Automatic License Plate Recognition

Challenges & Solutions

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August 16, 2019

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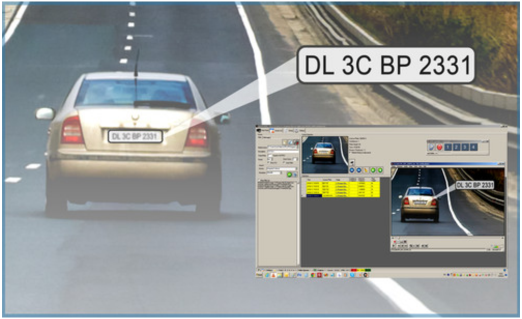
Visão
Robótica
Imagem

Summary

- Introduction and Challenges;
- Proposed ALPR System;
    - YOLO Detector;
    - Experimental Results.
- Other Works in the Literature.

Introduction



Source: Google Images

- Many **practical applications**, such as automatic toll collection, private spaces access control and road traffic monitoring.
- Automatic License Plate Recognition (ALPR) systems typically have three stages:
  1. License Plate (LP) Detection;
  2. Character Segmentation;
  3. Character Recognition.

Many solutions are still not robust enough to be executed on real-world scenarios

- An **ideal** scenario:

Source: `https://github.com/openalpr/`

Challenges - Real-World Scenarios

Many solutions are still not robust enough to be executed on real-world scenarios

- A **real-world** scenario:

Source: `http://platesmania.com`

False positives

Source: UFPR-ALPR dataset[1]

Detection: OpenALPR[2]

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[1] `https://web.inf.ufpr.br/vri/databases/ufpr-alpr/`

[2] `https://www.openalpr.com/cloud-api.html`

False positives

Source: UFPR-ALPR dataset[1] Detection: OpenALPR[2]

Solution → Vehicle Detection

[1] https://web.inf.ufpr.br/vri/databases/ufpr-alpr/

[2] https://www.openalpr.com/cloud-api.html

Challenges - Motorcycle Detection

Original Image

Expected result

Challenges - Motorcycle Detection

Original Image

Expected result

OpenALPR[3]

Sighthound[4]

[3] https://www.openalpr.com/cloud-api.html
[4] https://www.sighthound.com/products/cloud

Challenges - License Plate Layouts

Examples of different license plate layouts in the United States.

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Examples of different license plate layouts in the United States.

License plates from Mercosur, Argentina, Brazil and Paraguay.

Goal: a **single ALPR system** robust for different LP layouts.

Challenges - Character Recognition

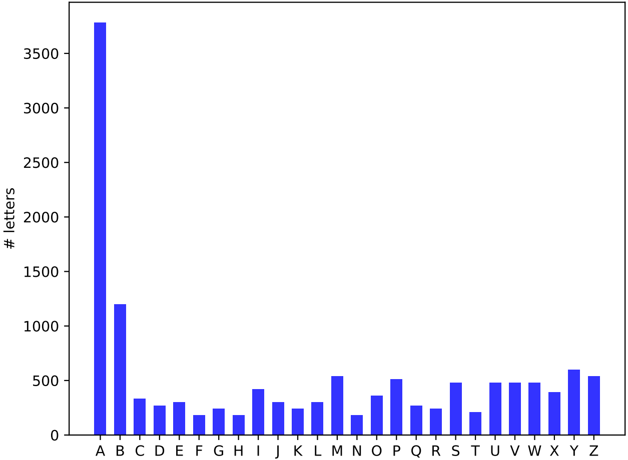
Training data is unbalanced

- License plates in Paraná: **A**AA-0001 to **B**EZ-9999;

Challenges - Character Recognition

Training data is unbalanced

- License plates in Paraná: **A**AA-0001 to **B**EZ-9999;

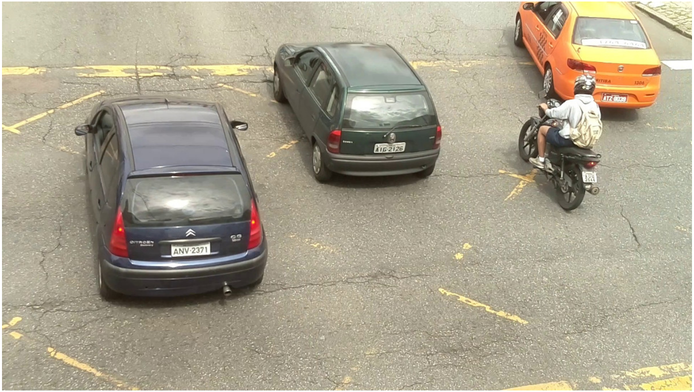


Letters distribution in the UFPR-ALPR dataset, acquired in Paraná.

Challenges - Accuracy vs Execution Time

“Real Time”

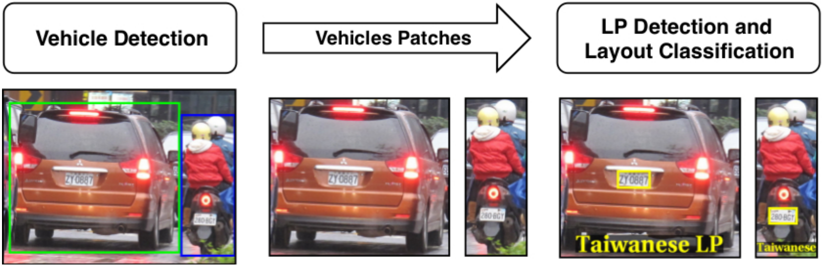
1. A fast-enough operation to not miss a single object of interest that moves through the scene.
2. A system able to process at least **30** frames per second (FPS).



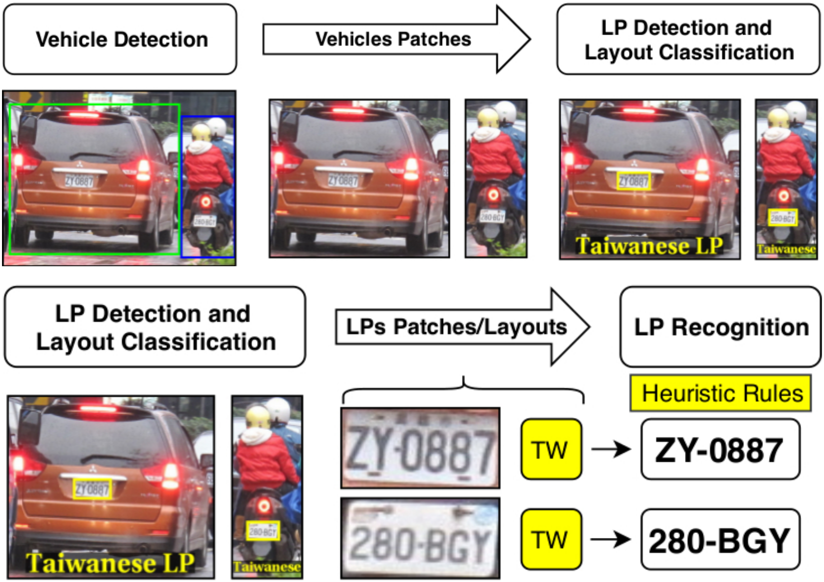
Source: `https://github.com/icarofua/siamese-two-stream`

Proposed ALPR System

Proposed ALPR System



Proposed ALPR System



How to detect objects in real time?

You Only Look Once (YOLO)[5,6]

- **State-of-the-art** results in **real time**;
- **Open source**: `https://pjreddie.com/darknet/yolo/`
- Video: `https://www.youtube.com/watch?v=VOC3huqHrss`

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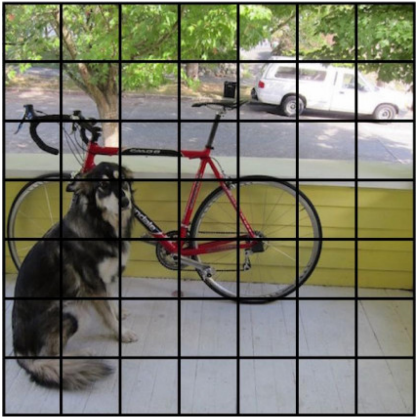
[5] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You only look once: Unified, real-time object detection," in IEEE Conference on Computer Vision and Pattern Recognition (CVPR), June 2016.

[6] J. Redmon and A. Farhadi, "YOLO9000: Better, faster, stronger," in *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, July 2017.

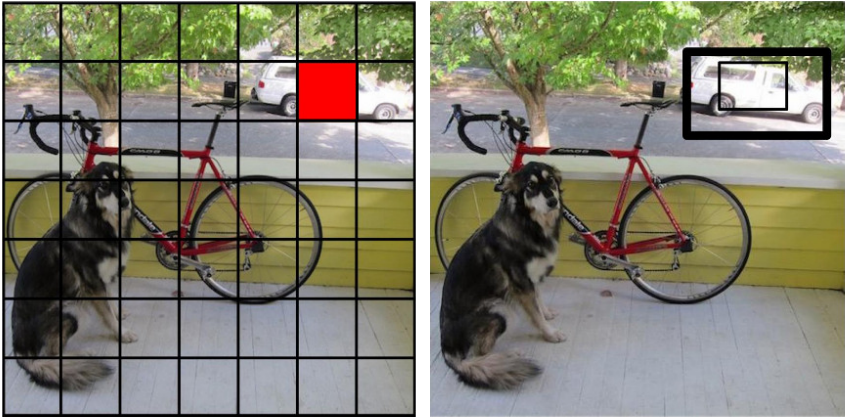
You Only Look Once (YOLO)

YOLO splits the input image into an $S \times S$ grid.



You Only Look Once (YOLO)

Each cell predicts boxes and confidences: P(Object)



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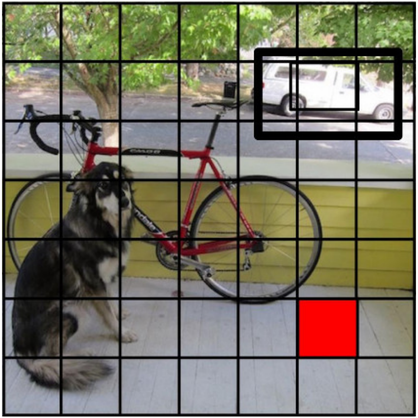
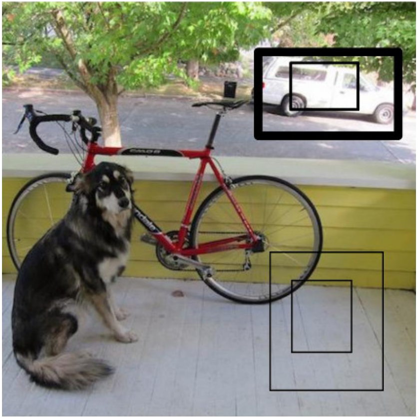


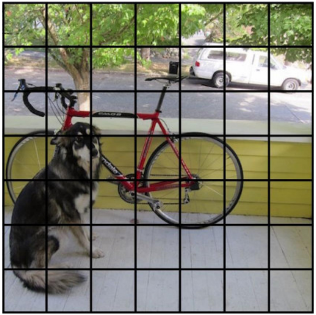


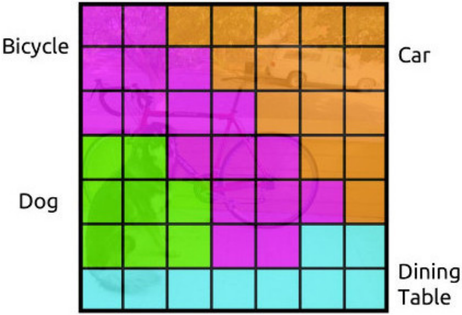
You Only Look Once (YOLO)

Each cell predicts boxes and confidences: P(Object)

You Only Look Once (YOLO)

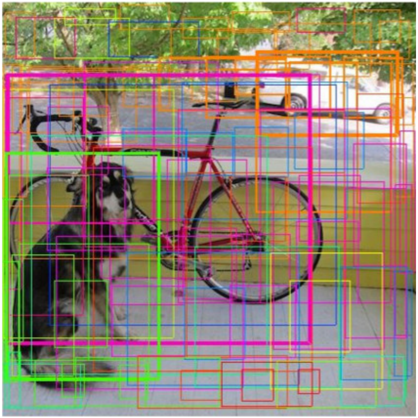
Each cell also predicts class probabilities.
Conditioned on object: P(Dining Table | Object)

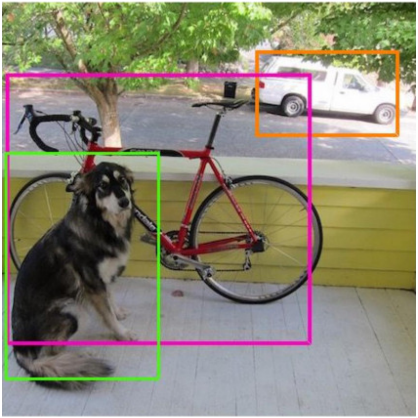




You Only Look Once (YOLO)

Then YOLO combines the box and class predictions.





Vehicle Detection

- **YOLOv2** + **adjustments**;

Vehicle Detection

Data Augmentation (flipping, rescaling and shearing).

- Many images with distinct characteristics from a single labeled one.

Vehicle Detection - Results

Correct detections (99.92% || 3765/3768 vehicles):

Vehicle Detection - Results

Incorrect detections (false negatives):

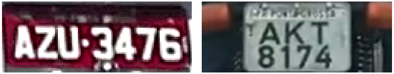
LP Detection and Layout Classification

- **Fast-YOLOv2** + **adjustments**.

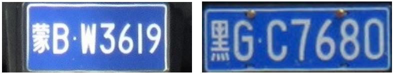
We classify each LP layout into one of the following classes:

- **American**, **Brazilian**, **Chinese**, **European** or **Taiwanese**.

(a) American



(b) Brazilian



(c) Chinese

(d) European

(e) Taiwanese

- We consider only **one LP per vehicle**;
- We classify as '**undefined layout**' every LP that has its position and class predicted with a confidence value below a threshold;

LP Detection and Layout Classification - Results

LP Detection and Layout Classification - Results

- Accuracy: **99.51%**.

LP Detection and Layout Classification - Results

(a) Examples of images in which the LP position was predicted incorrectly.

(b) Examples of images in which the position of the LP was predicted correctly, but not the layout.

LP Recognition

- We employ **CR-NET**[7], a YOLO-based model, for LP recognition.

[7] S. M. Silva and C. R. Jung, “Real-time brazilian license plate detection and recognition using deep convolutional neural networks,” in Conference on Graphics, Patterns and Images (SIBGRAPI), Oct 2017, pp. 55–62.

Data augmentation $\rightarrow$ negative images

(a) Gray LP $\rightarrow$ Red LP (Brazilian)

(b) Red LP $\rightarrow$ Gray LP (Brazilian)

LP Recognition

Data augmentation → character permutation[8]

[8] G. R. Gonçalves, M. A. Diniz, R. Laroca, D. Menotti, and W. R. Schwartz, "Real-time automatic license plate recognition through deep multi-task networks," in Conference on Graphics, Patterns and Images (SIBGRAPI), Oct 2018.

LP Recognition - Heuristic Rules

The **minimum** and the **maximum** number of characters to be considered in license plates of each layout.

LP Layout	# Characters	
	Min.	Max.
American	4	7
Brazilian	7	7
Chinese	6	6
European	5	8
Taiwanese	5	6

We **swap digits and letters** according to the LP layout.

- For example, on a Brazilian LP, A8C-123A $\rightarrow$ A**B**C-123**4**;
- We avoid errors in characters that are often misclassified;
- 'B' and '8', 'G' and '6', '**I**' and '1', and others.

LP Recognition (Overall Evaluation)

Recognition rates (%) obtained by the proposed system, previous works, and commercial systems in the datasets used in our experiments.

Dataset	[84]	[92]	[33]	[13]	[30]	Sighthound	OpenALPR	Proposed
Caltech Cars	–	–	–	–	–	95.7 ± 2.7	**99.1 ± 1.2**	98.7 ± 1.2
EnglishLP	**97.0**	–	–	–	–	92.5 ± 3.7	78.6 ± 3.6	95.7 ± 2.3
UCSD-Stills	–	–	–	–	–	**98.3**	**98.3**	98.0 ± 1.4
ChineseLP	–	–	–	–	–	90.4 ± 2.4	92.6 ± 1.9	**97.5 ± 0.9**
AOLP	–	**99.8***	–	–	–	87.1 ± 0.8	–	99.2 ± 0.4
OpenALPR-EU	–	–	93.5	–	–	92.6	90.7	**96.9 ± 1.1**
SSIG SegPlate	–	–	88.6	88.8	85.5	82.8	92.0	**98.2 ± 0.5**
UFPR-ALPR	–	–	–	–	64.9	62.3	82.2	**90.0 ± 0.7**
Average	–	–	–	–	–	87.7 ± 2.4	90.5 ± 2.3	**96.8 ± 1.0**

* The LP patches for the LP recognition stage were cropped directly from the ground truth in [92].

- [84] *IEEE Transactions on Intelligent Transportation Systems*, 2017;
- [33,92] *European Conference on Computer Vision (ECCV)*, 2018;
- [13] *Conference on Graphics, Patterns and Images (SIBGRAPI)*, 2018;
- [30] *International Joint Conference on Neural Networks (IJCNN)*, 2018.

LP Recognition (Overall Evaluation)

Examples of LPs that were correctly recognized:

UFD69K

018VFJ

281SGL


3WVM533


MCA9954


HJN2081

IOZ3616


AUG0936


AK6972


CG08I5

AK8888


A36296

ZG806KF

DU166BF

317J939

W0BVWMK4


0750J0


UH7329


F9F183


6B7733

LP Recognition (Overall Evaluation)

Examples of LPs that were incorrectly recognized:

AB0416 (AR0416)

2MFE674 (2MFF674)

HOR8361 (HDR8361)

AK04I3 (AK0473)

AYH5087 (AXH5087)

430463TC (30463TC)

YB8096 (Y88096)

DJ9A4AE (DJ944AE)

RL0020- (L0020I)

ATT4026 (ATT4025)

ZG594TSH (ZG594TS)

4NTU770 (4NIU770)

LP Recognition (Overall Evaluation)

Execution time (NVIDIA Titan Xp).

ALPR Stage	Model	Time (ms)	FPS
Vehicle Detection	YOLOv2	8.5382	117
LP Detection and Layout Classification	Fast-YOLOv2	3.0854	324
LP Recognition	CR-NET	1.9935	502
Total	-	**13.6171**	**73**

Other Works in the Literature

Other Works in the Literature (1/2)

License Plate Detection and Recognition in Unconstrained Scenarios[9]

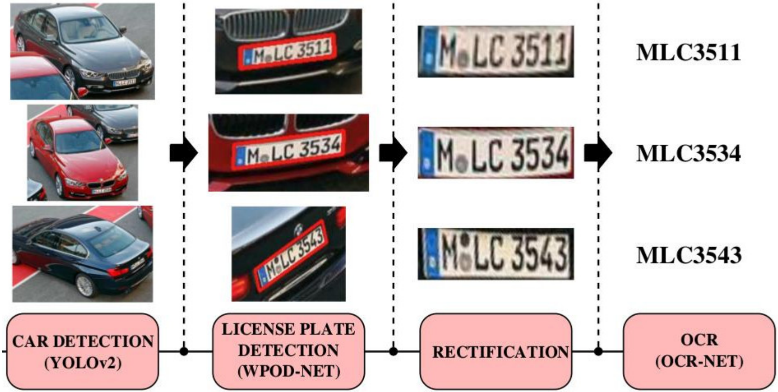
- Most systems assume a mostly frontal view of the vehicle and LP;
- More relaxed image acquisition scenarios might lead to **oblique views** in which the LP might be highly distorted yet still readable.

[9] S. M. Silva and C. R. Jung, "License Plate Detection and Recognition in Unconstrained Scenarios," in *European Conference on Computer Vision (ECCV)*, Sept 2018, pp. 593–609.

Other Works in the Literature (1/2)

License Plate Detection and Recognition in Unconstrained Scenarios[9]

- License plate **rectification**;



[9] S. M. Silva and C. R. Jung, "License Plate Detection and Recognition in Unconstrained Scenarios," in *European Conference on Computer Vision (ECCV)*, Sept 2018, pp. 593–609.

Other Works in the Literature (1/2)

License Plate Detection and Recognition in Unconstrained Scenarios[9]

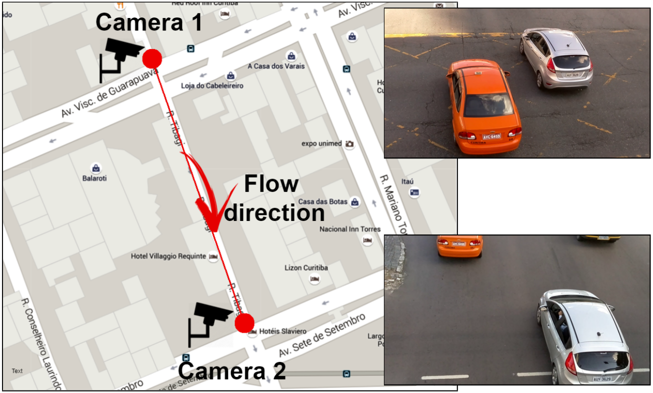
- The results do not vary much in the mostly frontal datasets;
- There is a considerable accuracy gain in datasets with oblique LPs.

Table 2: Full ALPR results for all 5 datasets.

	OpenALPR EU	OpenALPR BR	SSIG Test	AOLP RP	Proposed CD-HARD	Average
Ours	93.52%	91.23%	**88.56%**	**98.36%**	**75.00%**	**89.33%**
Ours (no artf.)	92.59%	88.60%	84.58%	93.29%	73.08%	86.43%
Ours (unrect.)	94.44%	90.35%	87.81%	84.61%	57.69%	82.98%
Commercial systems						
OpenALPR	**96.30%**	85.96%	87.44%	69.72%*	67.31%	81.35%
Sighthound	83.33%	**94.73%**	81.46%	83.47%	45.19%	77.64%
Amazon Rekog.	69.44%	83.33%	31.21%	68.25%	30.77%	56.60%
Literature						
Laroca et al. [17]	-	-	85.45%	-	-	-
Li et al. [18]	-	-	-	88.38%	-	-
Li et al. [19]	-	-	-	83.63%	-	-

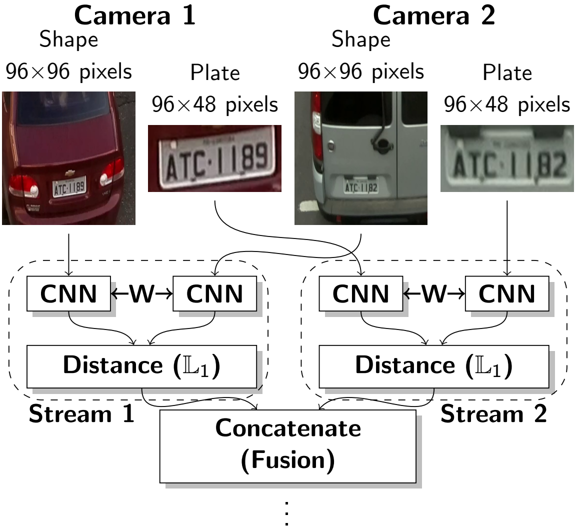
[9] S. M. Silva and C. R. Jung, "License Plate Detection and Recognition in Unconstrained Scenarios," in *European Conference on Computer Vision (ECCV)*, Sept 2018, pp. 593–609.

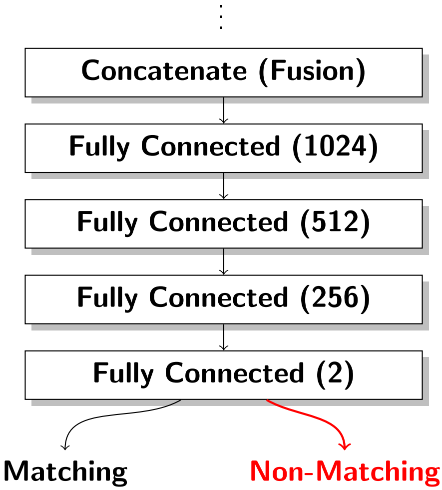
A Two-stream Siamese Neural Network For Vehicle Re-identification By Using Non-overlapping Cameras[10]



[10] I. O. Oliveira, K. V. O. Fonseca and R. Minetto, "A Two-stream Siamese Neural Network For Vehicle Re-identification By Using Non-overlapping Cameras," in *IEEE International Conference on Image Processing (ICIP)*, 2019.

A Two-stream Siamese Neural Network For Vehicle Re-identification By Using Non-overlapping Cameras





[10] I. O. Oliveira, K. V. O. Fonseca and R. Minetto, "A Two-stream Siamese Neural Network For Vehicle Re-identification By Using Non-overlapping Cameras," in *IEEE International Conference on Image Processing (ICIP)*, 2019.

Other Works in the Literature (2/2)

Siamese-Car (Stream 1): **non-matching** ✓
Siamese-Plate (Stream 2): **matching** ✗
Siamese (Two-Stream): **non-matching** ✓

Siamese-Car (Stream 1): **matching** ✗
Siamese-Plate (Stream 2): **non-matching** ✓
Siamese (Two-Stream): **non-matching** ✓

[10] I. O. Oliveira, K. V. O. Fonseca and R. Minetto, "A Two-stream Siamese Neural Network For Vehicle Re-identification By Using Non-overlapping Cameras," in *IEEE International Conference on Image Processing (ICIP)*, 2019.

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Thanks for your attention!

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