

# Can you enhance it?

Forensic Reconstruction of Severely Degraded License Plates

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# Can you read this?





# Can you read this?











# Turning the image enhancement problem on its head



Image in question





# Turning the image enhancement problem on its head





# Turning the image enhancement problem on its head





# **Conventional recognition**<sup>1</sup>

- 1. License plate detection
- 2. Character segmentation
- 3. Character recognition

<sup>&</sup>lt;sup>1</sup>M. Safraz, M. J. Ahmed, S. A. Ghazi, "Saudi Arabian license plate recognition system", in 2003 International Conference on Geometric Modeling and Graphics, Jul. 2003.



# **Related work**

#### Correlation by Hsieh et al.<sup>2</sup>

- Slide character templates across image
- Drawback: Requires knowledge of font style and character placement



<sup>&</sup>lt;sup>2</sup>P.-L. Hsieh, Y.-M. Liang, H.Y. M. Liao, "Recognition of blurred license plate images", in 2010 IEEE International Workshop on Information Forensics and Security, Dec. 2010.



## **Related work**

CNN-based recognition by Agarwal et al.<sup>3</sup>

- · Recognize the first and last three characters separately
- Drawback: Assumes six-character license plates



<sup>&</sup>lt;sup>3</sup>S. Agarwal, D. Tran, L. Torresani, H. Farid, "Deciphering severely degraded license plates", *Electronic Imaging*, Jan. 2017.



# Goal

#### Proposed method

• Work with variable number of characters (5 to 7)





#### **Performance evaluation**

- Fill license number label with null character ">" up to length seven
- · Assign integer score out of a maximum of seven points

True	Predicted	Top-1 accuracy
ABC123	ABC123◊	7/7 (100%)
ABC123	ABC12↔	6/7 (86%)
ABC123	ABC1234	6/7 (86%)
ABC123	AXXXX3	3/7 (43%)
ABC123	XABC123	0/7 (0%)

- · Report Levenshtein distance to take shifted recognition into account
- Address similar characters, e.g., "O" and "0", "I" and "1", by Top-5 accuracy



## Implementation as CNN architecture I

· VGG-like architecture with seven output layers consisting of 37 units each





# Synthetic data rendering

- Optimizing 55M parameters requires a lot of training data
- Generate synthetic training images based on measurements from real-world license plates





# Synthetic-I training image examples

• Vary characters, gap position, font, font size, character placement, contrast, background





# **Degradation levels**





# Synthetic-I results on 1,000 real-world images

#### Top-1 accuracies





## Example: "CDS7001"





# Synthetic-I results on 1,000 real-world images

#### Confusion chart





# Improving synthetic data rendering

- Place distracting object
- Add embossing effect
- Add frame and drop shadow
- · Colorize background, font, and frame and blend with natural images





## Synthetic-II results on 1,000 real-world images





## Example: "CDS7001"





#### **Real-world images from Plateshack**





## **Real-world:** Fine-tuning on Plateshack images

• Train on synthetic images, fine-tune all layers on Plateshack images with reduced learning rate



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#### Example: "CDS7001"





Idea: Highlight important regions for recognition by sliding occluding patch across image







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Idea: Highlight important regions for recognition by sliding occluding patch across image

License number "EKA548", resolution 25 pixels, SNR 7 dB















# Conclusion

- Even from low-resolution images we can extract useful information
- CNN outperforms humans at low-resolution and high amounts of noise
- · Performance increases with more realistic training data

#### Limitations

- Bad performance on special license plate configurations
- · CNN not robust to unknown degradations, e.g., motion blur

#### Outlook

- Include more types of degradation
- · Better training data generation, e.g., using GANs
- Train combined denoising and recognition CNN end-to-end



# github.com/btlorch/license-plates



#### Image sources

- https://9gag.com/gag/23853/enhance-that-license-plate
- http://plateshack.com/y2k/