Boosting 3D Adversarial Attacks with Attacking On Frequency

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Abstract
Deep neural networks (DNNs) have been shown to be vulnerable to adversarial attacks. Recently, 3D adversarial attacks, especially adversarial attacks on point clouds, have elicited mounting interest. However, adversarial point clouds obtained by previous methods show weak transferability and are easy to defend. To address these problems, in this paper we propose a novel point cloud attack (dubbed AOF) that pays more attention on the low-frequency component of point clouds. We combine the losses from point cloud and its low-frequency component to craft adversarial samples. Extensive experiments validate that AOF can improve the transferability significantly compared to state-of-the-art (SOTA) attacks, and is more robust to SOTA 3D defense methods. Otherwise, compared to clean point clouds, adversarial point clouds obtained by AOF contain more deformation than outlier.

1. Introduction
In recent years, with the widespread application of 3D vision technology in safety-critical scenarios such as autonomous driving, 3D adversarial samples have attracted more and more attention from researchers (Tsai et al., 2020; Xiang et al., 2019). The adversarial samples mislead the deep learning models by introducing small perturbation to the clean data. In the case of point cloud data, researchers mostly perform adversarial attacks on point cloud data by adding, deleting some points, or changing their coordinates (Tsai et al., 2020; Wen et al., 2020; Xiang et al., 2019; Zhou et al., 2020; Hamdi et al., 2020; Ma et al., 2020).

However, adversarial point clouds crafted by traditional 3D attacking methods (e.g., 3D-Adv (Xiang et al., 2019), kNN (Tsai et al., 2020)) often exhibit weak transferability due to overfitting to the source model. To improve the transferability of adversarial point cloud, a few studies attempted to alleviate such overfitting by introducing some regularization, e.g., Hamdi et al. (2020) enhanced the transferability by introducing a data adversarial loss from point cloud after an autoencoder. However, existing methods generate adversarial point cloud by indiscriminately perturbing point cloud without the awareness of intrinsic features of objects that a point cloud represent for, thus easily falling into model-specific local optimum. As pointed out in (Ilyas et al., 2019), deep learning models learn extra “noisy” features together with intrinsic features of objects, while the “noisy” features are treated equally with object-related features to support the final decision, and such “noisy” features will be model-specific. However, all the SOTA 3D adversarial attack algorithms treat the intrinsic features and the “noisy” features equally during the generation of perturbation.

Motivated by (Wang et al., 2020), which explored the generalization of neural networks from the perspective of frequency in image domain. We suppose that the intrinsic features of objects are highly related to the the low-frequency component (shortened as LFC) of objects. So we make an exploration of the intrinsic features of point cloud for neural networks from the perspective of frequency. However, unlike in image domain, we cannot simply split the LFC of point cloud using discrete Fourier transform (DFT). We divide the point cloud into LFC and high-frequency component (shortened as HFC) by applying graph Fourier transform to point cloud (Zhang et al., 2019; Xu et al., 2018; Shao et al., 2018; Zeng et al., 2019). From Figure 1, we can see that LFC of point cloud can represents the basic shape of point cloud. So we assume that LFC plays a major role in the recognition of point cloud for the current 3D neural networks. We design a simple experiment to validate our assumption. As shown in Table 1, firstly we split the LFC\(_{50}\), LFC\(_{100}\), and LFC\(_{200}\) (referred in Sec 3.1) of original point clouds, then we test the model classification accuracy on those different splitted LFCs, we found that classification accuracy only drops a little when throwing away HFC of point clouds. So we can conclude that LFC plays a major role in the recognition of point cloud, we therefore refer LFC as the intrinsic features and HFC as the “noisy” features.
In this paper, to improve the transferability of adversarial point cloud, we propose Attack on Frequency (AOF) attack. We first divide a point cloud into LFC and HFC, then we pay more attention to the LFC of point cloud and add the loss of LFC to avoid overfitting to the source model. Empirical evaluation over four famous point cloud classifier demonstrates the superior performance of our AOF in terms of transferability and robustness.

**Table 1.** Classification accuracies for different point cloud classifier on various lfc components of ModelNet40 train set.

| Network   | LFC<sub>50</sub> | LFC<sub>100</sub> | LFC<sub>200</sub> | ORIGINAL |
|-----------|------------------|-------------------|------------------|----------|
| PointNet  | 92.92            | 96.54             | 97.97            | 99.84    |
| PointNet++| 82.94            | 89.43             | 92.17            | 99.80    |
| DGCNN     | 76.34            | 88.51             | 92.02            | 100.0    |
| PointConv | 84.15            | 93.74             | 95.72            | 99.82    |

In summary, our main contributions are given as follows:

1) We propose a new adversarial attack AOF on point clouds which pays more attention to the LFC of point cloud and we introduce a new adversarial loss from the LFC of point cloud as a regularization in the process of optimization.

2) We perform extensive experiments to validate the transferability and robustness of our attacks. These experiments show that AOF can improve the transferability significantly compared to state-of-the-art (SOTA) attacks, and is more robust to SOTA 3D defense methods.

2. Related work

2.1. Adversarial attacks

The adversarial attacks are extensively investigated in recent years (Goodfellow et al., 2014; Kurakin et al., 2016; Dong et al., 2018; Carlini & Wagner, 2017). They can be roughly divided into two groups, *i.e.*, white-box attacks and black-box attacks. For white-box attack, the attackers have full knowledge of the victim model. In contrast, a black-box attack does not know any information about the victim model and can only obtain query access, *e.g.*, the prediction output of an input. In the early works, white-box settings are popular when attacking DNNs, for example the FGSM family (Goodfellow et al., 2014; Kurakin et al., 2016; Dong et al., 2018) that utilize the sign of the gradient of the victim model loss function. However, white-box attack settings are impossible to implement in practice since only query access is allowed in most realistic deep learning systems. Thus, black box attacks have received more and more attention in the adversarial machine learning community. There are two ways to perform black-box attack, one is query-based black-box attacks (Al-Dujaili & O’Reilly, 2019; Andriushchenko et al., 2020) which craft the adversarial samples by the response of the victim model to the given inputs. However, query-based black-box attacks suffer from excessive queries before a successful attack, which is unacceptable from a practical standpoint. The other one is transfer-based black-box attacks (Chen et al., 2020; Dong et al., 2018), which craft the adversarial samples via attacking a surrogate model they have white-box access to. This is promising because this approach can threaten realistic deep learning systems, *e.g.*, Google Cloud Vision. In this paper, we focus on transfer-based black-box attack for 3D point cloud.

2.2. 3D adversarial attacks

3D adversarial attacks aim to generate 3D adversarial samples in a human-unnoticeable way. 3D adversarial samples usually consist of two types: adversarial point cloud (Xiang et al., 2019; Tsai et al., 2020) and adversarial mesh (Wen et al., 2020; Zhang et al., 2021a). Currently, most 3D adversarial attacks are about point cloud. (Xiang et al., 2019) is the first work that crafts adversarial point cloud by adding points, small clusters or objects to clean point cloud. However, those adversarial point clouds usually contain a lot of outliers, which are not human-noticeable. To solve this problem, the following works (Wen et al., 2020; Tsai et al., 2020) focus on generating adversarial point cloud with much less outliers. Tsai et al. (2020) proposed kNN attack that aims to generating smooth perturbation by adding chamfer distance and kNN distance to loss function as the regularization terms during optimization. Wen et al. (2020) proposed the GeoA³ attack which crafts adversarial point cloud in a geometric-aware way and is more human imperceptible.
Attack on frequency

However, the kNN attack and the GeoA3 attack are less effective in real world scenarios. Unlike previous methods, the Mesh Attack (Zhang et al., 2021a) directly adds perturbation to mesh, which can avoid the information loss during 3D printing and scanning, thus boosting the performance in real world scenarios significantly. Moreover, although the above mentioned methods achieve satisfying performance in white-box setting, it is hard for them to attack the realistic 3D deep learning systems due to their weak transferability. In order to improve the transferability of 3D adversarial attacks, AdvPC attack (Hamdi et al., 2020) adopts a point cloud autoencoder during the generation of adversarial point cloud. The experiment results show that AdvPC attack improves the transferability of 3D adversarial attacks between PointNet (Qi et al., 2017a), PointNet++ (Qi et al., 2017b), DGCNN (Wang et al., 2019) and PointConv (Wu et al., 2019) significantly. In this paper, we aim to improve the transferability of 3D adversarial attacks, too.

2.3. Adversarial attacks in frequency domain

Recently, in the image domain, there also are some works that explore the generalization and the robustness of neural networks in the frequency domain. AdvDrop (Duan et al., 2019) generates adversarial examples by dropping imperceptible components in the frequency domain. SimBA (Gao et al., 2019) achieves satisfactory attack success rate with an unprecedented low number of black-box queries by restricting the search to the low frequency domain. Deng & Karam (2020) improved the performance of both white-box and black-box attacks by computing universal perturbations in the frequency domain. However, the exploration of frequency in the field of 3D point cloud adversarial attack is still lacking. This work improves the transferability and robustness of 3D point cloud adversarial attack from the view of frequency.

3. Method

3.1. The frequency of point cloud

For a point cloud $\mathcal{X}$, we construct an undirected graph $\mathcal{G}$ whose vertex set is points of $\mathcal{X}$. Each vertex connects only with its k nearest neighbors (kNN), the weight of edge between vertex $i$ and vertex $j$ is

$$w_{ij} = \begin{cases} \exp \left( -\frac{d_{ij}^2}{2\sigma^2} \right) & \text{if } p_j \in \text{kNN}(p_i) \text{ or } p_j \in \text{kNN}(p_j) \\ 0 & \text{otherwise} \end{cases}$$

where $\text{kNN}(p)$ represents k nearest neighbors of $p$ and $d_{ij}$ is the Euclidean distance between the two points $p_i$ and $p_j$.

$$d_{ij} = \|p_i - p_j\|_2$$

With the edge weights defined above, we define the symmetric adjacency matrix $A \in \mathbb{R}^{N \times N}$, with the $(i, j)$-th entry given by $w_{ij}$. $D$ denotes the diagonal degree matrix, where entry $D(i, i) = \sum_j w_{i,j}$. The combinatorial graph Laplacian matrix is $L = D - A$ (Shuman et al., 2013). $L$ is symmetric and can be decomposed as

$$L = V \Lambda V^T \tag{3}$$

where $V$ is an orthogonal matrix whose columns are eigenvectors of $L$ and $\Lambda$ is a diagonal matrix whose entries are the eigenvalues of $L$ (the eigenvalues are sorted in an increasing order). Then, the coordinate graph signals can be projected on the eigenvectors of the Laplacian matrix $L$ as follows:

$$\begin{cases} x = \alpha_0 v_0 + \alpha_1 v_1 + \cdots + \alpha_{N-1} v_{N-1} \\ y = \beta_0 v_0 + \beta_1 v_1 + \cdots + \beta_{N-1} v_{N-1} \\ z = \gamma_0 v_0 + \gamma_1 v_1 + \cdots + \gamma_{N-1} v_{N-1} \end{cases} \tag{4}$$

where $\alpha_i = \langle x, v_i \rangle$, $\beta_i = \langle y, v_i \rangle$ and $\gamma_i = \langle z, v_i \rangle$.

For any graph signal, we can divide it to low-frequency component (LFC) and high-frequency component (HFC) using the eigenvectors of Laplacian matrix. For example, we decompose the x-axis coordinate $x = x_{l,fc} + x_{h,fc}$, with $x_{l,fc}$ and $x_{h,fc}$ defined as:

$$\begin{cases} x_{l,fc} = \alpha_0 v_0 + \alpha_1 v_1 + \cdots + \alpha_{m-1} v_{m-1} \\ x_{h,fc} = \alpha_m v_m + \alpha_{m+1} v_{m+1} + \cdots + \alpha_{N-1} v_{N-1} \end{cases}$$

where $m$ is a hyper-parameter that represents the number of eigenvectors in LFC. We denote the LFC with the first $m$ eigenvectors of Laplacian matrix as $\text{LFC}_m$.

For a point cloud $\mathcal{X}$, we can divide it to low-frequency component (LFC) and high-frequency component (HFC):

$$\mathcal{X} = X_{l,fc} + X_{h,fc}, \tag{5}$$

where $X_{l,fc}$ denotes LFC of $\mathcal{X}$ and $X_{h,fc}$ denotes HFC of $\mathcal{X}$.

3.2. Attack on frequency

The goal of 3D adversarial attack on point cloud is to generate the adversarial point cloud example that misleads 3D point cloud classification model by adding subtle perturbation to the clean point cloud. Formally, for a classification model $F : \mathcal{X} \rightarrow \mathcal{Y}$, which maps a point cloud to its corresponding class label, the adversarial examples can be generated by adding perturbation limited in a $l_p$ ball of size $\epsilon_p$, where $p$ can be 1, 2 and $\infty$. The adversarial point cloud can be represented as $\mathcal{X}' = \mathcal{X} + \Delta$, where $\Delta$ is the additive perturbation.

In this paper, we propose a novel 3D adversarial attack based on attacking on frequency, dubbed AOF attack. The
We represent the corresponding adversarial example of $\mathcal{X}$ where
$y$ where $\gamma$ as defined as:

$$\Delta_{lfc} = (v_0, v_1, \ldots, v_m) \begin{pmatrix} v_0^T \\ v_1^T \\ \vdots \\ v_m^T \end{pmatrix} \Delta$$  \hspace{1cm} (6)

We represent the corresponding adversarial example of $\mathcal{X}_{lfc}$ by $\mathcal{X}'_{lfc} = \mathcal{X}_{lfc} + \Delta_{lfc}$. Then we optimize the perturbation $\Delta \in \mathbb{R}^{N \times 3}$ via solving the following problem:

$$\min_{\Delta} l_{aof}(\mathcal{X}, \mathcal{X}') \quad s.t. D(\mathcal{X}, \mathcal{X}') \leq \epsilon \quad (7)$$

As shown in Figure 2, unlike current 3D adversarial attacks, our AOF attack algorithm pays more attention to perturbing the LFC of point cloud for misleading the victim network. Moreover, we add an additional LFC adversarial loss in our AOF loss function:

$$l_{aof} = (1 - \gamma) l_{mis}(\mathcal{X}') + \gamma l_{mis}(\mathcal{X}'_{lfc})$$  \hspace{1cm} (8)

where $\gamma$ is used to balance the adversarial loss between the adversarial point cloud $\mathcal{X}'$ and $\mathcal{X}'_{lfc}$. And the $l_{mis}(\cdot)$ is defined as:

$$l_{mis}(\mathcal{X}') = \max_{y \neq y_{gt}} (Z(\mathcal{X}'))_y - Z(\mathcal{X}')_{y_{gt}, \kappa} \quad (9)$$

where $y_{gt}$ is the ground truth class, $y$ is any class that not equal to $y_{gt}$, $Z(\cdot)$ is the output of logits layer and $\kappa$ is the loss margin. In order to fairly compare with the kNN attack (Tsai et al., 2020) and the AdvPC attack (Hamdi et al., 2020), we also follow the C&W attack’s (Carlini & Wagner, 2017) optimization framework to optimize the perturbation. The AOF algorithm is summarized in Algorithm 2.

### 4. Experiment

In this section, we evaluate the performance of our AOF from two aspects: the transferability compared to other SOTA attacks and the performance against SOTA point cloud defenses. The basic setups of our experiments are described in Sec 4.1. To test the efficacy of our proposed AOF, we conduct ablation studies and sensitivity analysis in Sec 4.2 and 4.3 respectively. Then we present the black-box transferability of AOF compared to other SOTA methods in Sec 4.4, and test the AOF performance under several point cloud defenses in Sec 4.5. Finally, we discuss some characteristics of AOF in Sec 4.6.

#### 4.1. Setup

**Dataset.** We use ModelNet40 (Wu et al., 2015) to train the classifiers and test our attacks. ModelNet40 contains 12,311 CAD models from 40 different classes. These models are divided into 9,843 for training and 2,468 for testing. We use the whole test dataset to test our attacks. We trained four victim networks: PointNet (Qi et al., 2017a), PointNet++ (Qi et al., 2017b) in Single-Scale(SSG) setting, DGCNN (Wang et al., 2019) and PointConv (Wu et al., 2019).

**Evaluation metrics.** In the works of transfer-based black-box attack in image domain (Chen et al., 2020; Dong et al., 2018), due to clean accuracy on the test data can reach 100%, the transferability is evaluate by the top-1 error rate. However, for 3D point clouds, the clean accuracy of all victim models on test dataset are around 90%, which means there

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**Algorithm 1 LFCSplit**

1. **Input:** point cloud $x$, number of points $N$, number of eigenvectors in LFC $m$, number of nearest neighbors $k$
2. **Output:** low-frequency component $X_{lfc}$, basis vectors of point cloud graph laplacian matrix $V$
3. **Set up:** Connect each point with $k$ nearest neighbors and compute the weight of each edge as formula 1 to give $A$
4. **Initialize** $D = 0$
5. **for** $i = 0$ **to** $N - 1$ **do**
6. $D (i, i) = \sum_j A (i, j)$
7. **end for**
8. $L = D - A$
9. Compute the eigenvectors of matrix $L$ to give $V$
10. Initialize $V_{lfc} = V(:, 0 \cdots m - 1)$ //first m columns
11. $x_{lfc} = V_{lfc}V_{lfc}^T x$

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**Figure 2. AOF Attack Pipeline:** Firstly, we split the LFC of original point cloud and perturbation $\Delta$. Then we get the adversarial sample $\mathcal{X}'$ and $\mathcal{X}'_{lfc}$, which is composed of the LFC of original point cloud $\mathcal{X}_{lfc}$ and the LFC perturbation $\Delta_{lfc}$. The perturbed sample $\mathcal{X}'$ fools a trained classifier $F$ (i.e. $F(\mathcal{X}')$ is incorrect), meanwhile, $\mathcal{X}'_{lfc}$ also fools the classifier $F$ (i.e. $F(\mathcal{X}'_{lfc})$ is correct). We combine the original adversarial loss(blue) and LFC adversarial loss(yellow) to optimize the LFC perturbation $\Delta_{lfc}$. Dotted lines are gradients flowing to the LFC perturbation.
We denote the clean samples that are classified correctly by attack on frequency (Xiang et al., 2019), the number of iterations for the attack is brought by adversarial attacks or not. If we adopt the top-1 error rate to evaluate transferability of adversarial attacks, the difference between different attacks could not be significant. We argue that the top-1 error rate cannot reflect the real performance gap between attack algorithms. Therefore, unlike previous works (Hamdi et al., 2020), we use the percentage of the misclassified adversarial samples out of all the clean samples that are classified correctly to evaluate the transferability.

We denote the clean samples that are classified correctly by the victim model as set $S$ and the corresponding adversarial samples of $S$ as set $S_{adv}$. In the set $S_{adv}$, we denote the samples that are misclassified as set $T \subseteq S_{adv}$. Then the attack success rate (ASR) can be calculated by:

$$\text{ASR} = \frac{|T|}{|S_{adv}|} \quad (10)$$

**Baselines.** We compare AOF with the state-of-the-art baselines: 3D-Adv (Xiang et al., 2019), kNN attack (Tsai et al., 2020) and AdvPC (Hamdi et al., 2020). For AdvPC and all of our attacks, we use Adam optimizer (Kingma & Ba, 2014) with learning rate $\eta = 0.01$, and perform 2 different initializations for the optimization of $\Delta$ (as done in Xiang et al., 2019), the number of iterations for the attack optimization for all the networks is 200. We set the loss margin $\kappa = 30$ in Eq (9) for 3D-Adv (Xiang et al., 2019), AdvPC (Hamdi et al., 2020) and AOF and $\kappa = 15$ for kNN Attack (Tsai et al., 2020) (as suggested in their paper). For other hyperparameters of (Tsai et al., 2020; Xiang et al., 2019; Hamdi et al., 2020), we follow the experimental details in their paper. We pick $\gamma = 0.25$ in Eq (8) for AOF.

### 4.2. Ablation Study

In this section, we conduct a series of experiments on ModelNet40 test set to test the efficacy of AOF.

#### 4.2.1. HYPERPARAMETER $m$

Here, we study the effect of hyperparameter $m$ (number of eigenvectors of Laplacian matrix in LFC) on the performance of AOF attacks. When varying $m$ between 0 and 1024, the variation of attack success rate and the averaged transferability of attacks are shown in Figure 3, the averaged transferability denotes the averaged ASR on the transfer networks. The exact values we used for parameter $m$ are $\{10, 20, 30, 40, 50, 60, 70, 80, 90, 100, 200, 300, 400, 500, 600, 700, 800, 900, 1024\}$. We make the following observations. (1) Except for DGCNN (Wang et al., 2019), $m$ has little effect on the attack success rate of the victim networks. (2) As $m$ increases from 0 to 1024, the transferability first increases and then decreases to the minimum when $m = 1024$ (all frequency components). This phenomenon validates that paying more attention to LFC of point clouds can improve the transferability of attacks. But when $m$ is small, the transferability decreases for the information contained in LFC is not enough to transfer to other neural networks. We select $m = 100$ to balance the transferability and attack success rate in the following experiments.

#### 4.2.2. HYPERPARAMETER $\gamma$

The hyperparameter $\gamma$ is used to balance the adversarial loss between the adversarial point cloud and its LFC. The $\gamma$ is selected from $\{0.0, 0.25, 0.50, 0.75, 1.0\}$, other experiment setups are the same as Sec 4.1.

From Figure 4, one observation is that adding the LFC adversarial loss with $\gamma > 0$ tends to reduce the white-box attack success rate, even though it improves the transferability. Especially for DGCNN, when $\gamma$ is bigger than 0.5, the ASR decreased significantly. We therefore pick $\gamma = 0.25$ in our experiments to balance attack success rate and transferability.

### 4.3. Sensitivity Analysis on Norm budget $\epsilon_\infty$

Adversarial effects of attack methods are related with norm budget. In this section, we study the variation of attack

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**Algorithm 2** Attack on frequency

1. **Input:** point cloud $x$, number of points $N$, number of eigenvectors in LFC $m$, number of nearest neighbors $k$, binary search step $s$, number of iteration $n_{iter}$, balance coefficient $\gamma$, ground truth label $y_{gt}$, perturbation limit bound $\epsilon_\infty$
2. **Output:** optimized perturbation $\Delta$ of point cloud $x$
3. Initialize $x_{lfc}^{f}$, $V = \text{LFCSplit}(x, N, m, k)$
4. Initialize $\Delta = 0$
5. Initialize $x_{lfc}^{0} = x$
6. for $s = 0$ to $n_{iter} - 1$ do
   7. for $i = 0$ to $n_{iter} - 1$ do
      8. $V_{lfc} = V(:, 0 \cdots m - 1)$ (first m columns)
      9. $V_{hfc} = V(:, m \cdots N - 1)$ (last N-m columns)
      10. $\Delta_{lfc} = V_{lfc}V_{lfc}^T \Delta$
      11. $\Delta_{hfc} = V_{hfc}V_{hfc}^T \Delta$
      12. $x_{adv}^{0} = x^{0} + \Delta$
      13. $x_{adv}^{t} = x_{adv}^{0} + \Delta x_{lfc}^{t}$
      14. $y = F(x_{adv}^{t})$
      15. $y_{adv} = F(x_{adv}^{t})$
      16. $loss = (1 - \gamma)l_{adv}(y_{gt}, y) + \gamma l_{adv}(y_{gt}, y_{adv})$
      17. $\Delta_{lfc} = \text{min}_{\Delta} \Delta_{lfc} loss$
      18. $\Delta = \Delta_{lfc} + \Delta_{hfc}$
      19. Clip $\Delta$ to $\epsilon_\infty$
   7. end for
5. end for

are about 10% data we cannot ensure whether the misclassification is brought by adversarial attacks or not. If we adopt the top-1 error rate to evaluate transferability of adversarial attack algorithms, the difference between different attacks could not be significant. We argue that the top-1 error rate cannot reflect the real performance gap between attack algorithms. Therefore, unlike previous works (Hamdi et al., 2020), we use the percentage of the misclassified adversarial samples out of all the clean samples that are classified correctly to evaluate the transferability.
Figure 3. The effect of changing hyperparameter \( m \) on attack success rate (above) and transferability (below) of AOF. For a better view, we divide the value range of \( m \) into two parts: \([0, 100]\) (left) and \([100, 1024]\) (right). Here, we pick \( \epsilon_\infty = 0.18 \) and \( \gamma = 0.25 \) and the transferability score reported for each victim network is the average attack success rate on the transfer networks.

Figure 4. The effect of changing hyperparameter \( \gamma \) on attack success rate (left) and transferability (right) of AOF. Here, we pick \( \epsilon_\infty = 0.18 \) and \( m = 100 \). The transferability score reported for each victim network is the average of attack success rate on the transfer networks.

Figure 5. The influence of changing norm budget \( \epsilon_\infty \) on attack success rate (left) and transferability (right) of AOF. Here, we pick \( \gamma = 0.25 \) and \( m = 100 \). The transferability score reported for each victim network is the average attack success rate on the transfer networks.

4.4. Transferability of AOF

In this section, we compare our AOF with SOTA 3D adversarial attack algorithms in terms of transferability for untargetted attack following the experiment setup of (Xiang et al., 2019; Hamdi et al., 2020).

We compare AOF against the SOTA baselines (Xiang et al., 2019; Tsai et al., 2020; Hamdi et al., 2020) for \( \epsilon_\infty = 0.18 \) and \( \epsilon_\infty = 0.45 \). As discussed in Sec 4.1, we use ASR defined in Eq (10) as the real attack success rate. We report the transferability in Table 2. From the results of Table 2, it is clear that AOF consistently and significantly outperforms the baselines when transfer to other networks (up to nearly 70%).

For reference, We also report the top-1 error rate following (Hamdi et al., 2020) in the appendix. As shown in Table 5 and Table 2, using the top-1 error rate to measure the transferability of the attacks is not fair. The key reason is that the clean accuracy of point cloud on the ModelNet40 test set cannot reach 100%, therefore the point clouds that the victim model misclassified originally are also included when computing the top-1 error rate. As a result, the top-1 error rate cannot reflect the real gap between 3D adversarial attack algorithms. As shown in Table 2, the gap between our AOF and AdvPC is more obvious than using the top-1 error rate in Table 5. While these experiments are for untargetted
Table 2. **Transferability of Attacks.** We use ASR defined in formula (10) to evaluate the transferability. Compared to Table 5, the difference of transferability to PointNet between 3D-Adv and our AOF is more obvious, which reflects the real gap between attack algorithms.

| Victim Networks | Attacks   | $\epsilon_\infty = 0.18$ | $\epsilon_\infty = 0.45$ |
|-----------------|-----------|--------------------------|--------------------------|
|                 | PointNet  | PointNet++ | PointConv | DGCNN | PointNet  | PointNet++ | PointConv | DGCNN |
| PointNet        | 3D-Adv    | 100         | 5.01      | 2.06  | 4.22     | 100         | 5.12      | 2.01  | 4.18  |
|                 | KNN       | 100         | 11.1      | 3.62  | 10.7     | 100         | 10.8      | 3.53  | 10.2  |
|                 | AdvPC     | 100         | 30.4      | 13.6  | 14.8     | 100         | 30.4      | 13.1  | 14.9  |
|                 | AOF(ours) | 99.9        | 57.2      | 36.3  | 29.4     | 100         | 58.4      | 33.7  | 30.9  |
| PointNet++      | 3D-Adv    | 1.54        | 100       | 4.77  | 6.49     | 1.86        | 100       | 3.81  | 5.74  |
|                 | KNN       | 2.77        | 100       | 5.35  | 7.91     | 2.63        | 100       | 5.45  | 7.29  |
|                 | AdvPC     | 4.81        | 99.2      | 28.2  | 18.9     | 4.81        | 99.2      | 28.3  | 18.9  |
|                 | AOF(ours) | 7.89        | 99.6      | 48.4  | 33.3     | 8.62        | 99.9      | 48.4  | 34.3  |
| PointConv       | 3D-Adv    | 1.45        | 6.58      | 100   | 3.02     | 1.32        | 6.92      | 100   | 3.33  |
|                 | KNN       | 3.49        | 15.7      | 100   | 11.2     | 3.54        | 16.8      | 100   | 10.9  |
|                 | AdvPC     | 5.13        | 34.2      | 99.5  | 18.0     | 5.67        | 35.2      | 99.6  | 18.5  |
|                 | AOF(ours) | 6.85        | 50.0      | 99.9  | 25.5     | 7.44        | 49.3      | 99.8  | 25.7  |
| DGCNN           | 3D-Adv    | 0.91        | 6.63      | 5.21  | 100      | 0.77        | 6.41      | 5.18  | 100   |
|                 | KNN       | 5.58        | 31.1      | 19.4  | 100      | 5.44        | 32.2      | 21.0  | 100   |
|                 | AdvPC     | 7.44        | 60.0      | 44.5  | 93.7     | 8.08        | 60.4      | 44.3  | 93.6  |
|                 | AOF(ours) | 14.0        | 69.6      | 58.4  | 96.7     | 16.6        | 69.2      | 58.7  | 96.7  |

attacks, we perform similar experiments under targeted attacks and report the results in supplement for reference and completeness.

### 4.5. AOF under Defense

In order to explore the robustness of our AOF under various 3D adversarial defense algorithms, in this section, we first compare the attack success rate of AOF with other 3D adversarial attacks under various defense algorithms, then we compare the transferability of our AOF with other 3D adversarial attacks under various defenses, the results of which are in the appendix.

**Attack Success Rate under Defense.** We perform the SOTA 3D adversarial defenses to the adversarial point clouds crafted by our AOF and other 3D adversarial attacks. Several SOTA defenses: the Simple Random Sampling (SRS), Statistical Outlier Removal (SOR), DUP-Net (Zhou et al., 2019) and the IF-Defense (Wu et al., 2020) are selected. The results are showed in Table 3. The robustness against various defenses of our AOF are significantly better than all other 3D adversarial attacks under various defenses, the results of which are in the appendix.

We visualized some adversarial samples crafted by AOF and AdvPC to analyze why AOF is more robust than AdvPC. As shown in Figure 6, our AOF tends to cause tiny deformation of original point clouds, rather than outliers. Deformation is usually harder to defend than outliers.

### 4.6. Discussion

In this subsection, we explore the transferability of AOF when transfer to models trained with data augmentation. The complementing effect of AOF and spectral analysis of perturbation are discussed in the appendix due to page limits.

**Transferability with Data Augmentation.** The models trained with data augmentation are generally more robust than those without data augmentation (Zhang et al., 2021b; Yun et al., 2019). In this subsection, we explore the transferability of adversarial samples generated by AOF when transfer to models trained with data augmentation. The augmented models are trained on ModelNet40 with random scaling, random rotation, random shifting, random dropping and random point cloud jittering, the adversarial samples are generated by attacking DGCNN model trained without any data augmentation. Here, we pick $\epsilon_\infty = 0.18$, other experiment setting are the same as Sec 4.3. We denote the attack success rate on models without data augmentation as ASR$_{noaug}$ and the attack success rate on models with data augmentation as ASR$_{aug}$. Then, the drop rate of transferability can be expressed as

$$\text{DR}_{\text{ASR}} = (\text{ASR}_{\text{noaug}} - \text{ASR}_{\text{aug}})/\text{ASR}_{\text{noaug}}.$$  

From Table 4, we can observe that adversarial samples generated by our method have a relatively smaller drop rate of transferability than other SOTA methods when transferred to models trained with data augmentation, which further verifies the robustness of AOF.
Table 3. Attack success rate under various defense methods on PointNet++ (Qi et al., 2017b), PointNet (Qi et al., 2017a), DGCNN (Wang et al., 2019) and PointConv (Wu et al., 2019). The ConvNet-Opt, ONet-Remesh and ONet-Opt are three variants of IF-Defense.

| Victim models | Attacks | No defense | SRS | SOR | DUP-Net | ConvNet-Opt | ONet-Remesh | ONet-Opt |
|---------------|---------|------------|-----|-----|---------|-------------|-------------|---------|
| PointNet      | 3D-Adv  | 100        | 37.4| 18.4| 9.62    | 5.58        | 10.8        | 7.4     |
|               | kNN     | 100        | 92.1| 76.4| 30.5    | 10.1        | 12.9        | 9.1     |
|               | AdvPC   | 93.7       | 89.6| 53.6| 23.1    | 9.2         | 12.6        | 7.6     |
|               | AOF     | 96.7       | 99.7| 94.2| 75.4    | 27.9        | 19.4        | 16.9    |
| PointNet++    | 3D-Adv  | 100        | 65.9| 27.3| 22.9    | 12.8        | 25.7        | 16.1    |
|               | kNN     | 100        | 79.6| 95.7| 80.6    | 14.6        | 25.5        | 15.3    |
|               | AdvPC   | 93.7       | 86.8| 79.0| 72.1    | 28.8        | 34.5        | 24.7    |
|               | AOF     | 96.7       | 92.8| 91.0| 88.2    | 45.6        | 42.6        | 36.1    |
| DGCNN         | 3D-Adv  | 100        | 29.5| 23.7| 23.2    | 13.7        | 25.6        | 15.6    |
|               | kNN     | 100        | 59.5| 24.5| 83.9    | 18.7        | 25.5        | 17.4    |
|               | AdvPC   | 93.7       | 65.4| 68.5| 62.1    | 26.3        | 32.6        | 22.6    |
|               | AOF     | 96.7       | 75.8| 79.3| 76.0    | 41.2        | 39.5        | 32.5    |
| PointConv     | 3D-Adv  | 100        | 42.4| 48.0| 37.3    | 14.3        | 22.3        | 15.1    |
|               | kNN     | 100        | 73.9| 99.8| 95.9    | 21.1        | 24.2        | 19.5    |
|               | AdvPC   | 93.7       | 80.5| 94.0| 88.1    | 44.1        | 30.9        | 37.5    |
|               | AOF     | 96.7       | 90.3| 98.3| 96.0    | 59.6        | 36.9        | 46.0    |

Figure 6. The visualization of adversarial samples

Table 4. Transferability drop rate (smaller numbers are better) of attacks when transfer to 3D networks trained with data augmentation. **Bold** numbers indicate the best.

| Method | PN  | PN++ | PV  | GCN |
|--------|-----|------|-----|-----|
| 3D-Adv | 50% | 75%  | 36% | 98% |
| kNN    | 46% | 86%  | 55% | 87% |
| AdvPC  | 37% | 69%  | 23% | 79% |
| AOF    | **34%** | 51%  | **16%** | 64% |
adversarial attack algorithms and is more robust to SOTA 3D adversarial defense algorithms. In the future, we plan to explore the imperceptibility of adversarial attack by restricting the perturbation of point cloud to HFC.

References

Al-Dujaili, A. and O’Reilly, U.-M. Sign bits are all you need for black-box attacks. In International Conference on Learning Representations, 2019.

Andriushchenko, M., Croce, F., Flammarion, N., and Hein, M. Square attack: a query-efficient black-box adversarial attack via random search. In European Conference on Computer Vision, pp. 484–501. Springer, 2020.

Carlini, N. and Wagner, D. Towards evaluating the robustness of neural networks. In 2017 ieee symposium on security and privacy (sp), pp. 39–57. IEEE, 2017.

Chen, S., He, Z., Sun, C., Yang, J., and Huang, X. Universal adversarial attack on attention and the resulting dataset damagenet. IEEE Transactions on Pattern Analysis and Machine Intelligence, 2020.

Deng, Y. and Karam, L. I. Frequency-tuned universal adversarial attacks. arXiv preprint arXiv:2003.05549, 2020.

Dong, Y., Liao, F., Pang, T., Su, H., Zhu, J., Hu, X., and Li, J. Boosting adversarial attacks with momentum. In Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 9185–9193, 2018.

Duan, R., Chen, Y., Niu, D., Yang, Y., Qin, A. K., and He, Y. Advdrop: Adversarial attack to dnns by dropping information. In Proceedings of the IEEE/CVF International Conference on Computer Vision, pp. 7506–7515, 2021.

Goodfellow, I. J., Shlens, J., and Szegedy, C. Explaining and harnessing adversarial examples. arXiv preprint arXiv:1412.6572, 2014.

Guo, C., Gardner, J., You, Y., Wilson, A. G., and Weinberger, K. Simple black-box adversarial attacks. In International Conference on Machine Learning, pp. 2484–2493. PMLR, 2019.

Hamdi, A., Rojas, S., Thabet, A., and Ghanem, B. Advpc: Transferable adversarial perturbations on 3d point clouds. In European Conference on Computer Vision, pp. 241–257. Springer, 2020.

Ilyas, A., Santurkar, S., Engstrom, L., Tran, B., and Madry, A. Adversarial examples are not bugs, they are features. Advances in neural information processing systems, 32, 2019.

Kingma, D. P. and Ba, J. Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980, 2014.

Kurakin, A., Goodfellow, I., and Bengio, S. Adversarial machine learning at scale. arXiv preprint arXiv:1611.01236, 2016.

Ma, C., Meng, W., Wu, B., Xu, S., and Zhang, X. Efficient joint gradient based attack against sot defense for 3d point cloud classification. In Proceedings of the 28th ACM International Conference on Multimedia, pp. 1819–1827, 2020.

Qi, C. R., Su, H., Mo, K., and Guibas, L. J. Pointnet: Deep learning on point sets for 3d classification and segmentation. In Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 652–660, 2017a.

Qi, C. R., Yi, L., Su, H., and Guibas, L. J. Pointnet++: Deep hierarchical feature learning on point sets in a metric space. arXiv preprint arXiv:1706.02413, 2017b.

Shao, Y., Zhang, Q., Li, G., Li, Z., and Li, L. Hybrid point cloud attribute compression using slice-based layered structure and block-based intra prediction. In Proceedings of the 26th ACM international conference on Multimedia, pp. 1199–1207, 2018.

Shuman, D. I., Narang, S. K., Frossard, P., Ortega, A., and Vandergheynst, P. The emerging field of signal processing on graphs: Extending high-dimensional data analysis to networks and other irregular domains. IEEE signal processing magazine, 30(3):83–98, 2013.

Tsai, T., Yang, K., Ho, T.-Y., and Jin, Y. Robust adversarial objects against deep learning models. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 34, pp. 954–962, 2020.

Wang, H., Wu, X., Huang, Z., and Xing, E. P. High-frequency component helps explain the generalization of convolutional neural networks. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 8684–8694, 2020.

Wang, Y., Sun, Y., Liu, Z., Sarma, S. E., Bronstein, M. M., and Solomon, J. M. Dynamic graph cnn for learning on point clouds. Acm Transactions On Graphics (tog), 38(5):1–12, 2019.

Wen, Y., Lin, J., Chen, K., Chen, C. P., and Jia, K. Geometry-aware generation of adversarial point clouds. IEEE Transactions on Pattern Analysis and Machine Intelligence, 2020.

Wu, W., Qi, Z., and Fuxin, L. Pointconv: Deep convolutional networks on 3d point clouds. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 9621–9630, 2019.
Wu, Z., Song, S., Khosla, A., Yu, F., Zhang, L., Tang, X., and Xiao, J. 3d shapenets: A deep representation for volumetric shapes. In Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 1912–1920, 2015.

Wu, Z., Duan, Y., Wang, H., Fan, Q., and Guibas, L. J. If-defense: 3d adversarial point cloud defense via implicit function based restoration. arXiv preprint arXiv:2010.05272, 2020.

Xiang, C., Qi, C. R., and Li, B. Generating 3d adversarial point clouds. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 9136–9144, 2019.

Xu, Y., Hu, W., Wang, S., Zhang, X., Wang, S., Ma, S., and Gao, W. Cluster-based point cloud coding with normal weighted graph fourier transform. In 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pp. 1753–1757. IEEE, 2018.

Yun, S., Han, D., Oh, S. J., Chun, S., Choe, J., and Yoo, Y. Cutmix: Regularization strategy to train strong classifiers with localizable features. In Proceedings of the IEEE/CVF International Conference on Computer Vision, pp. 6023–6032, 2019.

Zeng, J., Cheung, G., Ng, M., Pang, J., and Yang, C. 3d point cloud denoising using graph laplacian regularization of a low dimensional manifold model. IEEE Transactions on Image Processing, 29:3474–3489, 2019.

Zhang, J., Chen, L., Liu, B., Ouyang, B., Xie, Q., Zhu, J., Li, W., and Meng, Y. 3d adversarial attacks beyond point cloud. arXiv preprint arXiv:2104.12146, 2021a.

Zhang, J., Chen, L., Ouyang, B., Liu, B., Zhu, J., Chen, Y., Meng, Y., and Wu, D. Pointcutmix: Regularization strategy for point cloud classification. arXiv preprint arXiv:2101.01461, 2021b.

Zhang, S., Wang, H., Gao, J.-g., and Xing, C.-q. Frequency domain point cloud registration based on the fourier transform. Journal of Visual Communication and Image Representation, 61:170–177, 2019.

Zhou, H., Chen, K., Zhang, W., Fang, H., Zhou, W., and Yu, N. Dup-net: Denoiser and upsampler network for 3d adversarial point clouds defense. In Proceedings of the IEEE International Conference on Computer Vision, pp. 1961–1970, 2019.

Zhou, H., Chen, D., Liao, J., Chen, K., Dong, X., Liu, K., Zhang, W., Hua, G., and Yu, N. Lg-gan: Label guided adversarial network for flexible targeted attack of point cloud based deep networks. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 10356–10365, 2020.


### A. Transferability with the Top-1 Error Rate

Table 5. Top-1 error rate of Attacks. We use norm-budgets (max $\ell_\infty$ norm allowed in the perturbation) of $\epsilon_\infty = 0.18$ and $\epsilon_\infty = 0.45$. All the reported results are the untargeted Top-1 error rate (higher numbers are better attacks). **Bold** numbers indicate the most transferable attacks. Our attack consistently achieves better transferability than the other attacks for all networks, especially on PointNet (Qi et al., 2017a). For reference, the classification accuracies on unperturbed samples for networks PointNet, PointNet++, PointConv and DGCNN are 89.3%, 90.7%, 90.6%, and 91.0%, respectively.

| Victim Networks | Attacks | $\epsilon_\infty = 0.18$ |  |  | $\epsilon_\infty = 0.45$ |  |  |
|-----------------|---------|-----------------|---|---|-----------------|---|---|
|                 |         | PointNet        | PointNet++ | PointConv | DGCNN           | PointNet | PointNet++ | PointConv | DGCNN |
| PointNet        | 3D-Adv  | 100             | 12.8       | 10.3      | 12.2            | 100       | 12.6       | 9.78      | 12.1   |
|                 | KNN     | 100             | 17.9       | 11.4      | 17.4            | 100       | 17.5       | 11.3      | 17.0   |
|                 | AdvPC   | 100             | 35.4       | 20.2      | 20.8            | 100       | 35.6       | 20.1      | 20.8   |
|                 | AOF(ours) | 99.9          | 60.7       | 37.6      | 32.7            | 100       | 61.2       | 38.6      | 35.5   |
| PointNet++      | 3D-Adv  | 11.7            | 100        | 12.3      | 13.9            | 12.1      | 100        | 11.8      | 13.5   |
|                 | KNN     | 12.4            | 100        | 12.9      | 14.4            | 12.3      | 100        | 13.2      | 13.9   |
|                 | AdvPC   | 14.4            | 99.2       | 33.0      | 24.7            | 14.4      | 99.2       | 33.1      | 24.8   |
|                 | AOF(ours) | 16.9          | 99.6       | 51.6      | 37.7            | 17.6      | 99.9       | 51.7      | 38.6   |
| PointConv       | 3D-Adv  | 11.8            | 14.3       | 100       | 10.9            | 11.8      | 14.7       | 100       | 11.1   |
|                 | KNN     | 13.3            | 22.7       | 100       | 17.3            | 13.2      | 23.4       | 100       | 17.0   |
|                 | AdvPC   | 15.1            | 39.1       | 99.5      | 23.7            | 15.5      | 39.9       | 99.6      | 23.9   |
|                 | AOF(ours) | 16.5          | 53.4       | 99.9      | 30.6            | 17.0      | 53.0       | 99.8      | 30.8   |
| DGCNN           | 3D-Adv  | 11.1            | 13.6       | 12.4      | 100             | 10.9      | 13.4       | 12.7      | 100    |
|                 | KNN     | 15.0            | 35.4       | 25.6      | 100             | 14.8      | 37.3       | 27.2      | 100    |
|                 | AdvPC   | 16.6            | 62.2       | 47.8      | 93.7            | 16.8      | 62.4       | 47.5      | 93.6   |
|                 | AOF(ours) | 22.3          | 70.6       | 60.8      | 96.7            | 24.6      | 70.1       | 61.1      | 96.7   |

### B. The Transferability of Targeted Attacks

As shown in Table 6, the transferability of targeted attack are much lower than untargeted attack, and our AOF has a comparable targeted transferability with kNN. Improving the transferability of targeted attack is a challenging but promising task. From Table 7, in terms of misclassification rate, our AOF still outperforms the other baselines when transfer to different networks.

Table 6. Transferability of Targeted Attacks. Here, we pick $\epsilon_\infty = 0.18$, $m = 100$, $\gamma = 0.25$ and select DGCNN as victim model. Other settings are the same as Sec 4.1. We use the targeted attack success rate (higher indicates better attacks) to evaluate the transferability.

| Model | PointNet | PointNet++ | DGCNN | PointConv |
|-------|----------|------------|-------|-----------|
| 3D-Adv | 0.16     | 0.73       | **99.76** | 0.69      |
| kNN   | **3.32** | **4.05**   | 75.85  | 3.16      |
| AdvPC | 1.01     | 1.90       | 76.56  | 1.70      |
| AOF   | 2.39     | 3.28       | 77.17  | **3.52**  |

### C. The Attack Transferability under Defense

Motivated by the impressive performance of our AOF under defenses, we also test the transferability of untargeted attack under defense. The results are shown in Table 8. Our AOF is significantly better than SOTA 3D adversarial attacks under various defenses. The results are impressive because the previous attack algorithm is difficult to be transferred under the defense. The results further validate the effectiveness of our AOF.
Table 7. Classification Accuracy (smaller indicates better results) of different models on targeted adversarial samples. Here, we pick $\epsilon_\infty = 0.18$, $m = 100$, $\gamma = 0.25$ and select DGCNN as victim model. Other settings are the same as Sec 4.1. In terms of misclassification rate, our AOF outperforms the other baselines when transferred to different networks.

| Model     | PointNet | PointNet++ | DGCNN | PointConv |
|-----------|----------|------------|-------|-----------|
| 3D-Adv    | 84.12    | 44.37      | 0.04  | 52.84     |
| kNN       | 71.72    | 49.07      | 8.06  | 47.08     |
| AdvPC     | 60.04    | 20.81      | 3.77  | 20.00     |
| AOF       | **53.60**| **13.56**  | 3.85  | **13.16** |

Table 8. Averaged transferability under various defense methods on Pointnet++ (Qi et al., 2017b), Pointnet (Qi et al., 2017a), DGCNN (Wang et al., 2019) and PointConv (Wu et al., 2019). The ConvNet-Opt, ONet-Remesh and ONet-Opt are three variants of IF-Defense.

| Victim models | Attacks | No defense | SRS | SOR | DUP-Net | ConvNet-Opt | ONet-Remesh | ONet-Opt |
|---------------|---------|------------|-----|-----|---------|-------------|-------------|----------|
| PointNet      | 3D-Adv  | 3.8        | 23.2| 4.40| 7.40    | 10.6        | 23.3        | 13.1     |
|               | kNN     | 8.5        | 27.4| 6.2 | 9.4     | 11.1        | 23.7        | 13.7     |
|               | AdvPC   | 19.6       | 42.3| 11.1| 14.3    | 12.5        | 26.0        | 15.0     |
|               | AOF     | **39.6**   | **63.9**| **33.5**| **35.5**| **25.0**    | **35.9**    | **25.3** |
| PointNet++    | 3D-Adv  | 4.3        | 16.0| 5.60| 9.40    | 8.80        | 19.4        | 10.5     |
|               | kNN     | 5.3        | 15.4| 5.8 | 9.1     | 8.3         | 19.2        | 10.7     |
|               | AdvPC   | 17.3       | 29.0| 16.0| 19.8    | 16.1        | 23.5        | 17.1     |
|               | AOF     | **29.8**   | **40.5**| **28.2**| **30.4**| **23.9**    | **28.7**    | **22.5** |
| PointConv     | 3D-Adv  | 3.7        | 22.3| 6.00| 8.80    | 9.60        | 20.2        | 12.2     |
|               | kNN     | 10.1       | 26.9| 13.7| 16.2    | 10.0        | 21.2        | 12.7     |
|               | AdvPC   | 19.1       | 39.3| 23.7| 24.8    | 16.7        | 25.9        | 17.1     |
|               | AOF     | **27.4**   | **46.0**| **33.0**| **34.3**| **22.5**    | **29.3**    | **21.3** |
| DGCNN         | 3D-Adv  | 4.3        | 25.2| 8.70| 11.3    | 10.1        | 19.4        | 11.9     |
|               | kNN     | 18.7       | 34.5| 23.1| 26.4    | 9.9         | 19.8        | 12.4     |
|               | AdvPC   | 37.3       | 48.9| 35.3| 36.1    | 24.4        | 27.0        | 23.0     |
|               | AOF     | **47.3**   | **55.9**| **45.2**| **46.6**| **35.0**    | **39.9**    | **30.9** |

D. The Performance of Targeted Attacks under Defense.

To evaluate the performance of targeted attacks under various defenses. Firstly, we adopt 1 - accuracy to evaluate the untargeted robustness of attacks. From Table 9, it is clear that AOF outperforms other SOTA attacks by a large margin. Then we assess the targeted robustness of attacks using targeted attack success rate. As shown in Table 10, our AOF outperforms other SOTA attacks under IF-Defense and reaches the second best position under SRS, SOR and DUP defenses.

E. Complementing Effect of AOF

In principle, our AOF is compatible with other transfer-based 3D black-box adversarial attacks. We can integrate the AOF with AdvPC. In this section, the victim model is PointNet, and we pick $\epsilon_\infty = 0.18$. Other experimental settings are the same as Sec 4.1. The experiment results are shown in Table 11. The AdvPC-AOF constructed by applying AdvPC to AOF, achieves the SOTA transferability.

F. Spectral Analysis of Perturbation

We found that the transferability to PointNet of attack algorithm is relatively lower than other networks. In order to briefly explore the cause of this phenomenon, we do a simple spectral analysis of the adversarial perturbation from different networks. We first get the spectral weight of perturbation by projecting the perturbation to the eigenvectors of Laplacian matrix of original point cloud. Then we calculate the cumulative distribution of spectral weights for each adversarial sample.
Table 9. In this table, we evaluate the performance of targeted attacks under different defenses using 1 - accuracy (higher indicates better attacks). We pick $\epsilon_\infty = 0.18$, $m = 100$, $\gamma = 0.25$ and select DGCNN as victim model. Other settings are the same as Sec 4.1. Our AOF consistently and significantly outperforms other SOTA attacks. The ConvNet-Opt, ONet-Remesh and ONet-Opt are three variants of IF-Defense.

| Defenses    | 3D-Adv | kNN   | AdvPC | AOF   |
|-------------|--------|-------|-------|-------|
| No defense  | 99.76  | 91.94 | 96.23 | 96.15 |
| SRS         | 54.42  | 71.11 | 88.02 | 91.26 |
| SOR         | 27.92  | 54.78 | 75.47 | 85.63 |
| DUP-Net     | 29.58  | 51.66 | 71.90 | 83.16 |
| ConvNet-Opt | 21.76  | 22.85 | 45.59 | 61.38 |
| ONet-Remesh | 30.27  | 30.19 | 49.51 | 58.46 |
| ONet-Opt    | 24.51  | 25.24 | 41.34 | 51.34 |

Table 10. The attack success rate (higher indicates better attacks) of targeted attacks under different defenses. We pick $\epsilon_\infty = 0.18$, $m = 100$, $\gamma = 0.25$ and select DGCNN as victim model. Other settings are the same as Sec 4.1. Our AOF outperforms other SOTA attacks under IF-Defense and reaches the second best position under SRS, SOR and DUP defenses. The ConvNet-Opt, ONet-Remesh and ONet-Opt are three variants of IF-Defense.

| Defenses    | 3D-Adv | kNN   | AdvPC | AOF   |
|-------------|--------|-------|-------|-------|
| No defense  | 99.76  | 75.85 | 76.56 | 77.17 |
| SRS         | 3.04   | 13.98 | 6.88  | 7.09  |
| SOR         | 1.54   | 22.00 | 8.54  | 14.05 |
| DUP-Net     | 1.38   | 13.25 | 7.04  | 11.38 |
| ConvNet-Opt | 0.57   | 2.84  | 1.09  | 4.66  |
| ONet-Remesh | 0.85   | 1.62  | 1.05  | 1.98  |
| ONet-Opt    | 0.65   | 1.94  | 1.01  | 2.91  |

Table 11. The attack success rate of AdvPC-AOF.

| Method     | PointNet | PointNet++ | DGCNN | PointConv |
|------------|----------|------------|-------|-----------|
| AdvPC      | 100      | 30.4       | 13.6  | 14.8      |
| AOF        | 98.7     | 58.2       | 32.7  | 28.1      |
| AdvPC-AOF  | 100      | 67.1       | 44.6  | 35.9      |

Finally, we compute the average of the cumulative distributions of all adversarial samples to get the averaged spectral weight cdf for a specific victim model in Figure 7. As shown in Figure 7, The spectral weight cdf curve of PointNet is obviously different from that of PointNet++, PointConv and DGCNN. The perturbation of PointNet has a higher proportion of LFC than PointNet++ and DGCNN, maybe that’s the reason why it is harder to transfer to PointNet than PointNet++, PointConv and DGCNN.
Figure 7. The spectral analysis of adversarial perturbation.