BlurNet: Defense by Filtering the Feature Maps

Affliates Meeting '19

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UW Madison ECE Dept.

Outline

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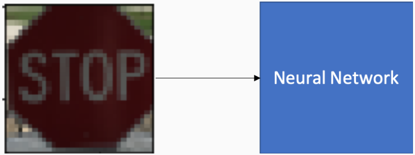
Learning the Filter Parameters

Concluding Remarks

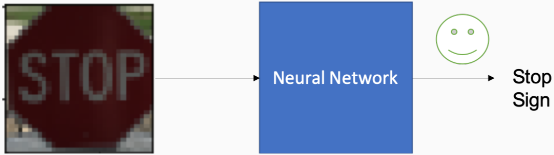
Introduction

Vulnerabilities in NNs



Neural Network

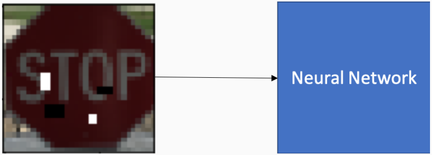
Vulnerabilities in NNs



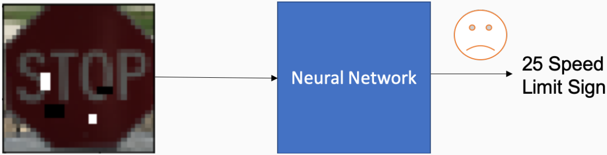
Neural Network

Stop
Sign

Vulnerabilities in NNs


STOP
Neural Network

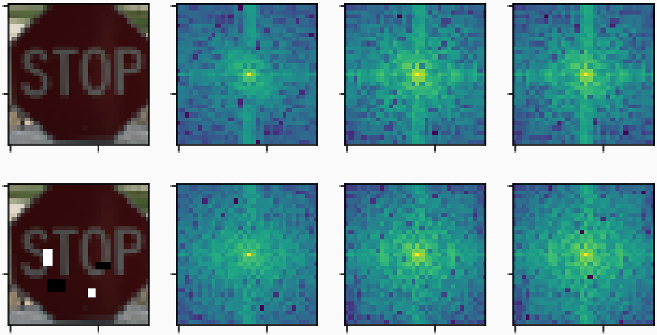
Vulnerabilities in NNs



Neural Network

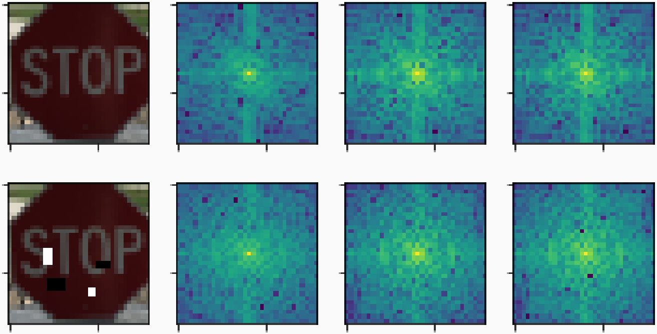
25 Speed
Limit Sign

FFT Spectrum of Input Channels



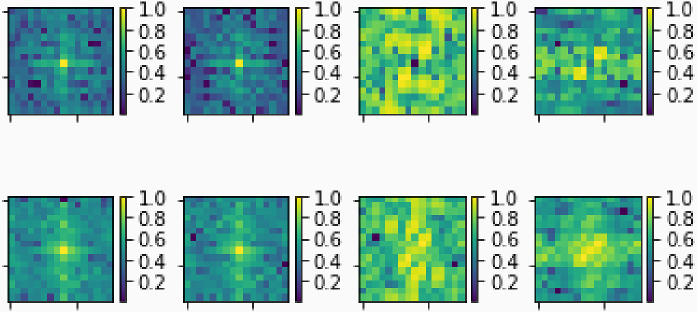
- Log-shifted and normalized frequency spectrum of RGB channels of a natural and perturbed stop sign image

FFT Spectrum of Input Channels



- 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



- Each row corresponds to a unique feature map from L1 layer of network.

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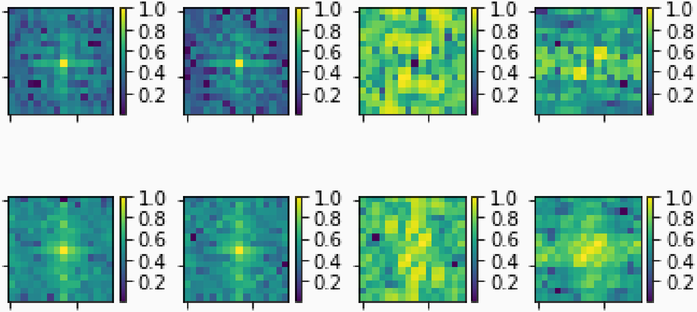

- Each row corresponds to a unique feature map from L1 layer of network.
- Difference image suggests that the perturbations induce high frequency components not found in natural stop signs

Background

Terminology and Preliminaries: Adverserial Robustness

Let x be an image and a neural network, $F(x) = y$, such that $F : \mathbb{R}^3 \rightarrow \mathbb{R}$ 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.

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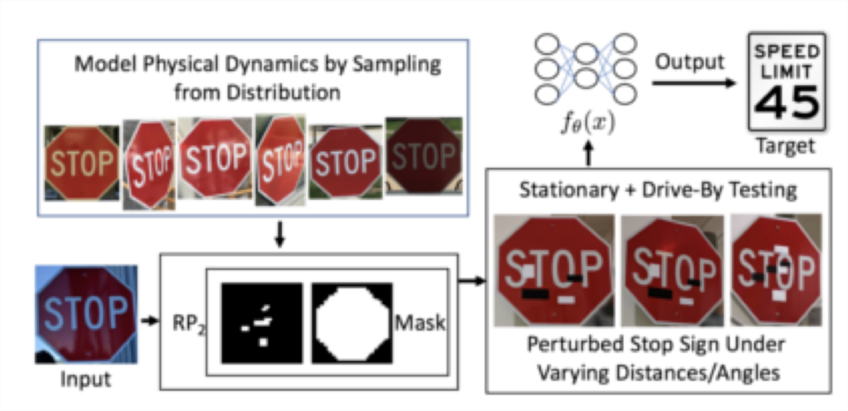
3. An attacker is considered strong if its attack success rate is high while having a low dissimilarity metric.

Attacker: Robust Physical Perturbation (RP_2) Attack


Model Physical Dynamics by Sampling from Distribution
$f_\theta(x)$
Output
SPEED LIMIT 45
Target
Stationary + Drive-By Testing
Input
RP₂
Mask
Perturbed Stop Sign Under Varying Distances/Angles

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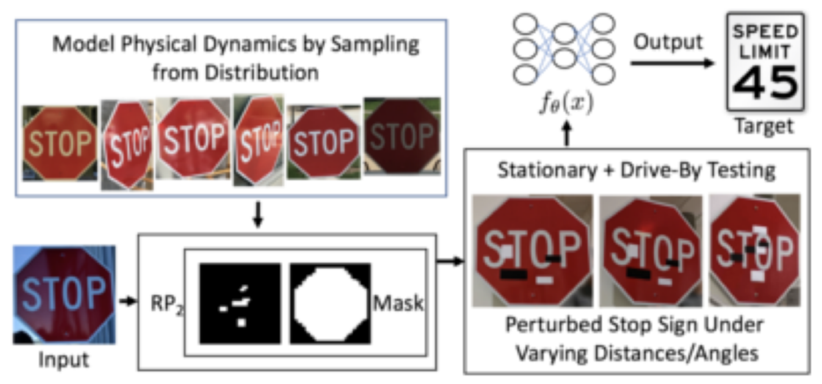

Model Physical Dynamics by Sampling from Distribution
STOP
Input
RP2
Mask
Stationary + Drive-By Testing
Perturbed Stop Sign Under Varying Distances/Angles
$f_\theta(x)$
Output
SPEED LIMIT 45
Target

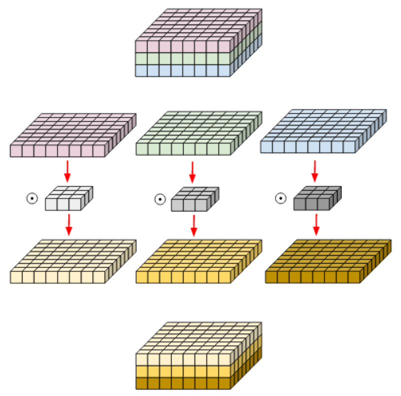
$$\arg\min_{\delta} \quad \lambda \|M_x \cdot \delta\|_p + \mathbb{E}_{x_i \sim X^V} J(f_\theta(x_i + T_i(M_x \cdot \delta)), y^*)$$

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



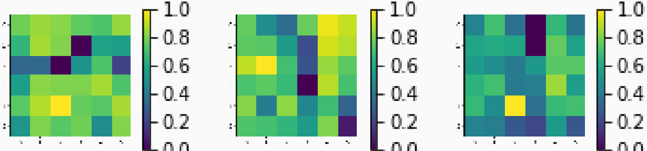
- Induce low-pass filtering with standard blur kernels by inserting a depthwise convolution after the first convolution layer.

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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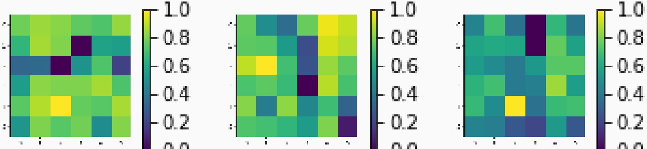

1. The FFT Spectrum of a subsampling of feature maps from the second layer of the network.
2. High frequency information is relevant to maintain decent classification.

Learning the Filter Parameters

Minimizing accuracy loss

- Can we learn the filter parameters so that we gain low-pass filtering without a significant degradation in accuracy?

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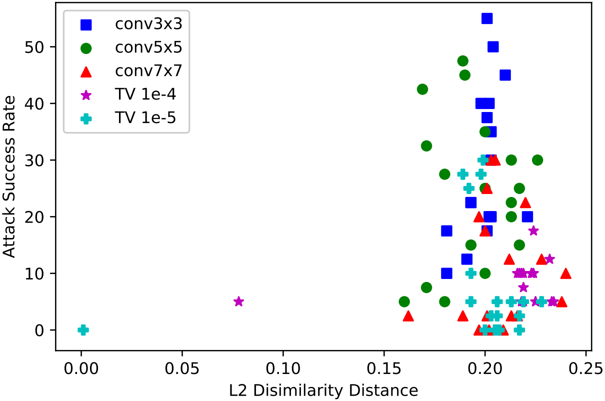
TV encourages the neighboring values in the feature maps to be similar so the high spike introduced by RP_2 would be diminished.

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.

Questions?