Image Processing Techniques to Automate Quantitative Thermography Diagnostics for the Efficient Use of Electric Motors

by
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IMAGE PROCESSING TECHNIQUES TO AUTOMATE QUANTITATIVE THERMOGRAPHY DIAGNOSTICS FOR THE EFFICIENT USE OF ELECTRIC MOTORS

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A practical and non-invasive method of calculating the efficiency of electric motors could help reduce anthropogenic greenhouse gas emissions by up to 6%. Such a method has been developed using quantitative thermography, however currently, the time required for its implementation is prohibitive.

In this thesis, registration and segmentation techniques are applied to the thermograms of the above method, particularly thermograms used in the lumped capacitance method (LCM) and those used to find the average temperature of motors, reducing the time required to process thermograms.

The processing of LCM thermograms was completely automated (±5% difference when compared to results obtained manually) while processing of motor thermograms required the location of the motor be provided manually the first time a motor is examined, but was completely automated for subsequent thermograms of the same motor (±0.9°C and ±0.6°C difference for non-occluded and occluded motors respectively compared to manual results).
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Chapter 1: Introduction

1.1 Context

The scientific consensus is that the earth is warming. Since 1850 the earth’s average surface air temperature has increased by 0.8°C ±0.2°C (Royal Society, 2010). This warming has been attributed to an increase in anthropogenic greenhouse gas (GHG) emissions, primarily carbon dioxide (CO$_2$), since pre-industrial times. Climate models that consider emission scenarios based on economic growth, population levels and energy use, project an increase between 1.1 and 6.4°C in average surface air temperature by the end of the current century (IPCC, 2007). This warming is projected to cause an increase in the frequency and severity of heat waves, droughts, extreme precipitation events as well as rising sea levels and acidification of the oceans.

The Intergovernmental Panel on Climate Change (IPCC) estimated that, in 2004, anthropogenic emissions of CO$_2$ totalled 38 gigatonnes (Gt) or 77% of all human-caused GHG emissions, with 56.6% (28 Gt) of all emissions attributed to CO$_2$ generated by fossil fuel use (IPCC, 2007). The International Energy Agency detailed in a 2011 report that, in 2006, electric motors accounted for 43 to 46% of global electricity consumption, resulting in the emission of 6.04 Gt of CO$_2$ (Waide and Brunner, 2011). Assuming emissions in 2006 were similar to those in 2004, electric motors account for 12% of all GHG emissions or approximately 22% of CO$_2$ emissions attributed to fossil fuel use.

Waide and Brunner (2011) indicate that small motors make up about 90% of all electric motors in the world but only account for 9% of electricity used by electric motors. These motors are mass produced and are often integrated into components such as refrigerator compressors and computer hard drives. Medium and large sized motors account for 68% and 23% respectively of all electricity consumed by electric motors and make up 10% and 0.03% of all motors in use today. These motors are used primarily in commercial, industrial and infrastructure applications controlling pumps, compressors, fans, converters etc. Bonnett (2000) indicates that a 50% reduction in energy use could be achieved, while still producing the same amount of work, by better application and use of AC induction motors. This would translate to a reduction in total anthropogenic GHG emissions of 6%, and electricity cost savings to motor owners.

It is difficult however to determine which motors, currently in operation, are running inefficiently. It would be impractical to analyze the efficiency of the billions of small motors in operation today. Furthermore, any improvements made would have a relatively minor impact. However, the 260 million medium and 0.6 million
large sized motors (Waide and Brunner, 2011) that are currently in service are much more practical to examine and present an opportunity to reduce CO$_2$ emission significantly. Unfortunately, there currently exists no practical solution for identifying which motors may be running inefficiently. Measuring the efficiency of these motors normally requires they be taken out of service, since the mechanical work they produce must be measured directly using a dynamometer. In industrial settings this is unacceptable as taking a motor out of service leads to downtime.

Faced with this problem, Narrol (2009) developed a method of using thermography (thermal imaging), to quantify the waste heat being emitted by an electric motor, thus allowing its efficiency to be calculated in a non-invasive manner. This method of quantitative thermography applied to electric motors was demonstrated to be successful using a group of 10 motors in an industrial setting (McNeil Consumer Healthcare, Guelph). However, the thermographic method requires that thermograms (infrared images) be processed manually by a trained person in order to extract the required data. This makes the method in its current form unsuitable for large scale application.

1.2 Hypothesis

The hypothesis of this thesis is that parts of Narrol’s quantitative thermographic method of measuring the efficiency of electric motors can be automated using software image processing techniques. Automation of the portions of this method relating to extraction of temperature data from thermograms, has the potential to reduce the manual processing time required to obtain an efficiency value for each motor. The scope of this thesis is not to provide an optimized solution for automating Narrol’s method but, by experimenting with image processing techniques, to demonstrate that automation of the most time consuming portions of his method is achievable.

1.3 Criteria for Success

The success of the automation processes will be measured using the following criteria:

Accuracy: Minimize the difference between Narrol’s results and those of the automated method.

User Input: Minimize the user input required to process thermograms.

Time: Minimize the computational time required to process the thermograms as well as the manual processing time required.

Simplicity: Existing and well established image processing packages and techniques should be leveraged whenever possible rather than implementing new solutions.
CHAPTER 2: BACKGROUND

In order to follow the research detailed in this thesis the reader must have a basic understanding of thermography and the quantitative thermographic method developed by Narrol (2009) as well as image processing techniques such as registration and segmentation. This chapter attempts to explain, as simply as possible, the core concepts behind the work detailed in this thesis.

2.1 QUANTITATIVE THERMOGRAPHY AND ELECTRIC MOTORS

2.1.1 Thermography

Traditional cameras record and store images by capturing light in the visible range of the electromagnetic spectrum. The images they produce represent the world as we see it through our own eyes. Infrared (IR) cameras on the other hand, capture light of longer wave-lengths known as infrared. Every object with a temperature above absolute zero emits infrared light. As the temperature of an object increases, so does the amount of IR radiation it emits (FLIR, 2011). Consequently, the images produced by IR cameras (called thermograms) map grey levels or colours to temperatures, and represent the world in terms of how hot it is. A comparison between a visible and infrared image can be seen in Figure 2.1.

![Visible Light Image](image1.png) ![Infrared Light Image](image2.png)

**Figure 2.1:** Comparison of visible light and infrared light images of a motor. Adapted from: Narrol (2009).

Thermography can be used in both qualitative and quantitative applications. Qualitative thermography
uses visual inspection of thermograms as its method of analysis e.g. thermograms of the windows of a house are captured; it is observed that one window is hotter or colder than another and it is interpreted that this corresponds to a difference in heat transfer. Quantitative thermography uses the actual temperature data provided in the thermogram to put a number to something e.g. thermograms are taken of all the windows of a house and the waste heat being emitted from the windows is calculated; it is determined that two windows in particular account for 50% of all heat lost through windows.

2.1.2 Quantitative Thermography Diagnostics for the Efficient Use of Electric Motors

Electric motors convert electrical energy into mechanical energy. In the process some energy is always wasted; the percentage of electrical energy that is converted to mechanical energy is termed efficiency. The bulk of the electrical energy not converted to mechanical energy takes the form of waste heat emitted via conduction, convection and radiation. An energy balance around an electric motor is pictured in Figure 2.2. The first law of thermodynamics states that all energy is conserved. Therefore, if the waste heat being emitted by a motor is known, along with the amount electrical energy being supplied, it is possible to estimate the motor’s efficiency.

Narrol’s method is based on the energy balance above. Waste heat emitted from electric motors is quantified by extracting temperatures from thermograms and using them to calculate values of conductive, convective and radiative heat loss. Each of the heat transfer modes requires a thermogram containing a part of the motor (conduction) or the whole motor (convection and radiation) be processed. Determining the convective heat loss requires additional thermograms. In order to calculate the waste heat emitted due to convection, an in-situ heat transfer coefficient (HTC) must be measured empirically for each motor. The HTC represents the rate of energy being emitted per unit surface area of the motor in proportion to the temperature difference between the motor’s surface and the surrounding air. This value changes from one

![Figure 2.2: The energy balance around an electric motor. Taken from: Narrol (2009).](image)
motor to the next.

To determine the in-situ HTC of a motor Narrol employs the *lumped capacitance method* using thermograms. A rectangular thermal mass, isolated on all but one side, is heated over a steam trap and placed on the motor’s surface with the uninsulated side facing away from the motor. As it cools, thermograms are captured (at least five) periodically until it reaches steady state i.e the temperature of the air around the thermal mass. The average temperature of the thermal mass is extracted from each thermogram and used to plot the temperature decay of the mass over time. This curve is normalized and linear regression is used to find its slope. The slope can then be used to calculate the HTC.

Narrol extracted temperatures of interest from thermograms using software created by the IR camera manufacturer FLIR. Boxes, used to measure average temperatures of areas of interest, and lines, for measuring temperature gradients, were traced over thermograms as seen in Figure 2.3. Once thermograms are loaded into the software it takes between 10 and 20 seconds for a proficient user to trace a line or box and record the temperatures of interest.

Assuming the minimum of five thermograms (at a location on the motor) is sufficient for calculating the HTC of a motor, it would take about 1.5 minutes just to process these thermograms. With many industrial facilities employing hundreds or even thousands of motors, this time dedicated to processing thermograms is significant. Moreover, this only accounts for calculating the HTC of each motor. Every time the efficiency of a motor is calculated (it is likely this could be done many times a year as preventative maintenance) it requires at least one thermogram of the motor itself be captured and processed. For a facility with 500 motors this works out to approximately two hours of thermogram processing time.

![Figure 2.3: Thermogram of a motor, showing box and lines around area of interest, used to manually extract temperature information. Taken from: Narrol (2009).](image-url)


2.2 Image Processing

2.2.1 Segmentation

Segmentation is the process of partitioning an image into segments usually defined by boundaries (lines, curves, etc.). It is often used to identify areas of interest in images as demonstrated in Figure 2.4. The segmentations shown are represented as binary images, where white pixels (assigned the value 1) represent pixels which are members of the segment, and black (assigned the value 0) are not members of the segment. In binary images it is only possible to represent a single segment. A special type of image can be generated called a label image which allows for multiple segments to be represented in one image. Label images assign each pixel a value, pixels of the same segment are all assigned the same value. In order to better visualize these images each label is assigned a colour as shown in Figure 2.5.

There are many different segmentation methods; they will be introduced and explained as needed in subsequent chapters of this thesis.

2.2.2 Registration

Image registration, as it is applied in this thesis, is the spatial transformation of one image relative to another in an attempt to align their commonalities.

A typical registration framework comprises four main components as shown in Figure 2.6. The framework has two inputs, a fixed image and a moving image. Registration is an optimization problem where the goal is to bring the moving image into alignment with the fixed image (Ibáñez et al., 2005). To achieve this, the moving image is compared to the fixed image using a metric. The metric outputs a fitness value to the optimizer, whose goal is to modify the transform parameters in order to achieve a better fitness value, during the next iteration of the registration process. The transform then evaluates the spatial mapping of the moving image to the fixed image using the new parameters. Finally the interpolator calculates the pixel
Performing image registration using a multi-resolution approach is widely used to improve speed, accuracy and robustness. The basic idea is that registration is first performed at a coarse scale where the images have fewer pixels. The spatial mapping determined at the coarse level is then used to initialize registration at the next finer scale. This process is repeated until it reaches the finest possible scale. This coarse-to-fine strategy greatly improve[sic] the registration success rate... (Ibánez et al., 2005)
The basic components of the registration framework are two input images, a transform, a metric, an interpolator and an optimizer.

**Figure 2.6:** Flow diagram of the main components of a registration framework. Taken from: Ibáñez et al. (2005).

**Figure 2.7:** Demonstration of registration on images of the brain.
Chapter 3: Automation of the Lumped Capacitance Method

As outlined in Chapter 2 the lumped capacitance method (LCM), used in Narrol’s work to aide in determining the HTC of an electric motor, requires significant time be spent manually processing thermograms, in order to extract average temperature values of the thermal mass’ pictured within. Due to the volume of thermograms generated by the LCM it was seen as the most important step to automate. This chapter describes the methods developed, along with associated results and discussion, to automate the extraction of average thermal mass temperatures from sets of thermograms used with the LCM. It also outlines calculations based on these temperatures used to generate a value, \( \tau \), which, along with data from sources outside these thermograms, is essential in calculating the in-situ HTC of an electric motor.

3.1 Approach

3.1.1 Overview

The first step to automate the process of calculating the average temperature of the thermal mass in a set of LCM thermograms is to define the thermal mass segment in each thermogram. Two approaches were considered:

- Define the segment of the thermogram that contains the thermal mass in each thermogram of a set separately.
- Define the segment of the thermogram that contains the thermal mass in the first thermogram of the set and register all subsequent thermograms to the first thermogram.

The Hough transform, an algorithm used to find features such as lines and rectangles, was seen as the most promising method of solving the segmentation problem using the first approach. Tests using the Hough transform ran into trouble however. Since the pixel intensities of the thermal mass segment change in each thermogram of the set as the thermal mass cools, in the final thermograms of a set it is sometimes hard to distinguish the boundary of the thermal mass. Without a boundary forming a rectangle, it would be impossible to detect the thermal mass segment in the final thermogram of a set. Ergo, the first approach was abandoned.
As such, the step required to determine $\tau$ using the LCM method was thought to be as follows:

1. Define a segment containing the thermal mass in the first thermogram of a set of thermograms for a LCM trial. (Section 3.1.4)

2. Register all subsequent thermograms of the set to the first thermogram. (Section 3.1.5)

3. Calculate $\tau$ based on the average temperature of the thermal mass segments in each thermogram of the set and the time at which each thermogram was captured. (Section 3.1.6)

### 3.1.2 Experimental Setup

All development for this chapter was performed using a MacBook Pro model MC375LL/A. All coding was performed in the Xcode 4 integrated development environment, in C++ (in order to ensure the code was as portable as possible), using the 64-bit LLVM compiler. The Insight Segmentation and Registration Toolkit (ITK) version 4 (beta), and open-source cross-platform image processing toolkit coded in C++, was used for all image analysis related tasks. In order to link and compile ITK, CMake version 2.8-5 was used. Finally, all data analysis was performed with MATLAB.

### 3.1.3 Dataset Selection

For each of the 10 motors Narrol worked with at McNeil, the lumped capacitance method was tested at multiple positions on each motor, and multiple trials at each position. On the first trial of each position Narrol took a greater number of thermograms than in subsequent trials at the same location. This was done to allow the thermal mass to reach $T_x$, the steady-state temperature, which is required to calculate $\tau$. With the $T_x$ value known, subsequent trials at the same position were not run until steady-state was reached.

Therefore, in order to test the automation process outlined in this chapter, for each motor, the set of thermograms corresponding to the first trial at each position was used. This allowed the automation process to calculate $\tau$ entirely on its own, given a set of thermograms, rather than requiring that a value for $T_x$ be supplied. A total of 34 sets of thermograms were selected as seen in Table 3.1.

Each thermogram in the dataset was obtained from Narrol in the form of Radiometric JPEGs which contain the raw temperature data associated with each pixel of the thermogram. However, this data is not accessible directly. As such, FLIR’s ThermaCam Researcher software was used to convert the Radiometric JPEGs into CSV files containing the temperatures. The CSV files containing the raw temperature values were used as input to the automation process.
Table 3.1: The dataset used for LCM automation testing.

<table>
<thead>
<tr>
<th>Motor</th>
<th># of Trials</th>
<th>Trial Numbers</th>
</tr>
</thead>
<tbody>
<tr>
<td>CFB</td>
<td>3</td>
<td>1, 5, 9</td>
</tr>
<tr>
<td>CR5</td>
<td>3</td>
<td>1, 5, 9</td>
</tr>
<tr>
<td>LR</td>
<td>3</td>
<td>1, 4, 7</td>
</tr>
<tr>
<td>P27</td>
<td>3</td>
<td>1, 5, 9</td>
</tr>
<tr>
<td>P28</td>
<td>3</td>
<td>1, 5, 9</td>
</tr>
<tr>
<td>ROA</td>
<td>3</td>
<td>1, 5, 9</td>
</tr>
<tr>
<td>UR</td>
<td>4</td>
<td>2, 3, 5, 8</td>
</tr>
<tr>
<td>V1</td>
<td>5</td>
<td>1, 2, 3, 4, 5</td>
</tr>
<tr>
<td>V2</td>
<td>7</td>
<td>1, 6, 9, 14, 17, 22, 25</td>
</tr>
</tbody>
</table>

3.1.4 Thermal Mass Segmentation

Context, Assumptions and Justifications

The thermal mass segment of the first thermogram in a set used with the LCM appeared be relatively uniform in intensity (temperature) and have a distinct boundary; this made them very suitable for region growing segmentation approaches. Of all the region growing segmentation methods provided in ITK, confidence connected (Ibáñez et al., 2005, pg. 514–518) was the selected implementation as it does not require any threshold values. Region growing implementations using threshold values, which would translate to minimum and maximum temperature values for the thermal mass segment, are not practical in this case as the appropriate threshold values may be different for each thermogram set.

One requirement that all region growing algorithms share is a seed point from which the segment is to grow i.e. an x and y pixel index. It was observed that in the first thermogram in each trial the thermal mass segment always contained the hottest point in the thermogram. This was assumed to always be the case. The assumption was reasonable since the thermal mass was heated by resting it on a steam trap, which would make it hotter than the surface of an electric motor in the background of the thermogram. In order to ensure that the region growing algorithm had the best chance of success, it was desirable for the seed point to be as near the centre of the segment as possible. That being the case, the indices of pixels within a certain intensity threshold of the pixel with the maximum intensity were averaged to determine the seed point. A threshold intensity of 10°C was selected using trial and error.

The last two inputs that the confidence connected implementation requires are the multiplier and iterations. The ITK Software Guide states the following regarding these two variables:
Small values of the multiplier will restrict the inclusion of pixels to those having very similar intensities to those in the current region. Larger values of the multiplier will relax the accepting condition and will result in more generous growth of the region... The number of iterations is specified based on the homogeneity of the intensities of the anatomical structure to be segmented. Highly homogeneous regions may only require a couple of iterations. Regions with ramp effects... may require more iterations. *In practice, it seems to be more important to carefully select the multiplier factor than the number of iterations.* [emphasis added] (Ibáñez et al., 2005, pg. 515–516)

Given this guidance, the iterations were left at their default value of 5 set in the example of the confidence connected implementation provided with the ITK, since the homogeneity of the thermal mass segment varies from set to set, based on qualitative observations. The value would be modified only if unsatisfactory results were obtain by varying the multiplier exclusively.

**Method**

1. **itk::ImageRegionIterator** was used to iterate through the pixels of the first thermogram of a set to find the pixel with the greatest intensity (temperature).

2. The iterator class was then used again to find every pixel within 10°C of the maximum temperature recorded in the thermogram.

3. The average pixel index of all the pixels within 10°C was calculated to obtain the seed point.

4. The thermogram was then passed to **itk::CurvatureFlowImageFilter** which smoothed it, facilitating segmentation by eliminating noise.

5. The output was then processed with **itk::ConfidenceConnectedImageFilter** which generated a binary image defining the thermal mass segment.

**3.1.5 Registration**

**Context, Assumptions and Justifications**

With a method established to identify the thermal mass segment in the first thermogram of a LCM set, it was then necessary to make that segment applicable to the remaining thermograms of that set. Unfortunately even with the use of a tripod the thermograms are never perfectly aligned. Consequently the location of thermal mass segments vary from one thermogram to the next. As such, one cannot assume that the segments generated, using the first thermogram, will apply directly to all subsequent thermograms of the same set. Figure 3.1 illustrates the issue well. In order to solve this problem, the thermograms of a set were
all registered to the first thermogram of that set in order to align the thermal masses. This allowed the thermal mass segment in the first thermogram to apply to all thermograms in the set.

As outlined in Chapter 2 a registration algorithm is composed of 4 components: a metric, an optimizer, a transform and an interpolator. There exists many well established implementations for each component. These implementations were examined to determine which would be most appropriate for constructing a registration framework suitable for the thermograms used with the LCM.

**Metric**  Metrics can be subdivided into two broad categories, those that are based on direct comparisons of grey levels and those that are not. The latter category is often used for multi-modal registration problems in medical imaging. In medical imaging, images captured of the same anatomical regions using different modalities can produce images with different grey levels representing the same regions, as seen in Figure 3.2. Registering these images using direct comparisons or grey levels is therefore not possible. A set of thermograms used for the LCM have similar properties. As the thermal mass cools the grey level (intensity) changes since pixel intensity represents temperature, as pictured in Figure 3.3. As such, metrics used for multi-modal image registration in medical applications were assumed to be a suitable approach for registering thermograms used for the LCM.

Mutual information metrics have been very successful in the medical field registering images of different modalities (Maes et al., 1996; Pluim and Maintz, 2003). Of the mutual information metrics available in ITK the **Mattes mutual information** metric (Mattes et al., 2003) was selected due to its simplicity compared to the other available methods. Namely, it does not require pre-normalization of the input images, only has one tuning parameter (the number of histogram bins) and a smoother cost function which allows for a more intelligent optimizer.
Original Caption: A T1 MRI (fixed image) and a proton density MRI (moving image) are provided as input to the registration method.

**Figure 3.2:** Two different medical imaging modalities showing different grey levels for the same anatomical regions. Taken from: Ibáñez et al. (2005).

**Optimizer**  The selection of the optimizer component was based entirely on examples provided with ITK. The *regular step gradient decent* optimizer was selected since it was used in all registration examples using the Mattes mutual information metric.

**Transform**  In order to select an appropriate transform, the capabilities required from the transform must be understood. First it was necessary to choose whether a non-linear transform was desirable. For the purposes of registering thermograms used with the LCM, a linear transform is all that is required, since changes in the position of the camera would not produce non-linear effects.

The movement of the camera between thermograms can have the following effects on the thermal mass pictured within:

- **Translation:** Caused by movement of the camera on the $x$ and/or $y$ axis (up–down or left–right).
- **Scale:** Caused by movement of the camera on the $z$ axis (closer–farther).
- **Rotation:** Caused by rotation of the camera around a tangent perpendicular to the centre of the lens.
- **Shear:** Caused by any other rotation of the camera.
A transform that could compensate for all these effects (parameters) would be ideal. As such, the *affine* transform was selected as it is the most popular and well established transform that is capable of mapping one image to another using the parameters listed above.

*Interpolator*  ITK has 4 interpolation methods to choose from, 2 of which that are first order or less and two of which that are higher than first order. It was assumed that the precision provided by greater than first order interpolation methods was not required for this application and, as such, would not be worth the increase in computational complexity. Therefore *b-spline* and *window sinc* interpolation were not considered. The remaining two interpolators were *nearest neighbour* and *linear* interpolation. The nearest neighbour method simply assigns an intensity value based on the nearest pixel. Of these two, linear interpolation was selected.
Multi-Resolution  As explained in Chapter 2 multi-resolution registration approaches are used to improve speed, accuracy and robustness. The registration framework outlined in this section was designed to perform multi-resolution registration in an attempt to harness some of these benefits.

Tuning Details  With all the components of the registration framework decided upon, the next step was to identify all parameters associated with said framework. Table 3.2 outlines these parameters.

Table 3.2: Parameters that require tuning in the registration framework.

<table>
<thead>
<tr>
<th>Component</th>
<th>Parameter</th>
<th>Description</th>
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<td>Number of bins the histogram contains.</td>
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<tr>
<td>Optimizer</td>
<td>Maximum step length</td>
<td>The initial step length of the optimizer.</td>
</tr>
<tr>
<td>Optimizer</td>
<td>Minimum step length</td>
<td>Step length at which registration is terminated i.e. precision tolerance.</td>
</tr>
<tr>
<td>Optimizer</td>
<td>Relaxation factor</td>
<td>The rate at which the step length is reduced when the direction of movement in the parametric space of the optimizer changes.</td>
</tr>
<tr>
<td>Optimizer</td>
<td>Iterations</td>
<td>The maximum number of iterations the registration algorithm will perform if the minimum step length is never reached.</td>
</tr>
<tr>
<td>Optimizer</td>
<td>Scales 0–3</td>
<td>Scales for the coefficients of the affine transform’s matrix which governs rotation, scaling and shearing.</td>
</tr>
<tr>
<td>Optimizer</td>
<td>Scales 4–5</td>
<td>Scales of the translation coefficients of the affine transform.</td>
</tr>
<tr>
<td>Transform</td>
<td>None</td>
<td>N/A</td>
</tr>
<tr>
<td>Interpolator</td>
<td>None</td>
<td>N/A</td>
</tr>
<tr>
<td>Multi-Resolution</td>
<td>Levels</td>
<td>The number of resolution levels at which registration is performed at, e.g. 3 level registration would be 1/4 resolution, followed by 1/2 resolution, then finally full resolution.</td>
</tr>
<tr>
<td>Multi-Resolution</td>
<td>Factor</td>
<td>The factor by which the minimum step length is decreased before the beginning of the next registration level.</td>
</tr>
</tbody>
</table>

Method

The implementation of the registration framework outlined in this section was adapted from example code (MultiResImageRegistration2.cxx) provided by ITK. The registration framework developed used the follow-
ing classes to implement the various components (which interact as explained in Chapter 2):

\texttt{itk::MattesMutualInformationImageToImageMetric}
\texttt{itk::RegularStepGradientDescentOptimizer}
\texttt{itk::AffineTransform}
\texttt{itk::LinearInterpolateImageFunction}

along with,

\texttt{itk::RecursiveMultiResolutionPyramidImageFilter}
\texttt{itk::MultiResolutionImageRegistrationMethod}

to create the down-sampled images and control the multi-resolution registration process respectively.

The tuning parameters listed in Table 3.2 were varied until, from a qualitative perspective, the registration appeared to be somewhat successful. At that point no more tuning was performed until the full automation method was completely developed. This was because a quantitative evaluation of the method’s success was dependent on other steps of the automation process.

3.1.6 Calculating $\tau$

Context, Assumptions and Justifications

$\tau$ is the negative inverse of the slope of a linear regression of the scatter plot formed by normalizing the average temperature value of each thermal mass segment in a set of thermograms used for the LCM, using Equation 3.1, and plotting them over time,

\begin{equation}
T_{\text{norm}} = \ln \left( \frac{T - T_x}{T_i - T_x} \right)
\end{equation}

where,

$T_{\text{norm}}$ is the normalized temperature;

$T$ is the average temperature of the thermal mass segment in a thermogram of the set;

$T_x$ is the steady-state temperature, the average temperature of the thermal mass in the last thermogram of the set; and

$T_i$ is the initial temperature, the average temperature of the thermal mass in the first thermogram of the set.

$T$, $T_x$ and $T_i$ can all be calculated using the thermal mass segment defined by the process outlined in Section 3.1.4 along with the registration framework outlined in Section 3.1.5. Since the thermograms were available in JPEG format it was possible to extract the time at which they were taken from the EXIF metadata attached to each thermogram. The automation process was setup in such a way that $T_{\text{norm}}$ and time
data of each thermogram in a set was added one at a time to the linear regression until $R^2$ fell below 0.99. When this occurred the $\tau$ value was calculated with the slope of the linear regression line up to that point.

**Method**

1. The average temperature, of the thermal mass in each thermogram of a set, was calculated by averaging the values of all pixels in the thermogram that had the same index as non-zero pixels in the thermal mass segment image.

2. The time between each thermogram was calculated using a software package called *Cexif* (Pizzolato, 2003).

3. A linear regression was performed, using code by David C. Swaim (Swaim, 1998), on the scatter plot of $T_{\text{norm}}$ over time, adding one point at a time until $R^2$ fell below 0.99.

4. The negative inverse of the slope of the linear regression containing the most points, while still maintaining an $R^2$ greater than 0.99, was assigned to $\tau$.

### 3.1.7 Testing Overall Performance

**Context, Assumptions and Justifications**

For the automation process to be deemed a success it must generate accurate $\tau$ values. The accuracy of the $\tau$ values was measured by comparing them to those that Narrol obtained given that his work is the current reference standard. Therefore success of the automation process was measured by how similar the results are to those he calculated. Tests were briefly performed on the segmentation process to ensure a multiplier value was selected that produced appropriate thermal mass segments. Likewise, preliminary testing of the registration framework ensured that it was appropriate for the thermograms of the dataset. However, neither was tuned exhaustively. Instead, once each component was functioning (segmentation, registration, and $\tau$ calculation) the output of the entire process was observed as the parameters were varied.

In order to have a finer understanding of the effects of changing a parameter on the process, a total of 13 metrics were tracked each time the automation process was tested. The 3 most important metrics (besides time) were percentages representing the proportion of trials that were “flagged”. The results from a set of thermograms, or trial, were flagged if:

- The $\tau$ value obtained by the automation process was greater or equal to $\pm 10\%$ compared to Narrol's results $(1 - \tau/\tau_{\text{Narrol}})$.

- The longest trend line with an $R^2$ greater or equal to 0.99 did not contain at least a reduction of 2 natural logarithms ($\ln$) of temperature decay data.
• The average temperature of any thermal mass segment in a set was greater than ±1° C from Narrol’s results \( T - T_{Narrol} \).

Next, the mean, standard deviation and maximum, of the absolute differences between the average temperature measure for all thermal mass segments by the automation process and Narrol, were calculated. The same was done for all \( \tau \) percentage differences. Metrics were also calculated to determine whether the automation method had a bias. In order to quantify this, two metrics were established. The first was the mean of all temperature differences between Narrol’s results and those of the automated process. The second was the same but for \( \tau \) percentage differences. The final 2 metrics were the average ln reduction value obtained across all sets and the average processing time per thermogram. It should be noted that the availability of computer resources between tests was not controlled for and thus may be inconsistent. Consequently, one must use the time per thermogram metric with caution.

**Method**

1. Select a tuning parameter and modify its value.

2. Run the automation process on the 34 sets of thermograms (trials) of the dataset.

3. Observe the performance metrics.

4. Keep the new value if performance improves.

Tuning parameters include those listed in Table 3.2 along with the multiplier of the segmentation algorithm.

### 3.2 RESULTS AND DISCUSSION

#### 3.2.1 Segmentation

Before the success of the overall automation process could be tested, it was essential to ensure that the segmentation process outlined in Section 3.1.4 was producing acceptable thermal mass segments. As such, the multiplier value was varied and its effect qualitatively observed using visual inspection. Since the default value was 2.5 in the example provided by ITK, tests were performed between 2–3 at an interval of 0.1, with the iterations constant at 5. A sample of the results are pictured in Figure 3.4. The smoothing filter was removed as it appeared to have little to no effect.

A trend was observed throughout the LCM thermograms sets where values below 2.5 did not produce large enough segments and values approaching 3 produced segments that extended beyond the thermal mass. No number appeared to be ideal for all sets. Generally, multiplier values of, 2.5–3, for 5 iterations generated favourable results for 33 of the 34 LCM thermogram sets selected. The failed segmentation is pictured in
Figure 3.4: Confidence connected region growing segmentation with 5 iterations and varying multipliers for the first thermogram of CFB Trial 1.

Figure 3.5. This was due to the surface temperature of the motor, in the bottom left of the thermogram, being within 10°C of the hottest pixel. This resulted in the coordinates calculated for the seed point not being located on the thermal mass segment. Changing the temperature threshold used to find the seed point from 10°C to a smaller value would solve this issue.

3.2.2 Testing Overall Performance

Tests Performed and Associated Results

The overall success of the automation process was largely a function of the success of the registration framework. Tests were conducted according to the method in Section 3.1.7 and are outlined in Table 3.3. The performance metrics are shown in Table 3.4. Figure 3.6 pictures an example of a successful registration
Figure 3.5: Confidence connected region growing implementation failure for first thermogram UR Trial 2. of a set of thermograms.
### Table 3.3: Parameters of tests performed to tuned automation of the LCM.

<table>
<thead>
<tr>
<th>Test #</th>
<th>Multiplier</th>
<th>Histogram Bins</th>
<th>Max Step</th>
<th>Min Step</th>
<th>Relax Factor</th>
<th>Iterations</th>
<th>Scales 0–3</th>
<th>Scales 4–5</th>
<th>Levels</th>
<th>Factor</th>
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<td>0.1</td>
<td>0.8</td>
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**Order of P28 Trial 1 thermograms corrected**

<table>
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<th>Histogram Bins</th>
<th>Max Step</th>
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**Set UR Trial 2, V1 Trial 1 and V1 Trial 5 removed from dataset**

<table>
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<tr>
<th>Test #</th>
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<th>Histogram Bins</th>
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<td>10⁻⁶</td>
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</tr>
</tbody>
</table>

**Bolded numbers indicate those that were changed.**
Table 3.4: Performance metrics for tests of LCM automation.

| Test # | $\tau$ | ln Temp | % flagged | $|T - T_{Narrol}|$ Stats ($^\circ$C) | $|1 - \tau/\tau_{Narrol}| \times 100$ Stats | Bias | Average |
|--------|--------|---------|-----------|----------------------------------|---------------------------------|-------|---------|
|        |        |         |           | $\mu$ | $\sigma$ | max | $\mu$ | $\sigma$ | max | T ($^\circ$C) | $\tau$ | ln Time/Image (s) |
| 1      | 20.6   | 17.6    | 44.1      | 1.1405 | 3.3478 | 25.7 | NaN   | NaN   | 98.9 | 0.165 | NaN   | 2.8667   | 6.99   |
| 2      | 26.5   | 20.6    | 47.1      | 1.1615 | 3.3640 | 25.7 | NaN   | NaN   | 100.8 | 0.155 | NaN   | 2.8232   | 26.91  |
| 3      | 17.6   | 26.5    | 35.3      | 1.0522 | 3.1161 | 25.7 | NaN   | NaN   | 106.8 | 0.228 | NaN   | 2.7636   | 7.58   |
| 4      | 23.5   | 20.6    | 26.5      | 1.3283 | 4.7043 | 45.3 | NaN   | NaN   | 111.6 | -0.081 | NaN   | 2.8425   | 8.44   |

Order of P28 Trial 1 thermograms corrected

|        |        |         |           |        |        |      |        |        |      |        |        |         |         |
|        |        |         |           |        |        |      |        |        |      |        |        |         |         |
| 5      | 17.6   | 17.6    | 29.4      | 0.8999 | 3.0149 | 35.6 | NaN   | NaN   | 15.9 | 0.069 | NaN   | 2.8741   | 12.03  |
| 6      | 14.7   | 17.6    | 29.4      | 0.7509 | 2.2872 | 20.2 | NaN   | NaN   | 175.7 | 0.196 | NaN   | 2.9146   | 5.50   |

Set UR Trial 2, V1 Trial 1 and V1 Trial 5 removed from dataset

|        |        |         |           |        |        |      |        |        |      |        |        |         |         |
|        |        |         |           |        |        |      |        |        |      |        |        |         |         |
| 7      | 19.4   | 16.1    | 22.6      | 0.2336 | 0.4487 | 4.2  | 5.6688 | 4.0356 | 15.8 | -0.060 | 0.046 | 3.0454   | 20.95  |
| 8      | 19.4   | 9.7     | 19.4      | 0.2470 | 0.4495 | 3.6  | 5.5431 | 4.0960 | 15.3 | -0.057 | 0.046 | 3.0849   | 10.72  |
| 9      | 19.4   | 16.1    | 29.0      | 0.3049 | 0.8576 | 14.9 | 6.8819 | 6.2672 | 31.1 | -0.045 | 0.041 | 2.9452   | 10.19  |
| 10     | 12.9   | 9.7     | 19.4      | 0.2848 | 0.4465 | 3.6  | 5.3495 | 4.0476 | 15.5 | -0.057 | 0.044 | 3.0545   | 7.53   |
| 11     | 9.7    | 9.7     | 19.4      | 0.2499 | 0.4352 | 3.5  | 5.8148 | 3.8735 | 15.6 | -0.058 | 0.048 | 3.0989   | 6.00   |
| 12     | 19.4   | 9.7     | 22.6      | 0.2502 | 0.4419 | 3.6  | 5.8911 | 4.1103 | 15.6 | -0.066 | 0.045 | 3.1392   | 5.51   |
| 13     | 12.9   | 9.7     | 19.4      | 0.2488 | 0.4256 | 3.6  | 5.8851 | 3.9977 | 15.4 | -0.058 | 0.049 | 3.1052   | 3.87   |
| 14     | 9.7    | 9.7     | 16.1      | 0.2483 | 0.4296 | 3.2  | 5.3704 | 3.9545 | 17.5 | -0.071 | 0.045 | 3.0689   | 2.62   |
| 15     | 22.6   | 32.3    | 41.9      | 0.7000 | 3.5117 | 55.2 | NaN   | NaN   | 348.8 | -0.350 | NaN   | 2.6934   | 2.74   |
| 16     | 12.9   | 9.7     | 19.4      | 0.2311 | 0.3782 | 3.7  | 5.3300 | 3.8784 | 15.7 | -0.051 | 0.044 | 3.0577   | 2.86   |
| 17     | 12.9   | 9.7     | 19.4      | 0.2553 | 0.4457 | 3.9  | 5.5208 | 4.4030 | 18.4 | -0.073 | 0.051 | 3.0879   | 3.54   |
| 18     | 19.4   | 6.5     | 16.1      | 0.2618 | 0.4553 | 5.2  | 5.6798 | 4.1101 | 14.4 | -0.104 | 0.047 | 3.0959   | 2.05   |
| 19     | 12.9   | 9.7     | 35.5      | 0.3299 | 0.5211 | 4.2  | 5.5492 | 3.9345 | 17.4 | -0.206 | 0.045 | 3.0443   | 2.89   |
| 20     | 12.9   | 9.7     | 19.4      | 0.2396 | 0.8612 | 16.1 | 4.9331 | 3.1424 | 10.5 | -0.060 | 0.034 | 3.0762   | 2.54   |
| 21     | 6.5    | 6.5     | 16.1      | 0.2316 | 0.3839 | 3.7  | 4.8984 | 3.5826 | 17.3 | -0.067 | 0.044 | 3.1194   | 2.60   |
| 22     | 16.1   | 12.9    | 19.4      | 0.2783 | 0.6513 | 9.8  | 6.9548 | 9.4322 | 52.3 | -0.053 | 0.032 | 3.0269   | 2.67   |
| 23     | 12.9   | 9.7     | 16.1      | 0.2584 | 0.3294 | 3.9  | 5.4994 | 3.5100 | 13.3 | 0.084  | 0.045 | 3.2062   | 2.55   |

Bolded numbers indicate best results.
Figure 3.6: Registration of set CFB Trial 5 from test 21 with thermal mass segments represented in black. (This represents one of the works cases)

**Modifications to the Dataset and Errors**

Through the course of testing, observations were made when analyzing the results that warranted changes to the thermogram dataset. In Table 3.3, it can be seen that after test 4 there is a note indicating that the thermograms of motor P28 trial 1 were reordered. This was done after examining an anomaly seen in the results where the first 9 thermograms of the set differed from Narrol’s results by between approximately 8 and 25°C while the next 6 were never more than 0.5°C away from his results. It was discovered that an error on the part of the author was to blame. Thermograms 1 through 3 were placed between thermograms
9 and 10. The thermograms were placed in their correct order which resolved the problem.

After extensively scrutinizing the results of test 6 in an attempt to better understand the noticeably poor performance of certain trials, three trials were removed from the test dataset, each for a separate reason. The first, UR Trial 2 was removed due to the issue relating to segmentation shown in Figure 3.5. Next, V1 Trial 1 was removed because the first thermogram of its set was out of focus and taken from a significantly different angle (camera user error), as can be seen in Figure 3.7, which caused registration to fail. Finally, V1 Trial 5 was removed due to differences between times pulled from the JPEG metadata of the thermograms and those recorded in Narrol’s results. These differences, affecting thermograms 2–4, were 15, 15 and 16 seconds respectively. Narrol’s results record the time elapsed since the first thermograms at 21, 28, 37, 28, 37 and 44 seconds for thermograms 2–7 respectively. The thermal mass temperature Narrol recorded for these thermograms also repeat themselves. Since, the manual results for this trial seemed to have been misrecorded, it could not be used in the test data set.

It should also be noted that the average time per image for test 7 was found to be incorrect. While looking over the results it was observed that the time of 20.95 seconds did not fit the parameters for the test. On closer examination of the data, it was revealed that trial 21 had a processing time of 4299 seconds or around 268 seconds per thermogram, which could not have been possible. Given the way the processing time was calculated, the difference in the computer’s clock time between when processing a trial started and finished, the laptop was likely interrupted inadvertently (likely by closing the lid) during test 7 while it was processing trial 21, and resumed at a later time.

**Tuning Rationale and Effects**

In the first six trials the effects of the minimum step length, histogram bins and relaxation factor were examined. However, after the trials were removed as explained above, the tuning process was started from scratch.
Examining Tables 3.3 and 3.4 together, tuning choices made and the effects of changing each parameter can be observed:

**Histogram bins** were tested at 25, 50 and 75. Fifty produced the best result, by decreasing both the trial flagged due to ln and temperature differences.

**Minimum step length** was then varied between 1 and 10. An increase from 1 to 5 had the best effect, reducing the processing time by approximately 44% to 6 seconds while reducing the percentage of trial flagged due to $\tau$.

**Multi-resolution factor** was modified from 10 to 5 then 2. Each step lower resulted in an improvement in time, with 2 reducing the processing time another 58%. Two also resulted in a decrease in trials flagged due to temperature to the lowest value observed, 16.1% or 5 out of 31 trials. After this change, time never improved again in any significant way.

**Maximum step length** was originally set to 16 as in the example provided by ITK. It was tested at 25 and 10, both of which produced less favourable results.

**Relaxation factor** was then changed from 0.5 to 0.75 and 0.25. Although 0.25 reduced the number of trials flagged due to ln to a new low of 2 out of 31 or 6.5%, it also increased those flagged due to $\tau$. As such, the value of 0.5 was maintained.

**Multiplier** was increased from 2.5 to 3 which resulted in more trials being flagged. As such it was kept at 2.5.

**Scale 4–5** was then varied from $10^{-7}$ down to $10^{-5}$ and up to $10^{-8}$. $10^{-6}$ produced the best result with lows for all flags: 2 flagged for $\tau$, 2 flagged for ln and 5 for temperature.

**Multi-resolution levels** was the last parameter to be tested. By this point, very few iterations (less than 5) were being performed at levels 2 and 3. Therefore the number of levels was changed to 1. This produced less favourable results which indicated that lowering the resolution of the thermogram before registration produces better results, since a 1 level registration uses a full resolution version of the thermogram.

Iterations were not modified since the maximum number of iterations of 200 was never reached after the first few parameters were tuned. Since scales 0–3 represent the magnitude of values in the affine matrix they were not changed from the value of 1.

**Analysis of Flags for Best Test**

Test 21 produced the fewest flags and as such was taken as the best result. However, flags do not necessarily indicate a failure on the part of the automation process. As such, each flagged trial was analyzed in order
to better understand why it was flagged. Table 3.5 lists the flagged trials for each of the 3 flag criteria for test 21.

Table 3.5: Trials flagged for test 21 by flag type.

<table>
<thead>
<tr>
<th>Flag Type</th>
<th># of Trials Flagged</th>
<th>Flagged Trials</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\tau$</td>
<td>2</td>
<td>6, 9</td>
</tr>
<tr>
<td>ln reduction</td>
<td>2</td>
<td>7, 8</td>
</tr>
<tr>
<td>Temperature</td>
<td>5</td>
<td>7, 9, 14, 20, 24</td>
</tr>
</tbody>
</table>

$\tau$ Flags  When examining the trials that failed due to $\tau$ it was observed that in each case, the ln to which the regression line extended was farther than Narrol. For trial 6 the automation process used 11 data points extending to 4.3 ln’s, whereas Narrol stopped at 9 data points or 2.1 ln’s. Temperature values were never more than $\pm 0.25^\circ C$ from Narrol’s values. As such, the difference in the results for $\tau$ of approximately 10% can be attributed directly to the difference in the number of data points used. It could even be argued that the results of the automation process were more accurate since it tracked the temperature decay over a longer period of time.

For trial 9 the automation process used 10 data points extending to 2.2 ln’s, as opposed to 9 points or 1.4 ln’s for Narrol. In this case some temperatures differed from Narrol’s by up to $\pm 1.5^\circ C$ which would flag the trial due to temperature difference. However, trials 14, 20 and 24 were flagged due to temperature differences of larger than $\pm 1^\circ C$, with some over 2 or even 3$^\circ C$, while still producing $\tau$ values within 10% of Narrol’s results. Therefore, it is likely that of the difference in $\tau$ values between the computed results and those obtained by Narrol, 17% was due to the use of an extra datapoint by the automation process.

ln Flags  Both trials 7 and 8 of test 21 were flagged due to the linear regressions not incorporating data up to 2 or more natural logs. However, there are excellent reasons for this in both cases. For trial 7, thermogram 6 was out of focus which created registration issues which resulted in a temperature reading of 3.7$^\circ C$ colder than Narrol recorded, the largest difference in the entire test. This difference in temperature was enough to push the $R^2$ below 0.99 when the next point was added to the regression. Trial 8 on the other hand did not reach 2 ln’s in Narrol’s results before $R^2$ fell below 0.99 and therefore the result of the automation process is justified.

Temperature Flags  Flags due to temperature were caused by small errors in registration. The flagging criteria of $\pm 1^\circ C$ was very strict and served more as a way to identify trials that had some small registration
problems than to actually suggest the automation process had failed. Besides trial 7, which was flagged
due to registration issues with a blurry thermogram, and trial 9 which was flagged based on $\tau$ due to a
difference in the number of data points used, trials 14, 20 and 24 were 5%, 6% and 2% away from Narrol’s $\tau$
results respectively, which is near the mean of 4.9% for the entire test. Therefore these differences in average
temperature for the thermal mass segments didn’t have a significant impact on the final value of $\tau$.

Bias

Examining the results for bias in Table 3.4, one can see that bias for temperature is negative for the best case
and most others. This indicates that the automation process produced an average thermal mass temperature
that was lower than those Narrol obtained more often than not. This is likely due to slight registration errors
caus ing the thermal mass segment to include pixels just beyond the boundary of the thermal mass, as can
be seen in Figure 3.6.

A positive value for the $\tau$ bias indicates that values of $\tau$ calculated by the automation process were also
on average lower than those Narrol obtained.

3.2.3 Effect of $\tau$ Differences on the Output of Narrol’s Method

It is important to understand the effect that changes in $\tau$ values can have on the overall output of Narrol’s
method. Included in the appendix of Narrol’s thesis is a spreadsheet (McNeil Industrial Motors.xls) detailing
the calculations for efficiency assuming full load and load assuming rated efficiency. These calculations are
performed many times per motor, from thermograms taken at different times, and averaged.

In order to observe the effect of differences in calculating $\tau$ on the averages of these values (for each motor),
values for HTC in the spreadsheet were varied by ±5% ($\tau$ and HTC are linearly related), the approximate
average difference of the values of $\tau$ calculated in test 21. The change in efficiency (for motors found to be
inefficient, V1 and V2) and load (for all motors found to be underloaded, the other 8) were observed for each
motor. The result was an average difference of ±4.2% for load and ±0.5% for efficiency. This indicated that
changes in $\tau$ produce roughly the same change for load while producing a very small change in the efficiency
value.

3.3 Summary

• The tuned automation process was able to generate $\tau$ values that were on average within 5% of Narrol’s
results with differences in thermal mass temperatures on average lower than ±0.25°C. No trial produced
an unacceptable result for $\tau$.

• The average ±5% difference from Narrol’s results for $\tau$ result in an average difference of ±4.2% for
load and ±0.5% for efficiency (across all motors).
• No user input was required, beyond supplying the correct thermograms.

• The average processing time per thermogram was on the order of a few seconds, and does not need to be supervised. Therefore the manual processing time associated with the task of processing LCM thermograms was reduced to 0.

• Blurry thermograms can pose serious problems to the registration framework. A method of detecting blurry thermograms in a set of LCM thermograms would be valuable.

• It is recommended that alternatives for each of the registration framework’s components be explored in order to compare them to the components used in this chapter.

• A method of obtaining raw temperature data from Radiometric JPEGs would be valuable as conversion to CSVs is an inconvenience.

• Only one type of segmentation was tested; it is recommended that others be explored to improve the segmentation of the thermal mass region.
Chapter 4: Automation of Motor Average Temperature Extraction from Thermograms

As outlined in Chapter 2, heat is emitted by a motor through radiation, convection and conduction, with the bulk of thermal energy being emitted through radiation and convection. In order to calculate the heat being emitted via these two mechanisms the average temperature of the surface of the motor must be known. To obtain this value, Narrol manually processed thermograms of motors by drawing a box over the motor in each thermogram using software provided by the infrared camera manufacturer. This served his purposes well. However, if his method is to be applied on a large scale by organizations with hundreds or thousands of electric motors, and repeated several times per motor in order to track their efficiency over time, this manual approach is not feasible as it would be too time consuming. This chapter proposes image processing techniques to automate the manual process used to determine the average temperature of a motor from a thermogram and demonstrates the effectiveness of these techniques.

4.1 Approach

4.1.1 Overview

A fully automated image processing algorithm to accomplish the task of calculating the average temperature of a motor from a thermogram needs to do the following:

1. Locate the motor in the thermogram. (Section 4.1.4)

2. Segment the thermogram or, if a thermogram of the motor has already been processed, register the thermogram. (Section 4.1.5 and 4.1.6)

3. Determine which segments are non-motor and dispose of them. (Section 4.1.7)

4. Calculate the average temperature of pixels in the motor segment(s). (Section 4.1.8)

5. Determine the quality of the results as a function of the percentage of the motor’s surface in the thermogram that isn’t occluded. (Section 4.1.8)
Step one was to be the most challenging. This is due to the fact that electric motors are not all identical, and although many share a common aspect ratio, occlusions of the motor and other elements in the image can make it difficult for a human, let alone an image processing algorithm, to locate a motor in a thermogram and define its boundaries. As such, user input was deemed to be acceptable for the first step. However, the user input was assumed to only be required the first time a motor was processed since, as long as subsequent thermograms of the same motor were taken from a similar distance and angle, registration could be performed to align the new thermograms with the initial thermogram. Once aligned, the location of the motor specified by the user in the initial thermogram would then apply to the new thermograms.

Steps two through five were implemented without any user input.

4.1.2 Experimental Setup

All development for this chapter was performed using a MacBook Pro model MC375LL/A. All coding was performed in the Xcode 4 integrated development environment, in C++ (in order to ensure the code was as portable as possible), using the 64-bit LLVM compiler. The Insight Segmentation and Registration Toolkit (ITK) version 4 (beta), and open-source cross-platform image processing toolkit coded in C++, was used for all image analysis related tasks. In order to link and compile ITK, CMake version 2.8.5 was used. Finally, all data analysis was performed with MATLAB.

4.1.3 Dataset Selection

Before an automation process could be developed, it was first necessary to select which thermograms would be used as a test dataset. Narrol worked with 10 motors at McNeil. For each of these electric motors he took many thermograms and recorded their average temperature manually as explained in Chapter 2. For some motors Narrol took upwards of 90 thermograms while for others as little as 11.

For the purposes of testing the processes developed in this chapter five thermograms of each motor were selected. These thermograms were selected such that, for each motor, the angle and distance were similar, but different enough to challenge the registration process. The first (oldest) of the five thermograms for each motor is shown in Figure 4.1.

Figure 4.2 shows an example of change in perspective between two thermograms of the same motor.

4.1.4 Motor Location

Context, Assumptions and Justifications

As discussed above, user input was deemed acceptable the first time a motor is processed in order to indicate where the motor is in the thermogram. It was decided that a graphical user interface (GUI) that allowed the user to trace a rectangle over the thermogram would be the simplest and most logical way of retrieving the
Figure 4.1: First (oldest) thermogram, selected from Narrol’s data, for each motor.

location information from the user. An alternative would be to simply present the user with the thermogram and have them click on the motor. The advantage of the latter is that it would require only one click as
opposed to two or a click and drag. The advantage of the former is that it communicates not only the location of the motor, but definite boundaries outside of which the automation process need not be concerned. Given that the time difference between the two methods was likely on the order of a couple of seconds, the method which involved tracing a rectangle was selected, since the additional information was seen as valuable in completing the subsequent processing steps to obtain an average temperature for a motor.

Although necessary for the end user, implementing a GUI was not necessary to test the method developed in this chapter for two main reasons. The first being that the user input is imprecise which, when testing the rest of the automation process, would be undesirable since this could confound comparisons made between trials of the entire automation process where changes were being made in later steps. The second is that it would take time to implement the GUI and time to trace out the location of the motor during each trial of the algorithm. Since the test dataset is known, it was far simpler to hardcode the required values, for each motor, into the software one time.

Since the background (non-motor/non-occlusion) segments of each thermogram vary significantly from one to the next, it was thought that this could pose a serious challenge to the segmentation process e.g. in Figure 4.1 motor ROA has a motor in the background making it difficult to tell when the motor of interest ends. As such, it was decided the rectangle representing the location of the motor would be traced such that only pixels of motor or occlusions would be included. Following this protocol, difficulties arising from the inclusion of background segments would be eliminated. However, this protocol would also ensure that some pixels were left out of the calculation of the motor average temperature. The impact of this compromise was deemed of little significance since temperature profiles on the surface of electric motors are generally radially symmetrical. That being the case, as long as the rectangle is traced in such a way that it runs from top to bottom, parallel to the motor shaft, the change to the average temperature measured should be insignificant.

Figure 4.2: Comparison of perspectives between 2 thermograms of the same motor.
Figure 4.3 demonstrates correct rectangle placement on a motor. This rectangle will be known as the *motor region*.

**Figure 4.3:** Demonstration of various motor location rectangles and their suitability on motor CR5.

*Method*

1. Image editing software was used to find the pixel coordinates of the top left corner of the motor region as well as the dimensions of the rectangle in the $x$ and $y$ directions.

2. The coordinates and dimensions were hardcoded into the automation software.

3. The motor region was cropped out of the thermogram of the motor, according to the coordinates and dimensions hardcoded into the software, using `itk::RegionOfInterestImageFilter`.

*4.1.5 Registration*

*Context, Assumptions and Justifications*

A registration algorithm was outlined in Chapter 3 for registering thermograms used for the LCM. The success of the registration algorithm could be easily measured indirectly based on comparisons between temperatures obtained from the automated process to those recorded by Narrol, among other metrics. The success of registering thermograms of motors cannot be measured as easily since no quantifiable metrics are available for comparison. This leaves qualitative measures (visual inspection) as the only available option for determining the success of registration. Without a quantifiable measure of performance it was decided that optimization of the registration framework would not be pursued for this new application unless initial trials demonstrated that it was not suitable for the new task.
Method

The tuned registration framework from Chapter 3 was applied directly to motor thermogram registration and would only be modified if registration did not produce desirable results. This would be determined by visual comparison and the success of subsequent steps in the automation process that may be affected by poor registration.

The first (oldest) thermogram of the set of five thermograms for each motor was used as the fixed image to which each of the other four thermograms was registered.

4.1.6 Segmentation

Context, Assumptions and Justifications

In Section 3.1.4 the region growing method was used to segment an image into two regions (thermal mass and non-thermal mass). This method was not appropriate for the task in this chapter however since no seed point is provided. Furthermore, if an occlusion such as a wire were to cut the motor segment in two separate halves, the region growing method would have no way of handling a second segment given a single seed point. It would be possible for the user to provide multiple seed points, located on each segment of the motor that is separated due to occlusions, but this could become very complicated for the user depending on the nature of the occlusions. A segmentation method capable of dividing a thermogram into multiple segments (more than two) was therefore desirable. ITK provides this type of functionality by way of the Segmentation Based on Watersheds method (Ibánez et al., 2005, pg. 524).

In order to perform watershed segmentation the input image is filtered producing an edge image. This edge image can be seen as a topographic relief where grey-levels indicate the height of the relief. It can then be imagined that water rains down onto the relief and flows to local minimums forming basins. As precipitation continues water levels in basins increase and smaller basins begin to merge forming larger ones. Figure 4.4 illustrates the process. Tuning of the watershed segmentation can be understood as defining the minimum watershed depth and maximum water level, known as threshold and level in ITK respectively.

![Original Caption: A fuzzy-valued boundary map, from an image or set of images, is segmented using local minima and catchment basins.](image)

**Figure 4.4:** Overview of watershed segmentation process. Taken from: Ibánez et al. (2005)
Method

1. The motor region was passed through `itk::GradientAnisotropicDiffusionImageFilter` to smooth the image while preserving edges.

2. An edge detection filter, `itk::GradientMagnitudeImageFilter`, was then used to generate a height function from the smoothed motor region.

3. The height function was then processed by `itk::WatershedImageFilter` in order to perform the segmentation.

In order to tune the segmentation algorithm the conductance parameter used by `itk::GradientAnisotropicDiffusionImageFilter` and the level parameter for `itk::WatershedImageFilter` were varied. Their effect was evaluated qualitatively using visual inspection.

4.1.7 Occlusions Segments Deletion

Context, Assumptions and Justifications

Once the cropped thermograms were segmented, it was then necessary to determine which segments were motor and which were not. Non-motor segments which result from occlusions must be filtered out. It was necessary to find an attribute or multiple attributes of occlusion segments that could be used to distinguish them from motor segments. This proved to be rather difficult since occlusions can be very different from one to the other. Measures relating to geometry were deemed unsuitable given the range of shapes and sizes occlusions could take. Temperature however, was found to be a promising attribute. It was observed that all occlusions in the dataset were colder than the majority of the motor that they cover. As such, if the average temperature of the motor region was measured and compared to all segments, motor segments should always be hotter relative to the occlusions segments.

In order to compare the average temperatures of segments the output of the Watershed Segmentation filter needed to be changed into a form that is easier to work with. `itk::WatershedImageFilter` outputs a label image where pixels belonging to a particular segment are all given the same integer number. Label images can be manipulated by a group of classes recently implemented in ITK. These classes are detailed in the article: Label Object Representation and Manipulation with ITK (Lehmann, 2008).

Method

1. The labeled image representing the segmented motor region was processed by `itk::LabelImageToStatisticsLabelMapFilter` which produced an `itk::LabelMap` composed of `itk::StatisticsLabelObject(s)` which represent each segment and contain information about all their statistical attributes (e.g. mean, standard deviation etc.).
2. \texttt{itk::AttributeOpeningLabelMapFilter} was then used to filter out segments \texttt{(itk::StatisticsLabelObject(s))} that had a mean (average temperature) below a specified value, calculated based on statistics of the entire motor region, determined by passing the cropped thermogram through \texttt{itk::StatisticsImageFilter}.

3. The filtered \texttt{itk::LabelMap} was then converted back to a labeled image using \texttt{itk::LabelMapToAttributeImageFilter} where the label for each remaining segment was set to the mean value (average temperature) of that segment.

4.1.8 Average Motor Temperature and Percent Occluded

\textit{Method}

With the occlusion segments filtered out the average temperature of the motor could be calculated along with the size of the motor region that was covered by occlusions.

1. Each non zero pixel in the segmented labeled image, with occlusions deleted, was counted and its temperature obtained from the pixel at the same coordinate in the original motor region.

2. The sum of all the temperatures, from each counted pixel, was divided by the total number of counted pixels to obtain the average temperature of the motor.

3. The pixel count was then subtracted from the total number of pixels in the motor region and divided by that same number in order to determine the percentage of the motor region that was covered by occlusions.

4.2 Results and Discussion

4.2.1 Motor Location

Figure 4.5 displays the chosen motor regions for each motor. As can be seen for motor CR5 and V1, the motor region was selected such that the occlusion was not included. It was thought that including the occlusions, in order to capture a larger area of visible motor, would bias the average temperature of the motor since more cool pixels (at the bottom of the motor) would be included relative to pixels in the middle of the motor which are generally warmer.

4.2.2 Registration

The parameters from trial 21 in Table 3.3 were initially used to register the motor thermograms with mixed results. This called for some tweaking of registration parameters. In order to identify the registration
parameters that might offer the most improvement if modified, sets of LCM thermograms were compared to those of electric motors to understand their differences. From this analysis two main observations arose:
The location of a motor from one thermogram to the next changed much more than that of the thermal mass.

Thermograms used for the LCM contain less variability than those of electric motors.

The former indicated that an increased focus on translation would likely be beneficial. As such the translation scales were increased. The latter was thought to make the registration process more prone to get caught in spurious local minima. In order to avoid this, the relaxation factor was increased so that the registration took more iterations to reach the minimum step length.

Following manipulation of both of these variables and evaluating their success, qualitatively using visual inspection, the following changes were made to the registration parameters:

- Translation scales were increased from $10^{-6}$ to $10^{-4}$.
- The relaxation factor was increased from 0.5 to 0.6.

This largely solved the problem. However, some registration issues remained with select thermograms, the worst of which can be seen in Figure 4.6. With no clear idea of what was causing the few remaining registration issues, the last two significant parameters, histogram bins and the step lengths, were modified. Changing the number of histogram bins from 50 negatively impacted the registration quality. However, reducing the maximum step length had a positive effect; when reduced from 16 to 10, all remaining registration issues were corrected. Figure 4.7 demonstrates some of the more notable successes, including the successful registration of thermogram 2 for motor V2 shown in Figure 4.6. In this figure it can be seen that not only did the registration perform well for thermograms taken at different angles (motor LR), but also when those angles greatly change the appearance of the motor, as the example for Motor P28 demonstrates.
Motor LR: Thermogram 1 of 5

Motor LR: Thermogram 3 of 5

Motor P28: Thermogram 1 of 5

Motor P28: Thermogram 5 of 5

Motor V2: Thermogram 1 of 5

Motor V2: Thermogram 2 of 5

**Figure 4.7:** Registered thermograms of motors followed to the right by their motor regions.

### 4.2.3 Segmentation and Occlusion Deletion

The final parameters for the segmentation algorithm are listed in Table 4.1. Three of the five were set once and never modified. They were iterations, time step and threshold.

Iterations were set to 10 as was suggested by the watershed segmentation example provided with ITK. It was not necessary to change this term since the effect of iterations and conductance are linked, i.e. a large conductance value with fewer iterations will produce a similar effect as a low conductance value with many iterations. As such, the number of iterations was held constant and conductance varied. The time step was set according to ITK’s recommendation. Due to the variability of temperatures (intensities) from
one thermogram to the next it was not helpful to set a minimum threshold. The conductance and level were modified until a segmentation was produced for all thermograms of occluded motors where occlusions and motor pixels were in different segments.

Once segmentation was able to distinguish between motor and occlusions, the cut-off temperature used to filter out occlusions was tuned. The method used to identify which segments were occlusions was based on the following logic: Assuming that the average temperature of occlusions segments are colder than that of motor segments, it follows that the average temperature of the motor region would be lower than that of motor segments.

Initially the cut-off value was simply set to the average temperature of the motor region ($\mu_{\text{region}}$). However, this did not perform as expected. In cases where occlusions separated the motor into multiple segments, and the average temperature of the occlusions were close to that of the motor, some motor segments were treated as occlusions; see Figure 4.8.

<table>
<thead>
<tr>
<th>Conductance</th>
<th>Iterations</th>
<th>Time Step</th>
<th>Threshold</th>
<th>Level</th>
</tr>
</thead>
<tbody>
<tr>
<td>7.5</td>
<td>10</td>
<td>0.125</td>
<td>0</td>
<td>0.45</td>
</tr>
</tbody>
</table>

**Figure 4.8:** Examples of failed occlusion deletion (green overlays indicate motor segments, red indicate occlusion segments).

It was apparent that the cut-off value needed to be set lower than $\mu_{\text{region}}$. A constant offset would not
suffice since average temperatures between motor and occlusions segments vary between thermograms. As such, an equation of the form,
\[
\text{cut-off} = \mu_{\text{region}} - \alpha \sigma_{\text{region}}
\] (4.1)
where \(\sigma_{\text{region}}\) is the standard deviation of the cropped motor region and \(\alpha \in [0.1 - 1]\) is an empirically determined weighting parameter, would be sufficient. However, it was found that for smaller values of \(\alpha\) the average temperature of some occlusions segments would not fall below the cut-off, and conversely for larger values of \(\alpha\) some motor segments would fall below the cut-off as before. No value that was tested could reliably set the cut-off such that occlusion segments fell below and motor segments did not. \(\sigma_{\text{region}}\) on its own did not correlate well with the cut-off value.

\(\sigma_{\text{region}}\) can be thought of as the noise of the motor region, and \(\mu_{\text{region}}\) the signal. Dividing \(\mu_{\text{region}}\) by \(\sigma_{\text{region}}\) is the signal-to-noise ratio (SNR). It was hypothesized that including the SNR into the second term of Equation 4.1, rather than just \(\sigma_{\text{region}}\), would produce a better result. Therefore Equation 4.1 was modified to the following:
\[
\text{cut-off} = \mu_{\text{region}} - \frac{\alpha \mu_{\text{region}}}{\sigma_{\text{region}}}
\] (4.2)
Initially this was tested was with \(\alpha = 1\) which produced a cut-off value far too low. The \(\frac{\alpha \mu_{\text{region}}}{\sigma_{\text{region}}}\) term needed to be an order of magnitude smaller, therefore \(\alpha\) was set to 0.1. This produced the desired result as can be seen in Figure 4.9. Motor V2 was not included in the figure due to its similarity to V1.

Motor P28 was the most challenging for the segmentation process. This was due to the fact that the motor regions contained occlusions with a wide variety of temperatures, some very close to the temperature of the surrounding motor, and edges that were less defined. As can be seen in Figure 4.10, depending on which occlusions were within the motor region, the occlusions that were detected varied. The occlusions that were not detected were thought to have little effect on the value of the average temperature calculated for the motor, since the segmentation algorithm wasn’t able to detect them largely due to their similarity in temperature to the motor.

It should be noted that the five occluded motors analyzed here do not make up a comprehensive set of possible ways in which a motor could be occluded. As such, the solution proposed to detect occlusion segments in this chapter will likely need to be revised as more data becomes available (more thermograms of motors). Furthermore, the assumption that occlusions will be colder than the motor they cover might not always hold. Therefore, it is recommend that a more refined method of detecting occlusions segments be explored. Comparing the statistical differences between segments themselves as opposed to only comparing them to statistics of the motor region may be useful.
Figure 4.9: Successful segmentation with occlusion deletion, where green overlays indicate motor segments and red overlays indicate occlusion segments.

Figure 4.10: Comparison of segmentation between thermograms of motor P28, where green overlays indicate motor segments and red overlays indicate occlusion segments.
### 4.2.4 Average Motor Temperature and Percent Occluded

#### Non-Occluded Motors

Results for non-occluded motors can be found in Table 4.2. In these results it can be seen that the average temperature of the motors ($T_{\text{motor}}$) is very similar to the results Narrol obtained ($T_{\text{Narrol}}$). The average absolute deviation from Narrol’s results was 0.9°C or 1.8%. The processing time was on the order of 1–2 seconds per thermogram.

#### Table 4.2: Numerical results for non-occluded motors (all temperatures are in °C).

<table>
<thead>
<tr>
<th>Thermogram</th>
<th>$T_{\text{motor}}$</th>
<th>$T_{\text{Narrol}}$</th>
<th>$T_{\text{Narrol}} - T_{\text{motor}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Motor CFB</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>35.8</td>
<td>35.7</td>
<td>-0.1</td>
</tr>
<tr>
<td>2</td>
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The most notable discrepancies resulted from motor LR which have an average difference of 2°C. This is likely due to differences in how the motor region was selected by this author. Given that the difference is positive, it is likely that Narrol traced his rectangle in a way that avoided the colder line on the motor that was included in this analysis; see Figure 4.5.

Apart from the results for motor LR, the only other noticeable discrepancy with Narrol’s results was for the fifth thermogram of motor CR5 which has a difference of 3.3°C. Upon examining the output of the software it was observed that this thermogram did not register well compared to the others, as seen in Figure 4.11. The registration produced a thermogram that was not properly scaled, which resulted in the motor location rectangle having a larger concentration of hotter pixels from the middle of the motor’s surface.

In order to understand this result, the unregistered fifth thermogram was compared to the fixed image (the first thermogram). From the comparison, shown in Figure 4.12, it is evident that the fifth thermogram was taken much closer. It was concluded that the difference between the two thermograms was likely too great.

Figure 4.11: Registration of the fifth thermogram of motor CR5 compared to the first.

Figure 4.12: Comparison of the first and the fifth thermogram for motor CR5
for the registration framework to handle. This phenomenon highlights the fact that, in certain situations, the placement of the motor region can have a noticeable impact on the average temperature calculated.

With the results from motor L5 and the fifth thermogram of motor CR5 excluded, the average absolute deviation from Narrol’s results was 0.5°C or 0.9%.

Occluded Motors

Results for occluded motors can be seen in Table 4.3. Again the results of the average temperature of the motors were very close to those obtained by Narrol. The average absolute deviation from Narrol’s results was 0.6°C or 1.3%. Again, the processing time was on the order of 1–2 seconds per thermogram.

**Table 4.3:** Numerical results for occluded motors (all temperatures are in °C).

<table>
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<tr>
<th>Thermogram</th>
<th>( \mu_{\text{region}} )</th>
<th>( \sigma_{\text{region}} )</th>
<th>( T_{\text{threshold}} )</th>
<th>( T_{\text{motor}} )</th>
<th>( T_{\text{Narrol}} )</th>
<th>( T_{\text{Narrol}} - T_{\text{motor}} )</th>
<th>Fraction Occluded</th>
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The most notable discrepancies were for motor P28, which were an average of 1.8°C difference. This again is likely due to differences between how Narrol defined his motor regions compared with those used in this analysis, shown in Table 4.5 (see discussion on motor P28 segmentation in Section 4.2.3).

With the results from motor P28 excluded, the average absolute deviation from Narrol’s results was 0.3°C or 0.7%.

4.2.5 Effect of Average Motor Temperature Difference on the Output of Narrol’s Method

Section 3.2.3 details how the differences in $\tau$, and consequently HTC, effect the overall output of Narrol’s method. The same analysis was performed varying average motor temperature instead of HTC, using an difference of $\pm0.9°C$. This resulted in an average difference of approximately $\pm6\%$ for load; 0.39 and -0.50% for efficiency. It should be noted that the effect of load varies greatly between motors. On the lower end the change of said values for UR was $\pm2.6\%$, while on the upper end changes for motor ROA and ROB were $\pm11.5–12\%$. This is due to motors ROA and ROB having temperatures much closer to that of their surroundings, a difference of just over 6°C, in contrast to UR where the difference was approximately 32°C on average. Given that there is no established protocol for “best” or “correct” motor region placement, it is difficult to say with certainty whether these differences are due to errors in the automation process or simply differences resulting from motor region placement conventions. As such, more research should be performed to establish a definitive protocol for defining motor regions.

Additionally, using the same method, calculations were performed to understand the cumulative effects of both differences in $\tau$ and average motor temperature. This resulted in an average difference of approximately 10.4 and -9.9% for load; 0.94 and -1.06% for efficiency.

4.3 Summary

• The automation process was a success. Given thermograms for a motor and initial user input to indicate the motor region, the software was able to accurately calculate the average temperature of the motor.

• Although user input is required the first time a motor thermogram is processed, it is not required for subsequent thermograms of the same motor.

• The registration framework from Chapter 3 did not work immediately with motor images, but was easily adapted by changing the translation scales, relaxation factor and maximum step length.

• The Segmentation Based on Watersheds method was able to properly segment the motor regions into motor and occlusion segments, except when the temperature differences between the two were very
small (which then has little impact).

- Average motor temperature calculated with the developed software closely match those obtained by Narrol, with average absolute deviation of 0.9°C or 1.8% for non-occluded motors and 0.6°C or 1.3% for occluded motors and processing time on the order of 1–2 seconds.

- The accumulated effects of differences in $\tau$ and average motor temperature were 10.4 and -9.9% for load; 0.94 and -1.06% for efficiency.

- It is recommended that research be performed in order to determine best practices for defining motor regions.

- The method of detecting occlusion segments will likely need to be revised since, although the method proposed in this chapter works for the 5 occluded motors in the dataset, this data set is not large enough to account for the many ways a motor could be occluded in the field.
CHAPTER 5: CONCLUSION

The hypothesis of this thesis was that portions of Narrol’s quantitative thermographic method of measuring the efficiency of electric motors, relating to extraction of temperature data from thermograms, could be automated using software image processing techniques, reducing the manual processing time required to obtain an efficiency value for each motor. This was accomplished by automating the steps required to process thermograms used in the lumped capacitance method (LCM) and those used to obtain the average temperature of motors. The main achievements were as follows:

1. Processing of thermograms used in the LCM was completely automated using image analysis techniques, along with the calculation of a value for $\tau$, with an average difference compared to Narrol’s results of approximately 5%. Processing time per thermogram was on the order of 2–3 seconds.

2. Thermograms of a motor can be processed automatically, to extract the average motor temperature, without user input after the motor location is given by the user in the first thermogram taken of a motor. The average temperature calculated by the automation process differed from Narrol’s by $\pm 0.9^\circ$C and $\pm 0.6^\circ$C for non-occluded and occluded motors respectively. Processing time per thermogram was on the order of 1–2 seconds.

3. Differences in calculating $\tau$ and average motor temperature, compared to Narrol’s results, have little effect on the efficiency value calculated for each motor (approximately $\pm 1\%$ on average). However, the effect on load averaged approximately $\pm 10\%$, with the difference more significant the closer a motor’s average temperature is to its surroundings. Since no “best” or “correct” protocol for placement of motor region rectangles exist, it is difficult to say with certainty whether these differences are due to errors in the automation process or simply differences resulting from motor region placement conventions.

The following is recommended for future work:

- Image processing techniques be applied to thermograms used to calculate conductive heat loss from motors, as they were not covered in this work.

- Analysis of more thermograms of occluded motors be performed in order to validate and/or improve upon the method used for occlusion detection in this thesis.
• Research be performed to determine best practices for defining motor regions.

• More thorough tuning of the registration frameworks and experimentation with different registration components.

• Software be developed to automate all the non-image processing related tasks in Narrol’s method, to be combined with the automation processes developed in this thesis with the goal of fully automating Narrol’s Quantitative Thermography Diagnostics for the Efficient Use of Electric Motors method.
REFERENCES


