Deblurring License Plates

Group 8

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Table of Contents

Introduction

- **Setting**: 30M CCTV cameras in China.

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- **Setting**: 30M CCTV cameras in China.
- **Problem**: Blurry license plates cannot be read by OCR.
- **Competition**: Find ways to deblur them.

Source: Smart City proposal by Huawei.

Competition Results

Runner-up prize in the Huawei Image Deblurring competition 2017.

Demo

Classical Image Processing

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- Input: image, output: image.

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- Manipulating images by treating them as matrices.

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Figure: Examples of blurry license plates(30x90)

Discrete Convolution

- Point-wise multiplication of two functions.

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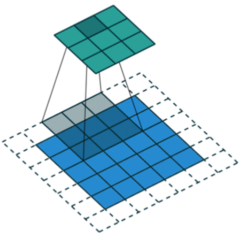

Figure: Classical & Upsampling Convolution

Discrete Convolution for Deblurring

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- **Point Spread Function**: kernel as probability distribution.

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- Impractical, instead...

CNN's

- Convolution layers produced by a linear transformation that preserves implicit structure.

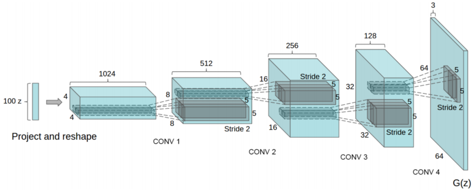

Figure: Convolution Layers in a Generative Network

CNN's

Models with greatest influence to our solution:

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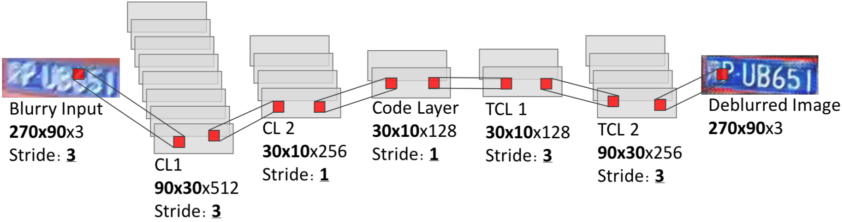
Figure: The inspiration behind the name 'Inception'

Our Nerual Network: Moussaka

Moussaka (*Noun*): A Greek dish made of minced lamb, aubergines and potatoes, with cheese sauce on top.

Our Nerual Network: Moussaka

Moussaka (*Noun*): A stacked auto-encoding Convolutional Neural Network (CNN).



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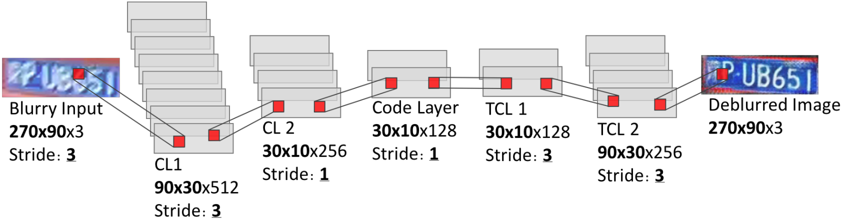


Training the Network: Batch size *64*

L2 Loss → Update weights (Decaying learning rate)

Optimisations

On each layer..

- Before: **Dropout** (50%)
- After: **ReLU** / **tanh** activation functions

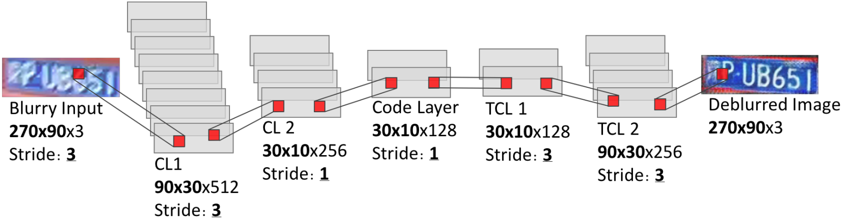
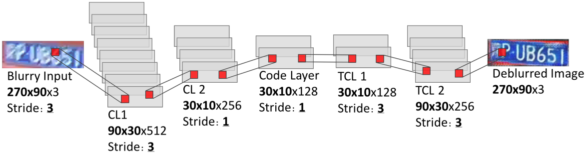


Image Propagation

Diagram of all channels:



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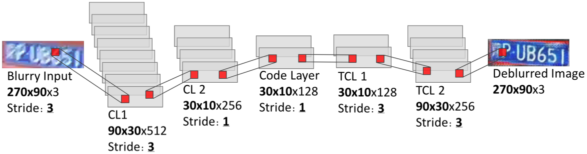

Example channel:

Image Propagation

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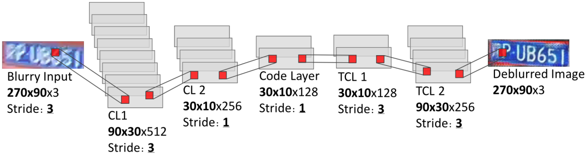

Example channel:

To scale:

The Code Layer

Table: Demonstration of variance in Code Layer (scale not preserved)

Shows dense, compressed information (Inception)

The Blurrer

Main Goal: Construct input images for Moussaka from the training data set.

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Figure: The transformation we wanted to achieve

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Figure: The transformation we wanted to achieve

- **Approximate** natural blurriness as a **combination** of image 'corruption' functions.
- The closer the effect is to the effect seen in the testing set, the better the network will perform.
- A lot of **trial and error**.

Data Generation: Artificial Blurring

The **corruptions** we combine to achieve the desired effect are:

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The **corruptions** we combine to achieve the desired effect are:

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- Motion blur
- Pixelation
- Perspective transformation
- Brightness variation
- Contrast increase

A **probabilistic** combination for the full blurrer.

Specific Blurs Approach

Corruption type	Usage %	Example
Main Blur	88%	

Table: Different types of corruption.

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Specific Blurs Approach

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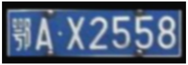
Mild Blur	2%	

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Handpicked 1378 from 4000 images.

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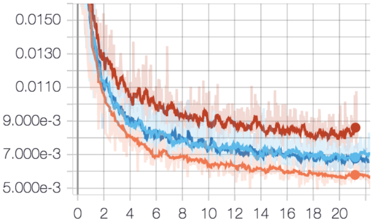
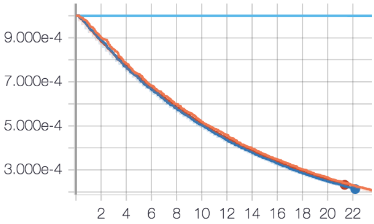
Figure: Frankenstein license plates

Numerical Results





Colour	Experiment	Cost	Epoch	Time
●	All	5.5336e-3	3629	21 hr
●	No decay	6.6555e-3	3777	21 hr
●	No dropout	6.9685e-3	3760	21 hr
●	No selection	7.9423e-3	1252	21 hr

Table: Numerical results of the direct comparison.

Visual Comparison of Optimisation

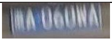
Blurred	No dropout	No selection	No decay	All
				
				
				

Table: Comparison of network optimisation on unseen data

Visual Results: Artificial Data

Clean Image	Artificial Blur	Deblurred

Table: Test results on training data and artificial blur

Visual Results: Real Data

Testing out model on blurry images from Huawei cameras

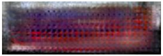
Camera Image	**Deblurred**
	
	
	
	
	
	

Table: Test results on unseen data

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- Generative Adversarial Network (GAN)

Meeting Experts

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Trip to China

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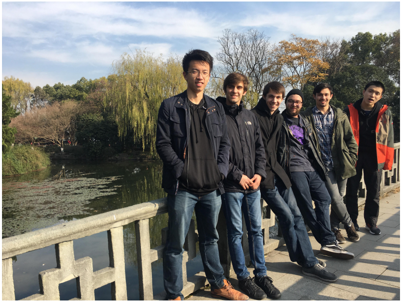

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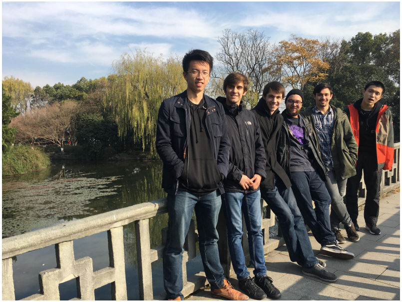

Final Remarks

1. Image deblurring problem in video surveillance
2. Research
3. Moussaka
4. Data generation
5. Results
6. Extensions

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"You can't trust your eyes when your imagination is out of focus."

- Mark Twain


THANK YOU