Revisiting Physical-World Adversarial Attack on Traffic Sign Recognition: A Commercial Systems Perspective

Ningfei Wang, Shaoyuan Xie, Takami Sato, Yunpeng Luo, Kaidi Xu^{*}, Qi Alfred Chen University of California, Irvine and *Drexel University



 Traffic Sign Recognition (TSR) system employs camera sensors with Deep Neural Networks (DNNs) to detect road signs

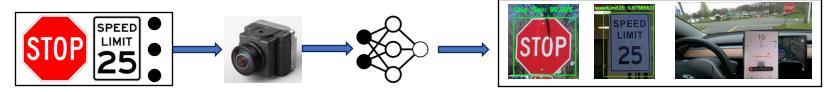
• Traffic Sign Recognition (TSR) system employs camera sensors with Deep Neural Networks (DNNs) to detect road signs



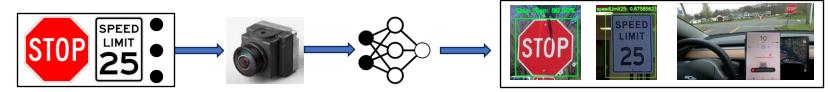
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• Such TSR systems generally exist in top leading car brands in the United States [1]



[1] Leading car brands in the United States in 2023, based on vehicle sales: https://www.statista.com/statistics/264362/leading-car-brands-in-the-us-based-on-vehicle-sales/ 6

Failure of TSR Can Lead to Accidents

Millions of people drive, ride, or walk through stop sign intersections daily.

However, nearly 70,000 accidents occur yearly due to people running stop signs; a third result in injuries.

There are many scenarios in which a person may find themselves in a stop sign car accident. For instance, a driver may be hit by someone running a stop sign, or the driver may hit the person running the stop sign. More than two cars may be involved in an intersection with a 3- or 4-way stop. Proving who is at fault can be challenging in stop sign violations that result in an accident. Consulting with a <u>St. Louis car accident lawyer</u> can help you determine liability and pursue fair compensation.



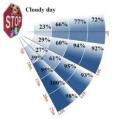
Prior Commercial TSR Security Research

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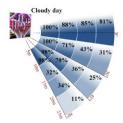
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Jon Fingas



Zhao et al.: ACM CCS 2019

You can confuse self-driving cars by altering street signs

It doesn't take much to send autonomous cars crashing into each other.





Jon Fingas: engadget

Importance of Commercial TSR Security

Limitations:

 Almost all only evaluate attack effects on <u>academic TSR models</u>, leaving the impacts on <u>commercial TSR systems</u> largely unclear.

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Limitations:

- Almost all only evaluate attack effects on <u>academic TSR models</u>, leaving the impacts on <u>commercial TSR systems</u> largely unclear.
- A few recent works tried to understand <u>commercial TSR system-level impacts</u>, but limited to <u>one particular vehicle model</u>, sometimes even an <u>unknown one</u>, making both the <u>generalizability</u> and <u>representativeness</u> questionable

Research Question

Research Question:

Can any of the existing physical-world TSR adversarial attacks achieve a general impact on commercial TSR systems today?

Our Contributions

- The **first large-scale** measurement of **physical-world** adversarial attacks against **commercial TSR systems**
- Discovery and analysis of a **spatial memorization design** that commonly exists in today's commercial TSRs
- Propose new attack success metric designs and use this metric to revisit the evaluations, designs, and capabilities of existing attacks in this problem space

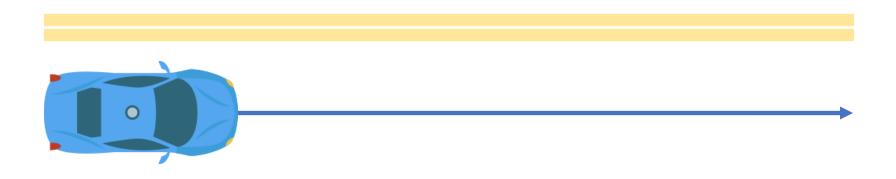
Measurement Study Setup Overview



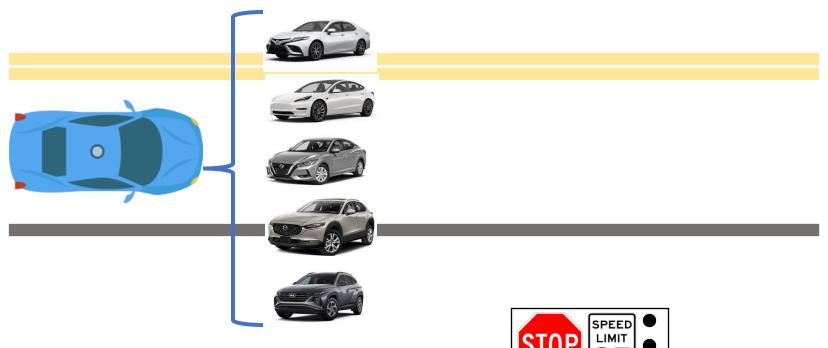
Test Environment Setups



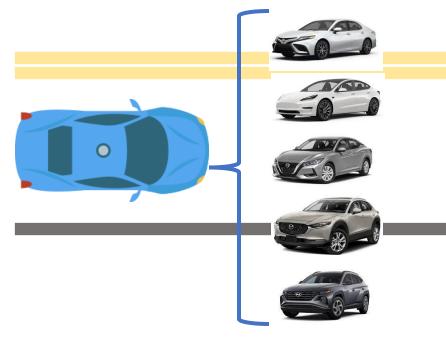
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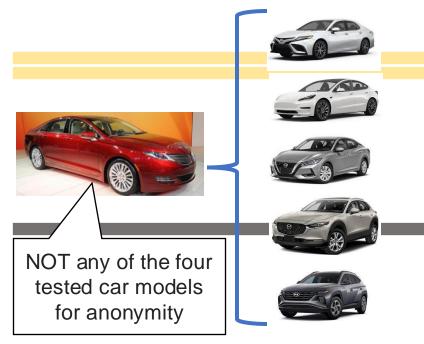
4 out of these 5 models are tested by us



Top 15 leading car brands in the United States based on vehicle sales in 2023

1,904,038 1,888,941	1
1 888 941	
1,000,941	. ∕
1,702,700	
1,156,591	1
834,091	1
796,506	1
782,468	1
641,166	1
632,083	
563,692	1
539,477	1
498,000	1
365,044	1
361,654	1
329,025	1
	1,156,591 834,091 796,506 782,468 641,166 632,083 563,692 539,477 498,000 365,044 361,654

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Top 15 leading car brands in the United States based on vehicle sales in 2023

Car brand	Sales number	TSR
Ford	1,904,038	✓
Toyota	1,888,941	✓
Chevrolet	1,702,700	
Honda	1,156,591	1
<u>Nissan</u>	834,091	1
Hyundai	796,506	1
Kia	782,468	✓
Jeep	641,166	1
Subaru	632,083	
GMC	563,692	1
Ram	539,477	1
<u>Tesla</u>	498,000	1
<u>Mazda</u>	365,044	1
BMW	361,654	1
Volkswagen	329,025	1

4 out of these 5 models are tested by us







TSR functions of the four vehicle models tested in our measurement study

	TSR functionality				
Vehicle model	STOP sign	Speed limit sign			
Car 1 (denote as C1)	1	×			
Car 2 (denote as C2)	1	\checkmark			
Car 3 (denote as C3)	×	\checkmark			
Car 4 (denote as C4)	×	1			





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- Three prior works so far that were able to demonstrate black-box attack transferability for the hiding attack effect in the physical world

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Physical Adversarial Examples for Object Detectors

Kevin Eykholt¹, Ivan Evtimov², Earlence Fernandes², Bo Li³,

Amir Rahmati^{4,6}, Florian Tramèr⁵, Atul Prakash¹, Tadayoshi Kohno², Dawn Song³

¹University of Michigan ²University of Washington ³University of California, Berkeley ⁴Stony Brook University ⁵Stanford University ⁶Samsung Research America

RP₂: Eykholt et al. WOOT 2017

Session 9B: ML Security III

CCS '19, November 11-15, 2019, London, United Kingdom

Seeing isn't Believing: Towards More Robust Adversarial Attack Against Real World Object Detectors

Yue Zhao^{1,2}, Hong Zhu^{1,2}, Ruigang Liang^{1,2}, Qintao Shen^{1,2}, Shengzhi Zhang³, Kai Chen^{1,2*} ¹SKJOS, Institute df Information Engineering, Chinese Academy of Sciences, China ³School of Cyber Security, University of Chinese Academy of Science, China ³Department of Computer Science, Metropolitan College, Boston University, USA (haoyue, Juhuong Liangurgiang, ahenpitanologileia aca.n.dhengihighue.du, chenkal@ia.ac.n Fooling the Eyes of Autonomous Vehicles: Robust Physical Adversarial Examples Against Traffic Sign Recognition Systems

Wei Jia School of Cyber Science and Engi Huazhong Univ. of Sci. & Ter jiaw@hust.edu.cn		Haichun Zhang Huazhong Univ. of Sci. & Tech homer@thesimpsons.com
Zhenglin Liu	Jie Wang	Gang Qu
Huazhong Uni. of Sci. & Tech.	Shenzhen Kaiyuan Internet Security Co., Ltdy	University of Maryland
liuzhenglin@hust.edu.cn	wangjie@seczone.cn	gangqu@umd.edu

SIB: Zhao et al. ACM CCS 2019

FTE: Jia et al. NDSS 2022

- Focus on the hiding attack on measurement study
- Three prior works so far that were able to demonstrate black-box attack transferability for the hiding attack effect in the physical world
 - Highest potential to successfully attack **commercial systems**

Physical Adversarial Examples for Object Detectors

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RP2: Eykholt et al. WOOT 2017

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Huazhong Uni. of Sci. & Tech.	Shenzhen Kaiyuan Internet Security Co., Ltdy	University of Maryland
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SIB: Zhao et al. ACM CCS 2019

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Surrogate Model

• Cover both one-stage and two-stage object detectors

Surrogate Model

Cover both one-stage and two-stage object detectors

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📄 data	Ultralytics Refactor https://	ultralytics.com/actions (#133	68) last week
models	Add https://www.reddit.com	n/r/Ultralytics/ badge (#1328	4) 2 months ago
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dockerignore	Add .git to .dockerignore (#	8815)	2 years ago
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Faster R-CNN S

The Faster R-CNN model is based on the Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks paper.

• WARNING

The detection module is in Beta stage, and backward compatibility is not guaranteed.

Model builders

The following model builders can be used to instantiate a Faster R-CNN model, with or without pre-trained weights. All the model builders internally rely on the torchvision.models.detection.faster_cnn.FasterRCNN base class. Please refer to the source code for

more details about this class.

Faster-RCNN (FR)

YOLO v5 (Y5)

Surrogate Model

- Cover both one-stage and two-stage object detectors
 - Generally used as surrogate model in the prior security research on TSR

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models	Add https://www.reddit	.com/r/Ultralytics/ badge (#13)	284) 2 months ago
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Faster-RCNN (FR)

YOLO v5 (Y5)

Generated Attack Visualization



TSR System-Level Attack Success Metric





TSR System-Level Attack Success Metric







NOT any of the four tested car models for anonymity

TSR System-Level Attack Success Metric



If the TSR system is able to correctly display the sign, the attack fails; otherwise, the attack succeed. Repeat *N* times.





NOT any of the four tested car models for anonymity

Overall Testing Results

	Original paper	Surrogate	C1	C	22	C3	C4	
	transferability	model	STOP	STOP	Speed limit	Speed limit	Speed limit	Ave.
Benig	n traffic sign		100% (3/3)	100% (3/3)	100% (3/3)	100% (3/3)	100% (3/3)	100%
RP_2	18.9%	Y5 FR	0% (0/3) 0% (0/3)	0% (0/3) 100% (3/3)	0% (0/3) 0% (0/3)	0% (0/3) 0% (0/3)	0% (0/3) 0% (0/3)	0% 20%
SIB	46.1%	Y5 FR	0% (0/3) 0% (0/3)	100% (3/3) 0% (0/3)	0% (0/3) 0% (0/3)	0% (0/3) 0% (0/3)	0% (0/3) 0% (0/3)	20% 0%
FTE	89.8%	Y5 FR	0% (0/3) 0% (0/3)	0% (0/3) 0% (0/3)	0% (0/3) 0% (0/3)	0% (0/3) 0% (0/3)	0% (0/3) 0% (0/3)	0% 0%
Ave. over all attacks	51.6%		0%	33.3%	0%	0%	0%	6.67%

Certain Commercial TSRs are More Vulnerable

	Original paper	r Surrogate	C1	С	2	C3	C4	
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Benig	n traffic sign		100% (3/3)	100% (3/3)	100% (3/3)	100% (3/3)	100% (3/3)	100%
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<u>Observation #1</u>: For certain commercial TSR systems, although from top brands in the US, their TSR functionality can **actually be much more vulnerable than academic TSR models** under black-box transfer attacks.

Attack Lacks Generalization across Commercial TSRs

	Original paper	Surrogate	C1	C	22	C3	C4	
	transferability	model	STOP	STOP	Speed limit	Speed limit	Speed limit	Ave.
Benig	n traffic sign		100% (3/3)	100% (3/3)	100% (3/3)	100% (3/3)	100% (3/3)	100%
RP_2	18.9%	Y5 FR	0% (0/3) 0% (0/3)	0% (0/3) 100% (3/3)	0% (0/3) 0% (0/3)	0% (0/3) 0% (0/3)	0% (0/3) 0% (0/3)	0% 20%
SIB	46.1%	Y5 FR	0% (0/3) 0% (0/3)	100% (3/3) 0% (0/3)	0% (0/3) 0% (0/3)	0% (0/3) 0% (0/3)	0% (0/3) 0% (0/3)	20% 0%
FTE	89.8%	Y5 FR	0% (0/3) 0% (0/3)	0% (0/3) 0% (0/3)	0% (0/3) 0% (0/3)	0% (0/3) 0% (0/3)	0% (0/3) 0% (0/3)	0% 0%
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Attack Lacks Generalization across Commercial TSRs

	Original paper transferability	Surrogate model	C1 STOP	C2		C3	C4	
				STOP	Speed limit	Speed limit	Speed limit	Ave.
Benign traffic sign			100% (3/3)	100% (3/3)	100% (3/3)	100% (3/3)	100% (3/3)	100%
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FTE	89.8%	Y5 FR	0% (0/3) 0% (0/3)	0% (0/3) 0% (0/3)	0% (0/3) 0% (0/3)	0% (0/3) 0% (0/3)	0% (0/3) 0% (0/3)	0% 0%
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Ave. over all attacks	51.6%		0%	33.3%	0%	0%	0%	6.67%

<u>Observation #1 (cont'd)</u>: Such black-box commercial system attack capability is currently not generalizable over different representative commercial system models and sign types.

	Original paper	Surrogate	C1	C	22	C3	C4	•	
	transferability	model	STOP	STOP	Speed limit	Speed limit	Speed limit	Ave.	
Benig	n traffic sign		100% (3/3)	100% (3/3)	100% (3/3)	100% (3/3)	100% (3/3)	100%	
RP_2	18.9%	Y5 FR	0% (0/3) 0% (0/3)	0% (0/3) 100% (3/3)	0% (0/3) 0% (0/3)	0% (0/3) 0% (0/3)	0% (0/3) 0% (0/3)	0% 20%	
SIB	46.1%	Y5 FR	0% (0/3) 0% (0/3)	100% (3/3) 0% (0/3)	0% (0/3) 0% (0/3)	0% (0/3) 0% (0/3)	0% (0/3) 0% (0/3)	20% 0%	
FTE	89.8%	Y5 FR	0% (0/3) 0% (0/3)	0% (0/3) 0% (0/3)	0% (0/3) 0% (0/3)	0% (0/3) 0% (0/3)	0% (0/3) 0% (0/3)	0% 0%	
Ave. over all attacks	51.6%		0%	33.3%	0%	0%	0%	6.67%	

	riginal paj ansferabil	tector and TS our knowledg YOLO v5 bas successfully 1	R system in a e, this is the fi sed object det aunch four a	rst set of advert tectors in the j	ehicle: To the rsarial attacks physical doma especially NT	best of against in. We TA and t	C4 Speed limit	Ave.
Benign tr	affic sign	AEs also exh	nibit satisfacto	ory transferab	ility when at	tacking	100% (3/3)	100%
RP ₂	18.9%	a production- vehicle.	grade TSR sy	stem of a bra	and-new 2021	model	0% (0/3) 0% (0/3)	0% 20%
SIB	46.1%	-	-	he Eyes of Autono Against Traffic Sig			0% (0/3) 0% (0/3)	20% 0%
FTE	89.8%	Y5 FR	0% (0/3) 0% (0/3)	0% (0/3) 0% (0/3)	0% (0/3) 0% (0/3)	0% (0/3) 0% (0/3)	0% (0/3) 0% (0/3)	0% 0%
Ave. over all attacks	51.6%		0%	33.3%	0%	0%	0%	6.67%

		tector and TS our knowledge	R system in a e, this is the fi	gainst YOLO 2021 model ve arst set of adven	ehicle: To the sarial attacks	best of against –		
	Driginal pa transferabil	successfully 1	aunch four a	tectors in the p ttack vectors,	especially N	ΓA and t	C4 Speed limit	Ave.
Benign t	traffic sign	AEs also exh	nibit satisfact	ng in the real ory transferab	ility when at	tacking	100% (3/3)	100%
RP ₂	18.9%	a production- vehicle.	grade TSR sy	ystem of a bra	ind-new 2021	model	0% (0/3) 0% (0/3)	0% 20%
SIB	46.1%	-	-	he Eyes of Autonc Against Traffic Sig			0% (0/3) 0% (0/3)	20% 0%
FTE	89.8%	Y5 FR	0% (0/3) 0% (0/3)	0% (0/3) 0% (0/3)	0% (0/3) 0% (0/3)	0% (0/3) 0% (0/3)	0% (0/3) 0% (0/3)	0% 0%
Ave. over all attacks	51.6%		0%	33.3%	0%	0%	0%	6.67%

<u>Observation #1 (cont'd)</u>: This further reveals the lack of generalizability of the reported commercial TSR system attack success in the original FTE paper, which cannot be revealed without the large-scale commercial system testing efforts in this paper.

Discrepancy in Commercial and Academic TSR

	Original paper transferability	Surrogate model
Benig	n traffic sign	
RP ₂	18.9%	Y5 FR
SIB	46.1%	Y5 FR
FTE	89.8%	Y5 FR
Ave. over all attacks	51.6%	



	C3	C4	
it	Speed limit	Speed limit	Ave.
3)	100% (3/3)	100% (3/3)	100%
	0% (0/3)	0% (0/3)	0%
	0% (0/3)	0% (0/3)	20%
	0% (0/3)	0% (0/3)	20%
	0% (0/3)	0% (0/3)	0%
	0% (0/3)	0% (0/3)	0%
	0% (0/3)	0% (0/3)	0%
	0%	0%	6.67%

• <u>Observation #2</u>: One major factor might be an unexpected **spatial memorization** design that commonly exists in commercial TSRs.

<u>Observation #2 (cont'd)</u>: **Spatial memorization design** exhibits an effect that once a sign is detected, both the **detected sign type** and the **detected location** are **persistently memorized** until **the sign's reaction task is finished**



• <u>Observation #2</u>: One major factor might be an unexpected **spatial memorization** design that commonly exists in commercial TSRs.



STOP sign is shown for 1 sec









Hide the STOP sign

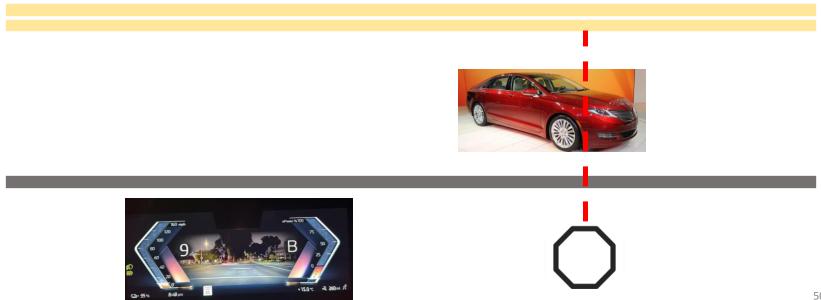








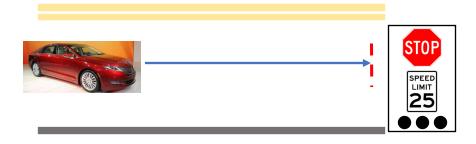


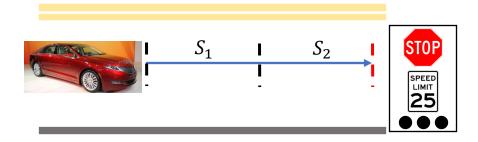


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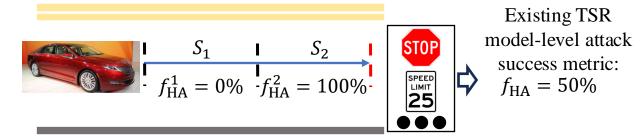


<u>Observation #2 (cont'd)</u>: **Spatial memorization design** exhibits an effect that once a sign is detected, both the **detected sign type** and the **detected location** are **persistently memorized** until **the sign's reaction task is finished**





$$f_{HA}^{1} = 0\% \quad f_{HA}^{2} = 100\%$$



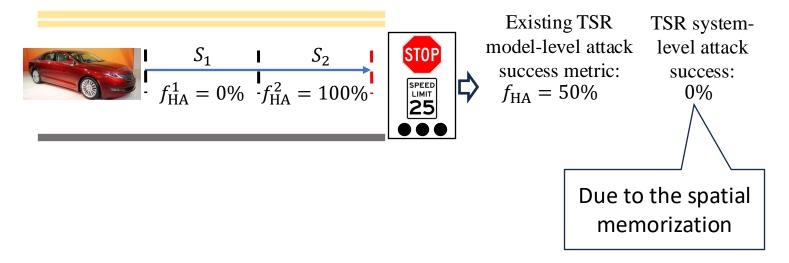
• The spatial memorization design can significantly impact the success of existing adversarial attacks at the TSR system level

$$f_{HA}^{1} = 0\% \quad f_{HA}^{2} = 100\%$$

Existing TSR
model-level attack
success metric:
$$f_{\rm HA} = 50\%$$

man

TSR systemlevel attack success: 0%



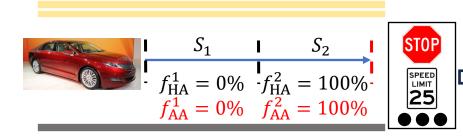
• The spatial memorization design can significantly impact the success of existing adversarial attacks at the TSR system level

$$\begin{array}{c|c} & S_1 & S_2 \\ \hline & f_{HA}^1 = 0\% & f_{HA}^2 = 100\% \\ f_{AA}^1 = 0\% & f_{AA}^2 = 100\% \end{array}$$

Existing TSR model-level attack success metric: $f_{\rm HA} = 50\%$

TSR systemlevel attack success: 0%

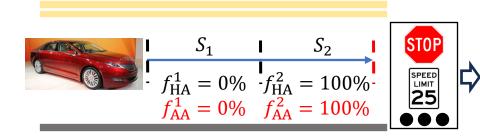
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Existing TSR T model-level attack 1 success metric: $f_{HA} = 50\%$ $f_{AA} = 50\%$

TSR systemlevel attack success: 0%

• The spatial memorization design can significantly impact the success of existing adversarial attacks at the TSR system level

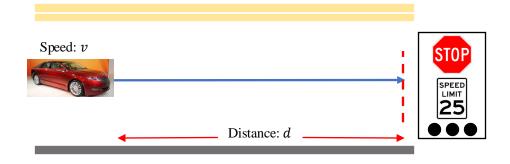


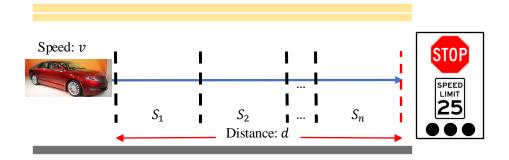
Existing TSR model-level attack success metric: $f_{HA} = 50\%$ $f_{AA} = 50\%$

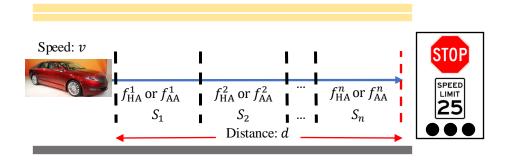
TSR systemlevel attack success: 0% 100%

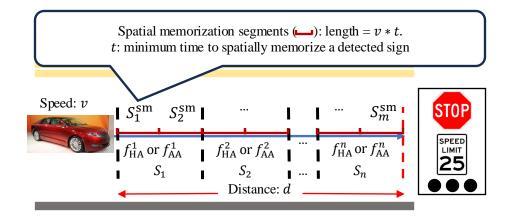
• The spatial memorization design can significantly impact the success of existing adversarial attacks at the TSR system level

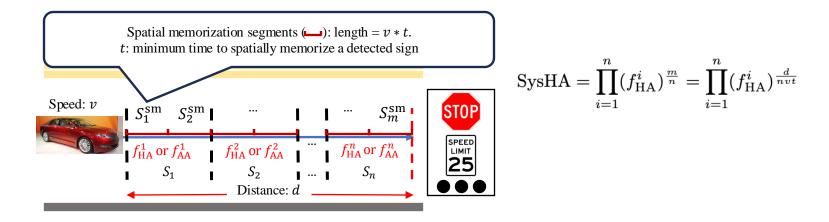
Given that such an unexpected **spatial memorization design** can create such a significant **discrepancy** between the **TSR model-level** attack effect and that at the **TSR system level**, we further design **new attack success metrics** that can mathematically model its impact on the **TSR system-level** attack success for both **hiding and appearing attacks**



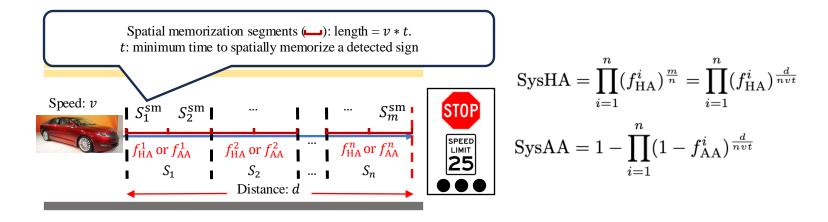




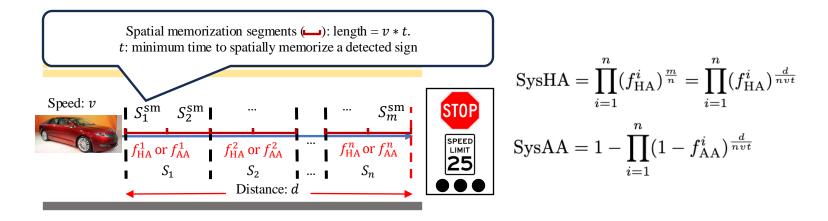




• <u>Hiding attack</u>: The attack has to be **continuously successful** at **all** possible detection moments that can trigger such memorization **before the vehicle passes the sign**.

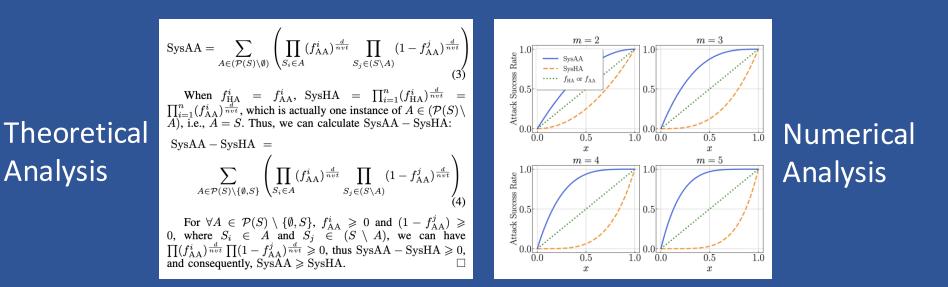


• <u>Appearing attack</u>: As long as attack can succeed in **any** of detection moments, the TSR system-level attack effect can be achieved.



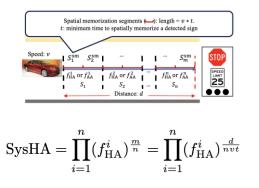
• <u>Appearing attack</u>: As long as attack can succeed in **any** of detection moments, the TSR system-level attack effect can be achieved.

Observation #3: Due to spatial memorization, hiding attacks are theoretically harder (if not equally hard) than appearing attacks in achieving TSR system-level attack success.



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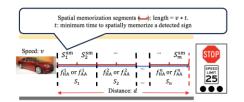
New Metric Design: Surrogate TSR System-Level Attack Success Metrics



$$SysAA = 1 - \prod_{i=1}^{n} (1 - f_{AA}^{i})^{\frac{d}{nvt}}$$

Revisiting Evaluations, Designs, and Attack Capabilities of Prior Works in this Problem Space

New Metric Design: Surrogate TSR System-Level Attack Success Metrics



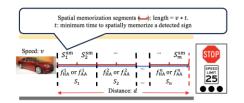
$$SysHA = \prod_{i=1}^{n} (f_{HA}^{i})^{\frac{m}{n}} = \prod_{i=1}^{n} (f_{HA}^{i})^{\frac{d}{nvt}}$$
$$SysAA = 1 - \prod_{i=1}^{n} (1 - f_{AA}^{i})^{\frac{d}{nvt}}$$

Revisiting Evaluations, Designs, and Attack Capabilities of Prior Works in this Problem Space

White-Box Attack Prior works **may not be effective** at TSR system level. (Drop from ~56% to ~7%)

	$f_{ m HA}$								
		Dista	ince ran	iges (me	eters)		Ave.	SysHA	
	0-5	5-10	10-15	15-20	20-25	25-30	Ave.		
RP_2	41.8%	10.0%	23.8%	65.4%	99.9%	100%	56.8%	6.6%	
SIB	84.6%	56.6%	82.0%	99.2%	100%	100%	87.1%	45.1%	
FTE	88.9%	57.1%	13.6%	3.1%	47.8%	74.5%	47.5%	5.2%	

New Metric Design: Surrogate TSR System-Level Attack Success Metrics



m

$$SysHA = \prod_{i=1}^{n} (f_{HA}^{i})^{\frac{m}{n}} = \prod_{i=1}^{n} (f_{HA}^{i})^{\frac{d}{nvt}}$$
$$SysAA = 1 - \prod_{i=1}^{n} (1 - f_{AA}^{i})^{\frac{d}{nvt}}$$

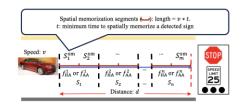
n

Revisiting Evaluations, Designs, and Attack Capabilities of Prior Works in this Problem Space

White-Box Attack Prior works **may not be effective** at TSR system level. (Drop from ~56% to ~7%) Black-Box Transfer Attack Attack success of prior works at TSR system level can **be much lower than expected** (~13%) for hiding attack.

		Transfer	r attack su	iccess rates	(averaged	over a set	of six tran	sfer target i	models (§IV
	Original paper				$f_{ m HA}$				CTI A
	transferability	0-5m	5-10m	10-15m	15-20m	20-25m	25-30m	Ave.	SysHA
RP_2	18.9%	36.4%	32.0%	29.6%	46.0%	61.3%	50.0%	42.6%	14.5%
SIB	46.1%	20.7%	26.5%	37.2%	42.6%	54.9%	51.2%	38.9%	12.4%
FTE	89.8%	29.2%	36.4%	29.3%	34.0%	45.5%	40.1%	35.7%	11.0%
Ave.	51.6%	28.8%	31.6%	32.0%	40.9%	53.9%	47.1%	39.1%	12.6%

New Metric Design: Surrogate TSR System-Level Attack Success Metrics



$$SysHA = \prod_{i=1}^{n} (f_{HA}^{i})^{\frac{m}{n}} = \prod_{i=1}^{n} (f_{HA}^{i})^{\frac{d}{nvt}}$$
$$SysAA = 1 - \prod_{i=1}^{n} (1 - f_{AA}^{i})^{\frac{d}{nvt}}$$

Revisiting Evaluations, Designs, and Attack Capabilities of Prior	
Works in this Problem Space	

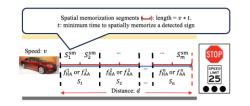
White-Box Attack Prior works **may not be effective** at TSR system level. (Drop from ~56% to ~7%) Black-Box Transfer Attack Attack success of prior works at TSR system level can **be much lower than expected** (~13%) for hiding attack.

Revisiting Existing Attack Success Metrics

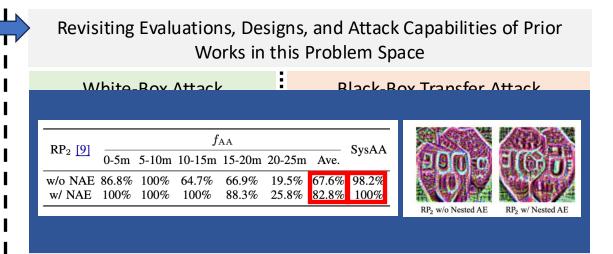
Using the **hiding and appearing attacks** proposed from the same prior work, the **hiding** one can be **much harder**. However, if using the **existing metrics**, such **relative attack hardness** can be the **completely opposite**

	Hiding	g attack	Appeari	ng attack
SIB [5]	$f_{ m HA}$	SysHA	$f_{ m AA}$	SysAA
White-box attack Black-box transfer attacks		45.1% 12.4%		87.6% 64.2%

New Metric Design: Surrogate TSR System-Level Attack Success Metrics



$$\begin{aligned} \text{SysHA} &= \prod_{i=1}^{n} (f_{\text{HA}}^{i})^{\frac{m}{n}} = \prod_{i=1}^{n} (f_{\text{HA}}^{i})^{\frac{d}{nvt}} \\ \text{SysAA} &= 1 - \prod_{i=1}^{n} (1 - f_{\text{AA}}^{i})^{\frac{d}{nvt}} \end{aligned}$$



Judgement of the Value of New Attack Designs The benefits of certain attack designs can be **seemingly high** (e.g., >20% attack success rate increase) using **prior TSR model-level success metrics**, but **nearly negligible** (e.g., only 1% increase) at the **TSR system level**

Conclusion

- <u>First large-scale measurement of physical-world adversarial attacks against</u> <u>commercial TSR:</u>
 - Uncover a total of **7 novel observations**
- Discovery and analysis of spatial memorization:
 - Discover a spatial memorization design that commonly exists in today's commercial TSRs
 - Create a **discrepancy** between TSR model-level attack effect and that at TSR system level.
- <u>New attack success metric designs:</u>
 - Mathematically model the impact of this design on the TSR system-level attack success
 - **Revisit** the evaluations, designs, and capabilities of existing attacks in this problem space

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 - **Revisit** the evaluations, designs, and capabilities of existing attacks in this problem space
- <u>Performed Responsible Vulnerability Disclosure:</u>
 - Informed AD companies under our measurements and provided anonymity to protect the affected vehicle manufacturer

Thank you!

Revisiting Physical-World Adversarial Attack on Traffic Sign Recognition: A Commercial Systems Perspective

Ningfei Wang, Shaoyuan Xie, Takami Sato, Yunpeng Luo, Kaidi Xu*, Qi Alfred Chen University of California, Irvine and *Drexel University



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