

UNIVERSITY OF TARTU
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Optical Character Recognition for Extremely Low Quality Images

Master's Thesis (30 ECTS)

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Optical Character Recognition for Extremely Low Quality Images

Abstract:

Optical character recognition (OCR) from printed and handwritten documents is virtually a solved problem for all practical purposes. Modern OCR systems are able to achieve a 99.9% detection rate which is on par with human capabilities. Where most OCR systems fall short is when the the input is of low quality, such as containing large amounts of noise or motion blur, or being of low resolution.

A real world use-case of this problem is detecting car licence plates from a security camera feed. Security cameras are often of low resolution, use high levels of compression, and have low framerate since the video footage needs to be stored for a long period of time and storage cost is paramount. In addition, cars can move unpredictably causing motion blur during the capture of a video frame.

The goal of this project is to test various methods of improving OCR accuracy with low quality input. Namely,

- Training a neural network (NN) on low quality images. And testing results on low quality images.
- Training a NN on high quality images and testing on digitally enhanced low quality images.
- Training a NN on digitally enhanced low quality images and testing on digitally enhanced images.
- Using multiframe registration of frames from a video feed to improve detection quality.

The tests will be conducted using frames from a blurry, noisy, and low resolution video feed containing text. Third party solutions are used to extract areas containing text from those frames.

Some of the training and test data is gathered specifically for this task by filming, and extracting frames from, an intentionally blurry video. Additional synthetic motion blur is added to some of the images. Some data is gathered from available open source databases, such as images containing vehicle licence plates.

Keywords:

OCR, Deblurring, Low Quality, Low Resolution

CERCS:

CERCS code and name: <https://www.etis.ee/Portal/Classifiers/Details/d3717f7b-bec8-4cd9-8ea4-c89cd56ca46e>

Is this necessary at all?

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Unsolved issues

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1 Introduction

Optical character recognition (OCR) is the conversion of text to a machine encoded form, such as images or printed documents. OCR is not a new concept by any means. A patent for a system which can be called the predecessor of modern OCR was already granted in 1931. Modern OCR systems are, of course, far more powerful.

1.1 Motivation

For all intents and purposes OCR is basically a solved problem for detecting text from clear and high resolution images containing printed or handwritten text. Modern systems perform on par with human capabilities in this regard, boasting a 99.9% detection rate. A problem still being researched, however, is OCR from low quality images. Low quality can mean low resolution, high levels of compression, containing artefacts generated by scanning for example, containing motion blur caused by movement of the object of the camera during image capture, or any combination thereof.

Accurate OCR from low quality images and video could solve several problems for automating processes where the system needs to detect some text. For example an autonomous parking garage, where a camera is filming approaching cars, a system analyses the video feed and opens the gate or barrier for cars with licence plate numbers matching authorized users.

1.2 Contributions

The goal of this thesis is test different approaches for such a system. Namely,

- Training a neural network (NN) on low quality images. And testing results on low quality images.
- Training a NN on high quality images and testing on digitally enhanced low quality images.
- Training a NN on digitally enhanced low quality images and testing on digitally enhanced images.
- Using multiframe registration of frames from a video feed to improve detection quality.

Add actual contribution after work is done.

1.3 Outline

Following is the outline of the thesis. **Chapter 2** describes both the history and the state of the art in OCR and low quality image enhancement and discusses the advantages and drawbacks of each of the approaches.

Chapter 3 describes the research problem and the necessity of finding a solution to the problem.

Chapter 4 describes in detail the approach taken to solve the problem.

Chapter 5 describes the evaluation process of the results as well as comparison to related works.

Chapter 5 concludes the thesis with a summary and research directions for the future

2 Background

This section gives an overview of the history of OCR and image enhancement solutions as well as research and commercial products related to the topic.

2.1 History

2.1.1 OCR

The history of OCR can be traced back to the late 1920s when inventor Emanuel Goldberg started developing a system he called a "Statistical Machine" which searched microfilm archives using an optical code recognition system. He was granted a patent for his invention in 1931, which was later acquired by IBM. [1]

2.1.2 Digital Image Enhancement

Digital image enhancement has been around for virtually as long as digital images have. In essence a very simple concept - take the pixel values of an image and, using some algorithm, modify them to produce a clearer image.

2.2 State of the Art

2.2.1 OCR

Most of modern OCR systems are based on artificial neural networks, often called just neural networks (NNs). Which makes this virtually a necessity is the fact is the number of different character sets and scripts that need to be supported.

2.2.2 Digital Image Enhancement

Same as with OCR, modern image enhancement largely relies on neural networks, because it is such a dynamic problem and as such finding a suitable algorithmic solution to the problem is difficult. In addition, there is no agreed upon metric for measuring the performance of an image enhancement method. The results of a process such as image deblurring are largely subjective.

OCR is a very good context for measuring image enhancement, since the results, in this case OCR accuracy, are directly measurable before and after the enhancement process. M. D. Kim et al propose a quantitative method of measuring image deblurring accuracy in their paper "Dynamics-Based Motion Deblurring Improves the Performance of Optical Character Recognition During Fast Scanning of a Robotic Eye". In addition, they note that computation time is extremely important to modern image processing solutions. [2] Indeed, since a lot of image processing happens in smartphones and

microcomputers computational requirements are crucial in comparing image enhancement methods.

2.2.3 Neural Networks

The theoretical base for NNs dates back to the end of the 1800s and is based on the structure of the human brain in which neurons interact with each other and the bonds between neurons can strengthen and weaken over time. [3]

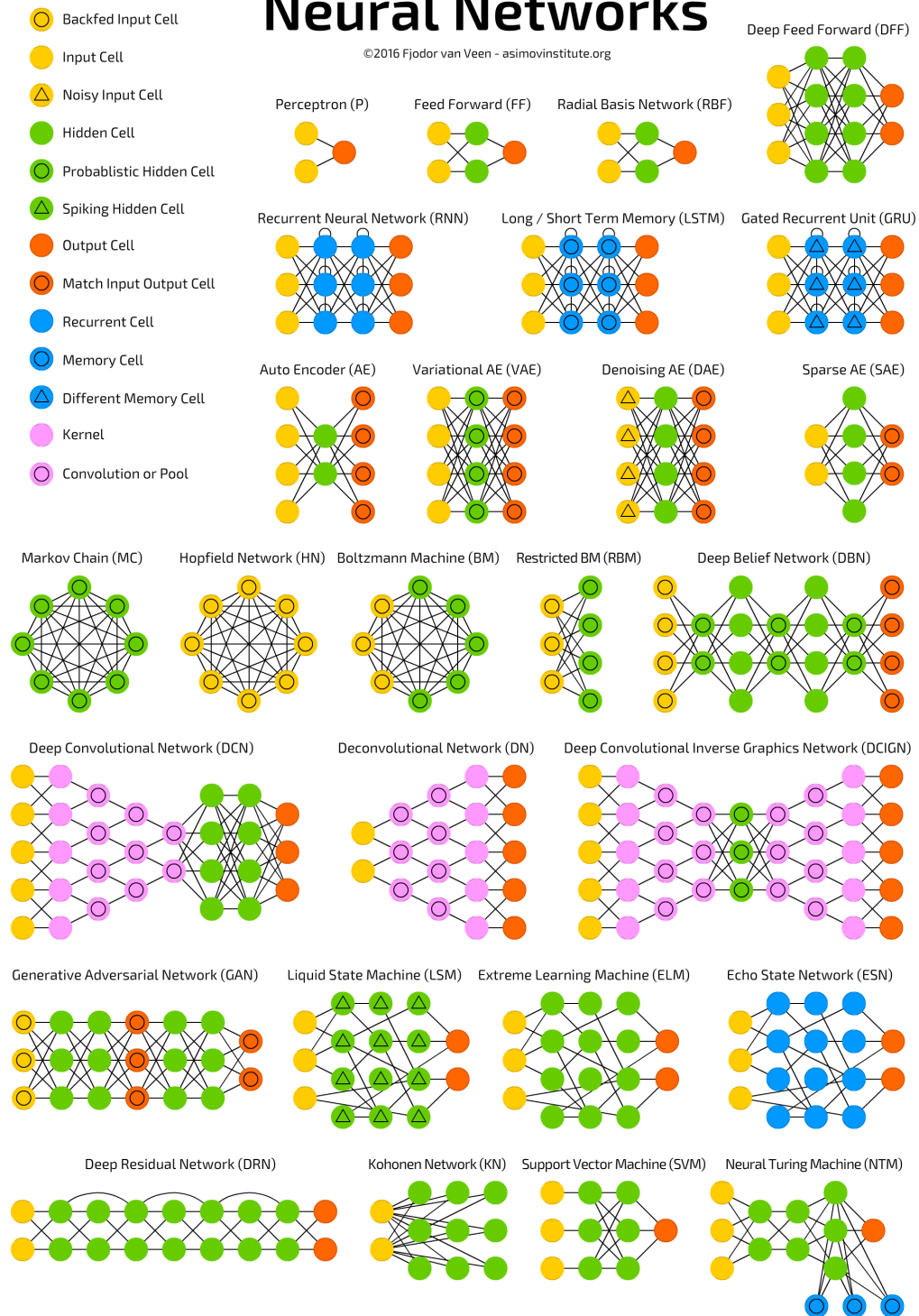
An artificial neural network consists of many simple connected processors, called artificial neurons, which produce activations based on an activation function producing real numbers in a predefined range. The simplest neural network consists of an input layer and an output layer. The neurons in the input layer produce activations based on the input. The output layer produces an output based on the activations of input layers. [3]

Most NNs are not as simple as that and contain any number of hidden layers between the input and output layers. These hidden layers each consist of any number of neurons which each produce an activation based on the output of another layer. There are various architectures used for NNs, some are combinations of other types of networks. This work mostly focuses on convolutional neural networks (CNNs) and recurrent neural networks (RNNs). [3]

A mostly complete chart of

Neural Networks

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[4]

CNNs are primarily used for image processing. CNNs are feedforward networks (FFNs), which means neurons do not back-propagate any information and only pass it forward to the next layer. A distinct feature of CNNs is that they consist of convolutional layers in which not all neurons are connected to all neurons in the previous and next layers. [3]

RNNs are primarily used for text and speech processing. RNNs are FFNs like CNNs. However, unlike CNNs they are stateful, meaning in addition to receiving data from the previous layer, each neuron retains data from previous passes. RNNs are also able to handle arbitrary input and output lengths unlike CNNs. [3]

1979: convolution + weight replication + subsampling (Neocognitron)

CNNs and RNNs are not mutually exclusive, however, and B. Shi et al devised one of the most promising novel OCR concepts in recent history in the form of a convolutional recurrent neural network (CRNN) in their 2015 paper "An End-to-End Trainable Neural Network for Image-based Sequence Recognition and Its Application to Scene Text Recognition". [5]

Their reasoning is that popular models like CNN cannot be applied to sequence prediction, since they operate on fixed size inputs and outputs. CRNN then behaves like an RNN in that it can accept inputs and return outputs of arbitrary size, while still retaining properties of CNNs which make them invaluable in image processing. [5]

2.2.4 Commercial OCR systems

Tesseract is probably the most well known OCR engine. It started as proprietary software developed by Hewlett Packard in 1985, but was open sourced in 2005. Since then its development is continued by the community. Development has been sponsored by Google starting from 2006.

citations

Tesseract supports over 100 languages by default and can be trained to work with any language or script.

3 Conclusion

what did you do?

What are the results?

future work?

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Appendix

I. Glossary

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