing [126] is based on the difference between each point and the average of its neighbors and is formulated as :

$$\mathcal{L}_S = \sum_{v_i \in V} \sum_{v_q \in \mathcal{N}(v_i)} \|\Delta v_i - \Delta v_q\|_2^2,$$

where $\Delta v_i = v_i^{adv} - v_i$ is the difference between the original and adversarial vertex positions, and $\mathcal{N}(v_i)$ is the set of neighboring vertices of v_i . Mesh regularization as proposed by the creators of SoftRas [82] was used by Tu, et al. [21] to stabilize the mesh.

$$\mathcal{L}_{lap} \sum_i \|\delta_i\|_2^2$$

where δ_i as the distance from the vertex $v_i \in \mathcal{V}$ jto the centroid of its immediate neighbors. TT3D [7] uses a Chamfer distance loss term [100] to penalize the perturbation:

$$\mathcal{L}_{cham} = |P|^{-1} \sum_{(p,q) \in \Lambda_{P,Q}} \|p - q\|^2 + |Q|^{-1} \sum_{(p,q) \in \Lambda_{P,Q}} \|q - p\|^2,$$

where p and q are two point sets, and the metric considers how similar the point clouds are, and the loss is minimized when the point clouds are similar. Other approaches include incorporating depth completion for occlusion handling and lighting approximation, ensuring realistic point cloud manipulations [21], and restricting the scale of the adversary using pre-defined axis-aligned bounding boxes.

5.2.2 Attack Scene Texture

Texture adversarial attacks involve perturbing an object's appearance by manipulating the color, pattern, or function that governs how light is reflected from its surface. In a differentiable rendering attack, the gradient of the model's loss is used to perturb the texture mapping—typically stored as a UV map—which assigns colors to the object's vertices or faces. This perturbation can be accomplished through three main approaches [28, 70]:

1. World-aligned methods: These involve optimizing a 2D texture image and repeatedly projecting it onto the target object.
2. UV map-based methods: These directly optimize the 3D texture in the form of UV maps, allowing for more precise control over the object's appearance. Requires 3D modeling expertise, making it less practical for attack transferability, since maps are specific to the object.
3. Neural-rendered methods: use neural networks to dynamically generate and optimize textures, allowing texture application without need for initial UV mapping by learning the optimal texture from the 3D representation.

Multi-Object Texture Attacks. Two works explore multi-object texture attacks, where an adversarial texture is applied to multiple objects in a scene or multiple different objects individually to study transferability.

One work attacks common objects used in 3D virtual environments to create poisoned training data for ML models focused on image recognition [14]. They start by rendering an object using non-differentiable renderer and obtaining a saliency map from an image classifier that is subsequently differentiably re-rendered using PyTorch3D. The saliency map is thresholded and converted to binary output to determine which texels of an object will be perturbed based on gradients from the image classifier. Another work [4] uses a diverse pool of input 3D objects as a canvas for a 2D adversarial example to enhance transferability [139]. A perturbed image is trained on source image classifiers and differentiably rendered and further optimized using PyTorch3D as a texture onto 3D objects (cup, ball, pillow, t-shirt, package, book) using PyTorch3D to attack a target classifier. They show improved transferability and find that multiple instances of an object (e.g., 3 balls with adversarial textures) in a single scene increase attack success rates. Additionally, they conduct impersonation attacks by projecting a perturbed face as a texture onto a 3D object to impersonate a target face, and dodging attacks by classifying a face as a different person using facial recognition classifiers.

Vehicular Camouflage. Several works have explored adversarial camouflage attacks on vehicles to evade or cause mis-classification for object detectors. A full-coverage attack (FCA) [22] was designed to completely cover the surface of a Audi e-Tron vehicle model with a camouflage texture to evade single stage and multi-stage object detectors by compositing the adversarially textured car model into scenes from the CARLA self-driving dataset [129]. Their use of the Neural Mesh 3D Renderer (NMR) [70] allows them to project the learned texture onto the model, without the need for a UV map beforehand. The Differentiable Transformation Attack (DTA) [19] also used NMR to create vehicular camouflage but opted to initialize an $N \times N \times 3$ dimension patch and use EoT [31] to apply multiple transformations to the patch before using world-aligned methods to repeatedly project it onto a 3D vehicle model. However, the projection method was limited to projecting onto simpler shapes, *i.e.*, they use a Tesla Model 3, and found that the attack was less effective on more complex shapes. The authors produced an improvement to this method with a follow-up work titled Adversarial Camouflage for Transferable and Intensive Vehicle Evasion (ACTIVE) [20], where they try improving the projection of an adversarial texture with a tri-planar mapping projection method that uses the surface normal and texture coordinate from a depth image that does not rely upon the use of texture maps, allowing textures to be flexibly applied to multiple objects. However, they only continue to use the Tesla Model 3 for their experiments.

Li, et al. [9] argued that neural rendering is limited due to the requirement of extensive training data and does not account for environmental conditions, *e.g.*, lighting and scene background. They proposed a multi-stage flexible physical camouflage attack (FPA) that uses a diffusion model to initialize and generate realistic looking camouflage textures for UV maps that can be precisely constrained to a desired region, termed “sticker-mode” for preserving physical transferability. In the first stage, they propagate gradients from the mesh using the PyTorch3D to a diffusion model, which refines the texture iteratively by adding Gaussian noise (ϵ_k) to the image at each step and then applies a generator to produce the next image $T_{k-1} = G_\theta(T_k + \epsilon_k)$. Separately, they generate another adversarial texture using a one-step backward method where isotropic noise is added based on the gradient of the loss function $\eta = \nu \nabla_T L(w, y, T_a)$, directly updating the texture $T_a = T_a + \eta$. Finally, they use the renderer to blend both textures together using a texture blending technique $T_{\text{blended}} = \sum_i^k \lambda_i \cdot T_i$ for a blending factor λ_i and the original texture T_i . Vehicle objects with the adversarial camouflage are rendered into CARLA using UE4 with grassland, desert, and highway backgrounds to test attacks against single-stage, multi-stage, and transformer-based object detectors. Zhou et al. [28] presented the Robust and Accurate UV-map-based Camouflage Attack (RAUCA) framework by incorporating environmental conditions training afforded by augmenting the NMR with an encoder-decoder Environmental Feature Extractor Network (EFE). The EFE network is then trained to predict fog, snow, daylight, and night, conditions from CARLA reference images and extracts environmental conditions to generate environmentally adapted adversarial textures.

Human Camouflage. Maesumi et al. [13] designed adversarial “cloak” clothing for evading object detectors using UV maps and meshes available within the skinned multi-person linear models (SMPL [86]) in the SURREAL dataset [125] and PyTorch3D. They experiment with creating various adversarial logos and patches that appear somewhat inconspicuous but found that the dataset resolution was too low to produce a useful adversarial texture, which they addressed by preprocessing their meshes using a subdivision surface modifier in Blender to increase the resolution of the mesh and texture, effectively increasing the pixel perturbation space available. They completed several studies that measured the effectiveness of an attack based upon the surface area coverage of the texture and the pose and position of the human mesh model, finding that the attack was more effective when the texture covered both the chest and legs and when the human was facing the camera.

Textures Attacks on Autonomous Driving Systems. As previously introduced in (Sec. 5.2) Abdelfattah et. al also attacked the texture of an adversarial object placed upon a car by designating each vertex of the adversarial object as a learnable parameter $c_i \in \mathbb{R}^3$, and train it to maximize the objectness loss. The resulting RGB colors are then projected back on to the object and they interpolate the colors between the vertices to create a smooth texture, similar to the method used by Tu et al. [21] adversarially textured icosphere used as a multi-modal attack on the MMF [80], rendered using SoftRas. This stage of the attack reduces the ability of the 2D region proposal network (YOLOv3) of the Cascaded model to detect the object, before the point cloud detector is attacked in the cascaded model. Adv3D [8] explores producing photorealistic patch attacks on birds-eye-view (BEV) and front-of-view (FoV) LiDAR object detectors using NeRF to generate adversarial textures on cars that evade detection and lower prediction confidence. Their pipeline uses a semantic branch augmentation of the Lift3D generation framework to initialize a NeRF object, enabling patch attacks on targeted areas of an object, e.g., windows or doors, to improve physical transferability. The initialized benign NeRF object is used to extract and disentangle the shape and texture latents and parametrize them for optimization during adversarial training. To generate the textures, they use the EoT technique to sample poses of the objects from trained NeRF that they want to render and then minimize the expectation of a binary cross-entropy loss over the sampled poses and images to create a texture that will minimize the predicted confidence of all objects in the scene. Zheng proposed 3D²Fool [27], an object-agnostic patch used to attack monocular depth estimation models by using NMR to generate an adversarial “seed” patch that is transformed using EoT and converted to the desired coverage size using their texture conversion method that repeats and randomly clips the patch to the desired size, allowing them to avoid using UV maps and localize to specific areas on a mesh. In their experiments, they show depth attacks on common objects encountered in autonomous driving perception, such as cars, buses, and pedestrians, but only test in white-box settings.

Texture Post-Processing and Stabilization. Similar to the Mesh Attacks, many works have explored the use of texture post-processing and stabilization to improve the appearance and physical transferability of adversarial textures. In addition to using hyperparameter to control the magnitude of the perturbation, the most widely used stabilization and post-processing techniques are the addition of Total Variation (TV) loss [88] or Smooth loss, and Non-Printability Score (NPS) [109] to the adversarial loss.

The TV loss penalizes the difference between adjacent pixels in the texture to promote smoothness and reduce the appearance of noise in the texture. If we consider the texture as a 2D image \mathbf{x} , TV loss is defined as:

$$TV(\mathbf{x}) = \sum_{i,j} ((\mathbf{x}_{i,j+1} - \mathbf{x}_{i,j})^2 + (\mathbf{x}_{i+1,j} - \mathbf{x}_{i,j})^2)^{\frac{1}{2}}$$

where $\mathbf{x}_{i,j}$ are pixel coordinates in \mathbf{x} . For determining physical transferability, the NPS can be computed to determine how faithfully the texture can be represented after printing. For the set of printable RGB triplets $P \subset [0, 1]^3$, the score of a pixel \hat{p} is:

$$NPS(\hat{p}) = \prod_{p \in P} |\hat{p} - p|$$

and if \hat{p} is in P or is reasonably close, the score will be low, indicating that the pixel is printable.

5.2.3 Attack Scene Object Pose/Translation

It is widely known that DNNs are susceptible to even subtle changes in the pose or position of an object [49] and there are tools that allow exploration of these vulnerabilities, such as 3DB [75]. However, an attacker using differentiable rendering can find precise poses or translations of an object to achieve their goals in arbitrary settings beyond the scope of existing tools available to researchers. To exploit this vulnerability, an attacker can use publicly available datasets, *e.g.*, ImageNet, and create similar scenes with the target object in a variety of poses and positions and then use the renderer to generate poses and translations of the object that are misclassified by the target model. Alcorn’s et al. used this method in Strike (With) a Pose [2] to discover that 97% of the pose space of poses for common objects in ImageNet are incorrectly classified by Inceptionv3 with high black-box transfer rate to AlexNet, ResNet-50, YOLOv3. Zeng et al., [26] used a similar attack pipeline to find adversarial poses but also extended their attack to evaluate vulnerabilities in Visual Question Answering algorithms, finding that shifts in the position of the object can also lead to incorrect answers regarding descriptions of the scene. ViewFool [6] constructed scenes using 3D objects from BlenderKit⁷, sampling 100 images from each model and then training a NeRF model to optimize adversarial poses to attack ResNet-50 and ViT-B/16, finding that the transformer model was more robust to pose attacks than the CNN model.

5.2.4 Attack Scene Illumination

The use of illumination sources in differentiable rendering attacks is relatively unexplored, potentially due to its global influence on a scene, but there are two works that have used illumination manipulation of light sources to explore attacks on DNNs using lighting conditions. In Liu, et al.’s study attacking various components of scene representation [11], they explored the use of spherical harmonic lighting to produce subtle changes in the lighting conditions of a scene. Spherical Harmonic lighting [56] is a technique used to create global illumination in a scene with only a few basis functions, *i.e.*, 2 coefficients can approximate distant lighting for diffuse objects with only 1% pixel intensity error [98]. Therefore, they can use the chain rule as described in (Eq. 1) to propagate gradients to these 2 coefficients and optimize them while preserving realistic lighting appearance. In Adversarial Attacks Beyond the Image Space [26], they used the ShapeNet [37] objects in various scenes with two point light sources for illumination and manipulated both position and intensity using differentiable rendering to find adversarial lighting conditions that can attack ResNet-34 and AlexNet.

5.2.5 Attack Scene Sensors

While attackers frequently explore the robustness of an attacked mesh or texture to differences in camera angle, one work directly manipulate camera parameters to induce an attack. Shahreza et al., [18] used NeRF to find poses of a face that can impersonate a target identity using facial recognition models. This attack involves impersonating a face by reconstructing a 3D facial models from leaked 2D images, known as a template inversion attack. Their method incorporates training a NeRF on the source images and optimizing the camera parameters corresponding to camera rotation, enabling discovery of poses that can be used in both digital replay attacks and physically printed photographs, also related to pose attacks discussed in (Sec. 5.2.3). Their future work discusses the psychically plausibility of impersonating a target identity involving manufacturing a wearable face masks using their technique.

⁷<https://www.blenderkit.com/>

6 Digital and Physical Domains for Attacks

Designating Attack Domain

6.1 - Attack Digital Domain

6.2 - Attack Physical Domain

In our survey, we classified attacks using differentiable rendering based on the target domain: digital (Sec. 6.1) or physical (Sec. 6.2), as summarized in Table 1. In this section we focus on the challenges of creating and evaluating attacks in both domains, and the tools and methods used to address these challenges. In the digital domain, evaluating the effectiveness of adversarial methods can be accomplished in controlled settings using simulation and non-differentiable (surrogate) rendering tools. These methods allow researchers to test attacks across various environmental conditions, camera angles, and object configurations. Physical domain attacks target real-world objects and require addressing the practical challenges of implementing attacks, such as manufacturing constraints and the application of adversarial textures.

6.1 Attack Digital Domain

Simulation. Despite the challenges of real-world attacks, there exist other tools to evaluate the robustness of an attack using simulation to evaluate the effectiveness of an attack in a controlled setting. Simulation enables scripted data capture, such as generating renderings of a model from many camera angles quickly, spawning clones of an object to determine if the attack is strengthened with more objects, scaling objects and textures rapidly to adjust viewable surface area, and testing attacks in a variety of scenery [9], weather [28], and lighting conditions using tools like CARLA [46], Unreal Engine [50], Unity [124, 14], and Blender. Some authors used CARLA to sample their attacks on car meshes in various locations within the city environment or to generate datasets [129] to train models to create the attacks. While Blender is more suited towards 3D modeling and rendering, it can be used to create new 3D objects and scenes for attacks [26], or to create UV maps [13] that can texture objects.

Surrogate Rendering. Many of the available differentiable rendering tools have limited features compared to more popular non-differentiable rendering tools, such as Blender, UE4, and Unity, that ship with out-of-the-box 3D assets and a wide range of rendering configurations. For example, the CARLA simulator uses the non-differentiable Unreal Engine 4 to render photorealistic scenes within the included city environment, complete with roads, buildings, other vehicles, and pedestrian actors. In an effort to further evaluate their attack methods, researchers have found that many of the attacks created within the differentiable renderer can approximate an attack that can be successfully transferred to attack a victim model through the use of a non-differentiable *surrogate renderer*. This is possible through the use of transferable file formats, such as .obj, .fbx, or .gltf, that can be imported into the surrogate renderer and then rendered with similar lighting and camera angles to the original attack. Zeng et al. [26] conducted side-by-side experiments using Blender for each differentiable rendering attack they created to test transferability in other digital domains, while TT3D [7] used Blender and Meshlab [42] to evaluate the robustness of their model due to the differences in rendering engines' appearance. Similarly, Meloni et al. [14] used PyTorch3D to generate adversarial textures and then rendered them in Unity, the target environment for the virtual environments they were attacking.

6.2 Attack Physical Domain

Physical Plausibility and Feasibility Attacks. While post-processing and stabilization techniques can smooth a mesh after an attack, manufacturing or 3D printing a mesh can introduce new challenges, such as the need for a watertight mesh, which can be accomplished by using a Marching Cubes technique [21] to realize a mesh that is printable. Additionally, meshes produced to attack a single mesh must be retrained to attack a

new mesh, suggesting that universal attacks using a single mesh that can be printed and placed upon a vehicle could address this challenge [1]. Adversarial textures may not require the same level of post-processing as a mesh, the texture must contain printable colors, sometimes requiring high resolution printing or use of non-printability scores to constrain the color space (Sec. 5.2.2). Additionally, applying the texture to the object is more practical if the texture can be easily applied to an object. [9] used “sticker-mode” to constrain the texture to a specific region of an object. Other approaches requiring full-coverage camouflage [22, 20, 28] would require application of a printed decal or paint to the entire object, which is more expensive to produce and apply and we observe that authors only used small scaled models in their real-world evaluations.

7 Research Directions and Open Problems

In this section, we present future research directions and open problems distilled from our survey on differentiable rendering attacks. The attacker-goals we identified enabled us to specify the required tasks (Sec. 2.2) that need to be carried out to accomplish an adversarial attack and simultaneously helped us identify areas where the research is lacking or yet to be explored. While differentiable rendering methods have shown promise in generating adversarial attacks by manipulating 3D objects and scenes, exposing vulnerabilities in deep neural networks (DNNs), the current focus on ground-based targets, limited use of modalities, and the under-explored state-of-the-art models highlight significant gaps in the application of differentiable rendering. Additionally, the lack of comprehensive tools and pipelines, along with the need for improved evaluation metrics, underscores the necessity for a more structured and diverse research approach. We discuss 4 research gaps in the context of an existing related attacker-goals and tasks using differentiable rendering or by proposing a new goals and tasks, paving the way for more sophisticated and resilient models in both digital and physical domains.

7.1 Target Diversity

A large amount of differentiable rendering attack research has been focused on attacks to autonomous driving systems [21, 1, 5, 27, 7, 20, 22, 9, 28], with limited attacks on other applications like robotics, surveillance, and augmented reality. In practice, we found that most attacks are limited to ground-based targets, focusing on cars, and a few on pedestrians [13, 27]. However, there is a lack of attack scenarios using drones, unmanned autonomous vehicles, and satellites, for which this is growing utilization for surveillance, reconnaissance, and other applications. Many of the techniques we surveyed could be applied to these settings to explore the robustness of models in these scenarios. Expanding research in this area would support Task 5.2.1 and Task 5.2.2 by increasing the number of models attacks and the domain of digital (Task 6.1) and physical attacks (Task 6.2).

7.2 SOTA Models and Other Modalities

Our survey revealed that most attacks are largely focused on image classifiers and object detector models, while only a few works explored attacks on other modalities, such as optical flow and depth estimation, facial recognition, and point cloud classifiers, shown in Table 3. However, there is a growing amount of research on multi-modal models [81, 73], which combine multiple modalities to improve performance and robustness, yet only 1 work attacked the Multi-task Multi-sensor Fusion Model (MMF) [21] and another work attacked a cascaded model [1]. There is also work in 3D scene representation understanding [136], which is critical for robotics, AR systems, and self-driving, tracking, and video recognition. While attacker goals for multi-modal models can be currently designated as *combinations* of goals, we realize that new attacker goals are needed to frame attacks on other modalities such as tracking, video recognition, and 3D scene understanding.

Additionally, in attacks on image classifiers and object detector models, there exists a lack of attacks conducted on state-of-the-art models, with most attacks targeting older models or early versions of AlexNet, VGG,

and ResNet, and fewer attacks on more recent models like EfficientNet, ViT, and DeiT, except in black-box settings. For example, recent work studying the robustness of Vision Transformer models (ViTs) show that they are less susceptible to high-frequency perturbations but can struggle with small or low-resolution inputs, and distribution shifts, such as lighting, color, and context [108]. Based upon our review of the capabilities of various differentiable rendering tools, these vulnerabilities could be feasibly studied and would broadly support all attacker-goals 4.1 - 4.5.

7.3 Attack Methods Considering Real-World Phenomena

There also exists a lack of attacks targeting additional camera parameters such as lens warping, field of view, focus distance, and exposure. Cameras used as capture devices in autonomous vehicles, drones, and surveillance systems can also be vulnerable to physical attacks, such as an attacker that places a lens cover on a camera, exploitations of the rolling shutter effect [105], and perturbations that can attack camera image processing pipelines (ISP) [95]. Furthermore, existing attacks have predominantly focused on simplistic adjustments to lighting conditions, with minimal exploration into more complex scenarios involving varying light shapes, shadows, colors, and weather conditions [11]. Designing further scenarios for attacks on scene sensors and illumination would both support Tasks 5.2.5, 5.2.4, respectively and Task 6.2.

7.4 Tools and Pipelines

Currently, there is a lack of user-friendly tools and graphical user interfaces (GUIs) that facilitate easy control over scene manipulation. Developing more accessible tools and interfaces would streamline the process of creating and evaluating attacks, making advanced research more efficient and opening the field to a broader range of researchers, as most of the existing work relies on limited simulation tools, such as CARLA, with only a few alternatives available. Additionally, there is some demand for UI interfaces specifically designed for differentiable rendering or direct integration into existing 3D rendering engines. Recently, the Mitsuba team has made progress on exporting scenes creating it Blender for use with Mitsuba with a plugin⁸, however, most of the available tools require manual configuration of scene files, and although many are open-source, they can only be used by experts with knowledge of 3D rendering and modeling. Developing tools or plugins that integrate existing differentiable renderers into easier to use GUIs would support digital attacks (Task 6.1) and create easier transference to the physical domain (Task 6.2).

8 Conclusion

Due to the evolving capabilities of differentiable rendering methods and their implications for adversarial attacks, understanding these techniques is critical for ensuring the security and robustness of deep neural networks (DNNs). Our survey has provided a comprehensive, attacker task-guided review of adversarial attacks that utilize differentiable rendering, detailing how these methods can manipulate 3D objects and scenes to compromise various DNN applications.

Specifically, we have categorized the key tasks and scene manipulations that adversaries use to generate these attacks, focusing on how they impact different models, such as image classifiers and object detectors. By connecting attacker goals to the required tasks, our framework offers a practical guide for understanding and comparing existing techniques, helping researchers and practitioners navigate this complex landscape.

Our findings underscore the need for continued research to address gaps in the current literature, particularly in the areas of scenario variety and attack methods that target scene parameters like lighting and camera configurations. Moreover, the limited availability of easy-to-use tools and pipelines for implementing and

⁸<https://github.com/mitsuba-renderer/mitsuba-blender>

testing these attacks highlights the necessity for more accessible and user-friendly resources that can facilitate further research and experimentation.

To advance the field, we have identified several directions for future research, exploration of novel attack methods, and investigation into the physical plausibility of these attacks in real-world scenarios. By addressing these challenges, researchers can contribute to the development of more secure and resilient DNNs that are better equipped to handle the threats posed by adversarial attacks using differentiable rendering.

In conclusion, the rapidly changing landscape of differentiable rendering and its growing potential for adversarial attacks demand continued vigilance and innovation. By building on the insights and frameworks provided in this survey, the research community can push forward to develop more sophisticated and effective strategies for defending against these emerging threats.

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