This is the Title of my Thesis

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Desember 2017

PROJECT

Department of Geomatics
Norwegian University of Science and Technology

Supervisor 1: The main supervisor

Supervisor 2: The co-supervisors (internal and external)

Preface

Here, you give a brief introduction to your work. What it is (e.g., a Master's thesis in RAMS at NTNU as part of the study program xxx and...), when it was carried out (e.g., during the autumn semester of 2021). If the project has been carried out for a company, you should mention this and also describe the cooperation with the company. You may also describe how the idea to the project was brought up.

You should also specify the assumed background of the readers of this report (who are you writing for).

Trondheim, 2012-12-16

(Your signature)

Ola Nordmann

Acknowledgment

I would like to thank the following persons for their great help during . . .

If the project has been carried out in cooperation with an external partner (e.g., a company), you should acknowledge the contribution and give thanks to the involved persons.

You should also acknowledge the contributions made by your supervisor(s).

O.N.

(Your initials)

Remark:

Given the opportunity here, the RAMS group would recognize Professor Emeritus Marvin Rausand for the work to prepare this template. Some minor modifications have been proposed by Professor Mary Ann Lundteigen, but these are minor compared to the contribution by Rausand.

Executive Summary

Here you give a summary of your your work and your results. This is like a management summary and should be written in a clear and easy language, without many difficult terms and without abbreviations. Everything you present here must be treated in more detail in the main report. You should not give any references to the report in the summary – just explain what you have done and what you have found out. The Summary and Conclusions should be no more than two pages.

You may assume that you have got three minutes to present to the Rector of NTNU what you have done and what you have found out as part of your thesis. (He is an intelligent person, but does not know much about your field of expertise.)

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Chapter 1

Introduction

Pattern recognition and feature extraction in remote sensing, has been a field of research for many decades. The ability to extract geospatial information directly from satellite imagery has been crucial for fields such as environmental and demographic research. A vast development within the field of machine learning and artificial intelligence the last years, has enabled many researchers to find useful applications of such algorithms within their own scientific fields.

With new satellite technology providing frequently updated imagery, with resolutions less than 0.5 meters, the amount of data that can be extracted is almost incomprehensible. What part will pattern recognition using machine learning play in the future of geospatial analyses?

1.1 Background

Satellites has been collecting earth observation data for decades. Since the satellite Explorer 6 took the first picture of the earth in 1959, millions of satellite images has been taken, processed and stored Esa (2009). This information however, has been very difficult to access, and even harder to analyze when accessible. However, during the last decade, the development of machine learning based methods for Earth Science applications has experiences a considerable leap forward Lary (2010).

In 2014 the first satellite in the new family of earth observation satellites, called the Sentinels, was launched from Kourou, French Guiana. Since then 7 different constellations, each consisting of two satellites, have been launched, and are now orbiting and monitoring the earths surface. The goal of these satellites is to produce a continuous stream of timely data for Europe's Copernicus program, which will be used for environmental monitoring. The different constellations have different missions when it comes to providing datasets for the Copernicus Service.

While some provide very specific data, such as monitoring the earths atmosphere, other constellations provide more general data, such as multi-spectral, high-resolution imagery of the earths surface. In order to maximize the usage of these temporal datasets, they have all been provided free of charge to the public. The fact that all of these datasets are given free of charge

World View constellation

Cushing Oklahoma

Problem Formulation

You should define your problem in a clear an unambiguous way and explain why this is a problem, why it is of interest—and to whom. It is also important to delimit the problem area.

Related work

You should here present the main books and articles that treat problems that are similar to what you are studying, and give proper references to each of these as they are reported. If you, later in your thesis, describe the “state of the art” – with a detailed literature survey, you may just give a very brief survey here (approx. a quarter of a page). If this is the only literature survey, you need to go into more details. An objective of the literature survey is to show the reader that you are familiar with the main literature within your field of research – so that you do not “reinvent the wheel.”

Sentinel-1 is a radar image mission, measuring both land and sea. It has two identical satellites orbiting 180 degrees apart.
Sentinel-2 provides multi-spectral, high resolution imagery of the earths surface.
Sentinel-3 is equipped with multiple instruments used to measure sea-surface topography, sea- and land-surface temperature, ocean color and land color.
Sentinel-4
Sentinel-5
Sentinel-5P
Sentinel-6

References to literature can be given in two different ways:

- As an *explicit* reference: It is shown by **?** and partly also by **?** that . . . .
- As an *implicit* reference: It is shown (e.g., see **?**, Chap. 4) that . . . .

In the example above, we have used "author-year" references, which is the preferred format.

Remark: Following agreement with your supervisor, you may also refer by numbers, for example, [1]. To do this, open the file `ramsstyle.sty` and comment out (by %) the command `\usepackage{natbib}` and un-comment the corresponding command `\usepackage[numbers]{natbib}`.[1]

You may include a link to the Internet in the text or in a footnote by using a command like: http://www.ntnu.edu/ross.

When you refer to the scientific literature, you should always write in *present* tense. Example: **?** show that . . . .

Remark: Hyperlinks are included by the command `\usepackage{hyperref}` in `ramsstyle.sty`. If you feel that the hyperlinks are disturbing when you enter the text, or want to avoid the hyperlinks in printed text, you may either comment out or edit this command in `ramsstyle.sty`.

What Remains to be Done?

After you have defined and delimited your problem – and presented the relevant results found in the literature within this field, you should sum up which parts of the problem that remain to be solved.

1.2 Objectives

The main objectives of this Master's project are

1. This is the first objective
2. This is the second objective
3. This is the third objective
4. More objectives

The objectives shall be written as *fundamental objectives* telling what to do and not *means objectives* telling how to do it.

[1] Notice the strange way we have to write the "backslash" in the text. This is because the "backslash" is a command in LaTeX.

All objectives shall be stated such that we, after having read the thesis, can see whether or not you have met the objective. “To become familiar with ... ” is therefore not a suitable objective.

1.3 Approach

Here you should describe the (scientific) approach and experiments that you will use or have used to solve the problem and meet your objectives and tasks. Experiments may in this context relate analyses you need to carry out in order to investigate a specific hypothesis, task objective, or similar. You should specify the approach and experiments for each objective and/or task. It is preferred that you supplement your explanation of the approach with an illustration.

If there are any ethical problems related to your approach, these should be highlighted and discussed.

1.4 Contributions

Here you give a list of your main contributions in the project or master work.

1.5 Limitations

In this section you describe the limitations of your study. These may be related to the study object (physical limitations, operational limitations), to the environmental and operational conditions, to the thoroughness of the analysis, and so on.

1.6 Outline

Here, you give an overview of how the remaining part of the report is organized. A proposed structure of the main chapters in the report can be as follows (note that some chapters are not numbered):

- Preface: Contains practical information about what you have done, and where the work has been carried out. Any assumed background of the reader should be specified here.
- Acknowledgments: Here, you show the gratitude to who have been supporting your work, professionally and family as relevant.

- Summary: Contains the management summary, and should be a layman's explanation of what you have done and why it is important. This would be the talk you could give if you in an interview is asked about what you did in your thesis, or if some of your relatives ask the same question. This chapter should therefore include as few domain specific words as possible, so that no detailed background in the topic is required.
- Chapter 1. Introduction: Structure already discussed in this chapter.
- Chapter 2. Theoretical background: Here you identify and give the theoretical background needed in this report, with proper references to each literature reference used. The selection of what to include should be discussed and agreed with the supervisors. Theory may involve concepts, definitions, methods, regulations/key standards, theory to explain specific system behavior, and so on.
- Chapter 3..N-2: The naming of the following chapters relies entirely on the specific topic in question. Proposed structure should be discussed with supervisor.
- Chapter N-1 Results: This chapter should be the last chapter *before* "Conclusions, discussion, and ideas for further work"
- Chapter N. Conclusions, discussion, and ideas for further work.
- Bibliography
- Appendix A etc (as needed): Appendix A may for example be acronyms as shown here.

Remark: Notice that chapter and section headings shall be written in lowercase, but that all main words should start with a capital letter.

The report should be no longer than 60 pages in this format for the master as well as the specialization project, with the possible exception of appendixes (which may take up some space if including e.g. code from programming). This does not mean that the report must be at least 60 pages, and the effort should be directed to be as concise as possible throughout the report.

Chapter 2

Theoretical background

In this chapter we are going to investigate some of the key concepts related to pattern recognition, shape detection in imagery and height estimation from remote sensing.

2.1 Shape detection

Identifying geometric shapes in computer vision has been a classical problem for decades. There are many theories related to what is the best way of detecting a particular shape in an image, with shapes defines as two dimensional features of an object that are invariant to scene factors, or whose variation can be modeled easily (Moon et al., 2002).

2.1.1 The Hough transform

In image analysis, the Hough Transform is a technique used for feature extraction. This technique uses a voting procedure from which object candidates are obtained as local maxima in a space constructed by the algorithm (called a accumulator space). Since the algorithm requires that the desired features are specified in some parametric from, the classical Hough transform is mostly used for the detection of regular curves (lines, circles ellipses, etc.).

The main idea of the algorithm is that each edge pixel contributes to a globally consistent solution, such as a curve. In order to detect a points contribution to this solution, the algorithm performs a point-to-curve transformation from the cartesian image coordinate space, to a polar Hough parameter space. In the cartesian coordinate space, a line segment can be represented by Equation 2.1.

$$x cos(\theta) + y sin(\theta) = r \tag{2.1}$$

In Figure 2.2 each point (x,y) on the line corresponds to a set of constant r and θ values.

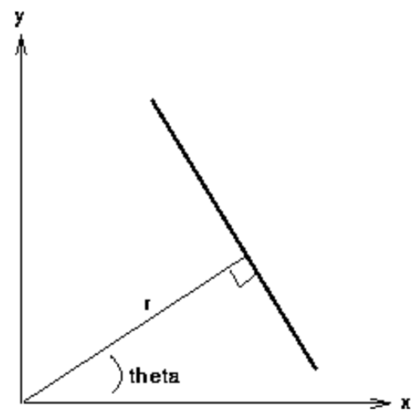


Figure 2.1: Parametric line represented by Equation 2.1 (Fisher et al., 2003)

Therefore when viewed in the Hough parameter space, points that are collinear in the cartesian space will yield curves which intersect at common r and θ values. Here bright areas (high degree of intersection) indicates collinearity between points in an image.

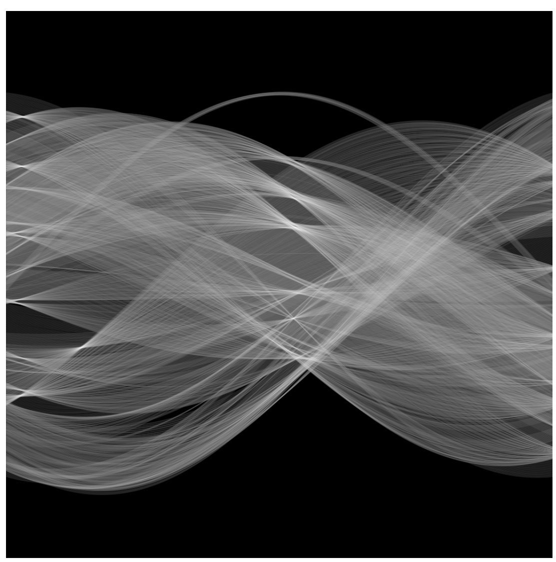


Figure 2.2: Parametric line represented by Equation 2.1 (Fisher et al., 2003)

For detecting circles the computational complexity of the algorithm increases, because the parametric equation representing a circle requires a three dimensional Hough parameter space (see Equation 2.2).

$$(x-a)^2 + (y-b)^2 = r^2 \tag{2.2}$$

2.1.2 Shape detection using superpixels

Most images are based on a raster format, meaning that pixels in the image are structured as an array or grid, where each pixel is associated with a position (row and column), and a numeric value. Raster images can represent a range of different shapes, where a point can be represented by a single pixel and a circle by a contiguous collection of pixels (Worboys, 2003). Even though rasters are easy to work with in most computer systems, since they are represented the way that they are, they do not contain any information about the topology of the objects in the image. For example, there is no way of knowing if a pixel is contained within a certain object or not. In order to identify objects, one approach is therefore to detect edge pixels.

In recent years shape detection algorithms have come to increasingly rely on superpixel algorithms, which groups pixels into perceptually meaningful atomic regions (Achanta et al., 2012). Such regions replace the regular, rigid structure of the raster grid, as shown in Figure 2.3.

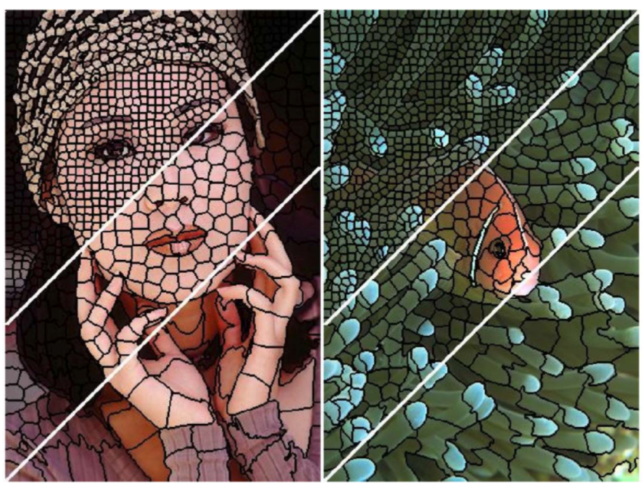


Figure 2.3: Visualization of image segmentation using SLIC (Achanta et al., 2012)

When constructing superpixels, there are some properties of the algorithm that are desirable, regardless of the problem that are being solved. These are, according to (Achanta et al., 2012), the following three points:

- Superpixels should adhere well to image boundaries
- When used to reduce computional complexity as a preprocessing step, superpixels should be fast to compute, memory efficient, and simple to use.

- When used for segmentation purposes, superpixels should both increase the speed and improve the quality of the results.

2.2 Artificial Neural Networks

In recent years, the development of machine learning, a branch of artificial intelligent systems, has become increasingly important in terms of pattern and object recognition in remote sensing and image analysis in general. One of the most commonly used approaches for data mining in remote sensing, has been artificial neural networks Lary et al. (2016).

The basic principle behind artificial neural networks (ANNs) is that it is built up by a network of many simple units that are working in parallel with no centralized control unit. The networks primary means of storage are the weights between the individual units, and the network learns by updating these weights in relation to being provided with a training example.

In order to understand the behavior of ANNs it is important to understand their structures. The most common structure for an ANN is what is called a Feed-forward neural network structure.

2.2.1 Feed-forward neural networks

A feed-forward neural network is build up by a given number of connected layers. A layer is a collection of simple units, called artificial neurons. All networks must consist of an input and output layer, but can also contain an optional number of hidden layers. A network that only consists of an input and output layer is called a perceptron, and it has been shown that these types of networks are only able to model linear functions (Minsky and Papert, 1969).

Input Layer The input layer is the layer that feeds the information into the network. Here the number of neurons are typically equal to the number of features in the data.

Hidden layer The hidden layers in an ANN is what enables the network to learn and model nonlinear functions. It is the weights on the connections between the different layers that enables the network to encode the information extracted from the training data.

Output layer In order to extract the answer or prediction from the model, an output layer has to be present. Depending on the setup of the neural network, the output value can either be a real value or a set of probabilities. The output type is dependent on the activation that is chosen for the layer. What an activation function is, and how it effects the output of a layer will be discussed later in this section.

A feed forward network can either be fully og partly connected. In a fully connected network, all the neurons in each layer has a connection to all neurons in the previous layer, and all neurons in the next layer, while in a partly connected layer only some of the neurons are connected.

2.2.2 Training a neural network

The main purpose of a well trained ANN is to be able, by using its weighted connections, to amplify the signal and dampen the noise of the data it has been trained on. It does so by altering the different weights and biases in a way that allocates significance to some features and removing it from other. This way the model can learn which features are tied to which outcomes.

Neural networks learn these relationships by making a guess based on the input, weights and biases, and then get feedback on how accurate the guess was. It is the loss function related to the model, such as stochastic gradient decent (SDG), which gives this feedback by rewarding good guesses and penalizing bad ones.

The most common learning algorithm associated with neural networks is the *backpropagation learning algorithm*.

Backpropagation learning

The backpropagation algorithm learns by first trying to compute a training examples output value, by taking a forward pass through the network. If the output matches the label associated with the example nothing happens, but if it does not the weights has to be updated.

In order to update the weights in the network, Equation 2.3 is used.

$$W_{j,i} \Leftarrow W_{j,i} + \alpha * a_j * Err_i * g'(input\_sum_i) \tag{2.3}$$

Equation 2.3 is called the weight update rule for the connection between neuron j and i as seen in Figure 2.4. Furthermore, α is the learning rate (discussed in subsection 2.2.5), a_j is the incoming activation function, Err_i is the error in i and $g'(input\_sum_i)$ is the derivative of the activation function over the input sum as seen in Equation 2.4.

$$a_j = g(input\_sum_j) \tag{2.4}$$

where the input sum is given by:

$$input\_sum_i = W_i * A_i + b \tag{2.5}$$

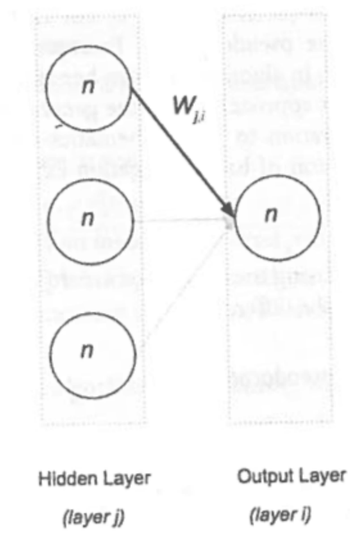


Figure 2.4: The two last layers of an multilayer feed-forward neural network Patterson and Gibson (2017)

The backpropagation algorithm traverses the network backwards, updating the weight of connection between each layer, as describd in Equation 2.3, until it reaches the input layer. This way the weights and biases that have been assigned the blame for the error are reduced, while the ones that supporting the correct answer are strengthened.

2.2.3 Activation functions

Activation functions are scalar-to-scalar functions which are used to propagate the output of one layer to the next, and it is what enables the network to model nonlinear functions. This section will discuss some of the most common activation functions used in ANNs.

Linear The linear activation function, $f(x) = Wx$ is the simplest activation function and is often associated with the input layer of the network. It says that the dependent variable x is proportional with the independent variable Wx.

Sigmoid The sigmoid activation function belongs to the class of logistic activation functions. It reduces extreme values or outliers in the example data, without removing them. One could see the sigmoid function as a machine that coverts independent variables of near infinite range into probabilities between 0 and 1.

Tanh (and Hard Tanh) Another class of activation functions are the hyperbolic trigonometric functions. The tanh function represents the ratio between the hyperbolic sine sine to the hyperbolic cosine, which means that unlike the sigmoid function, it has a normalized range between -1 and 1. The hard tanh activation function simply adds hard caps to the range, setting all values larger than 1 and smaller than -1 to respectively 1 and -1. The advantage of these functions are that they can deal more easily with negative numbers.

Softmax The softmax function, also referred to as the normalized, exponential function, is a generalization of the logistic function. Its function is that it returns the probability distribution over mutually exclusive output classes. For example, if the softmax activation function was applied to the vector [1, 2, 3, 4, 1, 2, 3], the result would be [0.024, 0.064, 0.175, 0.475, 0.024, 0.064, 0.175,]. As seen from this example, the function is most often used to weight the largest value and dampen values that are considerably smaller.

ReLU The rectified linear unit function is currently considered the state of the art activation function. It can be described as $f(x) = max(0, x)$, meaning that it, above a certain threshold the output has a linear relationship with the dependent variable, it is else zero.

2.2.4 Loss functions

When working with artificial neural networks, we often talk about the ideal state of the network, meaning the state that classifies all the examples correctly. The loss function is a way of quantifying how close a network is to this ideal state. This is done by aggregating the errors produced by the networks prediction over the entire dataset, and average this value to get a single number that represents how close the network is to its ideal state. In other words, by minimizing the loss function, the network gets as close as possible to its ideal state, resulting in an optimization problem where the solution can be approximated well with iterative optimization algorithms.

There are different loss functions that are appropriate for regression and classification problems, however for the purpose of this project report it is only relevant to discuss the ones related to classification problems.

Hinge loss For hard classification, for example with discrete classes [sell=0, buy=1], the hinge loss function is most commonly used. It is also used by a class of models called maximum-margin classification models such as support vector machines, which are discussed in **??**.

Logistic loss Often probabilities are of greater interest than hard classifications, in such situations the logistic loss function is of more value. An important remark when computing probabilities, is that all values has to be in the range 0 to 1 and that the probability of mutually exclusive outcomes should sum up to 1. Therefore, it is essential that the last layer uses the softmax activation function.

Optimizing the logistic loss function is the same as optimizing the "maximal likelihood", which means that the algorithm should maximize the probability that it predict the correct class, and do so for each single sample in the dataset.

NOT FINISHED HERE

2.2.5 Hyperparamenters

In machine learning, hyperparameters deal with controlling the optimazation functions during learning, making sure that they neither overfit or underfit the data, but at the same time learns as quickly as possible.

Learning rate The learning rate, as seen in Equation 2.3, is a coefficient that scales the size of each weight update step. In other words, the learning rate decides how much of the computed gradient that should be used for each step.

Regularization Regularization is important in order to control what is called out-of-control parameters. This is done by controlling the trade-off between finding a good fit on the training data and limiting the weight on features with high-polynomials. This is because such features tend to overfit the training examples.

Momentum Momentum is often described as the the learning rate of the learning rate. What it does is to prevent the learning algorithm from getting stuck in local minimas.

Sparsity Lastly, the sparsity hyperparameter helps recognize which features of the input examples that are relevant. This is important because in some datasets, the feature arrays for each example will be very different in terms of values.

2.2.6 Convolutional neural networks

In recent years, convolutional neural networks (CNNs) have been recognized as very suitable for object recognition in images Patterson and Gibson (2017). One of the main reasons why the world, research society recognizes the power of deep learning have been the efficancy of CNNs image recognition capabilities. The name comes from the networks use of convolutions, a mathematical operation on two functions in order to produce a third.

Biological Inspiration

As all neural networks, CNNs are very inspired by the biological neurons in animal brains. The CNNs are especially inspired by the visual cortex, which cells are very sensitive to small subregions of the input. One often say that these cells act as local filters over the input space, which also is the case for CNNs.

Difference from regular feed-forward multilayer neural networks

A well known problem when it comes to analyzing image data using regular feed-forward multilayer neural networks, is that they do not scale well with increasing image sizes. Imagine an color image with the size 400x400 pixels (which would be a regular sized picture) that are used as input for a ANN. Such an image, represented as a vector, would create $400 * 400 * 3 = 480000$ different weight connections for each neuron in the first hidden layer. For a fully connected network, this would be the case for all layers to come, which would create a tremendous amount of weight connections.

Convolutional neural networks solve this issue by representing the images in a three-dimensional structure, meaning that the input data is represented as a three-dimensional matrix with:

- Image width in pixels
- Image height in pixels
- RGB channels in depth

As will be discussed later, this structure is how CNNs have evolved from previous feed-forward networks, in terms of computational efficiency.

Architecture

The purpose of the network is to transform the input examples through a series of connected layers, into a set of class scores. A general architecture is presented in Figure 2.6.

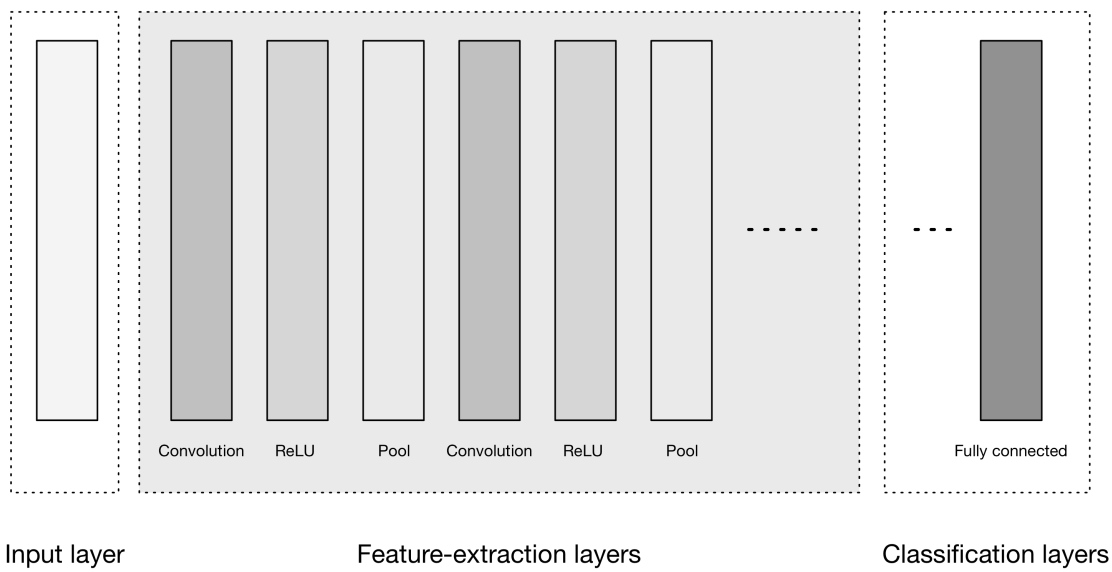


Figure 2.5: A general presentation of the architecture of CNNs Patterson and Gibson (2017)

As seen in Figure 2.6 the network can be divided into three sections; Input, Feature-extraction and Classification layer(s). The most interesting part of this structure is the feature-extraction layers, which is used to identify a number of features in the images, and from these construct higher-order features. The strategy of constructing high-order features is one of the key aspects of deep learning.

Remark: It is important to note that in a CNNs layers, the neurons are arranged in a three-dimensional structure, in order to match the input data, as described earlier.

Convolutional layers

The convolution layers, seen in Figure 2.6, detect features in an image through what is called the convolution operation. As mentioned in the beginning of this chapter is a convolution operation a mathematical operation that transforms two functions (or sets of information) into one, through Fourier transformations. The way that this works, is that the layer applies certain filters, called kernel filters, to segments of its input using a technique called sliding window.[1] The convolution operator is described in Equation 2.6, where I is the input data and K is the kernel filter of size $h * w$.

$$(I * K)_{xy} = \sum_{i=1}^{h} \sum_{j=1}^{w} K_{ij} \cdot I_{x+i-1,y+j-1} \tag{2.6}$$

Such filters can for example be an edge kernel, which only passes through information containing edges. In most cases applying a filter means reducing the size of the data, thus reducing the number of neurons in each, upcoming layer.

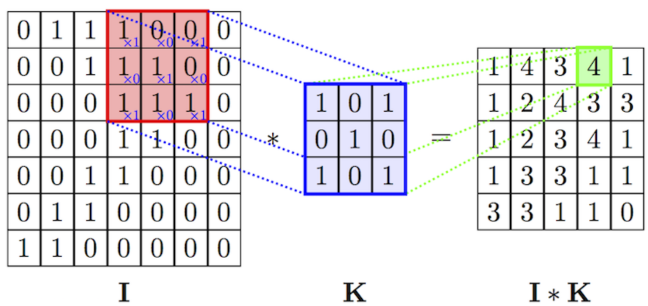


Figure 2.6: The convolution operation (applying a kernel filter) Cambridge (2017)

ReLU layers

As seen in Figure 2.6, ReLU activation functions are often used in separate layers. This layer does not change the dimension of the input volume, but can change some of the pixel values.

Pooling layers

The pooling layers is an other important part of the convolutional neural networks. They help prevent overfitting, by reducing the size of the input data using what is called max pooling, as shown in Figure 2.7

Figure 2.7 presents a max pool with a 2x2 filter size, and a stride of 2, meaning that 2x2 pixels are compared and that the sliding window moves 2 pixels for each comparison. I practice this means that the 75% of the activations from the previous layer is discarded.

[1] A technique that slides over a set of data, only analyzing a pre-defined patch size at a time Stanford (2017)

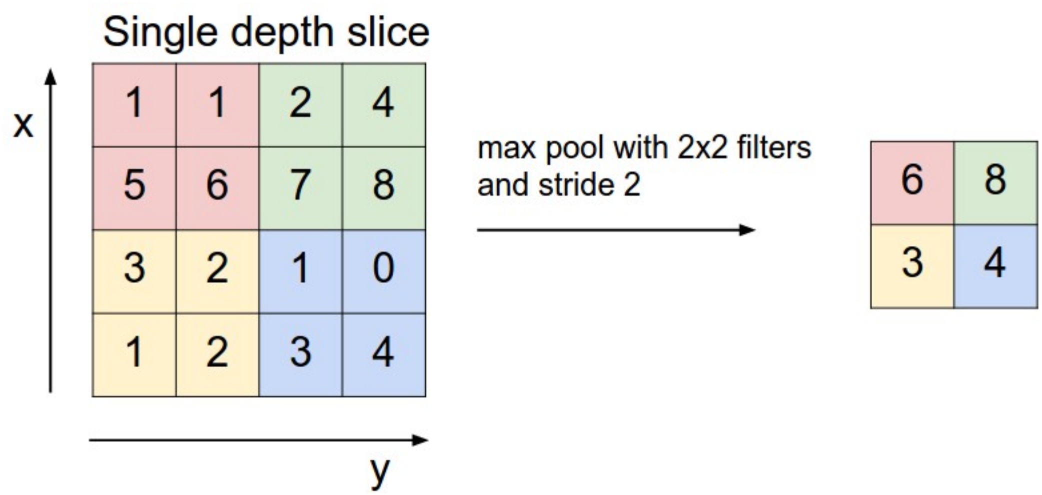


Figure 2.7: Example of max pooling operation Karpathy (2017)

Links:
https://www.pyimagesearch.com/2014/10/20/finding-shapes-images-using-python-opencv/
https://www.pyimagesearch.com/2016/02/08/opencv-shape-detection/
http://melvincabatuan.github.io/SLIC-Superpixels/
https://www.gislounge.com/shadows-angles-measuring-object-heights-satellite-imagery/

2.3 Height estimation using remote sensing

There are many different ways of estimating heights using satellite data, which involves using lidar data, SAR data and regular satellite multispectral imagery. This section will give the theoretical background for some of the most commonly used techniques.

2.3.1 Synthetic Aperture Radar (SAR)

The first technique involves using a Synthetic Aperture Radar on a moving platform, in this case a satellite. By sequentially transmitting electromagnetic waves onto the earths surface and collecting the reflected echos, the SAR satellites are able to collect high-precision, 3-dimensional data.

One of the key advantages of the SAR satellites is that they take advantage of the fact that they are moving quickly. Since the transmission and reception occurs at different times, the platform has moved, thus creating a synthetic aperture that is much larger than the satellite antenna (see Figure 2.8).

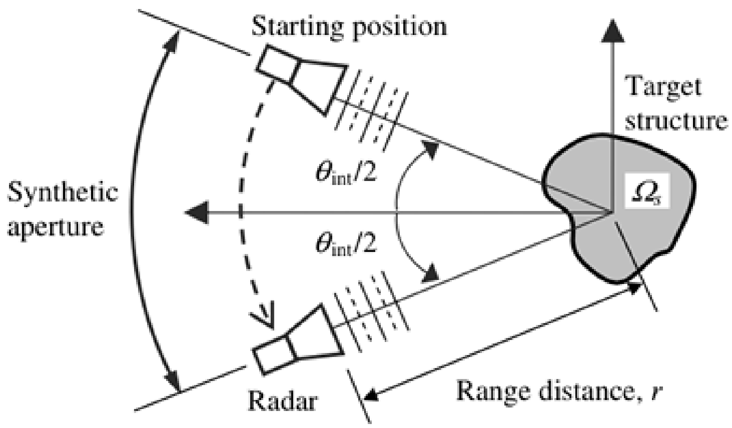


Figure 2.8: Concept of syntetic aperture **?**

The technique provides a finer spatial resolution to the collected data, making it possible to do height estimations with a sub-decimeter accuracy.

Interferometric synthetic aperture radar (InSAR)

While SAR makes use of amplitude and absolute phase of the returned signal, InSAR use a differential phase of the reflected signal, represented in what is called a phase image.

Looking at a phase image completely isolated will not prove very useful, as it would appear visually random. This is because in practice, the phase of the return signal is affected by a lot of different factors, resulting in no apparent correlation between the pixels in the image.

In order to get useful information these phase images, some of the factors, discussed above, has to be removed. The process of doing so is referred to as interferometry, and it uses two phase images taken from the exact same position in order to generate a interferogram (see Figure 2.9).

Producing an inferiogram consists of multiple steps:

Co-registration Using a correlation function the two images are co-registered by finding the offset and difference in geometry between them.

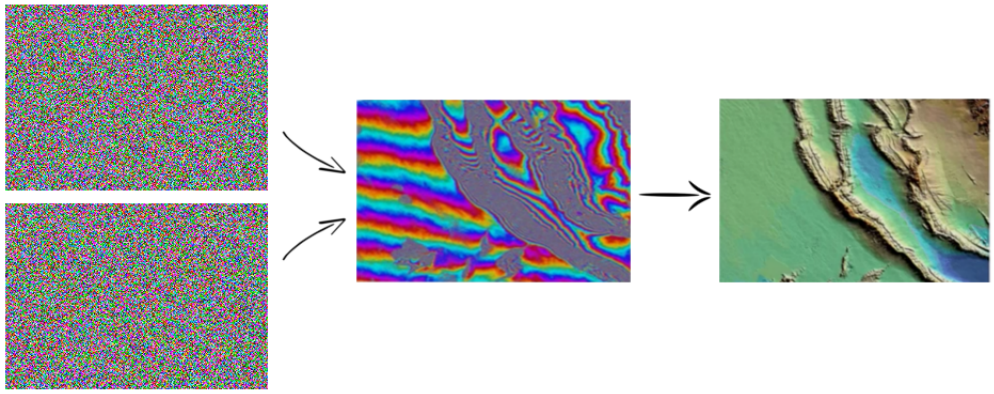


Figure 2.9: Generating an interferogram

Re-sampling In the re-sampling step, one of the images (referred to as the slave) is re-sampled in order to match the geometry of the other (called the master). What this means in practice is that each pixel represents the same area of ground in both images.

Cross-multiplication and flattening After re-sampling the images the inferiogram is generated by taking the cross product of each pixel, and the interferometric phase due to the curvature of the earth is removed (flattening).

Filtering Lastly, it is common to filter the basic inferiogram in order to amplify the phase signal, and to interpolate over phase jumps in order to produce a continuous deformation field.

2.3.2 Light Detection And Ranging (LIDAR)

Another high precision technique for generating height data using satellites is using LIDAR. LIDAR is a surveying method that uses a pulsed ultraviolet, visible of near infrared light laser to map an area or an object. In the same way as SAR and InSAR, it used the reflected signal to measure the distance from the transmitter to the object.

2.3.3 Height detection using shadows from imagery

For height estimation of specific objects, shadow estimations can be applied. This technique uses a high resolution image, as well as knowledge about the position of the sun, the position of the image projection center and the length of the projected shadow in order to estimate an objects height (Figure 2.10).

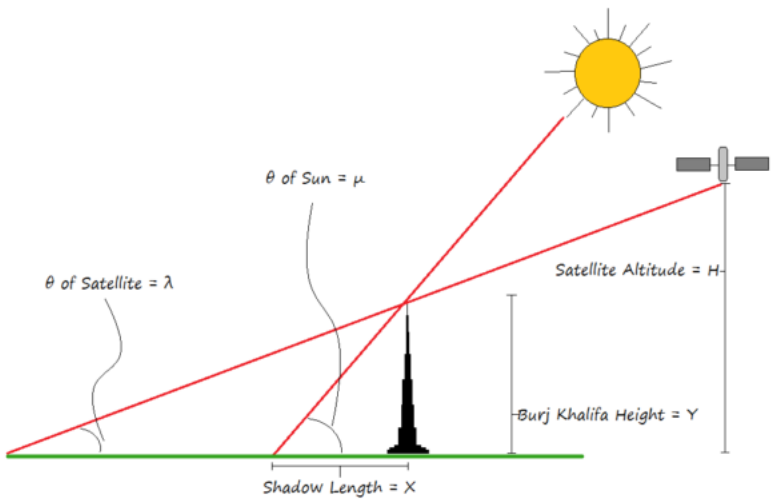


Figure 2.10: Height estimation of Burj Khalifa using shadow estimation (GISLounge, 2014)

Looking at Figure 2.10 the height of the object can be found by:

$$tan(\mu) = \frac{H_{object}}{L_{shadow}} \quad \Rightarrow \quad L_{shadow} = \frac{H_{object}}{tan(\mu)} \tag{2.7}$$

Since the satellite image rarely is taken with the projection center directly above the object (nadir angle = 0°), the blocked length of the shadow has to be estimated. Since the height of the object is the unknown, estimating the blocked length of the shadow is an iterative process, where a new calculated, temporary value for the height is used in each iteration. Calculating the length of the blocked shadow is also very straight forward:

$$tan(90-\lambda) = \frac{L_{blockedshadow}}{H_{object}} \quad \Rightarrow \quad L_{blockedshadow} = H_{object} * tan(90-\lambda) \tag{2.8}$$

In Equation 2.8 90-λ defined as the Off-nadir angle.

It is important to remember that if this technique shall produce exact results, some parameters has to be known in the moment of the capture:

- The position of the satellite
- The time
- The position of the object with the unknown height

Chapter 3

Related Work

3.1 Standard methods for shape detection

Before looking at the use of neural networks for shape recognition in images, some more standard approaches are presented.

3.1.1 Shape detection using the Hough Transform

Shape detection and feature extraction in images, using Hough Transforms has been a subject of research for many years. The algorithm was first popularized in computer vision in 1981 by Ballard (1981) which applied a generalized version of the algorithm in order to detect of curves in gray scale images.

The article describes how boundary detection plays a crucial role for feature extraction in images, and how a generalized Hough algorithm can use edge information to define a mapping from the orientation of an edge point to a reference point related to the shape.

3.1.2 Simple Linear Iterative Clustering (SLIC)

Achanta et al. (2012) proposes a superpixel-segmentation algorithm (SLIC), which in their opinion is best suited to meet these demands. They compare their algorithm to a variety of state-of-the-art superpixel methods, and conclude that none of the existing methods are satisfactory in regards to the points.

The SLIC algorithm is fairly simple to understand. One of its key principles is that, by limiting the search space for each cluster center (points in the regular raster grid), it reduces the search speed significantly. This is achievable due to the fact that one of the primary goals of algorithm is to create a set of approximately equal sized superpixels. Thus, instead of searching the whole raster grid for each cluster center, the algorithm only has to search for edge pixels at a distance equal to D, as shown in Equation 3.1.

$$D' = \sqrt{\left(\frac{d_c}{m}\right)^2 + \left(\frac{d_s}{S}\right)^2} \tag{3.1}$$

In Equation 3.1 d_c is the euclidean distance between two pixels in terms of color and d_s is the pixels euclidean, spatial distance. Furthermore, S is the sampling interval of the cluster centers ($S = \sqrt{N/k}$, where N is the number of pixels in the grid and k is the desired number of superpixels) and m is a fixed constant based on the color diversity in the image.

Since the algorithm generates superpixels by clustering pixels based on their color and spatial proximity, creating a 5 dimensional, *labxy* space, one would think that the distance could be found by simply taking the 5D euclidean distance. However, it turns out that for large superpixels, spatial distance outweigh the color proximity. Which is why the two distances d_c and d_s are weighted.

3.2 The development of Convolutional neural networks

Since McCulloch and Pitts created what is acknowledged as the first neural network in 1943, using simple electrical circuits (Mcculloch and Pitts, 1943), they have played an important role in the field of pattern recognition.

Since the late 1990's the idea of using convolutional operations in these networks has been considered more and more prominent (Le Cun et al., 1998), and this approach is still one of the leading research fields within ANN research (Wu et al., 2017). This section will discuss the development of the convolutional neural networks the last two decades.

3.2.1 Early adaption of convolutional neural networks

The earliest attempts of using convolutional operations for pattern and object recognition in neural networks was first done nearly twenty years ago.

MORE HERE (LeNet)

3.2.2 Deep Convolutional Neural Networks

It was however, not until Alex Krizhevsky, Geoffrey Hinton, and Ilya Sutskever won the ImageNet [1] 2012 competition (ILSVRC'12), that CNNs became acknowledged as one of the most sophisticated approaches for image recognition. Their deep convolutional neural network (commonly called AlexNet) consisted of five convolutional layers, each followed by a pooling layer (max-pooling), and three fully-connected softmax layers (Krizhevsky et al., 2012). In order to reduce overfitting, the network applied two different methods; Data Augmentation and Dropout layers.

Even though the AlexNet was a big break through for the convolutional neural networks, it was criticized for not presenting a good ground for understanding what was happening inside the network, thus making it hard to improve. One of the solutions to this problem are the ZF Net, which applies deconvolutional neural networks (Zeiler et al., 2011) in order to map the dense feature space produced by a CNN back to its original pixel space (Zeiler and Fergus, 2013). Figure 3.1 shown how a deconvolutional network can help visualizing the feature space of a CNN.

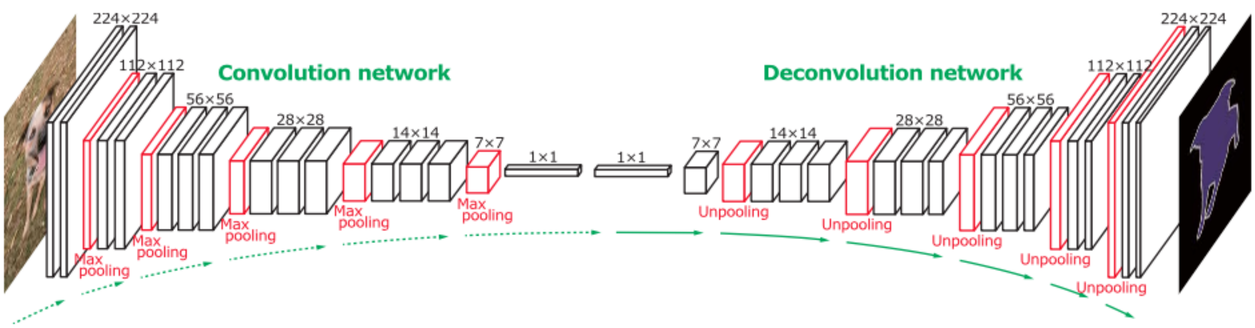


Figure 3.1: Process of visualizing the feature space of a CNN (Noh et al., 2015)

In order to do so, the ZF Net successfully unpool, rectify and filter the feature map, generated by the CNN, in order to reconstruct the activity inside the network.

Unpooling In general, the max-pooling operation is non-reversible, since there are no tracking of the positions of the selected features, as seen in section 2.2.6. Therefore, in order to reconstruct the feature map the location of each selected maxima had to be stored.

Rectification Their CNN used the common ReLU activation function for each Convolution Layer, therefore the reconstruction layers also need to use this activation function in order to prevent negative values.

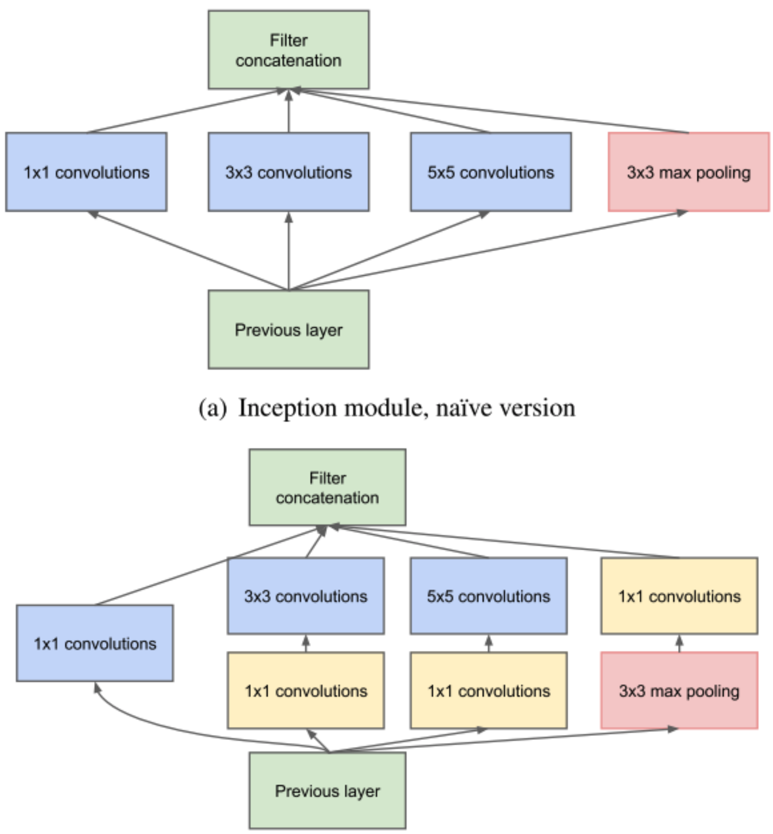
[1] ImageNet is a very large dataset consisting of 15 million labeled, high-resolution images divided into over 22.000 categories.

Filtering Since CNNs apply kernel filters to each convolution layers input volumes, the filtering has to be inverted when reconstructing. In order to do so, the same filters are transposed (remember that the filters are matrices) and applied to the rectified activation maps.

GoogLeNet

Another network, whose creators have criticized the standard structure of the convolutional neural networks, is the GoogLeNet (Szegedy et al., 2014). The authors of the article claims that their network was significantly more accurate than the AlexNet, while at the same time only using one twelfth of the parameters.

The GoogLeNet introduces what is called a Inception architecture (see Figure 3.3), which main idea is to cluster neurons in the network which have highly correlated outputs. This is because in images, the correlation between pixels tend to be local.



(a) Inception module, naïve version

(b) Inception module with dimensionality reduction

Figure 3.2: Two versions of the inception module (Szegedy et al., 2014)

The basic structure of the inception module is to do multiple convolution operations, in parallel, with different sized filters, and then concatenate the results before passing them on to the next layer. Additionally, a parallel pooling operation is added to each inception module, because such operations have proven them selfs successful in other CNNs.

The naive version of these "micro networks" is shown in Figure 3.3 (a). One issue with this naive version is that, even with a modest number of 5x5 convolutions, the computational cost can be quite expensive. This is solved by keeping the representation of the information as sparse as possible, and only compress the signals when they have to be aggregated. In order to do so, 1x1 convolutions are used to compute reductions before the 3x3 and 5x5 convolutional operations are applied (Figure 3.3 (b)).

VGGNet

Another example of a successful deep convolutional neural network is the VGGNet. This network does not present any new concepts, but the authors argue that by stacking multiple layers, doing small convolutional operations (3x3 and a few 1x1) they can outperform the other discussed networks (Simonyan and Zisserman, 2014).

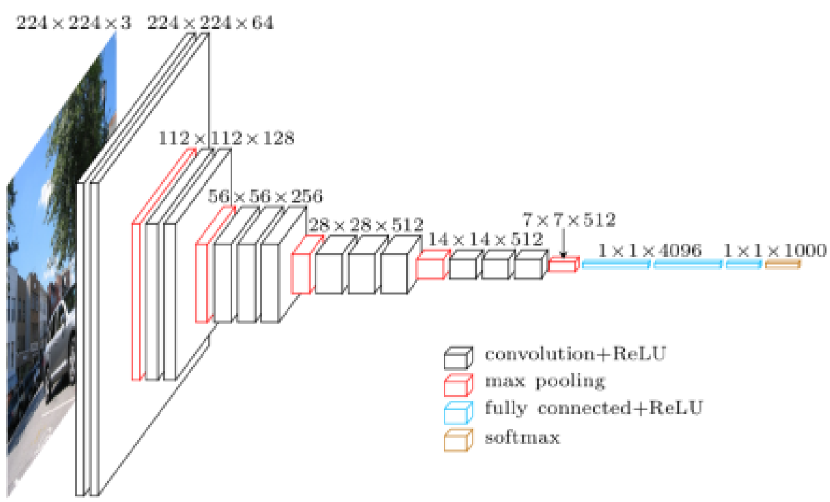


Figure 3.3: The 16-layer VGGNet (Frossard, 2016)

An important difference between this network and previous networks, is that the creators focuses on depth, thus calling the network a very deep convolutional network.

ResNet

A problem that arises with deeper convolutional neural networks is the degradation problem. As depth increases in the network, the accuracy decreases (Figure 3.4).

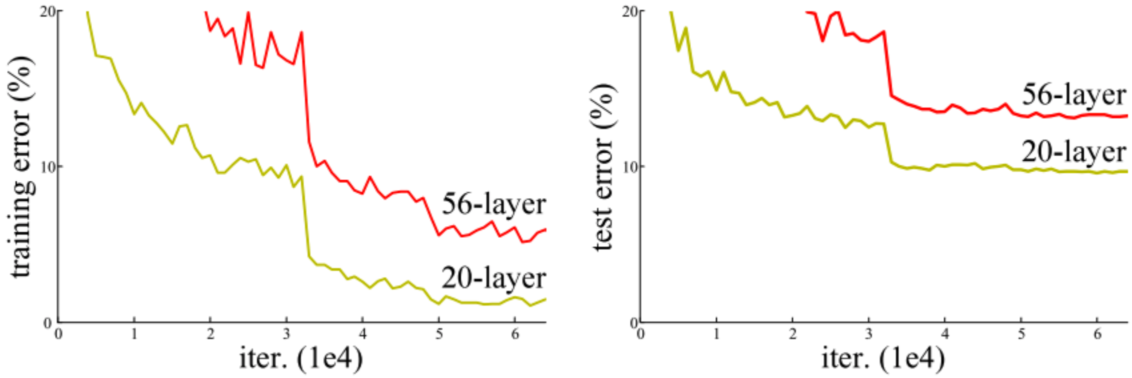


Figure 3.4: Degradation problem (Wu et al., 2017)

Suprisingly enough this decrease in accuracy is not due to overfitting, as adding more layers effects the training error as well (Wu et al., 2017). In theory any deep network should be able to perform at least as good as a shallower network, only by seeing the layers that differenciate the two networks as identity mappings.[2] This however, does not seem to be the case in practice, suggesting that networks have problems learning identity mappings by multiple, non-linear layers.

In order to solve the degradation problem, the authors of the paper introduces two new concepts, which sets the foundation for their residual neural network (ResNet).

Residual mapping The paper hypothesize that it is easier to optimize residual mapping, thus introducing the residual mapping function:

$$F(x) := H(x) - x \tag{3.2}$$

where H(x) is the desired, underlying mapping function after 2 weight layers.

Shortcut connections Connections which skip one or more layers, as seen in Figure 3.5, in order to obtain the desired mapping function H(x).

Using these concepts, the authors were able to create the winning 152-layer deep ResNet of the ILSVRC'15.

Check out http://yann.lecon.com/exdb/publis/pdf/lecun-89e.pdf

[2]The map which assigns every member of a set A to the same element id_A. It is the same as the identity function: $id(x) = x$

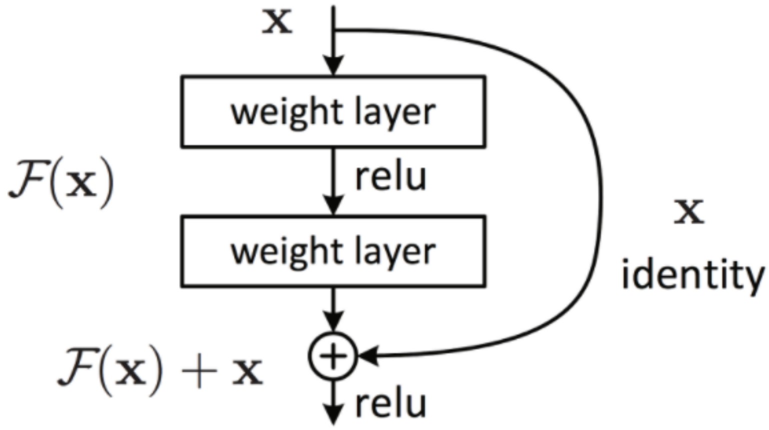
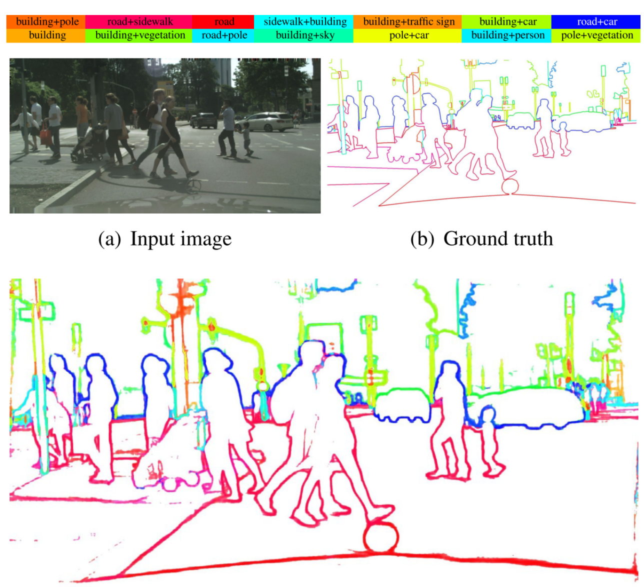


Figure 3.5: A residual building block (Wu et al., 2017)

3.3 Shape detection using convolution neural networks

In later years there have been a significant progress in the field of edge detection in imagery has been made due to advances in deep learning (Yu et al., 2017). Using an end to end deep semantic edge learning architecture based on ResNets (Wu et al., 2017) and further extending the networks architecture with a new skip-layer, Yu et al. (2017) are able to not only identify, but also categorize edges in an image (see Figure 3.6).



(a) Input image (b) Ground truth

(c) CASENet output

Figure 3.6: Edge detection using CASENets (Yu et al., 2017)

The skip-layer uses category-wise edge activations, which are added on top of convolution layer, which share and are fused with the same set of bottom layer features. Using this approach the network produces n different edge maps, where n is the number of defined categories. Each map indicates the edge probability of e certain category.

The proposed CASENet is a modification of the ResNet-101, with some modification to the convolutional blocks, in order to preserve low-level edge information. The authors compare their network to other similar architectures, and show that their architecture outperforms state-of-the-art networks.

3.4 Height estimation form a nadir perspective

As seen in section 2.3 there are many different techniques that can be applied in order to estimate the height of a building. This section will focus on different attempts to retrieve height data, using satellite imagery.

3.4.1 Building height retrieval from VHR SAR Imagery

After the launch of TerraSAR-X in 2007, a satellite that was designed to acquire high-resolution X-band radar images of the entire planet, it was possible to gather SAR data with a resolution of down to 1 meter (Airbus, 2017). In contrast to other optical, spaceborne sensors, such as Ikonos, Quickbird and WorldView, satellites using SAR overcome the difficulties of weather conditions and lack of sun illumination.

Using the SAR images provided by the satellite Brunner et al. (2008) was able to estimate the height of man-made structures with a sub-meter precision by automatically reconstruct 3-D models, using a "hypothesis generation-rendering-matching" procedure. The basic principle was that using a optimization algorithm, the height of a building is found by testing different height hypothesis against a single SAR image. The estimation is done without modeling its exact radiometry, since this would require extensive apriori knowledge about the roughness parameters and dielectric constants of the surfaces. Generating this height model becomes an optimization problem Equation 3.3.

$$\hat{h} = \underset{h,\vec{s}}{argmax} \left\{ M \left[\hat{X}_{\vec{s}}(\vec{H}), X \right] \right\} \tag{3.3}$$

In Equation 3.3 X is the true SAR image, $\hat{X}$ is the simulated SAR image at height h, M is the matching function, and $\vec{H}$ is the simulated hypothesis.

Brunner et al. (2008) tested their method on different types of buildings, where flat buildings gave a mean accuracy of $0.3 \pm 2.1m$.

3.4.2 Height estimation from InSAR analysis

Another approach for height detection using SAR satellites, is interferometric SAR (InSAR) analysis, as attempted by Liu et al. (2015). In their paper they used images taken on December 5 and 27, 2007 in order to generate an interferiogram over San Francisco. The technique was based on extracting potential layover areas from the interferiogram and use these areas to measure the height of the buildings using the relationship between the height of an object and the layover observed in the interferiogram (Equation 3.4).

$$\Delta\Phi = \frac{4\pi B_N}{\lambda H sin\theta}\Delta R \tag{3.4}$$

In Equation 3.4 $\Delta\Phi$ is the phase difference within one pixel in the layover area, B_N is the perpendicular baseline distance, λ is the radar wavelength, H is the satellite altitude and θ is the angle of incidence (see Figure 3.7).

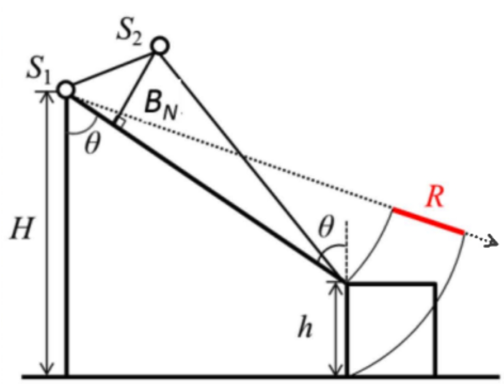


Figure 3.7: A schematic image of geometrical characteristics for a building in a slant-range SAR image (Liu et al., 2015)

Using this method Liu et al. (2015) were able to estimate the height of high-rise buildings in a crowded area with a RMS of 13m and an average difference between detected results and the reference values of 6.6m.

Chapter 4

Equations, Figures, and Tables

The content of Chapter 2 will vary with the topic of your thesis. This chapter only gives guidance to some technical aspects of LaTeX.

Remark: If you want a shorter chapter or section title to appear in the Table of Contents and in the headings of the chapter, you just include the short title in square brackets before the title of the chapter/section. Example:

```
\section[Short Title]{Long Title}
```

.

4.1 Simple Equations

Mathematical symbols and equations can written in the text as λ, $F(t)$, or even $F(t) = \int_0^t \exp(-\lambda x)\,dx$, or as displayed equations

$$F(t) = \int_0^t \exp(-\lambda x)\,dx \tag{4.1}$$

The displayed equations are automatically given equation numbers – here (4.1) since this is the first equation in Chapter 2. Note that you can refer to the equation by referring to the "label" you specified as part of the equation environment.

You can also include equations without numbers:

$$F(t) = \sum_{i=1}^{n} \binom{n}{i} \sin(i \cdot t)$$

More Advanced Formulas

Long formulas that cannot fit into a single line can be written by using the environment `align` as

$$F(t) = \sum_{i=1}^{n} \sin(t^{n-1}) - \sum_{i=1}^{n} \binom{n}{i} \sin(i \cdot t) \tag{4.2}$$

$$+ \int_0^\infty n^{-x} e^{-\lambda x^t} \, dt \tag{4.3}$$

In some cases, you need to write ordinary letters inside the equations. You should then use the commands

`\textrm  and/or \mathrm`

The first command returns the normal text font and will be scaled automatically, while the second command will be scaled according to the use.

$$\mathrm{MTTF} = \int_0^\infty R_{\text{avg}}(t) \, dt$$

Please consult the LaTeX documentation for further details about mathematics in LaTeX.

Definitions

If you want to include a definition of a term/concept in the text, I have made the following macro (see in `ramsstyle.sty`):

☞ **Reliability**: The ability of an item to perform a required function under stated environmental and operational conditions and for a stated period of time.

When text is following directly after the definition, it may sometimes be necessary to end the definition text by the command

`\newline`

I have not included this in the definition of the `defin` environment to avoid too much space when there is not a text-block following the definition.

Figure 4.1: This is the logo of NTNU (rotated 15 degrees).

4.2 Including Figures

If you use pdfLaTeX (as recommended), all the figures must be in pdf, png, or jpg format. We recommend you to use the pdf format. Please place the figure files in the directory **fig**. Figures are included by the command shown for Figure 4.1. Please notice the "path" to the figure file written by a *forward* slash (`/`). You should not include the format of the figure file (pdg, png, or jpg) – just write the "name" of the figure.

Each figure should include a unique *label* as shown in the command for Figure 4.1. You can then refer to the figure by the *ref* command. Notice that you can scale the size of the figure by the option `scale=k`. You may also define a specific width or height of the figure by replacing the `scale` options by `width=k` or `height=k`. The factor `k` can here be specified in mm, cm, pc, and many other length measures. You may also give `k` as a fraction of the width of the text or of the height of the text, for example, `width=0.45\textwidth`. If you later change the margins of the text, the figure width will change accordingly. As illustrated in Figure 4.1, you may also rotate the figure – and also do many other things (please check the documentation of the package `graphicx` – it is available on your computer, or you may find it on the Internet).

In LaTeX all figures are floating objects and will normally be placed at the top of a page. This is the standard option in all scientific reports. If you insist on placing the figure exactly where you declare the figure, you may include the command `[h]` (here) immediately after `\begin{figure}`. If you will force the figure to be located either at the top or bottom of the page, you may alternatively use `[t]` or `[b]`. For more options, check the documentation.

Large figures may be included as a *sidewaysfigure* as shown in Figure 4.2:[1]

4.3 Including Tables

LaTeX has a lot of different options to include tables. Only one of them is illustrated here.

[1] You can use a similar command for large tables.

NTNU – Trondheim
Norwegian University of
Science and Technology

Figure 4.2: This is the logo of NTNU.

Table 4.1: The degree of newness of technology.

Experience with the operating condition	Level of technology maturity: Proven	Limited field history or not used by company/user	New or unproven
Previous experience	1	2	3
No experience by company/user	2	3	4
No industry experience	3	4	4

Remark: Notice that figure captions (Figure text) shall be located *below* the figure – and that the caption of tables shall be *above* the table. This is done by placing the `\caption` command beneath the command `\includegraphics` for figures, and above the command `\begin{tabular*}` for tables.

4.4 Copying Figures and Tables

In some cases, it may be relevant to include figures and tables from from other publications in your report. This can be a direct copy or that you retype the table or redraw the figure. In both cases, you should include a reference to the source in the figure or table caption. The caption might then be written as: *Figure/Table xx: The caption text is coming here (**?**).*

In other cases, you get the idea from a figure or table in a publication, but modify the figure/table to fit your purpose. If the change is significant, your caption should have the following format: *Figure/Table xx: The caption text is coming here (adapted from **?**).*

4.5 References to Figures and Tables

Remember that all figures and tables shall be referred to and explained/discussed in the text. If a figure/table is not referred to in the text, it shall be deleted from the report.

4.6 A Word About Font-encoding

When you press a button (or a combination of buttons) on your keyboard, this is represented in your computer according to the *font-encoding* that has been set up. A wide range of font-encodings are available and it may be difficult to choose the "best" one. In the template, I have set up a font-encoding called UTF-8 which is a modern and very comprehensive encoding and is expected to be the standard encoding in the future. Before you start using this template, you should open the Preferences ->Editor dialogue in TeXworks (or TeXShop if you use a Mac) and check that encoding UTF-8 has been specified.

If you use only numbers and letters used in standard English text, it is not very important which encoding you are using, but if you write the Norwegian letters æ, ø, å and accented letters, such as é and ä, you may run into problems if you use different encodings. Please be careful if you cut and paste text from other word-processors or editors into your LaTeX file!

Warning

If you (accidentally) open your file in another editor and this editor is set up with another font-encoding, your non-standard letters will likely come out wrong. If you do this, and detect the error, be sure *not* to save your file in this editor!!

This is not a specific LaTeX problem. You will run into the same problem with all editors and word-processors – and it is of special importance if you use computers with different platforms (Windows, OSX, Linux).

4.7 Plagiarism

Plagiarism is defined as "use, without giving reasonable and appropriate credit to or acknowledging the author or source, of another person's original work, whether such work is made up of code, formulas, ideas, language, research, strategies, writing or other form", and is a very serious issue in all academic work. You should adhere to the following rules:

- Give proper references to all the sources you are using as a basis for your work. The references should be give to the original work and not to newer sources that mention the original sources.
- You may copy paragraphs up to 50 words when you include a proper reference. In doing so, you should place the copied text in inverted commas (i.e., "Copied text follows ..."). Another option is to write the copied text as a quotation, for example:

  > Birnbaum's measure of reliability importance of component i at time t is equal to the probability that the system is in such a state at time t that component i is critical for the system.
  >
  > **?**

Chapter 5

Conclusions, Discussion, and Recommendations for Further Work

In this final chapter you should sum up what you have done and which results you have got. You should also discuss your findings, and give recommendations for further work.

5.1 Summary and Conclusions

Here, you present a brief summary of your work and list the main results you have got. You should give comments to each of the objectives in Chapter 1 and state whether or not you have met the objective. If you have not met the objective, you should explain why (e.g., data not available, too difficult).

This section is similar to the Summary and Conclusions in the beginning of your report, but more detailed—referring to the the various sections in the report.

5.2 Discussion

Here, you may discuss your findings based on your results, their strengths and limitations. Note that this discussion is more high level than discussions made in relation to results you have achieved and presented in the previous chapter. The discussion here should put your work in larger context. You may address if you achieved what you had intended to do, why not (if you did not), if you got results in which you did not expect, why the results are important, why there are limitations in using the results, or if there are opportunities to transfer your results and findings into other domains, and so on.

5.3 Recommendations for Further Work

You should give recommendations to possible extensions to your work. The recommendations should be as specific as possible, preferably with an objective and an indication of a possible approach.

The recommendations may be classified as:

- Short-term
- Medium-term
- Long-term

Appendix A

Acronyms

FTA Fault tree analysis

MTTF Mean time to failure

RAMS Reliability, availability, maintainability, and safety

Appendix B

What to put in appendixes

This is an example of an Appendix. You can write an Appendix in the same way as a chapter, with sections, subsections, and so on. An appendix may include list of code (in case you are programming), more details about results that you have presented in the report (could be a more complete description of results, in case you decided to focus on the most important ones in the main report), supplementary information and descriptions you have found relating to the system you are analysing, such as drawings. You may discuss with your supervisor what are relevant information for appendixes.

B.1 Introduction

B.1.1 More Details

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