BlurNet: Defense by Filtering the Feature Maps

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Outline

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Learning the Filter Parameters

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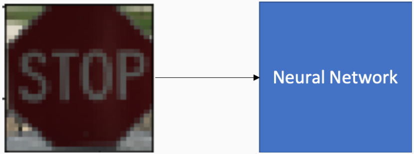
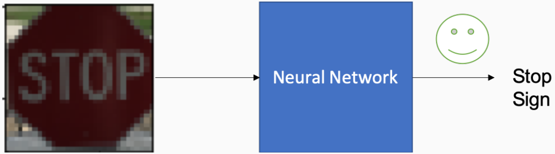
Introduction

Vulnerabilities in NNs



Vulnerabilities in NNs



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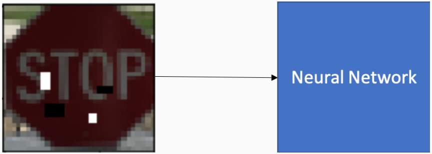

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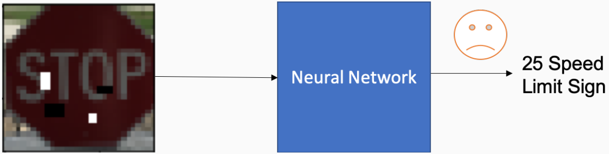
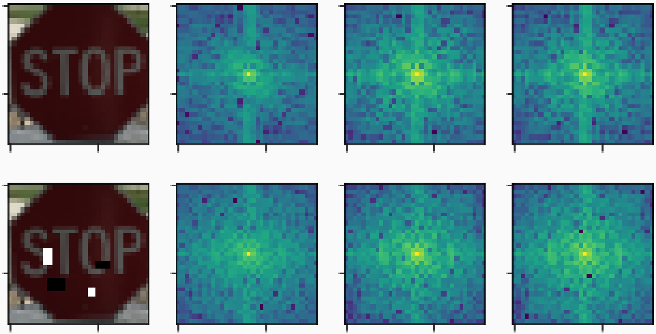


FFT Spectrum of Input Channels



- Log-shifted and normalized frequency spectrum of RGB channels of a natural and perturbed stop sign image

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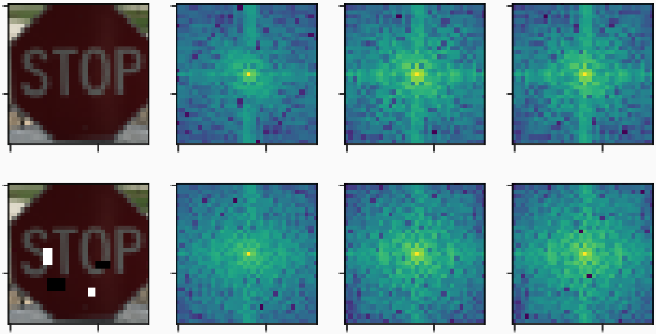
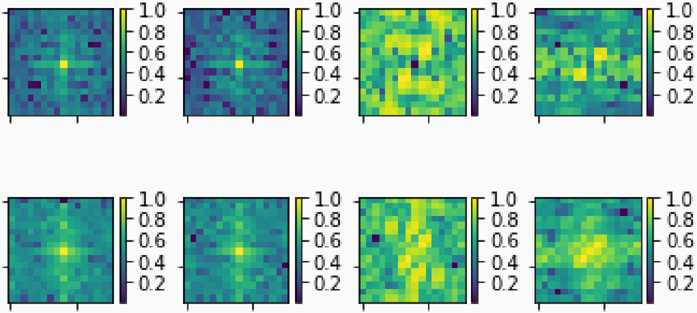


- Log-shifted and normalized frequency spectrum of RGB channels of a natural and perturbed stop sign image
- Lower freqencies correspond to the center and higher ones to the edge.

FFT of First Layer Feature Maps



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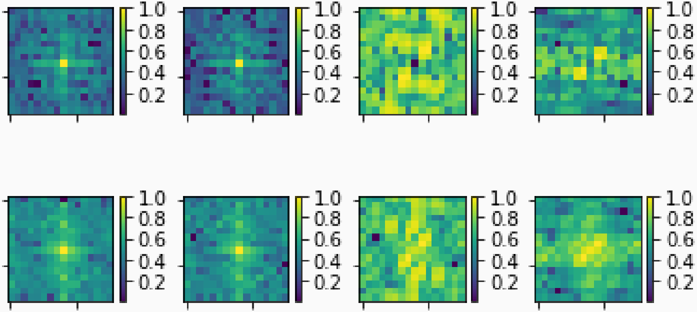

- Each row corresponds to a unique feature map from L1 layer of network.
- Difference image suggests that the perturbations induce high frequency components not found in natural stop signs

Background

Terminology and Preliminaries: Adverserial Robustness

Let x be an image and a neural network, $F(x) = y$, such that $F : \mathbb{R}^{h*w*c} \rightarrow \mathbb{R}$ where y is the correct label.

- Main goal of an attacker - generating an image, x_{adv} such that $F(x_{adv}) \neq y$ by perturbing the input pixels.

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    2. Black-box attacks (Transfer Attacks) - attacker has knowledge of model architecture but not parameters, etc.

Metrics

1. Attack Success Rate - number of predictions altered by an attack, $\frac{1}{N}\sum_{n=1}^{N} \mathbb{1}[F(x_n) \neq F(x_{nadv})]$.

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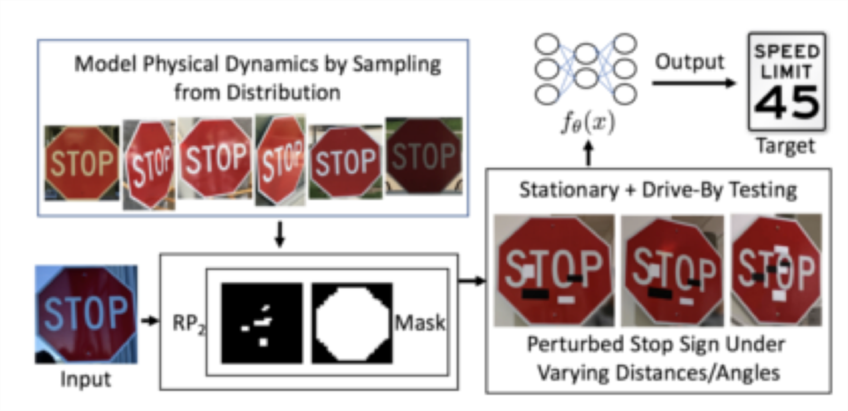
3. An attacker is considered strong if its attack success rate is high while having a low dissimilarity metric.

Attacker: Robust Physical Perturbation (RP_2) Attack



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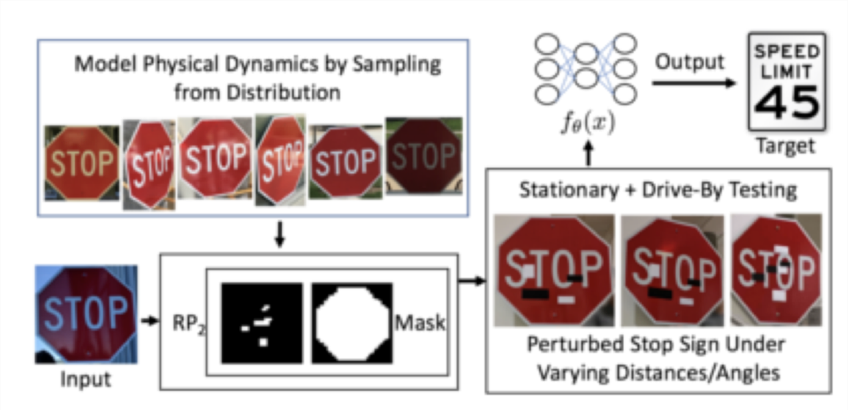


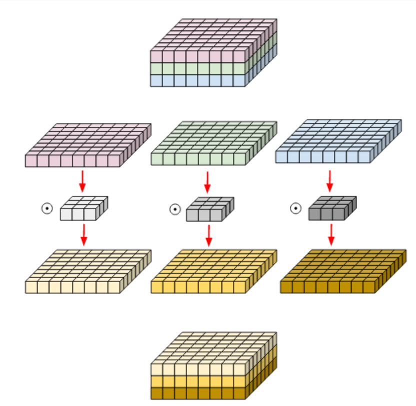
$$\arg\min_{\delta} \quad \lambda \| M_x \cdot \delta \|_p + \mathbb{E}_{x_i \sim X^V} J(f_\theta(x_i + T_i(M_x \cdot \delta)), y^*)$$

Dataset and Model

- Victim model 4-layer CNN
- LISA traffic sign dataset - consider the top 18 classes only
- Attacks focused on victim set of 40 stop signs

Proposal

Low-pass filtering



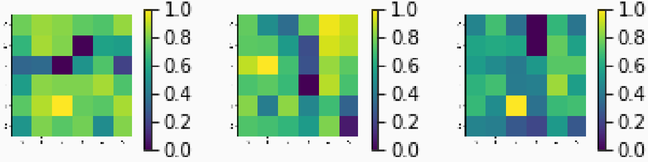
- Induce low-pass filtering with standard blur kernels by inserting a depthwise convolution after the first convolution layer.

Filtering input vs. Filtering Feature Maps

Table 1: Results from black box evaluation

	Accuracy	**Attack Success Rate**
Baseline	100%	90%
Input filter 3x3	100%	87.5%
Input filter 5x5	100%	67.5%
3x3 filter on L1 feature maps	100%	65%
5x5 filter on L1 feature maps	87.5%	17.5%

Filtering in the higher layers



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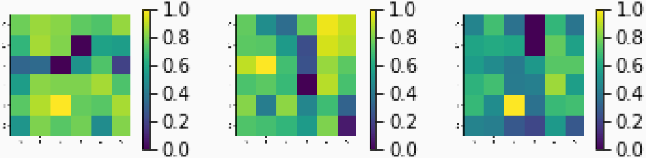

1. The FFT Spectrum of a subsampling of feature maps from the second layer of the network.
2. High frequency information is relevant to maintain decent classification.

Learning the Filter Parameters

Minimizing accuracy loss

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    1. L_∞ regularization of the depthwise convolution layer
    2. Total Variation (TV) regularization of the Layer 1 convolution weights

Ł$_\infty$ Regularization

$$\min \quad \frac{\alpha}{K}\sum_{j=1}^{K}\|W_{depthwise}[:,:,j]\|_\infty + J(f_\theta(x,y))$$

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L_∞ norm is an ideal choice for the depthwise weights. This will ensure that the weights in the kernel take similar values to each much like a low pass filter.

Total Variation Regularization

$$TV(x) = \sum_{i,j} |x_{i+1,j} - x_{i,j}| + |x_{i,j+1} - x_{i,j}|.$$

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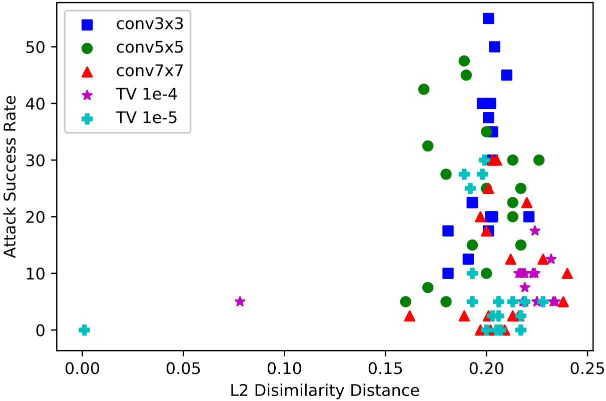
TV encourages the neighboring values in the feature maps to be similar so the high spike introduced by RP_2 would be diminished.

Whitebox Evaluation



Whitebox Evaluation

Table 2: Results from white box evaluation

	α	**Legitimate Acc.**	**Average Success Rate**	**Worst Success Rate**	L_2 **Distortion**
Baseline	0	91%	49.18%	90%	0.207
3x3 conv	10^{-5}	86.3%	30%	55%	0.201
5x5 conv	0.1	86.3%	24.11%	47.5%	0.189
7x7 conv	0.1	87%	11.61%	30%	0.203
TV	10^{-4}	85.6%	7.92%	17.5%	0.224
TV	10^{-5}	82.3%	8.47%	30%	0.199

Concluding Remarks

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- Adding low-pass filters after the first layers confers some robustness benefits
- Introduced two loss penalties to induce low pass filtering in the network.