Multi-Task Learning for LowResolution License Plate Recognition

Smart Sense Laboratory www.sense.dcc.ufmg.br

## Outline

- Introduction
- Proposed Approach
- Multi-Task CNN
- Deep Generative Network
- Experimental Evaluation
- Conclusions


## Outline

$\Rightarrow$ • Introduction

- Proposed Approach
- Multi-Task CNN
- Deep Generative Network
- Experimental Evaluation
- Conclusions


# Introduction 

Problem Definition

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

- Key challenges

O Recognize multiple vehicles at the same time
O Handle low-resolution or dirty license plates

- Predict correctly the majority of vehicles



# Introduction 

Standard ALPR Workflow

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

However, errors resulting of each task are propagated to the next step through the entire ALPR workflow.


In this work, we focus only on the license plate recognition phase assuming the license plate is already located

# Introduction 

Proposed Approaches

## Contributions:

$\rightarrow$ A license plate recognition approach aimed to recognize vehicle license plates without segmenting them
$\rightarrow$ A deep generative network created to generate low-resolution samples as data augmentation

## Hypothesis:

$\rightarrow$ It is possible to recognize license plates images that are not human-readable
$\rightarrow$ Low-resolution images can be generated synthetically and used to improve the performance of the ALPR model

## Introduction

Related Works

- Segmentation-free approaches were successfully used in other approaches
- Previous works already had focused on low-resolution resolution license plate recognition

Holistic Recognition of Low Quality License Plates by CNN using Track Annotated Data

Jakub Špañhel, Jakub Sochor"; Roman Juránek, Adam Herout, Lukáš Maršik, Pavel Zemčík Graph@FIT, Brno University of Technology

Brno, Czech Republic
\{ispanhe1, herout\}efit.vutbr.cz

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

Gabriel R. Gonçalves ${ }^{*}$, Matheus A. Diniz ${ }^{*}$, Rayson Laroca ${ }^{\dagger}$, David Menott ${ }^{\dagger}$, William Robson Schwartz ${ }^{*}$ ${ }^{*}$ Smart Sense Laboratory, Department of Computer Science, Universidade Federal de Minas Gerais, Brazil ${ }^{\dagger}$ Laboratory of Vision, Robotics and Imaging, Universidade Federal do Paraná, Brazil
\{gabrielrg, matheusad\}edec.ufmg.br, \{rblsantos, menotti\}einf.ufpr.br, william@dec.ufmg.br

Špaňhel, J., Sochor, J., Juránek, R., Herout, A., Maršík, L., Zemčík, P.: Holistic recognition of low quality license plates by cnn using track annotated data. In: AVSS (2017)

Gonçalves, G. R., Diniz, M. A., Laroca, R., Menotti, D., Schwartz, W. R.. "Real-time automatic license plate recognition through deep multi-task networks." In SIBGRAPI (2018)

## Outline

- Introduction
$\Rightarrow$ • Proposed Approach
- Multi-Task CNN
- Data Augmentations
- Experimental Evaluation
- Conclusions


## Proposed Approach

## Multi-Task CNN

As previously stated, our approach is designed to receive a license plate image as input and outputs its characters


As the network demands to train all tasks, we utilized the character permutation technique proposed by Gonçalves et al.


Gonçalves, G., Diniz, M.A., Laroca, R., Menotti, D., Schwartz, W.R.: Real-time automatic license plate recognition through deep multi-task networks. In: Sibgrapi. IEEE (2018)

## Proposed Approach

Data Augmentation: Deep Generative Network (DGM)

The goal is to generate low-resolution images instead of simply downscale the images in the dataset


## Outline

－Introduction
－Proposed Approach
－Multi－Task CNN
－Data Augmentations
$\checkmark$ • Experimental Evaluation
－Conclusions

## Experimental Results

Evaluation Protocol: Datasets

- SSIG-ALPR:

O 2,520 images for training
O 3,180 images for testing

- SSIG-SegPlate: 2,000 images used only for validation

We further increased the number of training images to $\mathbf{1 , 2 0 0 , 0 0 0}$ using both augmentation techniques

We also split the testing images in two sets:

- High-resolution set: 2,360 images
- Low-resolution set: 800 images


## Experimental Results

Evaluation Protocol: Baselines

- Cascade Networks:

O Segmentation network
O Recognition network

- Silva \& Jung ${ }^{1}$

O Only the recognition network

- Gonçalves et al ${ }^{2}$

O Handcrafted approach based on HOG-SVM classifier

- OpenALPR

○ Commercial system (www.openalpr.com)

## Experimental Results

## Results

| Approach | High-Resolution | Low-Resolution |
| :---: | :---: | :---: |
| Cascade Networks | $43,3 \%$ | $0,9 \%$ |
| Gonçalves et al. | $48,3 \%$ | $0,1 \%$ |
| Silva \& Jung | $35,4 \%$ | $0,4 \%$ |
| Proposed Network | $\mathbf{8 3 , 2 \%}$ | $\mathbf{3 5 , 4 \%}$ |

## Experimental Results

## Results

- OpenALPR needs to run a full pipeline for ALPR, therefore, we could not use only the license plate recognition network as it needs to detect the license plate before


## 'open ALPR

- We applied our approach only on license plate that were detected by OpenALPR

| Approach | High-Resolution (2032) | Low-Resolution (6) |
| :---: | :---: | :---: |
| OpenALPR | $86,3 \%(1755)$ | $0 \%(0)$ |
| Proposed Approach | $\mathbf{8 7 , 1 \%}(\mathbf{1 7 7 0})$ | $\mathbf{5 0 \% ~ ( 3 )}$ |

## Experimental Results

Results

... Experimental Results
Results


## Experimental Results

Results

| Approach | Accuracy |  |
| :---: | :---: | :---: |
|  | High-Resolution | Low-Resolution |
| without samples from <br> DGM | $83.2 \%$ | $35.4 \%$ |
| with samples from DGM | $\mathbf{8 3 . 2 \%}$ | $\mathbf{4 0 . 3} \%$ |

## Outline

## Introduction

- Proposed Approach
- Multi-Task CNN
- Data Augmentations

Experimental Evaluation
$\Rightarrow$ • Conclusions

## Conclusions

The main conclusions of this work can be pointed as follows:

- it is possible to recognize low-resolution license plates that are not human readable
- we were able to recognize $40.3 \%$ of all low-resolution license plates, which stands for an accuracy of $87.8 \%$ of character recognition
- we could also demonstrate that samples generated from DGM were able to improve the model accuracy by 4.9 percentage points

As future works:

- evaluate the technique using other license plate layouts
- create a superresolution or similar techniques to achieve better on lowresolutions license plates that can be used on real-scenarios


## Questions?

## senselab

If you have any further questions, reach us at gabrielrg@dcc.ufmg.br.


