Improving Transformation-based Defenses against Adversarial Examples with First-order Perturbations

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Abstract—Deep neural networks have been successfully applied in various machine learning tasks. However, studies show that neural networks are susceptible to adversarial attacks. This exposes a potential threat to neural network-based intelligent systems. We observe that the probability of the correct result outputted by the neural network increases by applying small first-order perturbations generated for non-predicted class labels to adversarial examples. Based on this observation, we propose a method for counteracting adversarial perturbations to improve adversarial robustness. In the proposed method, we randomly select a number of class labels and generate small first-order perturbations for these selected labels. The generated perturbations are added together and then clamped onto a specified space. The obtained perturbation is finally added to the adversarial example to counteract the adversarial perturbation contained in the example. The proposed method is applied at inference time and does not require retraining or finetuning the model. We experimentally validate the proposed method on CIFAR-10 and CIFAR-100. The results demonstrate that our method effectively improves the defense performance of several transformation-based defense methods, especially against strong adversarial examples generated using more iterations.

Index Terms—Adversarial examples, first-order perturbations, inference-time defenses.

I. INTRODUCTION

Deep neural networks have become the dominant approach for various tasks including image understanding, natural language processing and speech recognition [1], [2], [3], [4]. They can approximate highly complex functions through a number of linear (e.g., convolution) and nonlinear (e.g., ReLU activation) operations [5]. However, research shows that neural networks are vulnerable to adversarial examples [6], [7]. That is, these network models make an incorrect prediction with high confidence for inputs that are only slightly different from correctly predicted examples. This exposes a potential threat to neural network-based intelligent systems, many of which have been widely deployed in real-world applications.

The adversarial vulnerability of neural networks reveals fundamental blind spots in the learning algorithms [7]. Even with advanced learning techniques, neural networks are not learning the genuine underlying distribution of the training data, although they can obtain extraordinary performance on test sets. This phenomenon has now attracted much research effort. There have been increasing studies attempting to explain neural networks’ adversarial vulnerability and develop methods to defend against adversarial attacks [8], [9], [10].

While some progress has been made, most existing studies remain preliminary. Because it is difficult to construct a theoretical model to explain the adversarial perturbation generating process, defending against adversarial attacks is still a challenging task.

Existing methods of resisting adversarial perturbations perform defense either at training time or inference time [10]. Training time defense methods attempt to increase model capacity to improve adversarial robustness. One of the commonly used methods is adversarial training [6], in which a mixture of adversarial and clean examples are used to train the neural network. The adversarial training method can be seen as minimizing the worst case loss when the training example is perturbed by an adversary [7]. Adversarial training requires an adversary to generate adversarial examples in the training procedure. This can significantly increase the training time. Adversarial training also results in reduced performance on clean examples. Lamb et al. [11] recently introduced interpolated adversarial training that incorporates interpolation-based training into the adversarial training framework. This method helps to improve performance on clean examples while maintaining adversarial robustness.

For inference time defenses, the main idea is to transfer adversarial perturbations such that the obtained inputs are no longer adversarial. Tabacof et al. [12] studied the use of random noise such as Gaussian noise and heavy-tail noise to
resist adversarial perturbations. [13] introduced to apply two randomization operations, \textit{i.e.}, random resizing and random zero padding, to inputs to improve adversarial robustness. Guo \textit{et al.} [14] investigated the use of random cropping and rescaling to transfer adversarial perturbations. More recently, Pang \textit{et al.} [10] proposed the mixup inference method that uses the interpolation between the input and a randomly selected clean image for inference. This method can shrink adversarial perturbations to some extent by the interpolation operation. Inference time defense methods can be directly applied to off-the-shelf network models without retraining or finetuning them. These methods are much efficient as compared to training time defenses.

Though adversarial perturbations are not readily perceivable by a human observer, it is suggested that adversarial examples are outside the natural image manifold [15], [16]. Previous studies have suggested that the adversarial vulnerability is caused by the locally unstable behavior of classifiers on data manifolds [17], [18]. Pang \textit{et al.} [10] also suggested that adversarial perturbations have the locality property and could be resisted by breaking the locality. Existing inference time defense methods mainly use stochastic transformations such as mixup and random cropping and rescaling to break the locality. Strong adversaries, like projected gradient descent (PGD) [8], use the input’s first order information to find the adversarial perturbation. Because deep networks usually have a large number of parameters, the adversarial perturbation could overfit to input and therefore could be resisted by applying proper perturbations. We observe that applying small first-order perturbations generated for non-predicted categories to the adversarial example helps to counteract the adversarial effect, an illustration is shown in Fig. 1.

Motivated by this observation, we propose a method that uses first-order perturbations to counteract adversarial perturbations. In the proposed method, we generate small first-order perturbations using local gradient information for a number of randomly selected class labels. These small perturbations are added together and then projected onto a specified space before finally applying to the adversarial example. Our method can be used as a preliminary step before applying existing transformation-based defense methods.

Unlike random transformations, the proposed method employs the linear nature of neural networks, which is the primary cause of neural networks’ vulnerability to adversarial perturbation [7]. As far as we know, this is the first research on using local first-order gradient information to resist adversarial perturbations. We focus on defending against iterative optimization-based attacks. We show through experiments that our method is effective and complementary to random transformation-based defense methods to improve the overall defense performance.

The contributions of this paper can be summarized as follows:

- We propose a method that uses first-order perturbations generated for non-predicted categories for resisting adversarial examples. This is the first research that employs the linear nature of neural networks for transferring adversarial perturbations. Our method is applied at inference time and complementary to existing transformation-based defenses for defending against adversarial attacks.
- We evaluate our method on CIFAR-10 and CIFAR-100 against PGD attacks in different settings. The experimental results demonstrate that our method significantly improves the defense performance of three baseline methods against both untargeted and targeted attacks and that our method performs well in resisting strong adversarial examples generated using more iterations.

II. RELATED WORK

Szegedy \textit{et al.} [6] first identified that neural networks can be caused to misclassify an input by applying a small barely perceptible perturbation, which is obtained by maximizing the network’s prediction error. This attracted increasing research interests on studying neural networks’ vulnerability to adversarial perturbation. Early attempts have suggested this phenomenon is due to the highly nonlinearity of deep networks, possibly together with insufficient model ensemble and insufficient regularization of the supervised learning issue. Goodfellow \textit{et al.} [7] instead suggested that the primary cause of neural networks’ adversarial vulnerability is their linear property. Fawzi \textit{et al.} [19] demonstrated that for linear and quadratic classifiers, there exist adversarial perturbations that cause misclassification of $O(1/\sqrt{d})$, where $d$ is the dimension of input data. Fawzi \textit{et al.} [20] further studied adversarial vulnerability under the assumption that data are generated with a smooth generative model and derived upper bounds on the adversarial robustness for any classification functions.

Meanwhile, many defense methods have been proposed to improve the neural networks’ robustness to adversarial perturbations. These methods can be categorized into training time defenses or inference time defenses. The first approach focuses on improving models’ capability by using improved learning algorithms and regularization techniques, possibly employing knowledge about the adversary’s attack strategy [6], [11]. The second approach focuses on applying transformations to the input to resist adversarial perturbations. This approach is also referred to as transformation-based defenses [21].

For training time defenses, adversarial training [6] is one of the most successful methods. In adversarial training, a mixture of adversarial and clean examples are used to train the neural network. Mardy \textit{et al.} [8] formulated adversarially robust training of neural networks as the saddle point problem:

$$\min_{\theta} \rho(\theta), \text{where } \rho(\theta) = \mathbb{E}_{(x,y) \sim D} \left[ \max_{\delta \in \mathcal{S}} L(\theta, x + \delta, y) \right],$$

(1)

where $\theta$ denotes the parameters of the neural network and $\mathcal{S}$ is the allowed set for perturbations. The inner maximization aims to find an adversarial version of data point $x$ that achieves a high loss, while the outer minimization aims to find model parameters such that the adversarial loss given by the inner attack problem is minimized. Even though the inner maximization is non-concave, it has been shown that first-order adversaries can be reliably used to solve the saddle point problem for training robust networks. Lamb \textit{et al.} [11] proposed the interpolated adversarial training (IAT) method...
that integrates interpolation-based training into the adversarial training framework. In IAT, interpolated adversarial examples and interpolated clean examples are used for training network models. Compared with vanilla adversarial training, IAT can achieve high accuracy on clean examples while maintaining adversarial robustness.

There also have been studies that introduce additional losses and regularization to enhance the robustness of adversarially trained models. Li et al. [22] proposed the adversarial training with triplet loss method, which incorporates distance metric learning into adversarial training to provide further regularization to improve the adversarial robustness. Pang et al. [23] introduced to employ the hypersphere embedding mechanism in adversarial training to map features into compact manifolds to resist adversarial perturbations. Yan et al. [24] proposed to incorporate a perturbation-based regularization into the objective function to improve the adversarial robustness.

Inference time defenses attempt to remove or transfer adversarial perturbations from inputs and therefore are model-agnostic. Prakash et al. [25] proposed the pixel deflection method that corrupts adversarial perturbations by applying locally redistributed pixels. This method iteratively selects a random pixel and replaces it with another randomly selected pixel in a local neighborhood. Xie et al. [26] introduced the random resize and padding method for the defense purpose. Each image is first resized to a random size and then padded with zeroes to a fixed size in a random manner before feeding to the network. Guo et al. [14] investigated transformations including cropping and rescaling, bit-depth reduction, JPEG compression, total variance minimization, and image quilting for resisting adversarial attacks. Kou et al. [21] observed that clean images and adversarial images after applying transformations result in similar distributions after the softmax layer and proposed to train a separate distribution classifier to differentiate the softmax outputs of transformed inputs. This method is effective in resisting targeted attacks and also shows improved performance for clean inputs.

III. PRELIMINARIES

A. Adversarial Examples

We consider a neural network \( f(\cdot) \) with parameters \( \theta \) that outputs a vector of probabilities for \( L = \{1, 2, ..., l\} \) categories. In supervised learning, empirical risk minimization (ERM) [27] has been commonly used as the principle to optimize the parameters on a training set. Given an input \( x \), the neural network makes a prediction:

\[
c(x) = \arg \max_{j \in L} f(x; \theta)_j,
\]

where \( f(\cdot)_j \) denotes the \( j \)-th component of the output. The prediction is correct if \( c(x) \) equals to the actual target \( c^*(x) \).

Unfortunately, neural networks trained using the ERM principle are vulnerable to adversarial examples, inputs formed by applying small but intentionally crafted perturbations [6], [8]. That is, an adversarial example \( x' \) is close to a clean example \( x \) under a distance metric \( D \), but the neural network outputs an incorrect result for the adversarial example \( x' \) with high confidence. In most cases, the difference between the adversarial example and clean example is not readily recognizable to humans. In this paper, we use \( \ell_\infty \) in normalized \([0, 1]\) space as the distance metric, that is a distance of 0.016 corresponds to 4/255.

B. Attack Methods

Existing attack methods can be categorized into white-box attacks and black-box attacks. We focus on defending against white-box attacks, wherein the adversary has full access to the network model including the architecture and parameters. Most white-box attacks craft adversarial examples based on the input gradients. The fast gradient sign (FGSM) method [7] and PGD are two successful optimization-based attack methods.

The FGSM method is a one-step attack method. This method generates adversarial perturbations that yield the highest loss increase in the gradient sign direction. Let \( x \) be the input to a network model, \( y \) the label associated with \( x \) and \( L(\theta, x, y) \) be the loss function for training the neural network. The FGSM method generates a max-norm constrained perturbation as follows:

\[
\eta = \epsilon \text{sign}(\nabla_x L(\theta, x, y)),
\]

where \( \epsilon \) denotes the max-norm. This method was developed based on the view that the main cause of neural networks’ adversarial vulnerability is their linear nature. The required gradient can be computed efficiently using backward propagation.

The PGD method is a multistep attack method that iteratively applies projected gradient descent on the negative loss function [23] as follows:

\[
x^{t+1} = \Pi_{x+S}(x^t + \alpha \text{sign}(\nabla_x L(\theta, x^t, y))),
\]

where \( \alpha \) denotes the step size and \( \Pi \) denotes the projection operator that projects the perturbed input onto \( x + S \). We consider projecting the perturbed input onto a predefined \( \ell_\infty \) ball from the original input. The PGD attack method can be seen as a multistep FGSM method. It is a much stronger adversary that reliably causes a variety of neural networks to misclassify their input.

IV. METHODOLOGY

While many methods have been proposed to defend against adversarial attacks at inference time, these methods have not considered using local gradient information to resist adversarial perturbations. It has been suggested that the primary cause of neural networks’ adversarial vulnerability is their linear nature [7]. It would be more effective to employ the use of first-order gradient information to counteract adversarial perturbations such that the counteracted perturbations no longer result in the model making an incorrect prediction.

Adversarial perturbations are small crafted perturbations that slightly affect the visual quality of inputs but cause the neural network to misclassify the inputs in favor of an incorrect answer with high probability. As illustrated in Fig. 1 the prediction probability for the correct category increases and
Algorithm 1 Resisting adversarial perturbations with first-order perturbations.

Input: Network model $f$; input $x$; step size $\alpha$ used in PGD to generate perturbations to counteract the adversarial perturbation.

Output: Prediction result for $x$.

1: Randomly select $N$ class labels \{l_1, l_2, ..., l_N\};
2: for $i = 1$ to $N$ do
3: \[ \eta_i = PGD(l_i, \alpha, \text{step}=1) \] // generate perturbation $\eta_i$ for $l_i$ using the one-step PGD method.
4: end for
5: $x = x + \Pi_C(\sum_{i=1}^{N} \eta_i(x))$ // $C$ is a $\ell_\infty$ bounded space.
6: $x = \text{clip}(x, \min = 0, \max = 1.0)$
7: return $f(x)$.

that for the incorrect categories is suppressed by adding small perturbations generated for for non-predicted labels to the input. For an input $x$ with label $l_x$, let $x_{adv}$ be the adversarial example for $x$ and $l_{adv}$ is the prediction made by the neural network. This phenomenon can be formulated as follows:

\[
\begin{align*}
    f(x_{adv} + \eta_j)_{l_{adv}} &< f(x_{adv})_{l_{adv}}, \\
    f(x_{adv} + \eta_j)_{l_x} &> f(x_{adv} + \eta_j)_{l_x},
\end{align*}
\]

where $\eta_j$ is a perturbation generated for category $j$ subject to $j \neq l_{adv}$.

Based on this phenomenon, we propose a method for counteracting adversarial perturbations to improve adversarial robustness, specifically targeting defense against first-order adversaries. In the proposed method, we generate small first-order perturbations for a number of randomly selected class labels and apply these perturbations to the input to resist the adversarial perturbation. Let $x$ be the input to a model, which can be an adversarial or clean example. We randomly select $N$ class labels and generate small first-order perturbations for the $N$ selected labels. These $N$ small perturbations are aggregated together and then projected onto a $\ell_\infty$-bounded space before applying to the input. This procedure can be formulated as follows:

\[
\hat{x} = x + \Pi_C(\sum_{i=1}^{N} \eta_i(x)),
\]

where $\eta_i(x)$ denotes the small perturbation generated for the $i$-th selected class label, $C = \{t \mid ||t - x||_\infty \leq \mu\}$ is a $\mu$ bounded $\ell_\infty$ space. In this work, we use the one-step PGD method to generate first-order perturbations. This is the same as using the FGSM method and empirically achieves better performance than using multiple steps. The perturbations can be generated in an untargeted or targeted manner. The combined perturbation is projected onto the space $C$. This ensures that the obtained example is visually similar to the original one. We detail our method for counteracting adversarial perturbations in Algorithm 1 and a schematic illustration of the algorithm is shown in Fig. 2.

Discussion and Analysis Adversarial examples exposes underlying flaws in the learning algorithms. While much progress has been made in defending against adversarial attacks, it is difficult to theoretically understand neural networks’ vulnerability to adversarial examples. Previous work [29] has suggested that the adversarial perturbation $\delta$ can be obtained by solving the following optimization problem:

\[
\begin{align*}
    \min \quad & ||\delta||_p \\
    \text{s.t.} \quad & c(x + \delta) \neq c^*(x), ||\delta||_p \leq \xi,
\end{align*}
\]

where $\xi$ is a hyperparameter constraining the size of the perturbation. Optimization-based attack methods, such as PGD and FGSM, can reliably cause a wide variety of models to make an incorrect prediction. These attack methods primarily use local first-order gradient to find the optimal solution. Because neural networks, especially deep networks, are usually over-parameterized, perturbations obtained with these attack methods could overfit to the inputs. Therefore, perturbing and transferring these adversarial perturbations could be an effective way to resist the adversarial effect. Unlike random transformation-based methods, we employ the use of local first-order gradient information to counteract the adversarial effect. We show that the proposed method is effective in improving defense performance, especially against strong adversarial examples generated using more iterations.

Let $x_0$ be a clean example and $\delta$ be the adversarial perturbation. In our method, the following input is fed to the neural network:

\[
x_0 + \delta \cdot 1_{z(x_0)} + \Pi_C(\sum_{i=1}^{N} \eta_i(x_0)),\]

where

\[
1_{z(x_0)} = \begin{cases} 
0, & x_0 \text{ is not subject to adversarial attack}, \\
1, & x_0 \text{ is subject to adversarial attack}. 
\end{cases}
\]

The perturbation $\eta_i$ generated to counteract the adversarial perturbation should be small, otherwise it would be a new adversarial perturbation. This would essentially have no effect in suppressing the adversarial effect. Adversarial training that has been shown to be effective to improve adversarial robustness usually employs a first-order adversarial like PGD.
to provide adversarial examples in the training procedure. These adversarial examples help to regularize the model to be resistant to adversarial perturbations. We show through experiments that our method is complementary to adversarial training to improve overall defense performance against both untargeted and targeted attacks.

The proposed method is applied at inference time, it can be efficiently applied without retraining or finetuning the models. The required gradient for generating small perturbations can be computed efficiently in parallel using backward propagation. This would not increase much time for inference. Moreover, our method can be applied in combination with existing transformation-based methods to improve the overall defense performance.

V. EXPERIMENTS

This section provides experimental evaluations on the proposed method. We first introduce the setup for our experiments and then present the quantitative results on adversarial examples and clean examples and analysis of the impact of the hyperparameters.

A. Experimental Setup

The experiments are conducted on CIFAR-10 and CIFAR-100 [33], each consists of 50000 training images and 10000 test images. The images are categorized into 10 and 100 classes respectively. ResNet-50 [11] is used as the network model. We validate the proposed method on models trained using two methods: Mixup [30] and IAT [11]. For fair performance comparison, we follow the same experimental setup as [10] to train the models. The training procedure is performed for 200 epochs with a batch size of 64. The learning rate is initialized to 0.1 and divided by a factor of 10 at epoch 100 and 150. The values for interpolation are sampled from Beta(1, 1) for both Mixup and IAT. The ratio between clean examples and adversarial examples used in IAT is set to 1:1. The untargeted PGD\(_{10}\) method with a step size of 2/255 and \(\varepsilon\) set to 8/255 is used to generate adversarial examples in IAT.

We experiment against both untargeted and targeted PGD attacks with different iterative steps. The values of \(\varepsilon\) and step size for the PGD attacks are set to 8/255 and 2/255, respectively. The one-step PDG method is used to generate perturbations to counteract the adversarial perturbation. Unless stated otherwise, perturbations used for defense purposes are generated in a targeted fashion. The step size for the one-step PGD and number of randomly selected class labels are set to 4/255 and 9, respectively. The value of \(\mu\) is set to 8/255. We run each defense for 30 times and compute the average accuracy as the defense performance. Our method is implemented in Pytorch [32] and all experiments are conducted on one GPU.

Baseline Methods Three recently proposed transformation-based defense methods are used as baselines. These three methods are Xie et al.’s [13], Guo et al.’s [14] and MI-OL (mixup inference with non-predicted labels) [10]. We compare the performance our method and the baselines and report the improvements over the baselines in resisting adversarial examples. We also report the performance of using general-purpose random transformations, i.e., applying Gaussian noise or random rotation [12].

B. Experimental Results

We validate the proposed method against white-box attacks, where the adversary has full access to the network model including the architecture and weights. We test the defense performance of our method on the entire test set. Table I and Table II report the quantitative results on CIFAR-10 and CIFAR-100, respectively, demonstrating the effectiveness
of the proposed method in resisting adversarial examples. We see from Table I that the proposed method significantly helps to improve defense performance of the baseline methods against untargeted attacks, achieving at least 12.5% and 4.1% performance gains for the Mixup trained model and IAT trained model, respectively. For defending against targeted attacks, the proposed method performs well in combination with Xie et al.’s and Guo et al.’s for the Mixup trained model, and it performs well together with Xie et al.’s for the IAT trained model. It can be seen from Table I that, as with on CIFAR-10, the proposed method also helps improve the defense performance against untageted attacks on CIFAR-100, achieving at least 6.4% and 1.6% performance gains for the Mixup trained model and IAT trained model, respectively. For defending against targeted attacks, our method consistently helps to improve the defense performance when applied with Xie et al.’s and Guo et al.’s methods. We can also make the following three observations from the quantitative results.

1) In most cases, the proposed method helps improve the defense performance of the baseline methods. Especially for untargeted attacks in different settings, our method significantly improves the defense performance. This shows that our method is complementary to the baselines to resist adversarial perturbations. Among the three baseline methods, the joint use of our method with Xie et al.’s and Guo et al.’s methods performs well compared to with the MI-OL method. This could be because the perturbations used to counteract the adversarial perturbation are reduced due to the interpolation operation in MI-OL. Our method employs the linear nature of neural networks, which the adversaries use to generate adversarial perturbations, therefore our method transfer the adversarial perturbations more directly than other transformation-based methods.

2) The proposed method performs well against strong PGD attacks with more iterative steps. Previous studies show that adversarial perturbations generated using more iterative steps are more difficult to resist. The results of the baselines also show that PGD attacks with more iterations result in reduced performance. It is worth noting that the proposed method achieves improved performance for defending against most strong PDG attacks. And for the remaining attacks, the use of more iterations results in comparable performance as the use of less iterations. The results suggest strong adversarial perturbations generated using more iterations are offset to the inputs, and the strong adversarial perturbations can be easily counteracted using first-order perturbations.

3) For defending against targeted PGD methods and PGD methods on CIFAR-10, our method together with Guo et al.’s on the Mixup trained model achieve higher performance than those obtained on the IAT trained model, improving the classification accuracy 1.4% and 3.2%, respectively. Overall, our method together with Guo et al.’s achieves better or comparable performance than the vanilla IAT trained model. As far as we know, we are the first to outperform pure adversarial training-obtained models using only inference time defense methods. This shows that it is promising that adversarial training could be unnecessary if proper perturbations are applied to adversarial examples. Note that the baseline methods are evaluated against 1,000 randomly sampled examples from the test set [10], whereas our method is evaluated against all the test samples. From this we can see that our method is consistent in improving the overall defense performance.

Next, we analyse the impact of the step size used in the one-step PGD method on the defense performance. We experiment on CIFAR-10 and CIFAR-100 against both untargeted and targeted PGD attacks. The experimental results are reported in Figure 3. We see that the step size affects differently for untargeted and targeted attacks. The performance improves as...
Fig. 3: Impact of the size of perturbations generated for defense purposes on classification accuracy (%). We report performance of resisting both untargeted and targeted PGD_{10} attacks.

Fig. 4: Impact of the number of randomly selected class labels in our method on classification accuracy (%). We report performance of resisting both untargeted and targeted PGD_{10} attacks.

Fig. 5: Samples of aggregated first-order perturbations and adversarial examples with the aggregated first-order perturbations on CIFAR10. The adversarial examples are crafted using untargeted PGD with $\alpha = 2/255$ and 10 iterations.

the step size increases from 1 to 8 for untargeted tasks on the two datasets. For targeted attacks, the performance improves as the step size increases from 1 to 4 but starts to reduce or maintain similar performance as the step size further increases.

We also analyse the impact of the number of randomly selected class labels in our method on the defense performance. Figure 4 demonstrates the results of resisting untargeted and targeted PGD_{10} attacks on CIFAR-10 and CIFAR-100. We see that the performance improves for both untargeted and targeted attacks as the number increases from 1 to 9 on CIFAR-10. On CIFAR-100, the performance also improves as the number increases from 1 to 9 but begins to drop or remain similar as the number further increases.

**Discussion on the type of defense perturbations** In our experiments, the small perturbations used to counteract the adversarial perturbation are generated in a targeted manner other
Fig. 6: Samples of aggregated first-order perturbations and adversarial examples with the aggregated first-order perturbations CIFAR100. The adversarial examples are crafted using untargeted PGD with $\alpha = 2/255$ and 10 iterations.

TABLE III: Classification accuracy (%) of different method used in combination with Guo et al.’s (2018). We report performance of resisting targeted attacks on Mixup trained models.

| Method | CIFAR-10 (PGD) | CIFAR-10 (PGD) | CIFAR-10 (PGD) | CIFAR-10 (PGD) |
|--------|----------------|----------------|----------------|----------------|
| Guo’s [14] | 57.8 | 49.1 | 48.9 | 53.3 |
| Gaussian noise + Guo’s [14] | 63.9 | 63.8 | 63.3 | 40.8 |
| Random rotation + Guo’s [14] | 63.8 | 63.6 | 63.2 | 40.8 |
| Xie’s [13] + Guo’s [14] | 59.1 | 58.3 | 58.2 | 41.1 |
| MI-OL [10] + Guo’s [14] | 62.9 | 62.6 | 65.1 | 37.6 |
| Ours + Guo’s [14] | 74.1 | 78.0 | 79.8 | 50.8 |

TABLE IV: Classification accuracy (%) on clean examples.

| Method | CIFAR-10 | CIFAR-10 |
|--------|----------|----------|
| ResNet-50 (w/o defense) | 93.8 | 89.7 |
| Xie’s [13] | 82.1 | 82.1 |
| Guo’s [14] | 83.3 | 83.9 |
| MI-OL [10] | 83.9 | 84.2 |
| Ours (targeted perturbations) | 61.2 | 75.3 |
| Ours (untargeted perturbations) | 87.1 | 88.3 |

than for targeted attacks on the IAT trained model on CIFAR-100, the small perturbations are generated in an untargeted manner. On the whole, untargeted adversarial perturbations can be effectively counteracted using first-order perturbations generated in a targeted manner with our method. The results also suggest that adversarial training has an unstable behavior for different data distributions.

**Discussion on the number of steps used for generating defense perturbations**

The perturbations for defense purposes are generated using the one-step PGD method. We also experiment using multiple steps to generate perturbations for defense purposes. However, we find that this results in reduced performance in resisting adversarial examples. This could be because the perturbations generated using multiple steps have adversarial effects and they do not help much to counteract the original adversarial perturbation.

To demonstrate the advantage of our method, we further compare the performance of different methods used together with Guo et al.’s. The results of defending against targeted PGD attacks on Mixup trained models are reported in Table III. We see that although these methods, including Xie et al.’s, MI-OL, as well as random rotation and Gaussian noise, are effective in improving performance, our methods outperforms these methods by a large margin, especially when resisting adversarial examples generated with more iterations.

Finally, we evaluate our method on clean examples. Table IV compares the performance of our method and the baseline methods. We see that our method performs differently using different types of perturbations that are generated for defense purposes. Using first-order perturbations generated in an untargeted manner, our method mostly performs very well on clean examples when compared to the baselines.

Fig. 5 and Fig. 6 show samples of adversarial examples, aggregated first-order perturbations and the examples after applying the aggregated first-order perturbations. It can be seen that the difference between the adversarial examples and those after applying the aggregated first-order perturbations is barely perceivable.

**VI. CONCLUSION**

We proposed a method for counteracting adversarial perturbations to resist adversarial examples. In our method, we generate small first-order perturbations for a number of randomly selected class labels and apply these small perturbations to the input to counteract the adversarial perturbation. Unlike previous methods, our method employs the use of local first-order gradient information for defense purposes. Our method is applied at inference time and complementary to the adversarial training method to improve the overall performance. We experimentally validated our method on CIFAR-10 and CIFAR-100 against both untargeted and targeted PGD attacks. We presented extensive results demonstrating our method significantly improves the defense performance of the baseline methods. We showed that our method performs well in resisting strong adversarial perturbations generated using more
TABLE V: Parameter settings for experiments on CIFAR-10. For each experiment, the number of runs is set to 50 for Xie et al.’s \cite{13} and Guo et al.’s \cite{14} and to 30 for MI-OL \cite{30}. [T] denotes small perturbations are generated in a targeted manner and [U] denotes small perturbations are generated in an untargeted manner.

| Method          | Mixup Model          | IAT Model          |
|-----------------|----------------------|--------------------|
| Ours + Xie’s \cite{13} | Defense perturbation type: [T] Random crop size: [22 30] | Defense perturbation type: [T] Random crop size: [26 32] |
| Ours + Guo’s \cite{14} | Defense perturbation type: [T] Random crop size: [22 30] | Defense perturbation type: [T] Random crop size: [24 32] |
| Ours + MI-OL \cite{30} | $\lambda_{OL}=0.5$ | $\lambda_{OL}=0.6$ |

TABLE VI: Parameter settings for experiments on CIFAR-100. For each experiment, the number of runs is set to 50 for Xie et al.’s \cite{13} and Guo et al.’s \cite{14} and to 30 for MI-OL \cite{30}. [T] denotes small perturbations are generated in a targeted manner and [U] denotes small perturbations are generated in an untargeted manner.

| Method          | Mixup Model          | IAT Model          |
|-----------------|----------------------|--------------------|
| Ours + Xie’s \cite{13} | Defense perturbation type: [T] Random crop size: [26 32] for untargeted attack and [24 32] for targeted attack | Defense perturbation type: [T] Random crop size: [26 32] for untargeted attack and [24 32] for targeted attack |
| Ours + Guo’s \cite{14} | Defense perturbation type: [T] Random crop size: [24 32] | Defense perturbation type: [U] Random crop size: [24 32] |
| Ours + MI-OL \cite{30} | $\lambda_{OL}=0.5$ | $\lambda_{OL}=0.6$ |

iterations, demonstrating the advantage of using local first-order gradient to resist adversarial perturbations. Notably, our method together with Guo et al.’s achieved better performance than those obtained on the IAT trained model in resisting targeted PGD$_{50}$ and PGD$_{200}$ attacks. Adversarial training usually requires significant amounts of time for training. Our experimental results show that adversarial perturbations can be effectively counteracted and that it is promising adversarial training could be unnecessary when proper perturbations are applied to the inputs.

VII. ACKNOWLEDGEMENT

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APPENDIX A

The section provides more technical details of our experiments on CIFAR-10 (see Table V) and CIFAR-100 (see Table VI).

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