TTK4551
Engineering Cybernetics
Specialization Project

Automatic Inspection of Bridge Constructions

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Preface

This report is the result of the course TTK4551-Engineering Cybernetics, Specialization Project, a 7.5 SP course at the Department of Engineering Cybernetics, NTNU. The project assignment was given by SINTEF Digital and SINTEF Industry in a collaboration called the RINVE network. I would like to thank my supervisor from NTNU, Annette Stahl, for giving me feedback on my work with this project assignment. I would also like to thank Ole Øystein Knudsen, co-supervisor from SINTEF Industry, for advice regarding bridge inspection and corrosion damages. A special thanks to my supervisor from SINTEF Digital, Aksel Andreas Transeth, for regular meetings, guidance and helpful feedback during the project period this autumn.

Abstract

Using elements of existing automatic inspection methods, the aim of this project was to design a system for automatic inspection of bridge constructions, with focus on evaluating corrosion damages. The system is designed to be used in testing and development. Manual inspection methods have safety challenges and limitations related to both efficiency and subjectivity, and therefore this project explored the possibilities of using automatic inspection methods, including elements such as mobility hardware, inspection sensors and data handling and analysis. Necessary requirements and modifications to elements in existing automatic inspection methods were explained before designing the system. The proposed system consists of a drone as mobility hardware with a camera as sensor for inspection, and cloud computing is the main method for data handling. Sensors for autonomy are also suggested, but only briefly discussed. Previous work on identifying the existence of corrosion using computer vision techniques and deep learning approaches has inspired the work in this report. A method for both identifying the existence of corrosion and classification of corrosion damages using computer vision techniques and deep learning approaches, was proposed in the designed system. First, computer vision techniques are used for identifying the existence of corrosion. Next, through using deep learning approaches, including labeling images from previous inspections of bridge constructions combined with training of a neural network, one can create a method for classification of corrosion damages. The proposed system for automatic inspection of bridge constructions was not implemented or tested during this project. Testing of the method for classification of corrosion damages is considered future work, and will be performed in a master thesis next year.

Contents

Chapter 1

Introduction

1.1 Background

In Norway there are more than 17500 bridges to be inspected and maintained by The Norwegian Public Roads Administration [1]. Corrosion damages, cracks and faults in surface treatment are examples of elements of interest during inspection of bridges. Every year there are high economic costs related to inspection of bridge constructions, and there are also safety challenges related to implementation of certain types of manual inspection methods that require use of access equipment. Manual inspection methods also have challenges in terms of subjectivity when evaluating corrosion damages, which are eliminated when using automatic analysis methods instead. Therefore, it is important to investigate the potential in automatic inspection methods. This report is a result of a specialization project at NTNU, Department of Engineering Cybernetics, autumn 2018. The project assignment was given by SINTEF Digital and SINTEF Industry in a collaboration called the RINVE network.

1.2 The aim of the project

The aim of this project is to design a robotic inspection system for bridge constructions with focus on detecting and evaluating corrosion damages. This will be done through combining elements in existing automatic inspection methods and suggesting necessary modifications. The proposed robotic system is to be used in testing and development, and could potentially reduce inspection costs, as well as remove challenges with safety and subjectivity related to manual inspection methods.

1.3 Contributions

There are three main contributions in this report. One of the contributions is the design of a robotic system for inspection of bridge constructions combining elements from existing automatic inspection methods such as a drone, camera, data handling and data analysis methods. A robotic inspection system such as this eliminates safety challenges related to manual inspection methods using access equipment like lifts. A second contribution is the explanation of requirements and necessary modifications to be performed on standard products to function in a robotic inspection system. Possible challenges in implementation of such a system are also explained. The third contribution is a method for data analysis proposed in the design of the robotic system, showing how corrosion damages can be classified using deep learning approaches. Thus, subjectivity related to analysis is eliminated and necessary time for data analysis will be reduced. The method classifies images of corrosion in terms of severity, giving an overview of a bridge's condition.

1.4 Outline of the report

The report is structured as follows; chapter 1 introduces bridge inspection and why it is interesting to look at automatic inspection methods. In chapter 2 it is explained in more detail how inspection of bridge constructions is performed today, followed by chapter 3 where a selection of existing automatic inspection methods are presented. The aim of this project has been to design a robotic inspection system with sensors for use in testing and development, that could potentially reduce costs and eliminate both safety challenges and subjectivity related to inspection of bridges. The proposed system is described in chapter 4 before a discussion is given in chapter 5, and finally a conclusion is made.

Chapter 2

Inspection of bridge constructions

In this chapter the different elements in an inspection of bridge constructions are explained. First, types of inspections are introduced, followed by explanations of stages in planning of inspections. Next, equipment used in manual inspections, including access equipment, is shown, and the last section explains how results from inspections are evaluated in terms of severity and consequence of damages. Procedures and desriptions in this chapter are mainly obtained from [2], an inspection manual by The Norwegian Public Roads Administration.

2.1 Types of inspections

The inspection manual [2] refers to four types of routine inspections explained in table 1.

Table 1: The four types of routine inspections on bridges [2].

Type of inspection	**Description**
Simple inspection	The purpose of a simple inspection is to check if any serious damages have occurred that in short term may affect the load capacity of the bridge, road safety, future maintenance and inspection as well as bridge esthetics.
Main inspection	A main inspection consists of a condition monitoring of the bridge construction above water. This is done to verify that the bridge meets necessary function requirements.
Main inspection of cables	The purpose of this inspection is to check that load cables, rods and fasteners fulfill specified requirements.
Main underwater inspection	Consists of a condition monitoring of the bridge underwater construction.

A simple inspection is carried out by simple visual inspection of the bridge construction above water. A simple visual inspection means that there is no use of access equipment like lifts, so the construction is inspected at a certain distance. Measurements and material testing is usually not required, but in case of great wear and tear some measurements may be nescessary [2]. This type of inspection is carried annualy except from the year a main inspection is performed [3].

Main inspections are carried out every third year for ferry bridges and moving bridges, and every fifth year for all other types of bridge constructions [3]. In a main inspection the entire bridge construction above water, except from cables, is visually inspected. The visual inspection must be close visual, which means that operators must be able to touch the construction that is inspected. If expected damages are detected with complete certainty from a further distance, a close visual inspection is not necessary.

A main inspection of cables is carried out by close visual inspection as in a main inspection. The same applies for a main underwater inspection where the diver has to be able to touch the underwater bridge construction that is inspected.

Damages and causes of damages that are discovered during inspections like the four explained in table 1 can be further inspected through what is called a *special inspection*. A special inspection can also be carried out to acheive a basis for describing expensive and complicated measures [2].

2.2 Planning of inspections

The planning of inspections includes all tasks from deciding which bridges should be inspected to explaining how the inspection itself is to be performed. The Norwegian Public Roads Administration has their own management system for bridges called *BRUTUS* [4] that is used in planning of inspections, and where, among other things, information about maintenance and inspection plans, load capacities, security management and bridge condition is stored. Examples of tasks related to planning of inspections are shown in the list below [2]:

- Submission of inspection plans
- Processing of an inspection program
- Choice of inspection and acess equipment
- Safeguarding of HSE (Health, Safety, Environment) requirements

Table 2 explains the key parts of inspection planning in more detail.

Table 2: The tasks related to planning of inspections [2].

Task	**Explanation**
Inspection plan	All bridges must have an inspection plan stored in BRUTUS. This plan contains information about, for example, which type of inspection that should be performed and when, necessary measurements and test, and acess equipment needed.
Inspection program	This is a list of inspections, measurements and tests to be performed a certain year. The program is used to plan the annual inspections.
Forms from BRUTUS	Inspection forms made from the inspection programs.
Notifying of work	There has to be made a notification that contains information about when and for how long inspections are to be performed in such a way that the road traffic does not get unnecessarily delayed. A plan for the use of road signs is also made.
HSE	Work related to HSE contains making sure that personal safety equipment is used during inspection, that necessary safety training is given to executive personell, that a contingency plan is made and that a risk assessment is completed before inspection begins. Other elements regarding HSE are also included here.

2.3 Inspection equipment

Required equipment for the different types of inspections introduced in chapter 2.1 is shown in table 3. This is equipment used in today's inspections with operators performing inspection manually.

Table 3: Equipment for different inspection types [2].

Type of inspection	Equipment
Simple inspection	Flashlight, camera, binoculars, compass, measuring tape, knife, hammer, chisel, chalk, color spray, yardstick.
Main inspection	In addition to the equipment required for a simple inspection: Work alert equipment, dictaphone, video camera, thermometer, caliper, crack width gauge.
Main inspection of cables	Normally the same equipment as for a main inspection.
Main underwater inspection	Underwater camera, video equipment, hammer, chisel, measuring tape (50 meters), yardstick, leveling equipment.

In addition, different types of access equipment are used in inspection of bridges:

- Ladder.
- Scissor lift.
- Basket lift.
- Lift with a platform.

Inspection of a bridge using a basket lift and a lift with a platform is shown in figure 1 and 2 respectively.

Figure 1: Example of inspection using a basket lift [5].

Figure 2: Example of inspection using a lift with a platform [6].

2.4 Evaluation of faults

When evaluating faults or damages on the bridge construction it has to be decided what type of fault one is dealing with, and considerations on how serious the faults are, as well as on main causes of the faults, has to be made.

The Norwegian Public Roads Administration uses the terms *severity* and *consequence of damage* in the evaluation of faults [2]. Table 4 and 5 explain the two terms in more detail.

Table 4: Severity related to damage [2].

Code/numbering	**Explanation**	**Measures necessary**
1	Small damage	No
2	Medium damage	Yes, within 4-10 years
3	Large damage	Yes, within 1-3 years
4	Critical damage	Yes, latest within 6 months

Table 5: Consequence of damage [2].

Code/numbering	**Explanation**
B	Damage that affects the load capacity
T	Damage that affects traffic and road safety
V	Damage that may increase maintenance costs
M	Damage that may affect bridge estetics and surroundings

Chapter 3

Existing methods for automatic inspection

Automatic solutions can potentially reduce costs related to inspection as well as improve safety conditions by avoiding the use of access equipment like lifts shown in section 2.3. In this chapter, existing methods for automatic inspection of bridge constructions and automatic inspection methods in general will be shown. The chapter is divided into five main sections; mobility hardware, sensors for inspection, sensors for autonomy, data handling and data analysis. The existing methods within these sections will not be limited to methods used for bridge inspection only, but will show solutions used in other industries as well to get a greater overview of inspection possibilities. In the end of the sections regarding mobility hardware and sensors for inspection an evaluation of the methods will be done because choices made from these evaluations affect the focus in the next sections of the report regarding data handling and analysis. Sensors for autonomy are not evaluated in this chapter, but will be further discussed in section 4.3.1 when designing a robotic system for inspection.

3.1 Mobility hardware

Mobility hardware is in this report defined as a vehicle or robot carrying sensors. The list below shows types of existing mobility hardware used in automatic inspection that will be further explained in this section. These types of mobility hardware are chosen because some of them, like UAVs and cable inspection robots, are already being used for bridge inspection, while others have a great potential for this application.

- Unmanned Aerial Vehicle (UAV)
- Remotely Operated Underwater Vehicle (ROV)
- Autonomous Underwater Vehicle (AUV)
- Crawling robots
- Cable inspection robots

3.1.1 Unmanned Aerial Vehicle (UAV)

UAV is the actual flying unit in a larger system called Unmanned Aircraft System (UAS) which consists of both the flying unit, in this case a drone, and all systems controlling and communicating with the drone from the ground [7]. There exists several types of drones made for different applications. Three main categories of UAVs will be presented in this section; fixed wing drones, multirotor drones and single rotor drones.

Fixed wing drones have the longest range of these three categories, and are able to lift quite heavy objects. These drones are similar to a small aeroplane, so a suitable landing point is required [8]. A typical fixed wing drone is shown in figure 3.

Figure 3: Illustration of a fixed wing drone [9].

Multirotor drones are characterized by a relatively small range and a low loading capacity. These drones normally have four rotors or more, making them easy to maneuver and control in the air [8]. Multirotor drones are already used in inspection of bridge constructions by companies like Orbiton [10] and Aas-Jakobsen [11]. Figure 4 shows an illustration of a multirotor drone.

Figure 4: Illustration of a multirotor drone [12].

Single rotor drones, also called helicopter drones, are very similar to a traditional helicopter. Range and load capacities of these drones can be said to be somewhere in between those for fixed wing drones and multirotor drones [8]. Figure 5 shows a typical single rotor drone.

Figure 5: Illustration of a single rotor drone [13].

Table 6 classifies performances for the three categories of UAVs and some specific types of these.

Table 6: Classification of UAV performace from 1 to 3 (low:1, medium:2, high:3) [8].

UAV	Range	Flying time	Withstanding of weather	Maneuverability
Fixed wing drone with engine	3	3	2	2
Fixed wing drone without engine	3	2	2	2
Single rotor/ helicopter drone	2	2	2	3
Multirotor drone, 4 rotors	1	1	1	3
Multirotor drone, 4+ rotors	2	2	2	3

3.1.2 Remotely Operated Underwater Vehicle (ROV) and Autonomous Underwater Vehicle (AUV)

ROVs are widely used for performing underwater maintenance and inspections, especially in the oil and gas industry where they are used for tasks such as inspecting welds and pipelines, and operating valves on subsea constructions [14]. A typical ROV is illustrated in figure 6. ROVs are divided into five different classes by the NORSOK standard U-102 [15]. An autonomous underwater vehicle (AUV) is defined by this standard as a class 5 ROV. The classification is shown in table 7.

Figure 6: Illustration of a typical ROV. This is the Falcon ROV by DeepOcean [16].

Table 7: Classification of ROVs by the NORSOK standard U-102 [15].

Class	**Description**	**Details**
1	Pure observation	Vehicles limited to video observation. These ROVs have, in general, a video camera, lights and thrusters mounted. In order to perform other tasks these ROVs need modifications.
2	Observation with payload option	These ROVs can, in addition to a camera, carry sensors for inspection. For example measurement systems for cathodic protection and sonar systems. A class 2 ROV should be able to carry at least two additional sensors without loss of original functions when operated.
3	Work class vehicles	Class 3 ROVs are both larger and more powerful than the two first classes above. These ROVs can carry additional sensors and also manipulators. There are three types of class 3 ROVs classified by the amount of horsepower (hp); A (<100 hp), B (100 to 150 hp) and C (>150 hp).
4	Seabed-working vehicles	Class 4 ROVs maneuver on the seabed by thruster propellers, a water jet, wheels or a belt traction system. A combination of these methods is also possible. A class 4 ROV is typically both larger and heavier than a class 3, and they are made for tasks such as cable and pipeline trenching, excavation and dredging.
5	Prototype or development vehicles	Vehicles being developed, as well as prototypes. ROVs for special purposes that do not fit the previous classes are also assigned to class 5. AUVs are defined as a class 5 ROV.

Some examples of existing underwater vehicles are Hugin AUV by KONGSBERG [17] (figure 7), Magnum ROV by Oceaneering [18] (figure 8), the Eelume vehicle [19] (figure 9) and Falcon ROV by DeepOcean previously shown in figure 6.

Figure 7: The Hugin AUV by Kongsberg [17].

Figure 8: The Magnum ROV by Oceaneering [18].

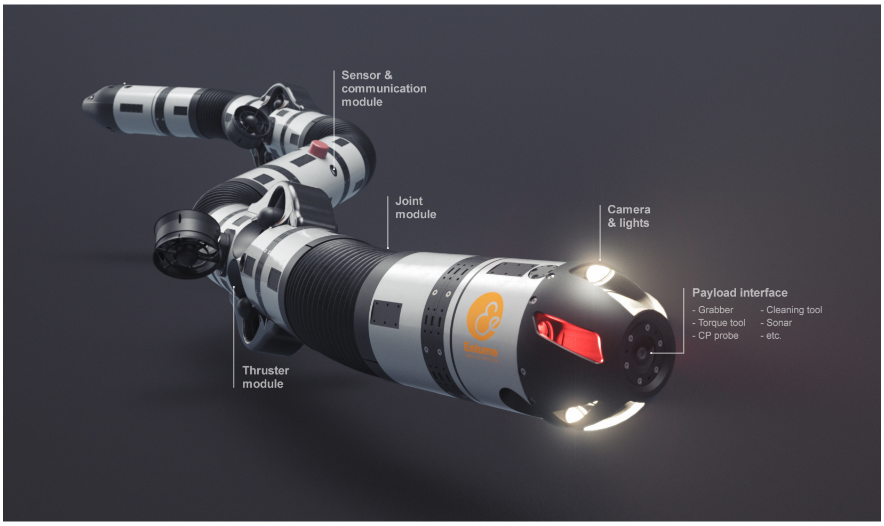

Figure 9: The Eelume underwater vehicle [19].

3.1.3 Crawling robots

Unmanned ground vehicles (UGV) is a category containing unmanned vehicles that can perform certain operations on the ground [8]. Examples of UGVs are humanlike robots with legs, autonomous transport vehicles and crawling robots. Crawling robots can be robots driven by wheels or belts that move along a surface. Some types are able to stick to a vertical surface and drive along it, for example using magnetic wheels, while others are made to move only on a horizontal surface. The FAST RVI by GE Inspection Robotics [20] (figure 10) is an example of a crawling robot. It is equipped with a pan-tilt-zoom camera (PTZ) for effective visual inspection, and has magnetic wheels so that it is able to perform overhead inspections.

A different crawling robot that has been tested on "Storebæltsbroen" [21] [22], a bridge in Denmark, is a robot made by Force Technology for inspection of nonmagnetic surfaces [23]. Using belts with a vacuum based concept the robot is able to stick to a nonmagnetic surface and drive along it.

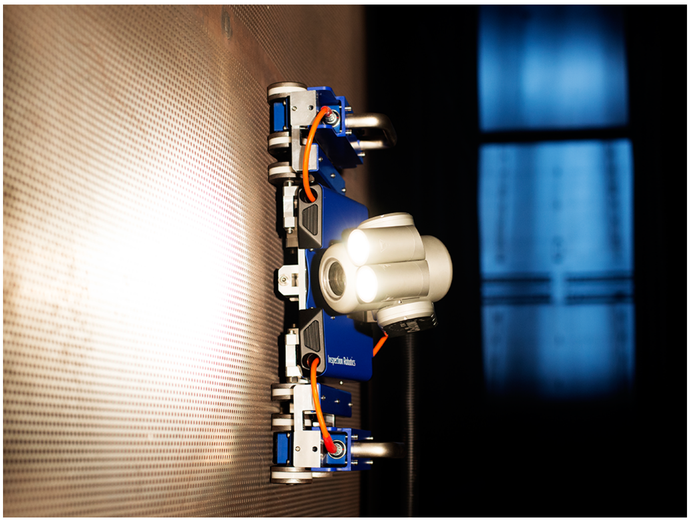

Figure 10: The FAST RVI by GE Inspection Robotics [20].

3.1.4 Cable inspection robots

A typical cable inspection robot is clamped over the cable to be inspected, and wheels makes it possible to move the robot up and down the cable. This is illustrated in figure 11. These types of robots equipped with, for example, a camera makes it possible to do thorough inspection of cables on cable-stayed bridges. In [24], a robotic wheel based cable inspection system is proposed. The suggested cable inspection robot is equipped with permanent magnets, CCD cameras for visual inspection and Hall effect sensors for detecting magnetic flux leakage in a cable. In [25], the development of both a robot for inspection of cable-suspension bridges and for cable-stayed bridges is presented, and non-destructive inspection techniques in combination with the robot are discussed. Figure 12 shows the CableScan inspection robot by a company called IPC [26].

Figure 11: Typical cable inspection robot clamped over a cable [27].

Figure 12: Inspection using the cable inspection robot CableScan by IPC [26].

3.1.5 Evaluation and choice of mobility hardware

Ideally, one should have looked at several possible combinations of mobility hardware and sensors for inspection of bridge constructions, but due to limitations in time available for implementation of this project it is decided to choose one specific type of mobility hardware from those presented in this section. When choosing what type of hardware the rest of this report should focus on, an important aspect is what hardware has the potential of inspecting most parts of a bridge construction.

Both crawling robots and cable inspection robots have a great potential in inspection of the bridge construction above water. Crawling robots can give close visual images of a surface, for example on the bridge deck, piers and beams. However, on the sides of a bridge, underneath and high up in towers, using a crawling robot can bring some safety challenges. For example, certain parts underneath and above a bridge can be difficult for the robot to reach or drive to without being placed there by a human operator. Then one does not avoid using access equipment like lifts shown in section 2.3. Cable inspection robots are well suited for inspection of main and suspender cables, but not any other parts of the bridge construction.

Using an ROV or AUV could be a good solution for bridge underwater inspection as mentioned in section 2.1, and these types of mobility hardware are the only ones from this section suited for underwater inspection. Since it is decided to choose only one type of mobility hardware, one must also choose between looking at either inspection above water, or under water. In this case, focus will be on inspection of a bridge's construction *above* water.

UAVs are able to reach most, if not all, parts of a bridge construction above water. Either by using a remotely operated drone or an autonomous drone, safety challenges related to the use of lifts or climbers to reach different areas of a bridge are eliminated. In table 6 multirotor drones with more than four rotors and single rotor/helicopter drones are given the highest performance score on maneuverability of UAVs. These types of drones also get a high score on withstanding of weather. These properties are considered important when it comes to inspection of bridges.

Based on the evaluations above, it is chosen to proceed with UAVs as mobility hardware, thus examples of sensors for inspection and autonomy in the next two sections will be based on sensors having a potential application on UAVs.

3.2 Sensors for inspection

Material testing is normally divided into two groups called *destructive testing* (DT) and *non-destructive testing* (NDT). The sensors in this section will be based on methods for non-destructive testing, and a selection of sensors considered most suited for use on a UAV are explained further. Examples of NDT methods used in industrial inspections are shown and briefly explained in table 8.

Table 8: Common methods for non-destructive testing [28].

Method	**Explanation**
Ultrasonic Testing (UT)	Ultrasonic waves are sent from a probe into the material. Internal faults in the material is detected by the reflection of the waves back to the probe.
Eddy Current Testing (ET)	ET is a method used on electrically conductive materials. A coil is applied a current and this results in a magnetic field around the coil. This magnetic field creates a second magnetic field in the material inspected. Changes in this second field reveals faults in the materials surface.
Visual testing (VT)	A visual inspection, manually or automatically. Using a camera images and videos can be taken and further analyzed.
Penetrant Testing (PT)	The method can be used on practically all types of materials. The surface of the material is cleaned, and a coloured, penetrating liquid is applied. After some time the liquid is removed. A different chemical is then applied to absorb the remaining liquid. In this way cracks in the surface are detected.
Magnetic Particle Testing (MP)	A method used for ferromagnetic materials to detect cracks in the surface. Iron powder is applied and the test object is magnetized. The powder will be drawn to the fault to be detected.
Radiography Testing (RT)	X-rays or gamma rays are sent through a material to check, for example, welds and internal faults.

3.2.1 Inspection cameras

There are different types of cameras made for inspection purposes, an the list below shows some types of inspection cameras. The list is made with inspiration from cameras as sensors mentioned in [8].

- RGB camera
- Multispectral camera
- Hyperspectral camera
- Time-of-flight camera

An RGB camera, most commonly known as a digital camera, has a reference to the colours red, green and blue (RGB). Through what is called photogrammetry, shapes and sizes of objects in images can be measured [8].

The principle of a multispectral camera is filtering of specific wavelengths on the electromagnetic spectrum, and capturing of image data within these wavelengths [8]. Examples of multispectral cameras made for drones are MAIA multispectral camera [29] and Sentera Double 4K sensor [30].

A hyperspectral camera combines digital imaging and spectroscopy, and it works very similar to a multispectral camera [8]. Table 9 shows examples of hyperspectral cameras made for UAVs.

Table 9: Examples of common hyperspectral cameras made for UAVs [31].

Manufacturer and model	**Resolution [Mpx]**	**Size** $[mm^2]$	**Pixel size** $[\mu m]$	**Weight [kg]**	**Spectral range [nm]**	**Spectral bands and resolution [nm]**
Rikola Ltd. Hyperspectral Camera	CMOS	5.6×5.6	5.5	0.6	500-900	40 and 10
Headwall Photonics, Micro-Hyperspec X-series NIR	InGaAs	9.6×9.6	30	1.025	900-1700	62 and 12.9

Using an infrared light source and a sensitive photon detector called a CCD detector, a time-of-flight camera (ToF camera) is able to measure the depth of a 3D scene and create an image of this [32]. Real time 3D data and video mode without post processing can be obtained with a ToF camera. These type of cameras can work as an alternative to LiDAR sensors, that will be introduced in section 3.3.2, but ToF cameras have a limited range of around 10 meters [8].

3.2.2 Ultrasonic sensors

Ultrasonic sensors or probes can, as mentioned in table 8, be used to detect internal faults in a material. Typical applications of ultrasonic testing are inspection of steel constructions, welds and machine components. The frequencies for ultrasonic waves are between 0.5 to 10 MHz. An ultrasonic sensor sends a pulse of high frequency waves into an object, as shown in figure 13, and the time delay from transmitting to receiving the echo of waves indicates the distance to a fault within the object inspected [33].

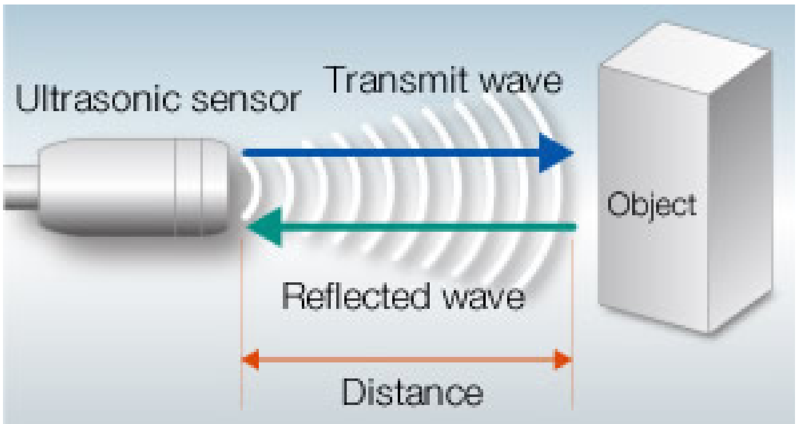

Figure 13: Principle of an ultrasonic sensor[34].

An ultrasonic sensor, also called an ultrasonic probe, consists of both a transmitter and receiver that are combined in the same tranducer. This is possible trough the use of what is called a piezoelectric material in the probe that can convert between electrical and mechanical signals. The high frequency, ultrasonic waves are attenuated in air. Therefore, to create a good acoustic connection, it is normally applied a type of gel so that it always is a film of liquid between the probe and the surface being inspected. [33]. Figure 14 shows a design of an ultrasonic probe.

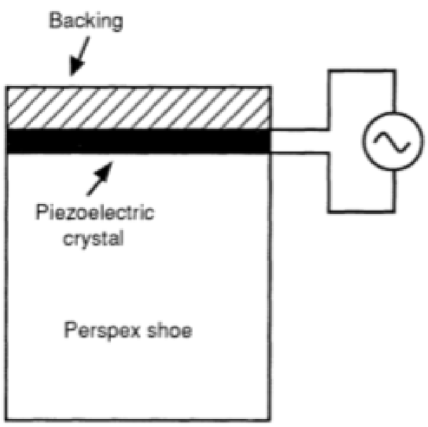

Figure 14: Illustration of a common ultrasonic probe design [33].

3.2.3 Eddy current sensors

An eddy current sensor consists of a coil being applied a current, which results in the radiaton of a magnetic field. When placing the coil close to a electrically conductive material the magnetic field creates what is called eddy currents in the material that results in a second, opposing magnetic field. This opposing magnetic field impacts the magnetic field in the coil, which can be detected as changes in the coils impedance. Some applications of eddy current sensors are within wire inspections, surface crack detection, and thickness layer measurements [33]. The principle of an eddy current sensor is shown in figure 15.

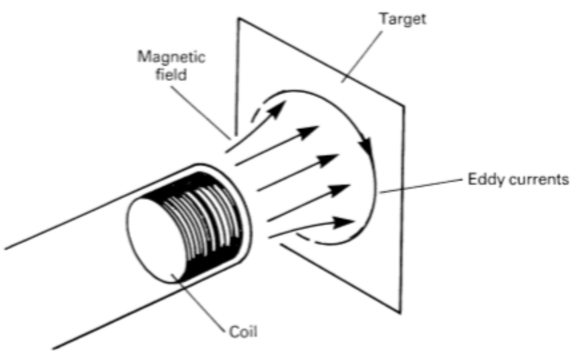

Figure 15: Eddy current sensor principle [33].

3.2.4 Evaluation and choice of sensor for inspection

In the same way as it would have been interesting to look at several combinations of mobility hardware and sensors for inspection, it would certainly be of value to look at methods for analysis of data provided by all the sensors for inspection mentioned in this section. However, in this project assignment it was necessary to limit the amount of methods to be explained. Therefore, it is chosen to proceed with only one of the sensors for inspection introduced in this section. When choosing what sensor to continue with, evaluations on how suited the sensor is in combination with an UAV must be done.

Ultrasonic sensors are well suited for detecting internal faults in a material, and this method is absolutely relevant for bridge inspection. When it comes to using an ultrasonic sensor in combination with a drone, one challenge would be the fact that the ultrasonic sensor needs to be in contact with the construction surface inspected, since ultrasonic waves are attenuated in air, as mentioned earlier. This would require the drone to be very close to the bridge construction. Some parts of a bridge it might not be able to reach since there might not be enough space for the drones rotors to move freely, for example underneath a bridge.

Some applications of eddy current sensors were mentioned in this section, and the sensors suitability for detecting surface cracks and for measuring thickness of surface protective layers, definitely makes it relevant for inspection of bridges. However, mounted on a drone, a similar challenge as in the case of using an ultrasonic sensor may occur.

An inspection camera mounted on a drone makes it possible to perform close visual inspection of practically the entire bridge construction above water. Of course, limitations on image quality depending on the camera must be taken into consideration. Especially when it comes to corrosion detection, visual inspection is one of the most used methods. Using a drone with a camera makes it possible to perform close visual inspection of areas otherwise hard to reach, and images can be analyzed either manually or automatically later.

The aim of this evaluation is not to make a conclusion that ultrasonic sensors and eddy current sensors are not at all suited in combination with a drone, but that using a camera overall seems to be a better solution for inspection of bridge constructions, in particular for inspection of corrosion. In a complete inspection system, it would most likely be preferable to use drones equipped with different sensors depending on the area to be inspected.

Based on the evaluation above it is decided to proceed with a camera as a sensor for inspection, thus section 3.5.2 regarding inspection data analysis will explain methods for analyzing images, with focus on automatic corrosion detection.

3.3 Sensors for autonomy

This section will briefly explain some types of sensors used on autonomous vehicles for finding their position, avoidance of obstacles and for example for being able to keep a certain distance to known objects. For example, if an autonomous UAV is used for inspection of a bridge it is important with a sensor that prevents it from colliding with the construction. Some examples of previous work on obstacle detection and avoidance will also be presented.

3.3.1 Ultrasonic sensors

Ultrasonic sensors, explained in section 3.2.2, can also be used on autonomous vehicles to measure distances from objects, thus preventing the vehicle form colliding with objects in its path. In [35], a method using ultrasonic sensors on UAVs for obstacle detection is shown. The paper presents a solution using time-of-flight data from ultrasonic sensors and four signal metrics to determine the position of an obstacle; maximum frequency, cross correlation of raw data and PSD, power and energy spectral density. In [36], a method for solving collision problems for a quad-rotor UAV with low flight altitude using ultrasonic sensors is devised.

3.3.2 Light detection and ranging (LiDAR)

Through measuring properties of scattered and reflected light, information about a distant object can be found. This optical sensing technology is called LiDAR, and the principle is shown in figure 16. To determine the distance to a certain object laser pulses are emitted, and the time delay between transmission and detection of the reflected pulses becomes a measurement for distance [37]. In [31], examples of short range LiDAR sensors for obstacle detection and avoidance being used on UAVs are given. Table 10 shows parts of a table taken from this article, and describes specific LiDAR based sensors used on UAVs.

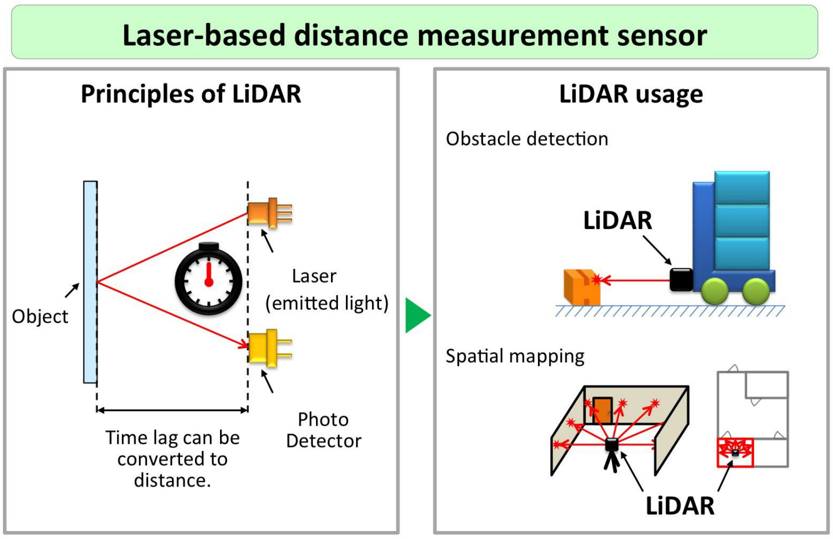

Figure 16: Principle and usage of LiDAR based sensors [38].

Table 10: Examples of common LiDAR based scanners/sensors for UAVs [31].

Manufacturer and model	**Scanning pattern**	**Range [m]**	**Weight [kg]**	**Laser class and wavelength [nm]**
Ibeo Automotive Systems Ibeo LUX	4 scanning, parallell lines	200	1	Class A, 905
Velodyne HDL-32E	32 laser pairs	100	2	Class A, 905
RIEGL VQ-820-GU	1 scanning line	$\geqslant$ 1000	-	Class 3B, 532

3.3.3 Stereo cameras

Estimation of a 3D model can be done using two or more cameras, which makes it possible to measure the depth of the scene one is interested in. This is done through finding matching pixels in images and then converting 2D position into 3D depth, a process called stereo matching [39]. Measuring depth makes it possible to decide the distance to objects, thus stereo cameras mounted on a drone can prevent the drone from colliding with obstacles.

As an example, the Intel RealSense R200 camera [40] uses two IR cameras to measure depth. It actually has a third camera as well, an RGB camera, to provide colour images. The Intel RealSense R200 is equipped with a IR laser projector, making it possible to perform 3D scanning for scene perception and improving photography [40]. There are also newer versions of this camera, like the Intel RealSense Depth Camera D400-Series [41]. [42] shows an Intel RealSense camera mounted on a Tyhoon H drone, making autonomous flights and obstacle detection possible.

3.3.4 Event cameras

Event cameras are inspired by the human vision system, and they output changes in pixel-level brightness rather than standard intensity frames. Compared with standard cameras, advantages of these cameras are high dynamic range, low latency and no motion blur. A disadvantage related to event cameras is that traditional computer vision algorithms can not be applied when processing their outputs. This is because the output is made out of a sequence of asynchronous events, and not intensity images like for regular cameras. Therefore, new algorithms are required to process the data provided by event cameras. Example of an event camera is the Dynamic Vision Sensor (DVS) [43].

3.3.5 Radar

The general principle of a radar can be explained through the illustration in figure 17, where the distance to an object can be measured by using radio waves being transmitted and received by an antenna. In [44] performance simulations of obstacle detection and collision avoidance using a radar sensor on an UAV are done. In this paper, obstacle awareness performance is analyzed by the probability of detecting obstacles through radar cross-section (RCS) models, and collision avoidance performance is evaluated through information like range and range rate during flights.

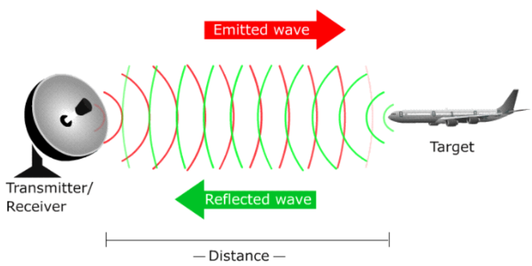

Figure 17: Illustration of the radar principle [45].

3.3.6 GNSS

GNSS (Global Navigation Satellite System) is a common term for satellite based systems for positioning and navigation, such as GPS (Global Positioning Sytem) and Galileo [46]. These systems consist of three segments; a space segment, control segment and a user segment [47]. The three segments are illustrated in figure 18. The space segment consists of satellites sending signals regarding distance and time to users. The control segment are ground centrals that follow and send data to the satellites to be forwarded to users. Finally, the user segment are receivers, for example on a drone, that collect data from the satellites and from this are able to calculate position, velocity and time [47].

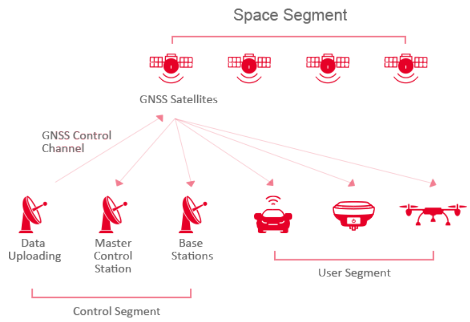

Figure 18: Illustration of the GNSS principle [48].

3.3.7 IMU

IMU (Inertial Measurement Unit) is a sensor or an instrument that senses translation or rotational motion. An example of IMUs that sense linear translation are accelerometers. To sense angular rate, IMUs called gyroscopes are used. An IMU has three axes associated with it called input, output and a third axis related to the instrument. The sensing axis is the input axis [49]. An IMU with the three axes is illustrated in figure 19.

Figure 19: Illustration of an IMU with three axes; roll, pitch, yaw [50].

3.4 Data handling

This section will present some existing methods for handling large quantities of data, including the process from reception of data to transferring, processing and storing. For bridge inspection it is important how data is stored during and after inspection in such a way that it is easily obtained for analysis. This chapter will be very brief because the project assignment does not have strong emphasis on data handling. However, general knowledge of data handling and existing methods for this is important when designing a robotic system for inspection, therefore this chapter is included. Relevant theory for data handling is first presented before some existing methods for reception, transferring and storage of data are explained.

3.4.1 Background theory and definitions

The term Internet of Things (IoT) is widely used today when it comes to data handling. IoT describes objects with a digital functionality such that they are able to communicate through the Internet. In many industres, IoT has become a useful concept that eases information flow to different parts of the world. [51]. Examples of objects communicating through the Internet are cars, smartwatches and industrial sensors for measuring physical properties. Through IoT, useful information from these objects are gathered and passed to other devices or storing units using the Internet [52]. A second term commonly used in the context of industrial applications of IoT is the Industrial Internet of Things (IIoT).

3.4.2 Existing methods for data handling

Existing methods for reception, processing and transferring of data can be be explained through a process or system containing three different layers; cloud, fog and edge. An illustration of these layers and the connection between them is shown in figure 20. The edge layer can, for example, consist of embedded systems, industrial computers and gateways. Processing of data in this layer is often done through embedded computing platforms connected directly to the sensor or controller [53]. Since computations and data processing is performed close to the data source without being sent to other systems, the performance of data transport can be improved [54].

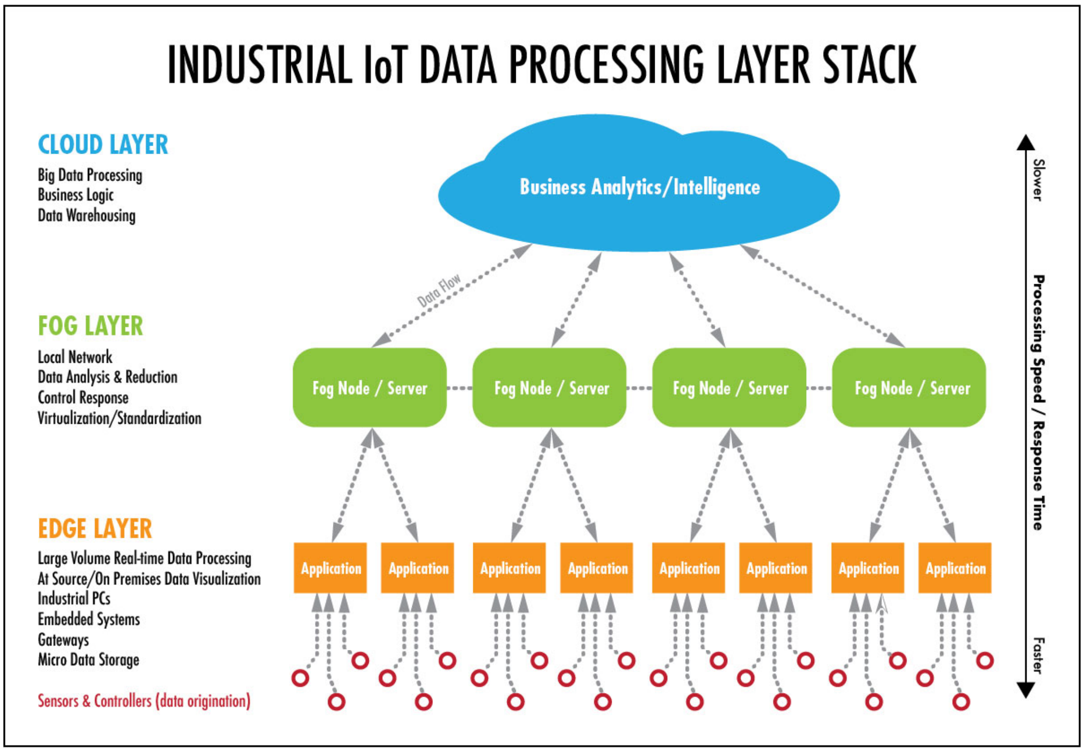

Figure 20: Illustration of the layers cloud (blue), fog (green) and edge (orange) in data processing[53]. The red circles illustrates sensors and controllers, and could, for example, be sensors detecting corrosion on a bridge.

In the fog layer data is typically transmitted through a local area network (LAN) to a source performing computations and analysis. The location of computational tools or systems are therefore the key difference between edge and fog computation. The cloud layer consists of a collection of servers that together make a distributed network. A cloud-based system can collect data from multiple locations, store it and make it easily accessible from almost anywhere. Data can be transmitted between the layers. For example, data from the cloud layer can be passed to the fog or edge layer for local processing, or large quantities of data retrieved from a sensor to an edge device can be passed to a cloud for computations in a different geographical location [53]. As illustrated with the black arrow on the right in figure 20 the processing speed increases the closer one is to the data source.

Examples of existing digital platforms for data handling are KONGSBERGs Kognifai platform [55], Microsoft Azure [56] and Watson IoT [57].

3.5 Inspection data analysis

In this section some existing methods for analyzing inspection data will be explained with focus on analysis of corrosion damages on bridge constructions from images. Important aspects like how the data is analyzed, types of software used for analysis, what type of information is relevant and how it is interpreted will be covered in this section. A brief introduction to relevant theory is included before some existing methods for data analysis are explained.

3.5.1 Introduction and definitions

There are several definitions of the term Artificial Intelligence (AI). One definition describes AI as “the study of how to make computers do things at which, at the moment, people are better” [58]. For example, in fast execution of many computational tasks computers outperform humans, but in the ability to enter an unfamiliar room and, within less than a second, being able to recognize surroundings and plan actions, humans clearly outperform computers today [58]. AI can also be defined as “the capability of a machine to imitate intelligent human behaviour” [59]. The branch of AI that makes computers able to learn, without explicitly being programmed to do so, is called Machine Learning (ML). The term *deep learning* is important in this context. Through the use of algorithms inspired by the human brain called Artificial Neural Networks (ANN) deep learning can give a computer the ability to self-learn models and patterns [59].

Computer Vision (CV) is a field of science where one seeks to describe the world through the analysis of images, and to reconstruct properties like shape, illumination and color distributions. Humans easily recognize, for example, people and different three-dimensional shapes, but for computers vision is more difficult. One of the reasons is that vision is an inverse problem where unknowns must be recovered to be able to fully specify a solution. Models based on physics and probability are used to differentiate between the potential solutions [39].

3.5.2 Existing methods for inspection data analysis

This section will focus on existing methods for analysis of data from cameras, more specific two approaches for automatic detection of corrosion; computer vision and deep learning techniques. First, some general methods will be explained, then examples of tests and results from previous work using elements from one, or both, of these approaches for corrosion detection will be presented.

Computer vision techniques

Computer vision was briefly introduced in section 3.5.1. In this section, computer vision techniques will be explained in more detail. The discrete colour values red, green and blue (RGB) that can be seen in a digital image comes from light, from different parts of the spectrum, being integrated into these colour values when incoming light hits an image sensor [39]. There exist alternative representations of the RGB colour space, for example: HSV- hue, saturation and value, and HSL- hue, saturation and lightness [60]. There is also a representation called HSI-hue, saturation and intensity.

The first stage in most computer vision applications is pre-processing and conversion of images into a form that is suitable for further analysis. *Point operators*, or *point-wise operations*, are simple types of image transforms where a pixel output value only depends on the value of the corresponding input pixel [39]. A point-wise operation does not change the spatial relationships in an image [60]. Examples of point-wise operations are contrast and brightness adjustment, colour transformations, image matting and compositing, and histogram equalization. Matting is the process of extracting a certain object from an image, and compositing is the process of inserting this object into a different image [39]. An *image histogram* can, for example, be a plot of colour channels, and this function could then show the amount of pixels having a certain value or intensity. Normalized, the function in an image histogram is also called a *pdf*- probability density function [60]. Histogram equalization is a process of finding an intensity mapping function that results in a "flat" histogram [39]. Figure 21 shows a very general example of an image histogram.

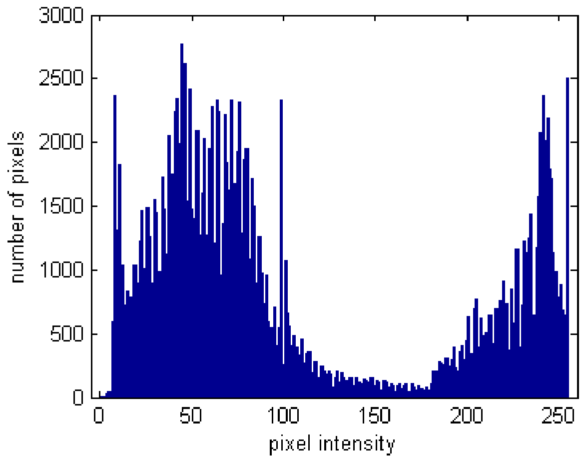

Figure 21: Illustration of a general image histogram showing the pixel intensity on the x-axis and the number of pixels with a specific intensity on the y-axis [61].

A *neighbourhood operator*, or a *local operator*, uses pixel values near a certain pixel to determine what its final output value should be. These operators can used to filter images, for example to remove noise. In *linear filtering*, the value of an output pixel is a weighted sum of the input pixel values. A *kernel*, containing the filter coefficients, is placed over some chosen values [39]. Figure 22 shows how a linear filtering process can be completed.

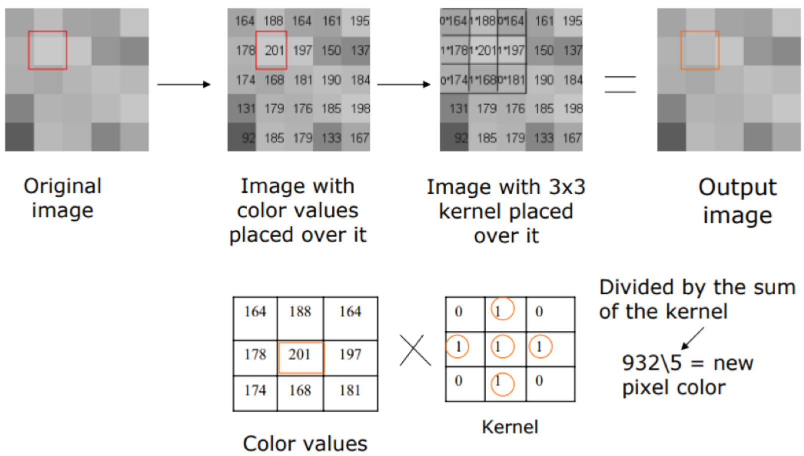

Figure 22: Illustration of linear filtering using a specific kernel, a 3 × 3 matrix [60].

Examples of existing computer vision libraries are OpenCV [62], VXL [63] and SOD [64].

Deep learning approaches

In section 3.5.1 an introduction to ANNs and deep learning was given. These two terms will be further explained in this section. ANNs consist of *neurons*, processing units, that are connected through *synapses*. Since ANNs are inspired by the human brain, expressions are based on physiological terms [65]. Neurons and synapses in ANNs are illustrated in figure 23, where the circles in the different layers are neurons, and the links (arrows) between them are synapses.

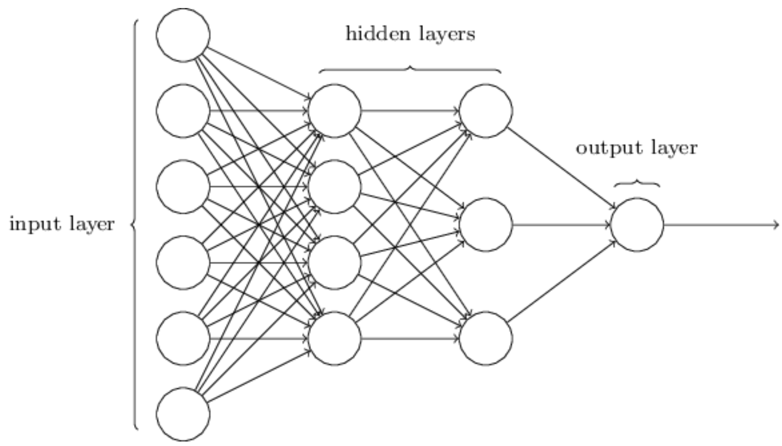

Figure 23: Illustration of a multi-layer artificial neural network [66].

When an artificial neural network has more than one hidden layer, as shown in figure 23, the term *deep learning* is used. Each neuron has a certain capacity for processing information, and they influence each other through the synapses. The learning process for ANNs consists of deciding how much one neuron should affect the other, and this is referred to as deciding the synaptic weightings. Data, called a *training set*, is provided the network in the input layer (figure 23), and the synaptic weightings are adjusted until the network is able to separate the given data in a desired way [65]. For example, if images of corrosion are the input to the ANN, one would need to adjust the synaptic weightings in such a way that the network is able to separate between the images that contain corrosion, and the ones that do not. Once the weightings have been adjusted based on the training set, the network performance is verified through providing it with what is called a *validation set*, containing data that is new to the ANN [65]. In the case of corrosion detection, a validation set would be a data set containing images of corrosion that the network has never seen before.

There is a class of neural networks called *convolutional neural networks* (CNN or ConvNets) that provides popular tools for image analysis. CNNs are highly suitable for analyzing inputs like images, text, and different continuous signals. This class of neural networks is inspired by the biological structure of a visual cortex, consisting of cells that are activated by subregions of a visual field called receptive fields. Unlike other types of neural networks, neurons in a convolutional layer connect to a subregion of a layer before the layer. Subregions may overlap, resulting in neurons producing spatially-correlated results. This is characteristic for CNNs, since neurons in other neural networks, like the type illustrated in figure 23, produce independent outputs because they are not connected. Examples of layers in a CNN are convolutional layers, average-pooling layers and fully-connected layers [67]. MATLABs Deep Learning Toolbox [68] is an example of software that uses CNNs, as well as other networks. Figure 24 illustrates several convolutional layers producing output suggestions based on the input image.

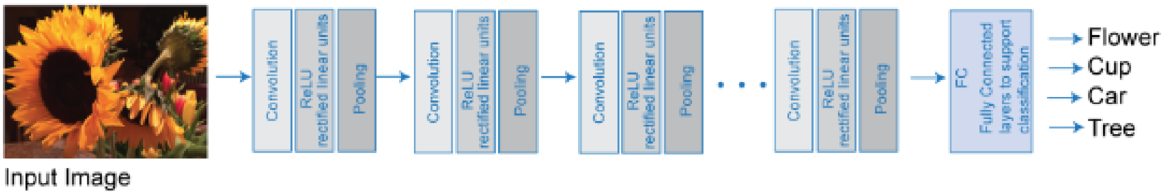

Figure 24: Illustration of convolutional layers in a CNN [67].

Examples of existing deep learning network models are Google AIs GoogLeNet [69], SqueezeNet [70] and Inception-v3 [71].

Previous work on automatic corrosion detection

In [72] two different approaches for automatic detection of corrosion (rust) are compared; standard computer vision techniques and a deep learning model. The paper is written by employees of the two companies Broentech Solutions AS and Orbiton AS. Orbiton AS is providing bridge inspection services using drones, and the corrosion detection methods explained in the paper are highly relevant for analysing images taken by these drones. The first approach, refered to in the paper as the classical approach, is a method based on classic CV tecniques that counts the amount of pixels in an image containing specific red components. The code for the classic approach was written in the programming language Python [73] using OpenCV libraries. Through a filtering process changing the image colour space from RGB to HSV and, briefly explained, a conversion of the image to black and white, the amount of white pixels could be used as a measure for corrosion. The classification of corrosion was set to images containing more than 0.3% white pixels [72].

The second approach was the use of deep learning methods. A framework called Caffe [74] was chosen beacuse of its suitability for image processing. A data set containing 1300 and 2200 images with and without corrosion respectively, was collected. Approximately 80% of the data set was used as a training set for the deep learning network, the rest was used as a validation set. An existing model called "bvlc_reference_caffenet" pre-trained with about one millon images was used to fine tune the network. Using pre-trained models is beneficial because it saves time through the reuse of information [72].

Figure 25: Examples of pictures used in tests of automatic corrosion detection [72].

Figure 26: Pictures of rust classified as non-rust by the deep learning algorithm [72].

Figure 25 shows examples of images used in the testing of the two approaches for corrosion detection. Images without corrosion, but with red or brown details were included to check if the two approaches detected this as corrosion or not. For the tests a total of 100 images were used. The total amount of images included 37 images of rust and 63 of non-rust. The total accuracy was found to be 69% for the approach using OpenCV, and 78% for the deep learning model, with accuracy defined as the ratio between correctly classified images and the total amount of images.

The OpenCV method classified all the four pictures in figure 25 as rust because all pictures had a large enough amount of red components to be detected as corrosion. The deep learning algorithm, on the other hand, was able to correctly classify all the pictures in figure 25 even though images of a desert or an apple were not used in the training set for the algorithm. Even though the overall accuracy for the classical approach was lower than for the one using deep learning, this approach had a higher accuracy in classifying images that actually contained rust as positive for corrosion. As an example, the deep learning algorithm classified the pictures in figure 26 as non-rust even though there was present of rust.

The papers conclusion mentions a combination of the two approaches as a possible solution for a real application, with the OpenCV model removing images that are non-rust and passing the remaining to the deep learning algorithm for further analysis [72].

In [75] deep learning approaches based on CNNs for corrosion detection are evaluated. The study presented in this paper aims to quantify performance of corrosion classification and find optimal inputs for a CNN to create robust systems for automatic corrosion detection. Figure 27 shows a basic structure of a CNN with output predictions “non-corroded” and “corrosion”, and this is the type of structure used in the study to classify image regions as corroded or not.

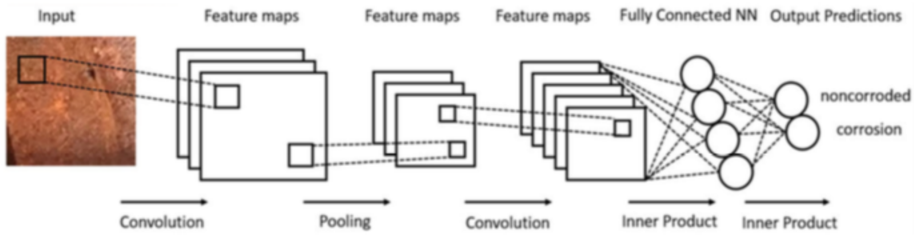

Figure 27: Illustration of a basic CNN architecture [75].

Two types of existing networks called VGG16 [76] and ZF Net [77] were used. Different colour spaces such as RGB, YCbCr, CbCr and grayscale were tested to find the optimal colour space for corrosion detection. A sliding window approach was used to classify different regions of an image. This is illustrated in figure 28.

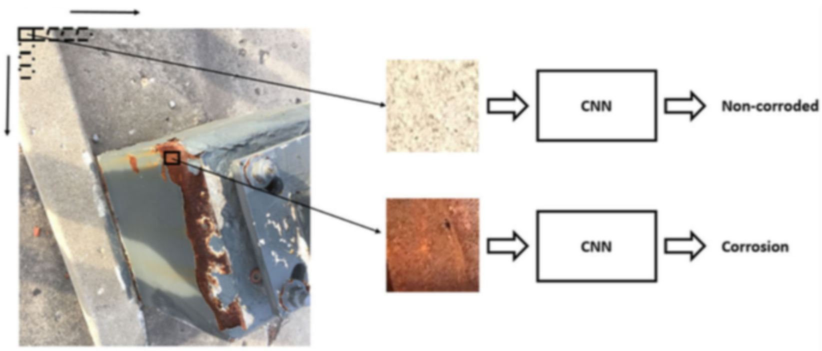

Figure 28: Illustration of region classification using a sliding window approach [75].

Through testing the two networks with different colour spaces and sliding window sizes it was found that the best input parameters were the RGB and YCbCr colour spaces, using a sliding window size of 128×128. After fine-tuning, the VGG16 network turned out to be the most robust architecture. However, with no fine-tuning, the two networks performed equally. For future work, the paper suggests using the results found to look at the possibilities for classification of different types of corrosion using CNNs [75].

Chapter 4

Design of robotic inspection system with sensors

In this chapter a robotic system for inspection of bridge constructions is designed. The suggested system is designed for use in testing and development. Specific UAVs and sensors for inspection will be evaluated, and brief considerations regarding sensors for autonomy and data handling will be done. In this chapter a method for data analysis, with focus on analysis of images of corrosion using CV techniques and deep learning, will also be presented. The data analysis method includes both corrosion detection and classification of corrosion damages, and relevant software and networks for this are suggested.

4.1 System concept

In this section the general concept of the robotic inspection system will be described. A suggested combination of mobility hardware and sensors, data handling and analysis is explained, giving an overall system architecture with requirements to be decided.

In section 3.1.5 and 3.2.4 evaluations of existing mobility hardware and inspection sensors were done. An UAV with camera as sensor for inspection was chosen to be in focus for this assignment. This is the combination of mobility hardware and sensor for inspection to be used in this suggested system for bridge inspection. A selection of existing methods for data handling and analysis introduced in section 3.4 and 3.5, respectively, will be used to retrieve and process data from the inspection camera mounted on the UAV.

The UAV and the inspection camera should be able to withstand rough weather conditions to a certain degree. In Norway, the weather during autumn and winter can be challenging, and it is not expected that bridge inspection is to be performed on the coldest days, or on days with heavy snowfall or rain. However, both the UAV and the inspection camera should be waterproof to withstand rain and a moderate amount of snow. A certain wind tolerance must also be required for the UAV so that it is able to maintain stable flights when exposed to moderate to strong wind speed. It must be required a certain resolution, megapixels (Mpx), on the inspection camera. This is because a high image quality is necessary when performing data analysis. The UAV should be able to reach most parts of a bridge's construction, preferably all. For example, both areas underneath a bridge and on the highest parts of the construction must be inspected. Therefore, an important feature for the UAV is maneuverability.

The UAV could be controlled manually by an operator, or it could be fully autonomous. In section 3.3, examples of existing sensors for autonomy were introduced. For the suggested system, there will be done brief evaluations regarding sensors for autonomy and what would be required for the UAV to be fully autonomous. It is important to specify that the UAV does not necessarily have to be fully autonomous, so it will be facilitated for manual control of the UAV as well. Manual control of the UAV is also considered preferable in the beginning, during testing of data handling and analysis performance of the robotic inspection system.

In section 3.4.2, three different methods for data handling, explained as layers in a data handling process, called cloud, fog and edge layers, were presented. For the robotic inspection system, inspection data provided by the camera on the UAV should, preferably, be accessible for analysis at all times from a different location than where the bridge is being inspected, for example in a different city or country. To achieve this, the data can be transferred from the inspection sensor (camera) through a fog layer, for example a LAN, to a cloud for storing and further analysis. If it's preferable for the end user of the system to do data analysis directly on the inspection site, it should also be possible to analyze inspection data through directly connecting to the camera with the use of embedded computing platforms. A challenge in data handling could occur if there is poor, or no, Internet coverage in the area a bridge is located. Therefore, the UAV must have a data storage device for temporarily storage of inspection data when it is not possible to send the data directly to a cloud, or to a computer through a LAN.

Methods for data analysis, with emphasis on automatic corrosion detection through image processing and classification, were presented in section 3.5.2. After inspection data have been transferred to a cloud or a local computer, it will be analyzed using relevant software, libraries and networks for image processing. The two methods for data analysis and automatic corrosion detection will be computer vision techniques and deep learning approaches. For automatic corrosion detection on bridge constructions to be able to fully replace today's methods with engineers visually evaluating images manually, a high precision detection system must be developed. Therefore, requirements on the accuracy of the system for automatic corrosion detection must be set.

Figure 29 shows a simple, self made illustration of the system concept, consisting of an UAV with sensors for both inspection and autonomy, and minimum one storage device. The system for data handling uses one, or more, of the three layers cloud, fog and edge, depending on the conditions for data transferring. The last part of the robotic inspection system is data analysis, using computer vision techniques and deep learning approaches.

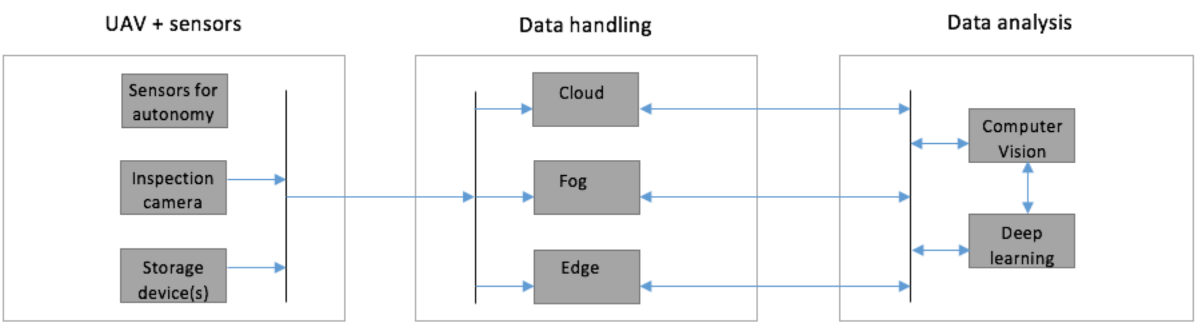

Figure 29: A simple illustration of the robotic inspection system concept. Images are passed, either directly from the inspection camera or from a storage device on the UAV, to a cloud or a local computer. Then, images are analyzed using CV techniques, deep learning, or a combination of these approaches.

4.2 Requirements specification

There are several requirements that need to be fulfilled for a well functioning robotic inspection system. Technical specifications and requirements to reliability and safety are examples of important factors in the work of designing a robotic system. Table 11 contains the requirements specification for the robotic inspection system to be designed in this chapter, based on the system concept described in the previous section.

Table 11: Requirements specification for the robotic inspection system. XX are numbers that need to be decided through testing, or that depend on combinations of sensors and equipment.

Number	**Requirement**	**Comment**
1	The UAV should be able to withstand rough weather conditions	Challenges due to rain, wind and snow must be handled
2	The UAV shall have a high degree of maneuverability	Important for being able to maneuver the UAV between the different areas of a bridge construction
3	A payload capacity of min. XX kg is required for the UAV	To be able to carry both a sensor for inspection (camera) and sensor(s) for autonomy. XX must be defined depending on what sensors are used
4	The UAV shall have min. one data storage device	For the possibiliy of temporarily storage of inspection data on the UAV. For example MicroSD, USB, or similar.
5	The inspection camera should be able to withstand rough weather conditions	As the UAV itself, the sensor for inspection must be robust. For example, waterproof
6	The inspection camera shall have a resolution of min. XX Mpx	A certain image quality is required for data analysis. Several cameras may have to be tested to find XX
7	Data analysis methods shall be accurate and reliable enough to make corrosion detection fully automatic	Combinations of analysis methods must be considered

4.3 System description

The first part of the system that will be described is mobility hardware and sensors. Next, considerations regarding data handling will be done. Finally, a method for analysis of images of corrosion using both CV techniques and deep learning approaches is presented. Choices in this chapter are based on the requirements set in table 11 and existing hardware, sensors and methods for data handling and analysis presented in previous chapters in this report.

4.3.1 Mobility hardware and sensors

This section is structured into three parts, including considerations and choices for the UAV, inspection camera and sensors and methods for autonomy to be used in the robotic inspection system.

UAV

In table 6 a classification of UAV performance is shown, and two types of drones that have an overall high score are single rotor drones and multirotor drones with more than 4 rotors. However, drones with four rotors are also relevant for bridge inspection. Two important characteristics for a drone to be used for bridge inspection is withstanding of weather and maneuverability, and both types of drones score high on these characteristics. As mentioned in section 3.1.1, multirotor drones are already being used for bridge inspection, which confirms that this is a type of drone well suited for the task. It is important to specify that there exists many different manufacturers of multirotor drones, so it is crucial to choose those most reliable and suited for mounting sensors for both inspection and autonomy.

In table 11 requirements 1-4 are set for the UAV to be used in this robotic system for inspection. From requirement 1, the use of a reliable and durable UAV is advised. With durable it is meant an UAV that withstands demanding conditions such as rain, wind (to a certain degree), snow and freezing temperatures. Examples of relevant multirotor drones to be used in the robotic inspection system are the Intel Falcon 8+ [78] and Action Drone USA's AD2 Inspection [79]. These two drones are shown in figure 30 and 31, respectively.

Figure 30: Illustration of the Intel Falcon 8+ [78]

Figure 31: Illustration of Action Drone USA's AD2 Inspection drone[80]

From [81] and [82] technical specifications on the Intel Falcon 8+ and Action Drone AD2 Inspection are gathered, respectively. A selection of technical specifications for the two drones are compared in table 12.

Table 12: Technical specifications for the Intel Falcon 8+ and Action Drone AD2 Inspection [81][82]. X is unknown information.

	Intel Falcon 8+	**Action Drone AD2 Inspection**
Max. wind tolerance	16 m/s (35.8 mph)	11.2 m/s (25 mph)
Rain/water tolerance	X	X
Operating temperature	$-5°C$ to $40°C$	X
Storage device	Yes. Made with slots for USB and Micro SD.	X
Flight time	16-26 min	10-30 min
Take-off weight	2.8 kg (6.17 lbs)	5.4-13.5 kg (12-30 lbs) Depending on configuration

Requirement 1 in table 11 says that the UAV should be able to withstand rough weather conditions. Table 12 shows the maximum wind tolerance for the two drones. From [83], wind speeds between 10.8-13.8 m/s and 13.9-17.1 m/s are classified as a strong breeze and near gale, respectively. Both drones can operate in the category strong breeze, and the Intel Falcon 8+ can also be used when near gale. For an UAV to be used in a system for testing and development, the wind tolerance for both drones in table 12 are considered acceptable. Regarding tolerance against rain, it is not explicitly stated in technical specifications how well these drones can withstand rain, or water in general. It might be necessary to cover parts of the drone with a protective film, or similar, to prevent water from damaging electrical components. The Intel Falcon 8+ can be operated at temperatures as low as $-5°C$. Operating temperature for the Action Drone AD2 Inspection is not specified in [82]. Regarding maneuverability, requirement 2 in table 11, both the Intel Falcon 8+ and the Action Drone AD2 Inspection are multirotor drones made for inspection purposes, and are therefore expected to have a sufficient degree of maneuverability for bridge inspection.

The UAVs payload capacity, requirement 3, is important because it should be possible to mount both a sensor for inspection and autonomy. However, the two drones introduced in this section are delivered with a complete setup for inspection, so they are made to be able to carry sensors. Of course, if the drones are to be fit with other sensors than the original ones, the weight of the new sensors must not exceed the weight limit of the drone. When it comes to storage devices, requirement 4, the Intel Falcon 8+ has slots for both USB and MicroSD, while it is uncertain if the Action Drone AD2 Inspection is made with similar solutions for data retrieval.

Inspection camera

The inspection camera is an important part of the inspection system, since this is the sensor providing relevant inspection data to be analyzed. Therefore, requirements 5-6 in table 11 are set for the inspection camera. Both the Intel Falcon 8+ and the Action Drone AD2 Inspection are delivered with different setups of cameras, batteries, GPS sensors and remote control systems. For example, the Intel Falcon 8+ has two different payload options including the cameras Sony Alpha 7R* and Panasonic ZS50 [78]. The Action Drone AD2 Inspection is delivered with a Sony a6000 camera [80]. Some technical specifications for the three different cameras are shown in table 13.

Table 13: Technical specifications for Sony Alpha 7R*, Panasonic ZS50 and Sony a6000 [84] [85] [86].

	Sony Alpha 7R*	**Panasonic ZS50**	**Sony a6000**
Image resolution [Mpx]	36.8	12.1	24.3
Lens	Sony E-mount	LEICA DC VARIO-ELMAR	Sony E-mount
Sensor	35 mm full frame Exmor CMOS sensor	1/2.3-inch Large Pixel Sized High Sensitivity MOS Sensor	APS-C type (23.5 x 15.6 mm)
Waterproof	No	No	No

The image resolution of the three cameras is quite different, varying from approximately 12 to 36 Mpx. Requirement 6 in table 11 says that a certain image resolution is required to ensure a high enough image quality for analysis. In a case study of bridge inspection by Orbiton [87], a camera with 24 Mpx was chosen after testing several cameras and lenses. Choosing an exact amount of Mpx to be required for the inspection camera is difficult. Therefore, testing of the three cameras in table 13 is advised to find the optimal combination of sensors and lenses for bridge inspection. The other requirement for the inspection camera, requirement 5 in table 11, is that it shall be able to withstand rough weather conditions. Table 13 shows that non of the three cameras originally mounted on the Intel Falcon 8+ or the Action Drone AD2 Inspection are waterproof. To fulfill requirement 5, one could either use a type of underwater housing on the camera or simply choose a different, waterproof camera. If modifications are done to the drone, one should be able to fit a different camera than the drone was delivered with originally. For example, GoPro delivers durable cameras like the GoPro Hero 7, which is waterproof and has an image resolution of 12 Mpx [88].

Sensors and methods for autonomy

Sensors for autonomy were introduced in section 3.3. As stated in section 4.1 when explaining the concept of the robotic inspection system, the UAV does not necessarily have to be autonomous. In the beginning, when testing system functions such as data handling and analysis it is considered preferable to control the UAV manually. Autonomy can be a later step for creating a fully automatic inspection system. However, it is of value to look at what sensors are available, and what is required to make the UAV autonomous.

The Intel Falcon 8+ is delivered with navigation sensors, both GPS and a triple redundant IMU [81]. The Action Drone AD2 Inspection is also delivered with systems for GPS supported flights [82]. To make one of these UAVs fully autonomous one can for example mount an Intel RealSense camera, introduced in section 3.3.3. The Intel RealSense Depth Camera D400-Series is made for both indoor and outdoor environments, and has a maximum range of approximately 10 meters, depending on calibration and light conditions. Regarding software, Intel RealSense Software Development Kit 2.0 is an open source, cross-platform library, including software wrappers that support programming languages such as Python and Matlab [89].

LiDAR based sensors are also relevant as sensors for autonomy. Velodyne HDL-32E was mentioned in table 10, section 3.3, as a common LiDAR based sensor for UAV. The Velodyne HDL-32E sensor has a range of 80 to 100 meters and 360 degrees horizontal field of view [90].

A potential challenge could be integrating new sensors, such as the Intel RealSense, in the existing control system for the UAV. This potential issue is not investigated further in this project assignment, but is considered an important factor in making a standard UAV autonomous. [89] explains some guidelines for integration of Intel RealSense D400-series into a system.

The use of VSLAM (Visual Simultaneous Localization and Mapping) is a possible extension of the robotic inspection system.

4.3.2 Data handling

This section will briefly explain what is required of a data handling method to function properly as a part in the robotic inspection system, and there will be done some considerations regarding data handling in general.

Existing methods for data handling were explained in section 3.4.2. The three methods cloud, fog and edge computing were explained as different layers in a data handling process. As explained in section 4.1, the main method for data handling in the robotic inspection system will be cloud computing, so that data can be easily accessed from different locations, both during and after bridge inspection. In case of poor, or no, Internet connection, inspection data will be temporarily stored on a storage device mounted on the UAV.

It is important to have a reliable system for data transferring and storage so that no inspection data is damaged or lost. Data availability is also a priority, since one should be able to access inspection data easily for further analysis. The robotic inspection system proposed in this chapter is made for use in testing and development, so for testing, any available data handling platform at time of implementation could be used. However, for an end user such as The Norwegian Public Roads Administration, it must be facilitated for a data handling platform that is compatible with their inspection management system. In section 3.4.2, examples of existing digital data handling platforms were mentioned. Among these were Microsoft Azure that provide cloud based services within, for example, storage, data analysis and machine learning [56]. Microsoft Azure is considered to be a good choice for a data handling platform.

4.3.3 Data analysis

In section 3.5.2 computer vision techniques and deep learning approaches for data analysis were introduced. Examples of previous work using one or both of these methods were also given in the same section. Requirement 7 in table 11 states that data analysis methods in the robotic inspection system shall be accurate enough to make corrosion detection fully automatic. To create a reliable method for automatic corrosion detection one must explore the possibilities of combining existing techniques and image libraries if that proves preferable. In this section, there will be suggested a data analysis process of three steps for automatic corrosion detection consisting of both computer vision techniques and deep learning approaches. A simple illustration of the suggested data analysis process is shown in figure 32.

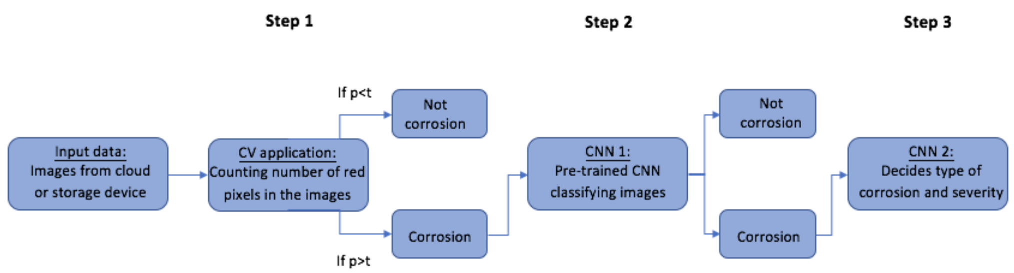

Figure 32: A self made illustration of the three steps in the robotic inspection system's data analysis process, where p is the number of red pixels and t is the threshold set for what is classified as corrosion.

The first step in evaluating the images provided by the inspection camera is to separate them into two categories; *corrosion* and *not corrosion*. In [72], the amount of red pixels (white pixels after conversion to black and white) in an image was counted, and if the the sum exceeded a certain threshold the image was classified as corrosion. This approach clearly does utilize the reddish colour which is characteristic for corrosion, but a challenge is that images of other objects containing a large amount of red pixels could be wrongly classified as corrosion. One could argue that this is not a great issue on a bridge since there, most likely, are not many foreign objects on the construction that could be interpreted as corrosion. However, leaves, objects thrown out of passing cars, or similar, are potential sources of error in image classification. An advantage with classifying images through counting red pixels is that one gets a high accuracy on discovering corrosion, so the chance of missing out on a case that could potentially be corrosion is minimal. The images that are wrongly classified as corrosion can be filtered out in the second step of the data analysis process. Therefore, the approach from [72] is considered to be a good choice for the first step in automatic corrosion detection in the robotic inspection system. What type of software that will be used depends on what is available at the stage of system implementation, but Python and MATLAB are both considered relevant choices of software.

After having classified images as positive for corrosion through the technique mentioned above, there could be that some of the images are wrongly classified. To deal with this issue, a second step in the data analysis process is applied. In this step the images will become inputs to a convolutional neural network, such as the one described in [75] and shown in figure 27. A CNN pre-trained with thousands of images, or more, would provide a strong basis for filtering out images that were wrongly classified as corrosion in the first step of the data analysis process. The Norwegian Public Roads Administration has many images from earlier bridge inspections that could be gathered in a data set and used to train a CNN. Other existing CNNs such as VGG16 and ZF Net, mentioned in [75], can also be used in this second step of automatic corrosion detection.

The two first steps suggested for the data analysis process of the robotic inspection system provides information about the existence of corrosion on the bridge construction, but does not tell what type of corrosion one is dealing with or what the extent of the corrosion damage is. A third step in the data analysis process is therefore suggested, where the type and severity of the corrosion damage seeks to be uncovered. This third step is also an analysis of images in a CNN, but with focus on classifying the severity of the corrosion damage found in the previous steps.

The severity of a corrosion damage is one of the elements in evaluations of faults done by the Norwegian Public Roads Administration. Table 4 from section 2.4 shows how severity is divided into four interpretations of a damage; *small*, *medium*, *large* and *critical*. To decide the severity of a corrosion damage using a CNN, it is necessary to have a data set of representative images for comparison with the retrieved inspection data. This data set can, for example, be generated from images in BRUTUS, the Norwegian Public Roads Administration's management system mentioned in section 2.2. By using images from BRUTUS, one can perform comparisons between images from previous inspections and new images from current inspection, taken of the same bridge. This is expected to give the CNN a relatively high accuracy, since the data set used to train the network becomes very similar to the input. In order to make the CNN capable of indicating the severity of the corrosion damage, the images in BRUTUS from previous inspections are labeled with one of the four classifications in table 4. The output of the CNN will then be four different folders containing images with the different degrees of severity. Thus, an overview of the bridge's condition is given. This is illustrated in figure 33.

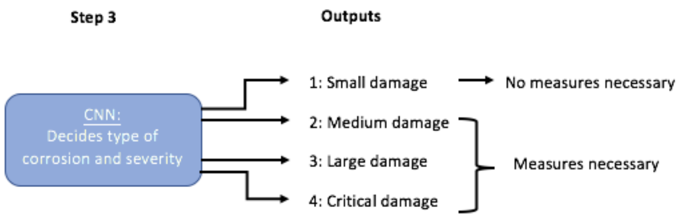

Figure 33: Illustration of outputs from neural network in step 3 of the data analysis process. The outputs are sorted in classes from 1-4 depending on the severity of the corrosion damage, as explained previously in table 4.

VSLAM was mentioned previously as a possible extension of the robotic inspection system, and this could be very relevant in the data analysis process as well. If the results from classification of corrosion damages in a neural network could be stored in a map of the relevant bridge, it would be possible to visit the exact same areas of a bridge during future inspections, to see if a damage has evolved or if it stays at the same level of severity as at the last inspection.

Chapter 5

Discussion

This chapter contains a discussion on choices done in this report and on the robotic inspection system designed in chapter 4. As stated previously, the inspection system is designed for use in testing in development, so further investigation of solutions in existing automatic inspection methods is advised before implementation of the system.

When mobility hardware was evaluated in section 3.1.5 it was mentioned that since only one type of mobility hardware is chosen, it is also chosen between either inspection above water or under water. In a complete robotic system for inspection it could definitely be of interest to be able perform inspection of the bridge construction both above and under water. However, due to limitations in time working with this project, only one of these solutions was possible to focus on.

An evaluation of sensors for inspection was carried out in section 3.2.4. Camera was chosen as sensor for inspection because of the possibilities for close visual inspection and image analysis. Especially since the focus in this report was set on inspection of corrosion damages, visual inspection, hence a camera, became the optimal choice. Use of ultrasonic sensors and eddy current sensors on an UAV requires that functional and reliable methods are developed for this. For special inspections of bridges, mentioned in section 2.1, use of ultrasonic sensors and eddy current sensors on an UAV is considered relevant to be able to perform an even better condition monitoring of the bridge construction.

Two specific UAVs, Intel Falcon 8+ and Action Drone AD2 Inspection, were given as examples of an UAV that can be used in the designed robotic inspection system. One may argue that there exist other UAVs as well that are suited for bridge inspection, and perhaps even better suited than the two examples given here. This might of course be the case, but the main purpose of giving these examples was to show some of the specific alternatives that exist, and what modifications are necessary in order to meet system requirements. In addition, there is an economic question to the choice of UAV, so one would have to choose the UAV affordable and available at the point of system implementation.

The two UAVs suggested in chapter 4 are delivered with a certain camera setup. It is difficult to decide exactly what camera would be best for bridge inspection, since testing is required to decide, for example, what type of lens gives the best image result. However, the cameras mentioned in section 4.3.1 are considered relevant candidates, except from the fact that they are not waterproof, which is a potential challenge.

Data handling is only briefly explained in the system description due to the fact that details around data handling are not emphasized in this project assignment. However, it was necessary to mention a possible data handling solution, such as using Microsoft Azure. When testing the system, one can use the data handling solution provided by employer or university, or whatever solution fits the chosen software and control system on sensors and UAV best.

The data analysis process described in section 4.3.3 shows a combination of computer vision techniques and deep learning approaches for both corrosion detection and classification. The first step in the data analysis process consists of counting red pixels in an image, but other computer vision methods may be relevant here. Also, not all corrosion damages have a reddish colour. The colour and look of a corrosion damage depends on the material. For example, zinc, which is used as coating material on bridge constructions, often gets a white-like colour when corroded. Step 1 in this process using computer vision techniques may not even be necessary if a neural network is trained to a high enough accuracy for performing this task alone. Thus, three steps can be reduced to only two. Also, it might be possible to do both corrosion detection and classification in a combined operation inside a neural network, but this solution has not been investigated.

Chapter 6

Conclusion

In this project report a robotic system for automatic inspection of corrosion damages on bridge constructions has been designed. The designed system includes elements from existing automatic inspection methods, and consists of four main parts; UAV, sensors, data handling and data analysis. Existing mobility hardware, sensors for both inspection and autonomy, methods for data handling and data analysis were introduced. Regarding data handling in the robotic inspection system, cloud computing was chosen as the main solution. Through evaluations considering important aspects such as inspection equipment access, safety and inspection data quality, it was decided to focus on an UAV as mobility hardware with a camera as sensor for inspection. Thus, for data analysis, emphasis was placed on image analysis, specifically on images of corrosion. The designed robotic inspection system includes a method for data analysis combining computer vision techniques and deep learning approaches for corrosion detection and classification. The robotic system was not implemented during this project. Testing of the method for corrosion damage classification using deep learning is considered future work, and will be performed in a master thesis next year at the Department of Engineering Cybernetics, NTNU in collaboration with SINTEF.

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