Non-destructive Testing Using Thermographic Image Processing

Examensarbete utfört i Datorseende vid Tekniska högskolan vid Linköpings universitet av

Kristofer Höglund

LiTH-ISY-EX--13/4655--SE

Linköping 2013
Non-destructive Testing Using Thermographic Image Processing

Examensarbete utfört i Datorseende vid Tekniska högskolan vid Linköpings universitet av

Kristofer Höglund

LiTH-ISY-EX--13/4655--SE

Handledare: Kristoffer Öfjäll
ISY, Linköpings universitet
Jörgen Ahlberg
Termisk Systemteknik

Examinator: Klas Nordberg
ISY, Linköpings universitet

Linköping, 17 februari 2013
Termisk Bildanalys För Oförstörande Provning

Non-destructive Testing Using Thermographic Image Processing

Kristofer Höglund

In certain industries, quality testing is crucial, to make sure that the components being manufactured do not contain any defects. One method to detect these defects is to heat the specimen being inspected and then to study the cooling process using infrared thermography. The explorations of non-destructive testing using thermography is at an early stage and therefore the purpose of this thesis is to analyse some of the existing techniques and to propose improvements.

A test specimen containing several different defects was designed specifically for this thesis. A flash lamp was used to heat the specimen and a high-speed infrared camera was used to study both the spatial and temporal features of the cooling process.

An algorithm was implemented to detect anomalies and different parameter settings were evaluated. The results show that the proposed method is successful at finding the searched for defects, and also outperforms one of the old methods.

Keywords: ndt, non destructive testing, thermography, hyperspectral, computer vision, image processing
Abstract

In certain industries, quality testing is crucial, to make sure that the components being manufactured do not contain any defects. One method to detect these defects is to heat the specimen being inspected and then to study the cooling process using infrared thermography. The explorations of non-destructive testing using thermography is at an early stage and therefore the purpose of this thesis is to analyse some of the existing techniques and to propose improvements.

A test specimen containing several different defects was designed specifically for this thesis. A flash lamp was used to heat the specimen and a high-speed infrared camera was used to study both the spatial and temporal features of the cooling process.

An algorithm was implemented to detect anomalies and different parameter settings were evaluated. The results show that the proposed method is successful at finding the searched for defects, and also outperforms one of the old methods.
Sammanfattning

I vissa industrier är det kritiskt att kunna utföra bra kvalitetstester, för att försäkra sig om att de komponenter som tillverkas inte innehåller defekter. En metod för att detektera dessa defekter är att värma upp föremålet som inspekteras och sedan studera dess avsvalningsförlopp med hjälp av en värmekamera. Forskning kring användandet av termografi i oförstörande provning är i ett tidigt stadium och därför finns det ett behov av att analysera dessa metoder och föreslå förbättringar, vilket är målet med detta arbete.

En provbit innehållande flera defekter skapades för detta arbete. En blixtlampa användes för att värma upp den och en höghastighets- värmekamera användes för att studera avsvalningsförloppet, både spatiellt och temporalt.

En algoritm implementerades för att detektera anomalier i provbiten och olika parameterinställningar utvärderades. Resultatet visar att den föreslagna metoden är framgångsrik i att hitta defekterna i provbiten. Den föreslagna metoden presterar även bättre än en av de gamla metoderna.
Acknowledgments

I would like to thank Jörgen Ahlberg and the people at Termisk Systemteknik for offering me a very interesting thesis and for assisting me in my work. I have learned a lot during this time.

I would also like to thank Kristoffer Öfjäll (supervisor) and Klas Nordberg (examinator) for quickly responding and giving comments to my work.

Linköping, Februari 2013
Kristofer Höglund
# Contents

1 Introduction .......................... 1
  1.1 Background .......................... 1
  1.2 Existing Methods ...................... 2
  1.3 Goal .................................. 2
  1.4 Disposition .......................... 2

2 Background Theory .................... 5
  2.1 Non-Destructive Testing ............... 5
  2.2 IR Thermography ....................... 5
    2.2.1 Emissivity ......................... 6
    2.2.2 IR Detectors ....................... 6
    2.2.3 Testing Using IR Thermography ..... 7
  2.3 The Heat Equation ..................... 8

3 Image Processing Methods ............... 9
  3.1 Thermographic Image Processing ........ 9
    3.1.1 Preprocessing ..................... 9
    3.1.2 Processing ....................... 11
  3.2 Self-Referencing Thermography ........ 11
  3.3 Hyperspectral Detection ............... 12
    3.3.1 Decision theory ................... 13
    3.3.2 Different Types Of Detection ....... 15
    3.3.3 Unstructured background models ..... 15
    3.3.4 Structured Background Models ..... 16
  3.4 Dimensionality Reduction Using PCA . . . 17
  3.5 Global and Local Backgrounds ........ 18

4 Experimental work ..................... 19
  4.1 Hardware Setup ....................... 19
  4.2 Data Set ................................ 21
  4.3 Pre-Processing ....................... 23
    4.3.1 Noise Removal .................... 23
    4.3.2 Normalization of data ............. 23
1.1 Background

In industries, such as the automotive- and aerospace industry, quality testing has become more important as demands on material and components to be stronger yet keep a low weight has increased. The thinner a component is the more crucial it is that it does not contain any defects. Tests can be carried out manually, although this is time consuming and if the method is unreliable, stronger components might have to be manufactured as a result. There are also automatised tests, such as vibration tests, in which an external force is introduced to the component being inspected. This can however in worst case cause damage to the component being checked for damages.

Non-destructive testing for detection of defects in various materials is popular mainly because it does not alter the object being inspected, and this can save both time and money. However, the performance of the tests need to be reliable or the components still have to be manufactured stronger and heavier just to be safe.

Non-destructive testing using thermography has become more common lately as the development of infra-red cameras has been rapid the past decade resulting in lower costs. Although testing using thermography has been around for decades the explorations of these methods is at an early stage.

When the surface of a material is heated, the energy will be distributed in a region over time according to the heating equation (see Section 2.3). Because of this there will be variation in temperature depending on how the heat is spread. Eventually the entire material will reach an uniform temperature. Traditionally non-destructive testing using thermography have dealt with heating the inspected
material and detecting temperature variations between defect areas and sound areas. The expected difference in temperature can be estimated as a function of the size of the defect. There are several problems associated with this approach:

- It is difficult to estimate the expected difference in temperature.
- The difference in temperature may vary spatially if the emissivity varies between different parts of the material.
- The temperature difference may be small and vary over time.
- It is difficult to know the optimal moment in time for making the estimation.

1.2 Existing Methods

Methods have been proposed to overcome the first two issues by comparing each point of interest with nearby points on the same surface. A method of self-referencing thermography for detection of in-depth defects was proposed by [Omar et al., 2005], in which the thermogram is divided into small, local neighbourhoods and the temperature threshold is set adaptively. This method only look at one image at a specific moment in time and therefore does not solve the third and fourth issues.

The third and fourth issues can be dealt with by observing the entire cooling process instead of choosing just a specific moment in time. This can be done using high speed cameras to collect samples. A common method is to approximate the cooling period with a polynomial and compare it with theoretical calculations. However, a lot of information is lost in the approximation and once again you have to deal with the first two issues.

1.3 Goal

This thesis focuses on making a spatio temporal analysis to improve on the already existing non-destructive testing methods using thermography. While the method proposed by [Omar et al., 2005] only studies one image this project take advantage of the temporal features from a sequence of images. Self-referencing will be used but not only for a single pixel value, but for the entire cooling process. Each pixel will be represented by a vector of temperature values, referred to in this project as pixel-vectors. The goal is to propose a method that outperforms the existing methods and to increase the sensitivity of the detection of anomalies.

1.4 Disposition

In Chapter 2, background theory on the subject is given, and terminology is explained more in detail. In Chapter 3 some common methods for image process-
ing and detection of anomalies such as self-referencing are explained. In Chapter 4 my own experiments are explained. In Chapter 5 results will be presented. Finally in Chapter 6 the results are discussed and improvements suggested.
Before going into the methods used in this thesis it is necessary to have an understanding for the background theory. In this chapter an overview of the underlying theory is presented and the terminology used in this paper is explained in detail.

2.1 Non-Destructive Testing

Non-destructive testing (NDT) is an analysis technique commonly used in the industry. It is used to assess the properties of a material or object without altering it or causing damage. The technique is both cost and time efficient, which is why it is so greatly valuable.

There are several different methods used to perform NDT. These methods include the use of sound, electromagnetic radiation and heat.

Applications that use NDT are common in medicine, where x-rays are used to create a model of the bone structure, and in manufacturing where it is used for instance to verify that there are no defects after welding. A scenario of NDT using IR thermography can be seen in Figure 3.1.

2.2 IR Thermography

IR thermography is explained in a booklet published by FLIR AB [FLIR]. Infrared (IR) thermography is thermal radiation converted into a visual image. This is accomplished with an IR camera calibrated to show temperature values across a scene. Since thermography allows non-contact measurement of the temperature
of an object, it is very suitable for NDT.

IR covers the range roughly between 900 and 14000 nanometers in the electromagnetic spectrum and is not visible to the human eye. All objects at temperatures above absolute zero emit IR, and the higher the temperature the more radiation is emitted.

IR has the same properties as visible light when it comes to reflection, transmission, and refraction. So in addition to emitting radiation, an object also absorbs and reflects portions of incident radiation from its surrounding. The relationship between the different properties can be described by the following formula:

\[
\text{Incident energy} = \text{absorbed energy} + \text{reflected energy} + \text{transmitted energy}.
\]

The incident energy is the amount of energy that strikes the object. The amount of energy that reflects off the object’s surface from a remote source is the reflected energy. Transmitted energy is the energy that passes through the object from a remote source. From this, the Total Radiation Law is derived:

\[
1 = a + p + t. \tag{2.1}
\]

The coefficients \(a\), \(p\), and \(t\) describe the object’s incident energy absorption, reflection, and transmission. All coefficients have a value between zero to one that depends on the object’s ability to absorb, transmit and reflect radiation, and the sum of the coefficients is 1. If there is no reflected or transmitted radiation, then all incident radiation is absorbed, which means that the object is a perfect blackbody. There are no objects in real life that are perfect blackbodies, yet the principle of the perfect blackbody is the foundation of relating IR radiation to an object’s temperature.

The perfect blackbody can be described mathematically by Planck’s Law as a function of temperature and radiation wavelength. Planck’s law is usually displayed as a series of curves (see Figure 2.1). These curves show that the higher the temperature the more intense the emitted radiation.

### 2.2.1 Emissivity

Emissivity can be described as a material’s ability to emit thermal radiation. This is usually the same as the \(a\) coefficient in Equation 2.1, describing the object’s energy absorption. It can be difficult to determine the emissivity for an object since different materials have different emissivity, and emissivity also vary with temperature and wavelength. Emissivity is the ratio between the emitted radiant energy of a blackbody of a certain temperature and that of a normal object with the same temperature. A material’s emissivity ranges from zero to one, where 0 means totally non-emitting and 1 means totally emitting (a blackbody).

### 2.2.2 IR Detectors

A camera that is calibrated to detect IR wavelengths in the electromagnetic spectrum stores a matrix of the captured intensity values. These values can then be
converted into a visual image that shows the temperature variations across the scene. The IR camera has similar components as a regular digital camera. These components include a lens that focuses IR onto a detector. The detector is a focal plane array of sensor elements made of materials sensitive to IR wavelengths. IR camera lenses are not made of glass like regular consumer camera lenses, but of either germanium or silicon. This is because glass do not transmit IR wavelengths as well as germanium (for long wavelengths) and silicon (medium wavelengths). There are usually also software and electronics for processing and displaying the image, as well as a cooler for the detector (for the more expensive cameras).

While most cameras only uses a few wavelength bands (e.g three for red, green and blue in color cameras), there are also cameras with hyperspectral sensors that uses hundreds of spectral bands. Each pixel in the image is then a vector of measurements.

### 2.2.3 Testing Using IR Thermography

There are two approaches of IR thermography: passive and active. In the passive method the IR radiation emitted by the test material itself is compared to the ambient surrounding. In the active approach however, an external stimulus is introduced to create a temperature difference between the test material and the surrounding. This external stimulus can for instance be hot air, flash light, laser or even hot water.

One of the benefits of IR thermography is that it enables large surfaces to be inspected in a short amount of time. IR thermography can be used by the airline industry to inspect aircraft hull for defects [Wandelt, 2008] as well as in noninvasive inspections of artwork [Gavrilov et al., 2008].

![Figure 2.1: Planck’s law displayed by curves.](image-url)
2.3 The Heat Equation

In order to understand how non-destructive testing using thermography works it is important to know of the heat equation. The heat equation describes the distribution of heat in a region over time as

$$\frac{\partial u}{\partial t} = \alpha \left( \frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2} + \frac{\partial^2 u}{\partial z^2} \right)$$  \hspace{1cm} (2.2)

where $u$ is a function describing the temperature at a location $(x,y,z)$ at time $t$ and $\frac{\partial u}{\partial t}$ is the rate in which a point in time changes temperature. The coefficient $\alpha$ is the thermal diffusivity. The thermal diffusivity is a quantity specific to the material being heated. It can be described as the rate at which heat diffuses in a material and depends on the thermal conductivity, heat capacity, and mass density of the material.
In this chapter specific image processing methods and theory related to non-destructive testing and IR thermography is presented. The theory brought up in this chapter is later used in Chapter 4.

3.1 Thermographic Image Processing

In active thermographic image processing for NDT a specimen is heated and the subsequent cooling process is monitored using an IR camera. The temporal development of the cooling process is analysed to detect anomalies in the behaviour of the cooling likely caused by sub-surface defects. These defects causes the surface to cool at a different rate than in a non-defect area.

Data acquisition is carried out by stimulating the specimen with an external energy source, such as a flash light (see Figure 3.1). The heat created at the surface of the specimen travels trough the specimen to the defect and then back to the surface according to the heat equation (Section 2.3). The energy may be delivered either in a transitory or a steady state way. In pulsed thermography, which will be used in this project, a heat pulse from a flash light of a few milliseconds is used to heat the surface.

A full review of the preprocessing, processing and depth classification is presented by [Maldague et al., 2007].

3.1.1 Preprocessing

Before processing the image, it might be necessary to take some preprocessing steps in order to fix problems that might appear during data acquisition. A common issue in this project was shot noise, caused by variation in the number of
Figure 3.1: NDT scenario for IR Thermography.

photons sensed by the photon detector. The absorption process of the photo detector is probabilistic which means that each time that the charge difference at the sensor is measured there will be a small variation in the results. Shot noise approximately follows a Poisson distribution.

*Noise smoothing* is a very useful technique in removing unwanted data and enhance the contrasts in an image. This can be done with the use of neighbouring methods [Gonzalez and Woods, 2008] in which each pixel value is replaced by the mean or median value of nearby pixels.

Other examples of common problems that appear during data acquisition include fixed pattern noise, bad pixels, and vignetting. Although the experiments in this project were not noticeably affected by these issues, a short description of them follows.

*Fixed pattern noise* is a common problem when working with focal plane arrays and is caused by differences in responsivity of the detectors to incoming irradiance. This can be solved by taking an image of an approximation of a blackbody and then subtract those values from the thermographic images.

*A bad pixel* is a pixel behaving differently from the rest of the focal plane array. A pixel that is permanently black (unlit) is called a dead pixel while a pixel that remains white (lit) is called a hot pixel. Which pixels are bad is usually known by the focal plane array manufacturer and the value of those pixels are replaced by the average value of neighbouring pixels. However, if an investigated defect is located on the same spot as a bad pixel then the results may be misleading even with preprocessing.
Vignetting is a source of noise that causes a darkening of the image edges and corners. This is due to limited exposure at these areas. Incident light hitting the sensor at an oblique angle does not produce as strong a signal as light hitting the sensor at a right angle.

Apart from fixing problems with noise it can also be necessary to calibrate the pixel intensity relative to the temperature. Although this was not necessary for this project it can still be good to know of. During calibration a transformation function is used to convert grayscale values into a linearly increasing temperature. This is done by positioning the camera in front of reference temperature sources of known temperatures. The source is usually an approximation of a blackbody. While its temperature is varied, images are taken with the IR camera. The central pixels in the field of view are then used to calculate the average value for that temperature. All the averages from all the different temperatures are then used to create a polynomial equation for the calibration curve.

### 3.1.2 Processing

There are several methods for processing thermographic data as explained by [Maldague et al., 2007]. One of the most common ones is contrast based techniques. In these methods you compare the region of interest with a non-defective region to see if there is a defect. The absolute thermal contrast $\Delta T(t)$ can be defined as:

$$\Delta T(t) = T_d(t) - T_{Sa}(t)$$

(3.1)

Here $T_d(t)$ is the pixel we try to determine if it is defective or not, at the time $t$. It might also be the average value of a group of pixels. $T_{Sa}(t)$ is the temperature of the non-defect area $Sa$ at time $t$. So if $\Delta T(t) = 0$ that means there is no defect detected at that specific time $t$. Determining $Sa$ can be difficult, especially if the process is automated. Due to non-uniform heating, significant variations in thermal contrasts can occur when changing the location of $Sa$. One solution to this problem is to compute an ideal temperature instead of searching for a non-defective area. For instance, a local point within the first few images of the object being investigated is chosen to represent the sound area.

Other techniques in processing are TSR (Thermographic Signal Reconstruction), PPT (Pulsed Phase Thermography), and PCT (Principal Component Thermography), described by [Maldague et al., 2007].

### 3.2 Self-Referencing Thermography

As mentioned in Section 1.1 a common problem facing computation of thermal contrast is that it requires prior knowledge of a non-defect area. This problem is solved by a technique called self-referencing [Omar et al., 2005]. In self-referencing, the thermal image is divided into small local neighbourhoods, and the average temperature of those pixels is used as the non-defective behaviour in the thermal contrast computation. This is done to avoid the problems of uneven...
emissivity and non-uniform heating. The local neighbourhood should therefore be selected so that it is larger than the defect sought to assure a stable temperature across the region, but small enough to be within the smallest area of non-uniformity. The thermal contrast is computed as

$$C(i, j, t) = T_{pix}(i, j, t) - T_{surr(i,j)}(t)$$  \hspace{1cm} (3.2)$$

where $T_{pix}(i, j, t)$ is the temperature at time $t$ and coordinates $(i, j)$. $T_{surr(i,j)}(t)$ is the average temperature of the surrounding pixels at the time $t$.

Apart from overcoming the problem of uneven emissivity and non-uniform heating, self-referencing also has the advantages of not needing any prior knowledge of the non-defect area, as well as not needing a separate reference since each thermal image is referenced to itself. This technique also has short processing time due to its simplistic nature.

Experiments were done by [Omar et al., 2005] using static infrared hot spot detection to illustrate the effectiveness of the self-referencing technique. Static hot spot detection is intended to inspect large fields of view in real time for surface features such as dents or dust particles. Due to difference in thermal properties or emissivity those features will have a different thermal signature from their surroundings. A challenge is the non-uniform heating on the large field of view. To reduce the data content to the pixels that deviate from their surrounding only, and to automate the detection of surface features, the thermal image can be thresholded by

$$\eta \cdot \sigma_{surr(i,j)}$$  \hspace{1cm} (3.3)$$

where $\sigma_{surr(i,j)}$ is the standard deviation of the neighbourhood surrounding the pixel at $(i, j)$, and $\eta$ is a constant that depends on the signal to noise ratio of the thermal image.

The self-referencing technique was found to be very effective in detecting surface defects, even in thermal images with uneven emissivity and non-uniform heating.

### 3.3 Hyperspectral Detection

While a regular consumer camera typically only uses three wavelength bands (corresponding to red, green, and blue), hyperspectral sensors often use several hundred spectral bands. In the image, each pixel then forms a vector of measurements from the different wavelength bands, which can then be used for detection and classification. Methods for detecting targets and anomalies in hyperspectral images are described in detail by [Ahlberg et al., 2004]. Since the data collected with the high-speed camera in this project is, in many ways similar to hyperspectral data, the theory in this section is relevant to this work.

An important property that characterize the hyperspectral sensor is the spatial resolution. Spatial resolution is an important factor for good performance as
3.3 Hyperspectral Detection

it (along with the distance from the sensor to the target) determines if the target is spatially resolved or not. A target is spatially resolved if it covers at least one pixel completely. Pixels that are completely covered by the target are called "pure pixels" while pixels of a sub-pixel target are referred to as "mixed pixels". Spatially resolved targets are a lot easier to detect than sub-pixel targets, which has to deviate more from the surrounding in order to be distinguishable.

Other properties that characterize the hyperspectral sensor are spectral resolution (determines the number of spectral bands), radiometric resolution (determines the number of bits per sample), and temporal resolution (determines the frequency of new pixels to be produced).

An anomaly detector detects pixels that deviate from the background. No prior information about the target or background is needed. Classification or signature based detection on the other hands, requires that spectral properties are known from previous measurements. Observed pixels are compared to the measured data, and then statistical probabilities are taken into consideration during analysis.

3.3.1 Decision theory

When determining if a defect is present, a good method is to create two hypotheses to decide between. Hypothesis $H_0$ will here mean that there is no defect present and $H_1$ means that there is a defect present. The observation can be regarded as a random variable $x$, and be characterized by the probability density function

$$\int_a^b p_k(x)dx = Pr(a < x \leq b \mid H_k), k = 0, 1$$  \hspace{1cm} (3.4)

where the hypotheses are

$H_0 : x \sim p_0(x)$

$H_1 : x \sim p_1(x)$  \hspace{1cm} (3.5)

Usually the probability distributions $p_k(x)$ are unknown and therefore a model is assumed, which will be described further below.

A threshold $h$ can be defined to decide between the two hypotheses. When picking a value for $h$, the probability density function is taken into consideration, as well as the cost of mistakenly choosing the wrong hypothesis. If $h$ is chosen so that hypothesis $H_0$ is accepted if $x \leq h$, and $H_1$ is accepted otherwise, then the probability of mistakenly choosing $H_1$ when $H_0$ is true is

$$Q_{10}(h) = \int_h^\infty p_0(x)dx.$$  \hspace{1cm} (3.6)

This is referred to as false positive. The probability of choosing $H_0$ when $H_1$ is
actually true is referred to as *false negative* and can similarly be described as

\[ Q_{01}(h) = \int_{-\infty}^{h} p_1(x) dx. \]  

(3.7)

The probability of correct detection is called *true positive*

\[ Q_{11}(h) = \int_{h}^{\infty} p_1(x) dx. \]  

(3.8)

A high threshold value might reduce the false-alarm rate (FAR) but it will also give a lower detection rate (DER). The threshold has to be carefully balanced to minimize the risk of false detection while at the same time keeping the detection rate high. One way of measuring the performance of a detector is to draw a graph with FAR and DER on the axes, and a curve showing DER as a function of FAR with varied values on h (see Figure 3.2). This is called the receiver operator characteristics (ROC). How you select h is usually dependent on the specific application to be used.

![Figure 3.2: Example of ROC curve.](image)

If there is no prior knowledge about the source outputting the sample measurements, the samples can be used to build a model of the source. The easiest way to create the model would be to calculate the mean of the samples. The samples used to create the model of the source are referred to as "training samples". New samples, referred to as "test samples", are then compared to the model by computing the deviation from the mean. If the deviation is larger then a set threshold then the new sample can be regarded as an anomaly.
3.3 Hyperspectral Detection

3.3.2 Different Types Of Detection

Target detection is about finding samples that either does not measure up to a model of the background (anomaly detection) or that corresponds to a specific target model (signature-based detection). The detector is a function that determines whether a test sample (as a vector in $\mathbb{R}^N$) is a target or not, and can be described as

$$D : \mathbb{R}^N \rightarrow \{true, false\}. \quad (3.9)$$

In anomaly detection we do not know the signature of the target and instead check for samples that deviate from the background model $B$. If $d()$ is a function that measures distance and $h$ is the threshold then we regard a sample $x$ an anomaly if $d(x, B) > h$, and the detector can be expressed as

$$D(x \mid B) = [d(x, B) > h]. \quad (3.10)$$

In signature-based detection a target probe is created that model the target signature $T$. Samples are then looked for that resemble the target probe. This is done by measuring the distance from the sample signature to the target model. A sample $x$ can then be regarded as a target if $d(x, T) < h$. The signature-based detector can therefore be described as

$$D(x \mid T) = [d(x, T) < h]. \quad (3.11)$$

To enhance the performance of the target detection it is possible to incorporate anomaly detection into the algorithm. One way of doing this is to first run the anomaly detection, and then run the target detection only on the samples classified as anomalies. Another way is to run both the target detection and anomaly detection on all samples and then threshold the compared results:

$$D(x \mid B, T) = [d(x, T) > h]. \quad (3.12)$$

3.3.3 Unstructured background models

Unstructured models (also called probabilistic or statistical models) are used without any prior knowledge of the structure of the data. This model need a lot of training data to give reliable results and is optimal when the data has a Gaussian distribution. An easy way of creating a model is to compute the mean of the training samples as a prototype vector $\mu$ and then use the squared Euclidean distance from the prototype to the sample vector $x$

$$d_{E}(x, \zeta) \triangleq ||x - \mu||^2 = (x - \mu)^T(x - \mu), \quad (3.13)$$

where $\zeta$ is either the background or the target class.

In a more advanced detector the within-class variance $\sigma^2$ is used for weighting the distance. Since hyper spectral bands work in multiple dimensions, and the variance might differ between them, it is possible to use different weights for
different dimensions. The distance function then becomes

\[ d_E(x, \zeta) \triangleq \sum_{n=1}^{N} \frac{(x_n - \mu_n)^2}{\sigma_n^2} = (x - \mu)^T \Sigma^{-1} (x - \mu), \quad (3.14) \]

where \( \Sigma = \text{diag}(\sigma_1^2, \ldots, \sigma_N^2) \). Since samples are often correlated between different dimensions it is possible to calculate the Mahalanobis distance by using the full covariance matrix \( \Gamma \):

\[ d_M(x, \zeta) \triangleq (x - \mu)^T \Gamma^{-1} (x - \mu). \quad (3.15) \]

If we have training vectors \( (x_k)_{k=1}^{K} \) of \( N \) dimensions, then we can estimate the mean, covariance and variances using

\[ \hat{\mu} = \frac{1}{K} \sum_{k=1}^{K} x_k \quad (3.16) \]

\[ \hat{\Gamma} = \frac{1}{K - 1} \sum_{k=1}^{K} (x_k - \hat{\mu})(x_k - \hat{\mu})^T \quad (3.17) \]

\[ \hat{\sigma}_n^2 = \frac{1}{K - 1} \sum_{k=1}^{K} (x_k)_n - \hat{\mu}_n)^2 \quad (3.18) \]

The higher the dimensionality of the training vectors the more of them are needed. As a general rule, at least \( N^2 \) training samples are needed to give a reliable estimate of a full covariance.

An anomaly detector using the Mahalanobis distance will look like

\[ D_{RX}(x \mid B) = [d_M(x, B) > h] \quad (3.19) \]

where \( h \) is the threshold parameter determining the compromise between false-alarm and detection rates.

### 3.3.4 Structured Background Models

In a structured model prior knowledge about the data is used. This model does not need as much training data as the unstructured model to give good results, and it is optimal when the data has characteristic features. A subspace is spanned by the spectral data from which the distance is measured to the new test samples. This subspace is referred to as the feature space. A subspace is made up of a set of basis vectors, and if the origin of the test sample is not included in the subspace then an offset vector is also needed.

If a subspace is spanned by the vectors \( \{a_1, \ldots, a_K\} \) then any vector \( x \) in the sub-
space is a linear combination
\[ x = \sum_{k=1}^{K} a_k a_k = Aa, \quad (3.20) \]
where the columns of \( A \) spans the subspace and \( a \) is a weight vector.

The projection matrix for the subspace \( A \) is defined as
\[ P_A = A(A^T A)^{-1} A^T \quad (3.21) \]

The projection matrix perpendicular to the subspace \( A \) can be described as
\[ P_A^\perp = I - A(A^T A)^{-1} A^T \quad (3.22) \]

The distance from feature space (DFFS) is defined as
\[ d_{DFFS}(x, A) = x^T P_A^\perp P_A^\perp x \quad (3.23) \]

If the background is modeled as a subspace the distance from feature space can be used as an anomaly detector
\[ D_{DFFS}(x \mid B) = [d_{DFFS}(x, B) > h] \quad (3.24) \]

A vector \( x \) within the subspace \( A \) can be written as
\[ \hat{x} = P_A x \quad (3.25) \]

If the origin is not included in the subspace then \( \hat{x} \) need to be subtracted with an offset vector.

### 3.4 Dimensionality Reduction Using PCA

Working with hyperspectral data, one problem is the large dimensionality, which leads to massive amounts of data. One solution to this problem is to use principal component analysis (PCA) to reduce the dimensionality of the data. PCA converts a set of observations or test samples into a set of variables called principal components. The number of principal components is less than or equal to the number of dimensions in the observations and they are ordered so that the first component has the largest possible variance and the following components are ordered so that they have the highest variance possible while also being orthogonal to the previous component. By only using the first few (most important) principal components the dimensionality of the data is reduced.

If we have \( K \) samples of \( N \) dimensions that we want to perform PCA on, the first step is to compute the mean and covariance of the data
\[ \mu = \frac{1}{K} \sum_{k=1}^{K} x_k \quad (3.26) \]
\[ \Gamma = \frac{1}{K-1} \sum_{k=1}^{K} (x_k - \mu)(x_k - \mu)^T \]  \hspace{1cm} (3.27)

The matrices \( \Gamma = U \Sigma U^T \) are found by using either singular value decomposition or eigenvalue decomposition on the covariance matrix. The columns of \( U \) contain the subspace basis while \( \Sigma \) is a diagonal matrix where the diagonal entries \( \sigma_i^2 \) specify the energy distribution of the samples. \( \sigma_i^2 \) are ordered in descending order. The vectors \( u_i \) are the principal components spanning the M-dimensional subspace basis \( \Phi = [u_1...u_M] \). How small \( M \) is depends on how much of the signal energy that you want to preserve.

To reduce the dimensionality of a sample \( x \) (project it on the subspace) the following formula is used

\[ y = \Phi^T (x - \mu) \]  \hspace{1cm} (3.28)

### 3.5 Global and Local Backgrounds

The spatial area in the image used to represent the background model need to be defined. The pixel-vectors in this area are used as training vectors for the model. When the entire image is used to build the background model this is referred to as global background. When only pixels within a certain distance from a selected pixel (the center pixel) are used this is referred to as the local background. The local neighbourhood is usually square.

When constructing a local neighbourhood the guard distance is typically defined. Pixels within this distance from the center pixels are excluded from the background model. The target area is usually used as well. This is the area containing pixels whose average is used to estimate the target signature.

In Figure 4.7 an example of a local neighbourhood used in this project can be seen.
In this chapter the experiments performed within this thesis are presented. The hardware setup and specimen used in the experiments are described in Section 4.1. In Section 4.2 data collection is mentioned. In Sections 4.3-4.4 preprocessing and processing of data is described. These two sections mention all the different parameters that were evaluated. Finally, in Section 4.5, the methods used to evaluate the performance of the tests are presented.

### 4.1 Hardware Setup

The specimen used in this project was created out of stainless steel (which has a low emissivity). A layer of soot was placed on the surface of the specimen to achieve a high emissivity. The layout for the specimen can be seen in Figure 4.1. The specimen has three rows of holes drilled into it. The insertions in the middle row are of different depths ranging from 2.0 mm to 3.5 mm and are the defects we are trying to find in this project. The top and bottom rows are drilled throughout the specimen so that they are clearly visible from both sides. These are to be used as reference points to help us locate the defects when evaluating the results. The insertions have a diameter of 2.0 mm. The non-defect areas of the specimen has a thickness of 4.0 mm.

The final product of the layout can be seen in Figure 4.2. The specimen is placed so that the middle row of insertions (the ones we are trying to detect) is facing away from the camera.

A flash lamp and an IR camera connected to a laptop were setup according to the description of the NDT scenario in Section 3.1. The flash lamp used in this project was a Hensel EH Pro 6000 which has the capability to extract a 6000 Joule...
Figure 4.1: Layout for the specimen.

Figure 4.2: Photograph of the specimen.
flash in 0.04 seconds. The specimen was placed approximately 20 cm from the camera and the flash lamp. The actual physical setup can be seen in Figure 4.3.

4.2 Data Set

Data for validation and evaluation was recorded with images of size 320x256 pixels at 200 fps. Each image sequence was 5 seconds long (1000 frames) and contained two defects as well as their corresponding reference holes. After each recording the specimen was moved horizontally in front of the camera and placed so that new defects would be in field of view.

In Figure 4.4 three images from a sample can be viewed. The first image (a) is taken before the specimen has been stimulated by the flash light, (b) is during the flash (the values are overly saturated) and (c) is taken 0.275 seconds after the flash. As can be seen in (c) the middle row of insertions (or defects) are visible to the human eye. The right defect has a depth of 3.5 mm while the defect to the left has a depth of 3.0 mm. The defect to the right is more visible than the one to the left which might be partly due to uneven heating but also because defects of large depths are easier to detect.

For the sake of my experiments the data was cropped into sizes of 190x180 containing only one defect per sequence. This was so that the results would not be influenced by the reference holes as well as a second defect. All frames prior to the flash were ignored. Each such sequence is referred to as a sample in this project.
Figure 4.4: Images taken (a) before flash, (b) during flash, (c) 0.275 seconds after flash.
One data set consisting of six samples was created for each of the depth sizes (a total of 24 samples). Each data set represent a difficulty level as small defects are harder to detect.

### 4.3 Pre-Processing

#### 4.3.1 Noise Removal

The problems of noise was mentioned in Section 3.1.1. In Figure 4.5 (a) the values for two neighbouring pixel-vectors can be seen over a period of 60 frames. The vertical axes show the intensity while the horizontal axes specify the frame number. Although the values for the two non-defect pixels should be almost identical, they deviate from each other somewhat, especially at frame 33 where the value for one of the pixels drops significantly. To avoid such deviations caused by the camera and to smooth out irregularities, a temporal median filter was applied to each pixel-vector in the sample (see Figure 4.5b). Several different sizes on the median filter were evaluated.

![Figure 4.5: Two pixel vectors (a) without median filter, (b) with median filter.](image)

#### 4.3.2 Normalization of data

Normalization of the data was performed to change the range of pixel intensity values, in order to get some consistency in the dynamic range of the data. This is done to compensate for varying reflectivity and emissivity across the surface of the specimen. Several different methods were evaluated. Mostly the data was scaled between the values 0 to 1, but since principal component analysis is sensitive to the relative scaling of the original data, other scales were tested as well to see how it effected the results.

A frame is represented by a matrix of intensity values. One possible method
to normalize the data between the values 0 and 1 is to (for each frame in the sequence)

$$\text{NewFrame}(x, y) = \frac{\text{Frame}(x, y) - \text{LastFrame}(x, y)}{\text{FirstFrame}(x, y) - \text{LastFrame}(x, y)}$$  (4.1)

This method is referred to as First-last frame normalization and assumes that the values in the first frame are the greatest and the values in the last frame are the smallest.

Another method, referred to as Min-max normalization, more accurately normalize each pixel vector in the range of 0 to 1 is to (for each pixel-vector in the image)

$$\text{NewPixelVector} = \frac{\text{PixelVector} - \text{min} (\text{PixelVector})}{\text{max} (\text{PixelVector}) - \text{min} (\text{PixelVector})}$$  (4.2)

### 4.4 Processing

#### 4.4.1 Dimensionality Reduction

Most of the variance in the cooling process occur within the first second from that the heat pulse has stimulated the specimen. Because of that, this project has focused on the first 300 frames after the flash.

Working in 300 dimensions takes a lot of computational processing and since using all available dimensions might not even give the best results experiments were done using only some of these dimensions. Different intervals between the frames were tested as well as investigating were to start and end the range of frames to give the best results.

Principal component analysis (PCA) described in Section 3.4 was then used on the selected frames to reduce the number of dimensions furthermore and to retrieve the most important feature vectors of the data. The experiments in this project were done using several different number of feature vectors to evaluate how the number of feature vectors affected the results.

#### 4.4.2 Distance From Feature Space

The structured background model described in Section 3.3.4 was used to detect anomalies. The feature vectors from the principal component analysis were used to span the feature space of the background model. A distance image was created were the value of each pixel is the distance from the corresponding pixel-vector in the sample to the feature space, calculated according to Equation 3.23. A typical distance image can be viewed in Figure 4.6.

#### 4.4.3 Spatial Filter

In the distance image in Figure 4.6a no filter has been used. As a result there is a lot of random pixels with really high values caused by the camera noise discussed
In Figure 4.6b a temporal median filter was used on the same sample. The pixels with really high values are now gone and the looked for defect at position (80,95) is clearer. There can still be artifacts spread out through the image with high values even after the temporal filter has been used. To remove some of these unwanted features a spatial 2-dimensional median filter is used on the distance images to smooth out spatial noise (Figure 4.6c). The defect is clearly visible in the center of the image, although in this particular example there is still a large area at the bottom left of the image that could be mistaken for a defect. The size of the spatial filter should be chosen so that it does not remove the looked for defects. Therefore the spatial filter is not very useful on unwanted artifacts larger than the looked for defect.

Figure 4.6: Distance image (a) without any filter, (b) with temporal filter, (c) with both temporal and spatial filter.
4.4.4 Global and Local Tests

Global and local background models were described in Section 4.4.4. Tests where the subspace was spanned by all the pixel-vectors in the sample are referred to as global tests. Tests were also done dividing the sample into small local neighbourhoods, this is referred to as local tests. Tests were done using both methods.

In the local variant a specialized kernel was used to run through every pixel in the sample (see Figure 4.7). Three parameters have to be set for the kernel, specifying the sizes of three rectangles surrounding the pixel being investigated. The inner rectangle specifies the target area to be investigated, from which the mean is calculated. The area between the inner rectangle and the middle rectangle is ignored (the guard distance). The area between the middle rectangle and the outer rectangle specifies which pixel-vectors are to be used to span the feature space (the background neighbourhood). The distance from feature space to the vector being inspected is then calculated. This is done for all pixel-vectors and a distance image is created just as described in Section 4.4.2.

As was mentioned in Section 3.3.3, the higher the dimensionality of the vectors the more of them are needed to give a reliable estimate of a full covariance. Therefore the kernel has to be chosen so that more pixel-vectors are selected when more dimensions are used in a test. If $N$ dimensions are used then at least $N^2$ pixel-vectors are needed.

Figure 4.7: A specialized kernel used in Local tests.

4.5 Performance Measure

4.5.1 Calculating False Detection Rate

In order to estimate the performance of each test, a method for measuring the false detection rate was introduced.

The position of the actual defect in the distance image is estimated manually with
help from the reference holes. A kernel roughly the size of the defect is placed on that position. All pixels outside the kernel with greater values than the pixel with the largest value within the kernel are then considered to be false positives. Obviously a low value is desirable.

### 4.5.2 Comparing Results With Alternative Method

The self-referencing method described in Section 3.2 was implemented so that the experiments could be compared to an alternative method.

Equation 3.2 was used to calculate the thermal contrast between a pixel and its surrounding. Similarly to the local tests mentioned earlier a kernel of three rectangles surrounding the targeted pixel was used to specify which pixels were to be used as the target mean respective the mean of the surroundings. A few different sizes for the three rectangles were tested and the ones with the best performance were used when calculating the false detection rate.

As mentioned in Section 1.1 it is difficult to know the optimal moment of time for calculating the thermal contrast. This was solved by calculating the contrast for every frame of each sample and to use the optimal value as the final result.

The self-referencing method was used on the same data set as the previous experiments and false detections for this method was also calculated with the method described in Section 4.5.1.
In this chapter the results of my experiments are presented. In the plots presented in this chapter, the horizontal axes shows the test numbers if nothing else is specified. Each test number has a different frame range attached to it (as was mentioned in Section 4.4) that is used on the data set for a specific parameter setting. Frame range has to do with which frames are selected for the test. The first and last frames are varied as well as the interval of frames between them. Which frames give the best results are also studied in this chapter. The vertical axes, if nothing else is specified, is the mean (over the 24 samples) of the false positives for that test. In a few of the tests however, only 12 samples were used to save time.

In the diagrams in this chapter there are also lines indicating the corresponding results from the alternative self-referencing method described in 4.5.2. If this line is not visible in the plots it's because its values are out of range.

5.1 Temporal Filter

Tests were performed both with and without a temporal median filter applied to the pixel-vectors. Results improved significantly in tests using the filter. In Figure 5.1 the results from tests using 100 different frame ranges can be seen. The x-axes specify a different test setting while the y-axes specify the mean value of the false-positives from 12 samples. Measurements were done using three different block sizes on the temporal filter (these were 3, 5 and 7).

The results indicate that there is a distinct relationship between block size and the number of false-positives. All measurements of block size 7 gave fewer false-positives than block size 3, and in some cases by two thirds. A block size larger
then 7 was not tested but it is likely that it would improve the results slightly.
A too large temporal filter however, carries the risk of smoothing out important
features and cause more false-positives. The shape of the curves has to do with
selection of frame ranges as will be described later on.

From here on a temporal filter of block size 7 was used in all the tests.

![Figure 5.1: Tests of temporal median filters of different block sizes. The blue, green and red lines are results for sizes 3, 5 and 7 respectively.]

### 5.2 Normalization Methods

Different methods for normalization of the data were evaluated. These are sum-
marized in Table 5.1. Method 1 and 4 are similar, the difference is that method
4 is scaled between 0 and 1 while method 1 is between 0 and a number much
smaller than 1. Method 6 is scaled between 0 and 1, while method 3 is between 0
and values much greater than 1.

First normalization methods 1-6 were used during 226 global tests. As can be
seen in Figure 5.2 the results were significantly better with methods 1, 3 and 5
than with the other three methods. Again, it can be worth pointing out that the
shapes of the curves have to do with how the range of frames is selected.
## 5.3 Dimensionality Reduction

### Table 5.1: The normalization methods evaluated.

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Min-max norm. but scaled between 0 and &lt; 1</td>
</tr>
<tr>
<td>2</td>
<td>First-last frame norm. but using a frame before the flash instead of the last frame</td>
</tr>
<tr>
<td>3</td>
<td>First-last frame norm. but scaled between 0 and $\sim 2645$</td>
</tr>
<tr>
<td>4</td>
<td>Min-max norm.</td>
</tr>
<tr>
<td>5</td>
<td>Same as method 1 but with slightly smaller values</td>
</tr>
<tr>
<td>6</td>
<td>First-last frame norm.</td>
</tr>
</tbody>
</table>

**Figure 5.2: Global tests with normalization methods 1-6.**

Methods 1, 3 and 5 have been zoomed in on in Figure 5.3. The dotted line in the graph shows number of false positives given by the alternative self-referencing method. As shown by the plots methods 1 and 5 give better results than method 3. Method 1 gives marginally better results than method 5. All three methods give fewer false positives than the alternative method for some frame settings. It is therefore necessary to determine which frames that should be used. For the rest of the experiments normalization method 1 is used.

### 5.3 Dimensionality Reduction

Principal component analysis (PCA) was used to extract the feature vectors of the data to span the feature space. Different number of feature vectors were used to evaluate how the performance was affected (see Figure 5.4).

As can be seen from the results, using more feature vectors does not give better results. The best results were achieved using only two feature vectors. It is pos-
Figure 5.3: Global tests with normalization methods 1, 3 and 5.

It is possible that by using only two vectors, irrelevant features are discarded (e.g. noise, redundant features) and the accuracy of the system is improved.

Tests were also performed in which only one feature vector was used. The results were significantly worse however, than it was using two feature vectors.

Figure 5.4: Global tests with 2, 4 and 6 feature vectors.
5.4 Selecting Frame Range

As was seen in the previous sections, the tests were sensitive to the range of frames that were used. Tests were performed to evaluate which range gave the best results. Factors that were evaluated were:

• How soon after the flash to start the tests?
• The interval between the frames. Does 200 fps really give better results than a much smaller frame-rate?
• At what frame should the tests end?
• How does the total number of frames used affect the results?

While the choice of temporal filter and normalizing method gave consistent results for both global and local tests, the range of frames could give varying results depending on which background model that was used. Therefore the frame range was evaluated separately for both the global and local methods.

5.4.1 Local Method

Starting directly after the flash gives bad results with high number of false positives. This is probably related to how the heat is distributed through the material (see Section 2.3). The heat need time to penetrate the material and then resurface before important features can be detected. Therefore it might be convenient to wait a few frames and let the cooling process stabilize. In Figure 5.5 it can be shown that there is a big steep in false-positives when starting at frame 30 instead of frame 35.

Figure 5.6 shows the same tests as Figure 5.5 but here focuses on frames 35-70. The average number of false positives for each start frame is displayed. It can be seen in the figure that the results improve slightly the later we start the tests, although somewhere around frame 70 the number of false positives starts to increase. These tests were only done on 12 samples (depths of 3,0 mm and 3,5 mm).

In Figure 5.7 three different intervals between the frames were tested (6, 8 and 10). The tests seem to indicate that there is no big loss in performance in having large intervals, although an interval size of 10 gives a somewhat higher false-positive rate then the others.
Figure 5.5: Local tests with different start frames. The horizontal axis is the test number and the vertical axis the number of false-positives.

Figure 5.6: The relation between start frame and the average number of false positives.

Finally, it was evaluated how the results were affected by selecting which frame to end the range. The results of the tests can be seen in Figure 5.8. Frame 180
Figure 5.7: Local tests with different intervals.

gives slightly worse performance than the others, but it is difficult to draw any conclusions from the results.
5.4.2 Global Method

Starting immediately after the flash gives a high false-positive rate also for the global method. Figure 5.9 shows that starting at frame 20 gives significantly fewer false-positives than to start at frame 10. Starting at frame 30 gives somewhat better results than staring at 20, but the improvements are not obvious and in some tests it even gives a higher false-positive rate. Unlike the local method which gave really bad results before frame 35 and good results at around frame 65, the global method start giving more unstable results after frame 30.

It was also evaluated how the results of the global method was affected by the choice of the last frame in the range. In Figure 5.10 the results from using three different last frames can be viewed (180, 230, 290). From the results it is clear that ending at frame 290 gives less false-positives than ending at frame 180.

Figure 5.8: Local tests with different end frames.
5.5 Comparing The Methods

The alternative method was able to detect the defects of depth 3.5 mm without a problem but already at 3.0 mm the performance become more unreliable. In Figure 5.11 the best detections from one of the best parameter settings for the alternative method can be seen. In (a) the position of the defect can be clearly seen. In (b) it can still be distinguishable at the center of the image. In (c) and (d)
it is more difficult to visually detect the defects. The sample in (d) gave no false detections, however judging from the image this can possibly be a coincidence as high value pixels are scattered all around the image. Testing this method on other samples of same depth supports this theory as they gave far more false positives.

![Figure 5.11: Alternative method (a) 3.5 mm, (b) 3.0 mm, (c) 2.5 mm, (d) 2.0 mm.](image)

Shown in Figure 5.12 are distance images created with the global method using one of the parameter settings with least false detections. Which parameter settings were used can be seen in Table 5.2. Although other parameter settings sometimes gave fewer false positives, visually they did not always display the defects as well.
5.5 Comparing The Methods

<table>
<thead>
<tr>
<th>Normalization method</th>
<th>1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nr. of feature vectors</td>
<td>2</td>
</tr>
<tr>
<td>Temporal filter</td>
<td>7-frame median</td>
</tr>
<tr>
<td>Spatial filter</td>
<td>10x9 pixels median</td>
</tr>
<tr>
<td>Start frame</td>
<td>25</td>
</tr>
<tr>
<td>Frame interval</td>
<td>4</td>
</tr>
<tr>
<td>Last frame</td>
<td>265</td>
</tr>
</tbody>
</table>

**Table 5.2: Parameter setting for global test.**

Here defects are clearly distinguished even at depths as small as 2.5 mm. At 2.0 mm you can still see the defects in certain samples, but the contrast between the defect and the background is small and in certain samples completely undistinguishable.

The local method produced the best results. In Figure 5.13 distance images created with one of the best parameter settings can be seen. The parameter settings are given in Table 5.3. In Section 4.4.4 a specialized kernel for the local tests was mentioned. The rectangle sizes for this kernel were not evaluated meticulously, but a set was chosen for all tests that seemed to give good enough results.

In Figure 5.13 the defect is clearly visible even at 2.0 mm. However, as with the global method the results can vary somewhat between samples. Some samples may not show the defect as clearly, even though the false positive rate is low.

<table>
<thead>
<tr>
<th>Normalization method</th>
<th>1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nr. of feature vectors</td>
<td>2</td>
</tr>
<tr>
<td>Temporal filter</td>
<td>7-frame median</td>
</tr>
<tr>
<td>Spatial filter</td>
<td>10x9 pixels median</td>
</tr>
<tr>
<td>Start frame</td>
<td>50</td>
</tr>
<tr>
<td>Frame interval</td>
<td>10</td>
</tr>
<tr>
<td>Last frame</td>
<td>24</td>
</tr>
<tr>
<td>Target area(kernel)</td>
<td>4x4 pixels median</td>
</tr>
<tr>
<td>Safe distance(kernel)</td>
<td>20x20 pixels</td>
</tr>
<tr>
<td>Surrounding(kernel)</td>
<td>40x40 pixels median</td>
</tr>
</tbody>
</table>

**Table 5.3: Parameter setting for local test.**
Figure 5.12: Global method (a) 3.5 mm, (b) 3.0 mm, (c) 2.5 mm, (d) 2.0 mm.
Figure 5.13: Local method (a) 3.5 mm, (b) 3.0 mm, (c) 2.5 mm, (d) 2.0 mm.
In this chapter the results will be discussed and some suggestions for future work will be presented.

6.1 Discussion

A spatio-temporal analysis of non-destructive testing using thermography was performed according to the goal of this thesis. The results of the proposed method were promising and far exceeded the performance of the alternative method that it was compared to.

The window sizes for the alternative self-referencing method were chosen so that it gave as good results as possible. It should be noted however that the alternative method might be tweaked and modified to give slightly better results by testing different window sizes or using weighting to emphasize the importance of certain pixels in the kernel. Due to time constraints, not too much time was spent optimizing the this method.

The global method gave some very promising results (especially for the samples in Figure 5.12). However for some samples the defects were not clearly visible even though they had few false-positives.

The local method gave better results than the global method, however it is a computationally heavy method. Because of this, the range of tests were not as thorough as for the global method and it was more difficult to draw conclusions from the results.

Because of camera noise a temporal filter was needed to smooth out irregularities. However, with a camera that has less noise such a filter might be redundant.
The filter might even remove important features and therefore might possibly be discarded altogether to give a better result in that case.

In this thesis prior knowledge about the specimen was known. The size and shape of the defects were taken into consideration when specifying the sizes of the kernels and spatial filters. These would have to be modified when searching for other types of defects.

The results might be less reliable close to the image borders, especially for the local method in which the values of the kernel are set to zero when they fall outside the image. This could potentially lead to more false positives.

If there are several or large defects present in the image these might affect what is considered to be anomalies. The outcome could theoretically lead to unexpected results, such as that the method is not able to detect the specific anomalies that are searched for.

### 6.2 Future Work

Because a lot of time consuming calculation were performed, a rather small data set (36 samples) was used to evaluate the proposed method. Although the method performed well in the tests it ought to be evaluated on a larger data set.

Since the results indicated that frame rate had little influence on the results, it might also be of interest to collect a data set of lower frame rate and test the method on this set. A camera with a lower frame rate might also have less camera noise which in itself might improve the results somewhat.

A temporal filter improved the results significantly in the tests that were done in this project, so it might be interesting to test a filter of larger block size than was used in these experiments. Replacing the temporal median filter with a Gaussian filter might also give better results. For a camera that has less noise it might instead be interesting to try a smaller block size on the filter or to use no temporal filter at all.

The unstructured background model in Section 3.3.3 was never evaluated in this project due to time constraints. It might be of interest to study how this method compares to the structured background model that was used.


Upphovsrätt

Detta dokument hålls tillgängligt på Internet — eller dess framtida ersättare — under 25 år från publiceringsdatum under förutsättning att inga extraordinära omständigheter uppstår.

Tillgång till dokumentet innebär tillstånd för var och en att läsa, ladda ner, skriva ut enstaka kopior för enskilt bruk och att använda det oförändrat för icke-kommersiell forskning och för undervisning. Överföring av upphovsrätten vid en senare tidpunkt kan inte upphäva detta tillstånd. All annan användning av dokumentet kräver upphovsmannens medgivande. För att garantera äktheten, säkerheten och tillgängligheten finns det lösningar av teknisk och administrativ art.

Upphovsmannens ideella rätt innefattar rätt att bli nämnd som upphovsman i den omfattning som god sed kräver vid användning av dokumentet på ovan beskrivna sätt samt skydd mot att dokumentet ändras eller presenteras i sådan form eller i sådant sammanhang som är kränkande för upphovsmannens litterära eller konstnärliga anseende eller egenart.

För ytterligare information om Linköping University Electronic Press se förlagets hemsida http://www.ep.liu.se/

Copyright

The publishers will keep this document online on the Internet — or its possible replacement — for a period of 25 years from the date of publication barring exceptional circumstances.

The online availability of the document implies a permanent permission for anyone to read, to download, to print out single copies for his/her own use and to use it unchanged for any non-commercial research and educational purpose. Subsequent transfers of copyright cannot revoke this permission. All other uses of the document are conditional on the consent of the copyright owner. The publisher has taken technical and administrative measures to assure authenticity, security and accessibility.

According to intellectual property law the author has the right to be mentioned when his/her work is accessed as described above and to be protected against infringement.

For additional information about the Linköping University Electronic Press and its procedures for publication and for assurance of document integrity, please refer to its www home page: http://www.ep.liu.se/

© Kristofer Höglund