# Real-Time Automatic License Plate Recognition Through Deep Multi-Task Networks

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# Outline

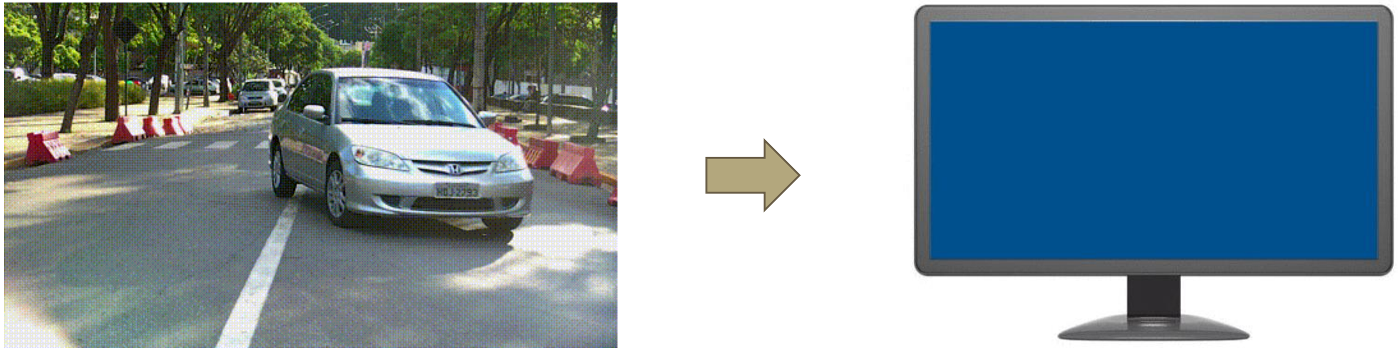
- Introduction
- ALPR Approach
  - Detection Net
  - Recognition Net
- Data Augmentation
- SSIG-ALPR Dataset
- Experimental Evaluation
- Conclusion

# Introduction

# Introduction

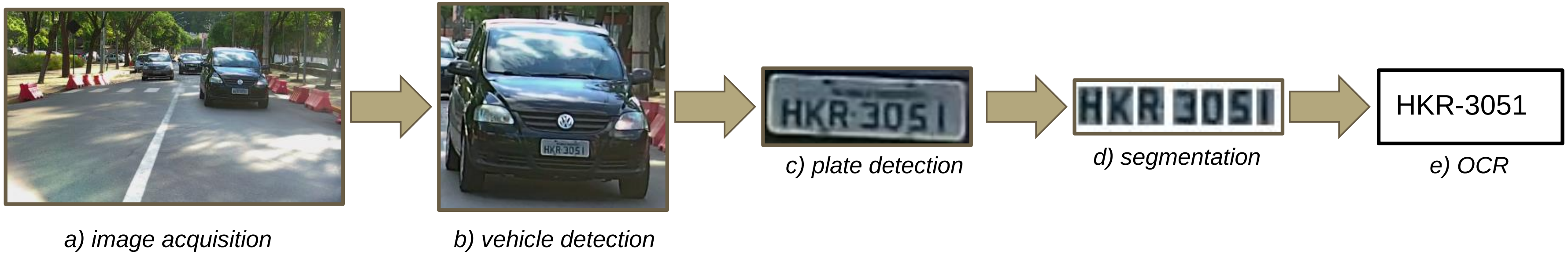
Automatic License Plate Recognition (ALPR) consists on perform on-track license plate recognition.

- **Key challenges**
  - Handle multiple vehicles
  - Execute on real-time
  - Predict correctly the majority of vehicles



# Introduction

Usually, approaches divide license plate recognition into five subtasks and execute them in sequence:




**Drawback:** errors resulting of each task are propagated to the next step through the entire ALPR workflow.

# Introduction

**Contributions:**

➔ A new public available ALPR dataset
➔ A new ALPR approach composed by two deep multi-task networks
➔ Three techniques to augment the training data

**Hypothesis:**

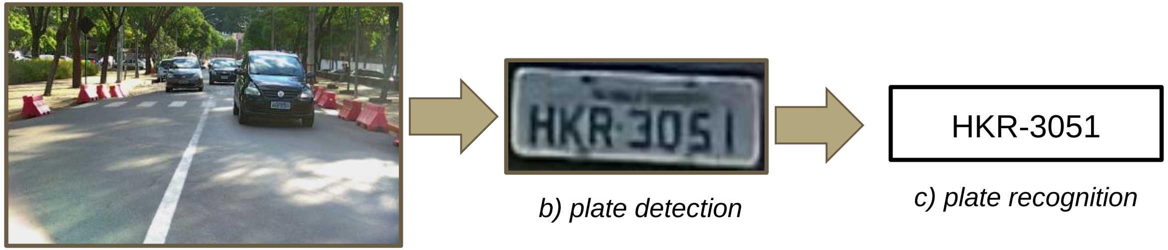
➔ We can overcome the error-rate propagation problem by performing ALPR with fewer tasks
➔ Some ALPR tasks such as character segmentation do not need to be explicit performed

# ALPR Approach

# ALPR Approach

**Detection Network:** detect on-road license plates directly on the frame

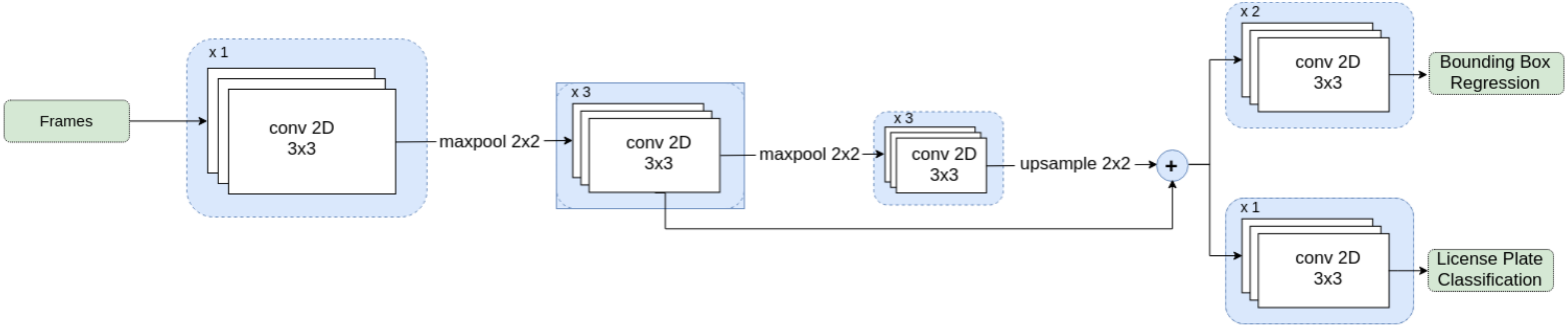
**Recognition Network:** recognize license plates with implicit segmentation




*a) image acquisition* *b) plate detection* *c) plate recognition*

# ALPR Approach

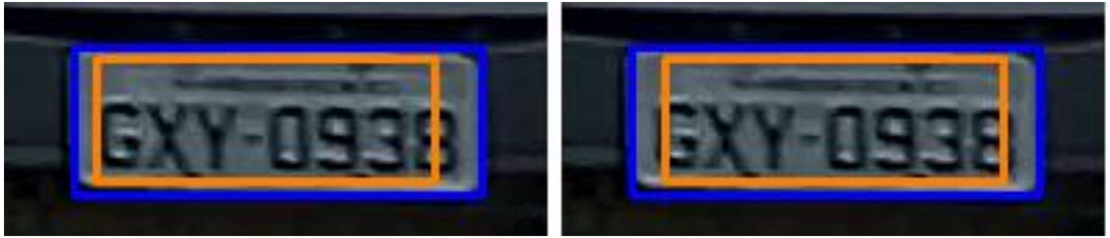
## Detection Net



# ALPR Approach

## Detection Net

Our loss penalizes regressions inside the license plate bounding box to **ensure all characters will be completely visible**.

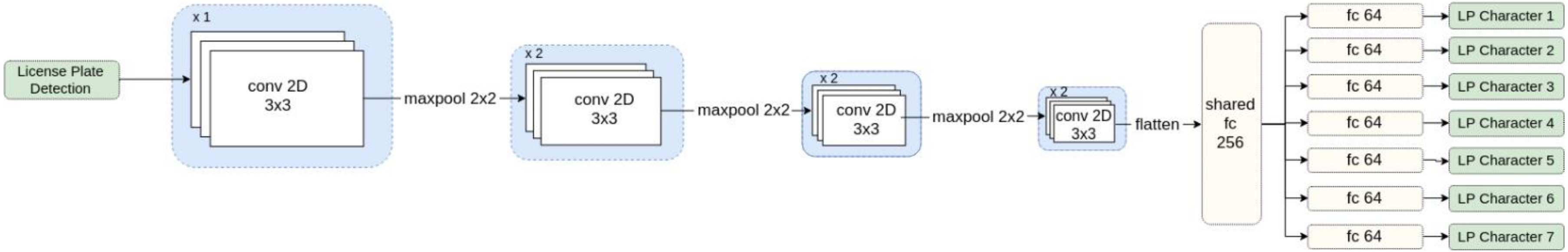


a) underdetection


a) overdetection

# ALPR Approach

## Recognition Net



# Data Augmentation

# Data Augmentation

## **Detection Net:** Zoom

- We need to train all anchors to ensure robustness for multiple scales

- **Solution:** Zoom-in and zoom-out the frames



# Data Augmentation

## **Recognition Net:** Character Permutation

- Every task of the proposed network has to learn the representation of each letter/digit
- Very hard due to the Brazilian license plate allocation policy

- **Solution:** Permutate license plate characters

# Data Augmentation

## **Recognition Net:** Synthetic License Plates

- Since the permutations occur only between characters in the same plate, an undesired correlation between the characters in different positions was created

- **Solution:** Use synthetic license plates to train the fully-connected layers


# SSIG-ALPR Dataset

# SSIG-ALPR

## Proposed Dataset

Our proposed dataset contains:

- **8,683** license plates images
- **815** different vehicles
- ***3,368*** *images do not contain text annotation as they have very low resolution*

**2 cameras**

a) static camera

b) moving camera

# Experiments

# Experiments

## Overview

- Detection Network Evaluation
- Recognition Network Evaluation
- Comparison with State-of-the-Art Approaches
  - **Baselines:** Silva and Jung [2], Gonçalves et al [3], Laroca et al [4], OpenALPR [5], Sighthound [6]
  - **Two datasets:** SSIG-SegPlate [3], UFPR-ALPR [4]
  - ***Frame rate evaluation***

**[2]** S. M. Silva and C. R. Jung, "Real-time brazilian license plate detection and recognition using deep convolutional neural networks" in SIBGRAPI, 2017.
**[3]** G. R. Gonçalves, D. Menotti, and W. R. Schwartz, "License plate recognition based on temporal redundancy" in ITSC, 2016.
**[4]** R. Laroca, E. Severo, L. A. Zanlorensi, L. S. Oliveira, G. R. Gonçalves, W. R. Schwartz, and D. Menotti, "A robust real-time automatic license plate recognition based on the YOLO detector" CoRR, 2018
**[5]** http://www.openalpr.com/
**[6]** http://www.sighthound.com/

# Experiments

## Detection Network Evaluation

| Approach | Accuracy (%) |
|---|---|
| no modification | 76.73 |
| loss only | **+1.74** |
| zoom only | **+1.95** |
| ***zoom + loss*** | ***+2.59*** |

# Experiments

## Recognition Network Evaluation

| **Approach** | **Accuracy (%)** |
| --- | --- |
| no augmentation | 82.96 |
| permutation only | **+0.76** |
| synthetic only | **-33.43** |
| ***permutation + synthetic*** | ***+2.64*** |

# Experiments

## Comparison with State-of-the-Art Approaches

**SSIG-SegPlate**

- Static camera
- 2,000 images
- 101 vehicles

**UFPR-ALPR**

- Moving camera
- 4,500 images
- 150 vehicles

# Experiments

## Comparison with State-of-the-Art Approaches

| Approach | SSIG-SegPlate (%) | UFPR-ALPR (%) |
|---|---|---|
| Silva and Jung [2] | 63.1 | - |
| Gonçalves et al. [3] | 81.8 | - |
| Sighthound | 73.1 | **-** |
| OpenALPR | 87.4 | 57.9 |
| Laroca et al. [4] | 85.4 | **72.2** |
| **Proposed Approach** | **88.8** | 55.6 |

# Experiments

## **Comparison with State-of-the-Art Approaches:** Frame Rate Evaluation

| **Approach** | **Max # of license plates** |
|---|---|
| Silva and Jung [2] | 3 |
| Gonçalves et al. [3] | 1 |
| Laroca et al. [4] | 1 |
| **Proposed Approach** | **6** |

# Final Remarks

# Final Remarks

- **Data augmentation techniques are very helpful** to improve the network learning process
- License plate detection **robustness is considerably diminished** when the images were acquired from a **non-static cameras**
- In SSIG-SegPlate, our approach was able to **outperform all baselines** composed by multiple steps using static background
- By creating two small networks, **we were able to run our approach with more 30 fps** even with 6 vehicles to recognize at the same time

- As future works:
    - Jointly train both networks
    - Apply our approach with other license plates layouts
    - Adapt the network to work with motorcycles

# Thank you

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