MULTI-SPECTRAL REMOTE THERMAL IMAGING FOR SURFACE EMISSIVITY AND ESTIMATION OF ROOF R-VALUES USING PHYSICS-BASED AND DATA MINING MODELS

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MULTI-SPECTRAL REMOTE THERMAL IMAGING FOR SURFACE EMISSIVITY
AND ESTIMATION OF ROOF R-VALUES USING PHYSICS-BASED AND DATA
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ABSTRACT

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Remote thermal imaging of buildings is notable for providing interesting but generally qualitative images of buildings. A recent study showed that if accurate measurements of exterior surface temperatures could be obtained from single-point-in-time-imaging, then it would be possible to infer envelope R-values and thermal capacitances with reasonable accuracy. This research seeks to answer the question, “How can we make possible reasonably accurate measurements of the external temperatures from at-scale remote imaging?” Without knowledge of the emissivity of the exterior surfaces, accurate thermal assessment is seemingly impossible. Here, we exploit the unique spectral characteristics of the most common exterior building surfaces using multi-spectral imaging. Four to five images of exterior surfaces in the 1-5-micron range, where the spectral emissivity of different building materials changes most, is posed. The pattern of
the emission can be correlated to various envelope component surface spectral emissivities. A neural network pattern matching algorithm is used to ‘find’ the surface type. Then, with known emissivity, the surface temperature can be inferred from the magnitude of the emission. Theoretical results indicate that temperature error in measuring the surface temperature in using this approach can be less than ±1°C. This error is sufficient for identifying envelope R-values based upon the research posed by Salahaldin and Hallinan [1]. Most exciting is the prospect of this technique for effectively measuring building R-values at scale via fly-over or drive by imaging.

Conventional residential building energy auditing needed to identify opportunities for energy savings is expensive and time consuming. On-site energy audits require quantification of envelope R-values, air and duct leakage, and heating and cooling system efficiencies. There is a need to advance lower cost automated approaches, which could include aerial and drive-by thermal imaging at-scale in an effort to measure the building R-value. However, single-point in time thermal images are generally qualitative, subject to errors stemming from building dynamics, background radiation, wind speed variation, night sky thermal radiation, and error in extracting temperature estimates from thermal images from surfaces with generally unknown emissivity. This work proposes two alternative approaches for estimating roof R-values from thermal imaging, one a physics based approach and the other a data-mining based approach. Both approaches employ aerial visual imagery to estimate the roof emissivity based on the color and type of roofing material, from which the temperature of the envelope can be estimated. The physics-based approach employs a dynamic energy model of the envelope with unknown R-value and
thermal capacitance. These are tuned in order to predict the measured surface temperature at the time of the imaging, given the transient weather conditions prior to the imaging. The data-mining approach integrates the inferred temperature measurement, historical utility data, and easily accessible or potentially easily accessible housing data. A data mining regression model, trained from this data using residences with known R-values, is used to predict the roof R-value in the unknown houses. The data mining approach was shown to be a far superior approach, demonstrating an ability to estimate attic/roof R-value with an r-squared value of greater than 0.88 using as few as nine training houses. The implication of this research is significant, offering the possibility of auditing residences remotely at-scale via aerial and drive-by thermal imaging coupled with utility analysis.
Dedicated to my parents, wife and son. I hope that this achievement will complete the dream that you had for me.
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This journey would not have been possible without the support of my family, professors mentors, and friends. To my family, thank you for encouraging me in all of my pursuits and inspiring me to follow my dreams. I am especially grateful to my parents, who supported me. I always knew that you believed in me and wanted the best for me. Thank you for teaching me that my job in life was to learn, to be happy, and to know and understand myself; only then could I know and understand others.

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without her continuous support and encouragement I never would have been able to achieve my goals.
# TABLE OF CONTENTS

ABSTRACT ............................................................................................................................... iv
DEDICATION .......................................................................................................................... vii
ACKNOWLEDGEMENTS ......................................................................................................... viii
LIST OF FIGURES ................................................................................................................ xiii
LIST OF TABLES .................................................................................................................... xv
CHAPTER I INTRODUCTION ................................................................................................. 1
  1.1 Motivation ...................................................................................................................... 1
  1.2 Building Energy Consumption ..................................................................................... 2
  1.3 Big Data Driving Energy Efficiency ............................................................................ 6
  1.4 Energy Auditing .......................................................................................................... 9
  1.5 Remote Measurements for Improved Auditing ........................................................... 12
  1.6 Overview and Scope of Approach .............................................................................. 13

CHAPTER II MULTI-SPECTRAL IMAGING POTENTIAL FOR SURFACE
DETERMINATION AND TEMPERATURE MEASUREMENT ................................................... 16
  2.1 Abstract ....................................................................................................................... 16
  2.2 Background ................................................................................................................ 17
    2.2.1 R-Value from Temperature Measurements .......................................................... 17
    2.2.2 Objectives ........................................................................................................... 21
    2.2.3 IR Thermography ............................................................................................... 21
  2.3 Multi-Spectral Emissivity Estimation ........................................................................ 24
    2.3.1 Surface Spectral Emissivity .............................................................................. 24
    2.3.2 Wavelength Selection ....................................................................................... 27
  2.4 Neural-Network Surface Identification and Temperature Measurements ............. 30
    2.4.1 Temperature Estimation ................................................................................... 34
2.5 Results .................................................................................................................... 35
  2.5.1 Multi-Spectral Surface Signatures ...................................................................... 35
  2.5.2 Neural Net (NN) Classification Performance ................................................................ 38
  2.6 Conclusions ............................................................................................................. 39

CHAPTER III MULTI-SPECTRAL IMAGING EXPERIMENTAL VALIDATION .... 41
  3.1 Experimental Design ............................................................................................... 41
  3.2 Experimental Procedure .......................................................................................... 43
  3.3 Data Analysis ......................................................................................................... 44
  3.4 Conclusions ............................................................................................................. 46

CHAPTER IV VISUAL IMAGING FOR SURFACE DETERMINATION ........ 47
  4.1 Visual Determination of Roof Type ......................................................................... 47
  4.2 Temperature Estimation ......................................................................................... 49

CHAPTER V ESTIMATION OF R-VALUES OF RESIDENTIAL ROOFS VIA
AERIAL THERMAL IMAGING USING PHYSICS-BASED AND DATA MINING
MODELS ....................................................................................................................... 52
  5.1 Abstract ................................................................................................................ 52
  5.2 Background ........................................................................................................... 53
    5.2.1 Motivation ........................................................................................................ 53
  5.3 Energy Audits ......................................................................................................... 54
    5.3.1 IR Thermography for Auditing ........................................................................ 54
    5.3.2 Utility Analysis ................................................................................................. 58
    5.3.3 Objectives ....................................................................................................... 58
  5.4 Data Description .................................................................................................... 59
    5.4.1 Raw Data ....................................................................................................... 59
  5.5 IR-based Roof Temperature Measurement ................................................................ 61
    5.5.1 Normalized Annual Heating Consumption (NAHC) ............................................ 62
    5.5.2 Physics-Based Energy Model to Estimate R-Value ............................................ 64
  5.6 Data-Mining Approach for Estimating the Roof R-Value ........................................ 68
    5.6.1 Data-Mining Models ....................................................................................... 69
  5.7 Results .................................................................................................................... 70
    5.7.1 Physics-based Modeling Results .................................................................... 70
5.7.2 Data Mining Results ................................................................. 72
5.8 Conclusions ............................................................................. 74
REFERENCES ................................................................................ 78
LIST OF FIGURES

Figure 1. Energy saving by building type [21] ................................................................. 4
Figure 2. The energy-saving potential for buildings [22]................................................... 5
Figure 3. Utility analysis regression fitting example .......................................................... 8
Figure 4. Temperature transient of a low R-value wall for a step change in exterior
temperature and constant interior temperature predicted from ASHRAE 1052 V 1.0
[42] .................................................................................................................................. 19
Figure 5. Spectral emissivities for eight different materials versus wavelength .......... 25
Figure 6. Sub-bands for multi-spectral data collection.......................................................... 28
Figure 7. Average emissivity values for each surface for the three MWIR sub-bands. .... 29
Figure 8. Measured intensities for all surfaces at three MWIR sub-bands, at 289 K. .... 30
Figure 9. Measured intensities for all surfaces at three MWIR sub-bands, at 260 K. .... 30
Figure 10. Example Neural Network Diagram [46] ............................................................ 32
Figure 11. Neural network based model for estimating surface type. .............................. 33
Figure 12. Linear relationship between temperature and the log of intensity in the 8-12
micron region ...................................................................................................................... 35
Figure 13. Photographs of the wall panels with sample building materials .................... 42
Figure 14. Diagram of the experimental set-up for multi-spectral IR data collection....... 43
Figure 15: Example image of the asphalt shingle target from the MWIR camera, with
the 4-5 micron filter ........................................................................................................... 45
Figure 16. High resolution IR thermography image (left) registered to visual image (right) .................................................................47

Figure 17. Google Earth Imagry ................................................................................................................................. 49

Figure 18. Aerial thermal image of an artificial turf stadium used as a reference area........ 51

Figure 19. Temperature transient of a low R-value wall for a step change in exterior temperature and constant interior temperature predicted from ASHRAE 1052 V 1.0 [42] ........................................................................................................................................57

Figure 20. Aerial thermal image of residential neighborhood targeted.......................... 60

Figure 21. Roof R-value measurements versus roof surface temperature measurement for 79 homes .............................................................................................................................. 62

Figure 22. Roof R-value measurements versus NAHC for the 79 homes. .......................63

Figure 23. Dynamic energy model for characterizing the thermal behavior of the attic space (not to scale) ......................................................................................................................... 65

Figure 24. Rooftop and ceiling temperatures versus time, found from numerically solving equations (20) and (21) for a sample house ..........................................................................................72

Figure 25. Measured and predicted R-value for sample size of 30 sorting by NAHC sorting ........................................................................................................................................74
LIST OF TABLES

Table 1: Center wavelengths and bands for multi-spectral measurements .................. 28
Table 2. Distances between the emissivity vector for each material pair .................... 36
Table 3. Absolute difference between average FWIR emissivities for each pair of materials ......................................................................................................................... 37
Table 4. Categories and associated emissivities for the shingles roof ...................... 48
Table 5. Shingles color vs emissivity ........................................................................ 61
Table 6. Predictor variables for data-mining approach ............................................ 64
Table 7. R-square performance values for each model, as applied to homes not in the training set .................................................................................................................. 73
CHAPTER I
INTRODUCTION

1.1 Motivation

Most of the world’s energy, about 87%, is currently provided by burning fossil fuels, mostly coal, oil, and natural gas [2]. Even though climate change is increasingly recognized as a problem which is created by the burning of fossil fuels, worldwide consumption of fossil fuels is still increasing. For example, global natural gas consumption grew by 2.2% in 2012 and coal consumption grew by 2.5% in 2012. These increases are happening even though technology is improving energy efficiency (for example, hybrid cars) and industrialized nations are reducing their reliance on the most carbon intensive fossil fuel, namely coal [2]. Part of the reason for this increase is that countries like China and India, which had lower per capita energy consumption, are increasing their demand, as they grow their economies.

Using renewable energy sources is one way to reduce the dependency on fossil fuels and to lower carbon emissions. Another way is to improve energy efficiency, so that it takes less energy to do the same task. For example, compact fluorescent light bulbs and LED technology are making household lighting much more efficient [3]. Appliances, computers, vehicle technology, airplane engines, et al. are technologies where energy effectiveness has improved [4].
1.2 Building Energy Consumption

One sector where there is a lot of potential for impacting climate change is in buildings, because approximately 40% of world energy consumption and 24% of all CO2 emissions are due to energy use in buildings [5]–[7]. Because buildings remain in use for many decades, and because the retrofitting existing buildings is cheaper than constructing new energy efficient ones, retrofitting is currently the most feasible and practical method to reduce energy demand in the building sector [8].

To further break this down, more than 60% of building energy consumption is used for heating, ventilation, air conditioning, and lighting. According to a report from the Intergovernmental Panel on Climate Change (IPCC), CO2 emissions from buildings have doubled from 4 gigatonnes (Gt) per year in 1971 to about 8 Gt per year in 2004 and are expected to reach up to 14 Gt per year in 2030 mainly as a result of increasing energy consumption from developing countries [9].

The U.S. EIA predicts that residential electricity consumption will increase by 13% from 2013 to 2040, industrial consumption will increase by 17%, and commercial electricity consumption will increase by 19%, leading to increased CO2 emission [10]. On average, in 2009 every MWh of power that is produced in the US generates 1,216 pounds of CO2 [11]. Assuming a social cost of $35 per ton of CO2, an annual social cost of $28 billion is associated with electricity use in buildings in the US [11].

Directives like 2002/91/EC [12] and 2010/31/EU [13] have been issued by the European Union in order to mitigate the environmental and economic impacts of energy consumption in buildings. The national transposition of such directives have generated
national and regional regulations in order to establish minimum requirements on the energy performance of new and existing buildings subject to major renovations [14]. Several worldwide organizations which have established targets for carbon emission reduction in this sector. The American Institute of Architects (AIA) has set a carbon neutrality goal for all new buildings by 2030 [15]. Many architecture firms in the US have adopted their plan. The Climate Policy Initiative (CPI) for China, Germany, and the United States also established a detailed set of carbon reduction goals for the building sector, including four categories: plans for new construction, retrofitting old buildings, more efficient equipment for buildings, and building management [16]. Germany has established a gigantic lead in the goal setting, having set a goal of 80% reduction in primary energy use in buildings by 2050. The US goal and timeline pale in comparison. The Building Technologies Office (BTO) reports a US building energy reduction of 20% commercial building energy reduction by 2020 and a residential energy reduction of 30% with no timeline attached [17].

Beyond regulatory requirements, retrofitting buildings to improve their energy efficiency can be economically beneficial, with simple paybacks for many measures less than 3 years [9]. Many statewide governments put into place different policies to impact energy efficiency in existing buildings [18]. Some of these policies include strengthening the regulatory energy standards for new buildings, controlling the quality and maintenance of existing buildings, encouraging energy-saving behavior by home owners and stimulating the diffusion and innovation of energy-efficient technologies. Technological innovation, in particular, could play a large role in reducing further the energy consumption of buildings.
More specifically, the energy efficiency of heating systems and other appliances has greatly improved over the past decades and recent developments in solar boilers, geothermal energy or lighting technologies are also having impact (IEA, 2008) [19]. Standard retrofit measures provide cost-effective and low-risk efficiency upgrade options for building owners who are limited to making incremental capital upgrades to their building. Standard retrofit measures include equipment, system and assembly retrofits.

Because most buildings are older and less energy efficient, there is a large potential for decreasing energy, CO2 emissions, and cost by retrofitting buildings. It was recently reported that up to $1 trillion could be saved in the US over the next decade through energy retrofits [20]. Potential savings for different building types are shown in Figure 1. This chart shows that there are significant energy and energy cost savings using existing technologies for all types of buildings [21].

![Energy Savings by Building Type (Trillions of Btu)](source: Deutsche Bank, Retrofiticiency)

Figure 1. Energy saving by building type [21]
The Rocky Mountain Institute has studied the energy-saving potential for buildings for the next 40 years as shown in Figure 2 below [22]. If the efficiency stays the same during this time and construction continues as predicted, there would be 58.4 quadrillion BTU’s (quads) of energy used by buildings in 2050. However, it is expected that due to improved efficiency, this number will be reduced by 5.8 quads. Further improvements can be made through their Reinventing Fire initiative. These improvements could potentially reduce predicted building energy demand by an estimated 54% to 69% [22].

Figure 2. The energy-saving potential for buildings [22]
Another organization that studies potential energy savings for buildings is the US Department of Energy (DOE), which commissioned a detailed study of HVAC technology, to identify and list which technologies could save most energy [23]. The DOE has a Zero-Net Energy Commercial Building Initiative (CBI), which has the goal to develop marketable Zero-Net Energy Commercial Buildings using new technologies and on-site renewable energy generation to offset their energy use from the electricity grid by 2025 [24].

1.3 Big Data Driving Energy Efficiency

Retroficiency, a start-up building efficiency intelligence company for utilities and energy service providers, has offered one solution. Their solution uses a “big data” approach to collect and analyze energy and weather related data. Its proprietary software platform creates a unique energy model of any building to provide actionable insights that address the full efficiency delivery lifecycle. It enables the fastest, most cost-effective way to target the worst buildings for energy savings, engage customers with tailored opportunities, convert projects, track new opportunities, and verify savings at scale. Retroficiency has evaluated billions of square feet of buildings [25].

Utility analysis is a key feature of Retroficiency and others in their effort to reduce the on-site audit needs, relying upon increasingly sophisticated analytics to develop information about building energy use effectiveness, even disaggregated by energy use categories.

The basic idea in utility analysis is to correlate energy consumption with external temperature, and perhaps other factors, especially if interval energy data is available for a
facility [26], [27]. For temperature only considerations, linear regressions have been used to fit monthly utility data with monthly average outdoor temperature since the 1990s [28], to create fits for cooling and heating seasons [29], of the form below:

\[ E_h = B_h + H_s(T_{bal,h} - T_{ext}) \]  \hspace{1cm} (1)

\[ E_c = B_c + C_s(T_{ext} - T_{bal,c}) \]  \hspace{1cm} (2)

As shown in Figure 3. In equations (1) and (2), \( E_h \) and \( E_c \), respectively represent the amount of energy in kWh used per month, \( T_{ext} \) is the average monthly external temperature, and \( B_h \) and \( B_c \) are the temperature-independent monthly baseline energy consumptions for hot and cold temperatures, respectively. The heating slope \( H_s \) and cooling slope \( C_s \) provide information about how many kilowatt-hours of energy are consumed per month (or some other time interval) for each degree of external temperature change. If the average monthly temperature drops below the heating balance temperature \( T_{bal,h} \), then the first equation is used to model the heating energy consumption. If the average monthly temperature rises above the cooling balance temperature \( T_{bal,c} \), then the second equation is used to model the cooling energy consumption. The heating and cooling slopes represent an effective building R-value divided by the respective heating and cooling system efficiencies [30]. These can be defined as follows:
\[ H_s \sim \frac{UA_{tot}}{Eff_{heating}} \]  

(3)

\[ C_s \sim \frac{UA}{Eff_{cooling}} \]  

(4)

where

\[ UA_{tot} = UA_{roof} + UA_{walls} + UA_{windows} + UA_{infiltration} \]  

(5)

\[ Eff_{heating} = \text{Heating system efficiency} \]

\[ Eff_{cooling} = \text{Cooling system efficiency} \]

Figure 3. Utility analysis regression fitting example

In general, this approach has been used to increase information about building energy use effectiveness, disaggregated by energy use categories. However, at least presently, these approaches are not capable of resolving savings from specific actionable measures. For example, utility analysis permits disaggregation of energy consumption into
weather and weather independent components through the use of a regression analysis of monthly energy consumption with weather data for the respective billing period, but it cannot illumine where problems exist, e.g., it cannot tell whether the heating or cooling system or controls, or envelope characteristics represent the biggest problem.

Badr et al. have combined results from utility analysis with available or potentially available residential building data (R-values of walls, windows, and attic; heating and cooling system and water heating efficiencies) and used data mining to predict savings for all measures that could reduce heating and cooling energy. The savings predictions they developed for specific measures are within 5% of the actual savings [26], far better than what has been realized from use of energy models [26], [27].

The important point from this recent research by Badr et al. is this. If the envelope thermal characteristics can be estimated, the overall heating and cooling system effectiveness and/or infiltration/make-up air issues may be capable of being resolved.

1.4 Energy Auditing

There are clearly lots of opportunities for cost effective energy reduction. However, there is difficulty in finding these opportunities. An energy audit is an essential ingredient in determining how much energy can be saved in each facility. But, the number of audits that can be performed is small relative to the number of buildings. This is particularly true in the residential sector.

A recent survey indicated that very few homeowners are aware of the potential savings available to them. Lack of information about specific ways to improve energy efficiency and reduce unnecessary energy use has long been identified as an important
reason why all types of building owners, including homeowners, do not make apparently cost-effective improvements in their buildings or upgrade to more efficient appliances or equipment. Energy audits are a way to provide homeowners and building occupants of all types with information about current energy use, inefficiencies, and ways to improve the energy performance of their homes [31].

The goal of an energy audit for a building is to determine energy consumption levels, in terms of where the energy is used, how much is used, when it is used, and especially in determining where energy is wasted [32]. Before physically inspecting the building, the building’s utility data are collected and compared to similar buildings. Depending on the size of the building and the budget for an audit, there are several possible levels of auditing. An examination of energy bills and a site walk-through by an auditing expert is a starting point, which can lead to easy to find changes to lower energy consumption. Higher levels of auditing include measurements of key building systems, such as HVAC and lighting, performing blower tests to look for air leakage, and thermal imaging. A full economic assessment can lead to concrete analysis of the potential cost savings by implementing changes that the audit finds.

Auditing a building is technically challenging, and often the results of an audit are inconsistent and may not lead to the best energy-saving solutions [33]. It requires trained experts to accurately collect, analyze and summarize data and create an accurate recommendation for energy savings. For example, if an auditor incorrectly identifies the type of windows or insulation, the audit may lead to a bad recommendation. Also, the technology for performing an audit, such as blower doors and thermographic cameras, only provide information on efficiency at one point in time, and that information is very limited.
It has been shown that the auditing industry has a lot of wrong and inconsistent auditing procedures [34]. Furthermore, auditing will often overestimate the amount of savings that an energy improvement will realize, which discourages building owners and investors from using an audit. Another impediment is the cost of energy auditing, costing on average about $0.50 per square foot of building space [35].

One measure of the usefulness of the information in audits is how often building residents who do have audits follow up on the recommendations. In the residential sector, one study showed that homeowners rarely adopt all the improvements recommended from an audit. While most respondents indicated that homeowners usually follow up with at least one improvement, almost 30 percent reported that homeowners make at least one improvement only about half the time or less. This leaves a significant number of consumers paying for audit services but doing very little to improve the energy efficiency of their homes. Also, many who do have an audit do not follow up on the recommendations that the audit made [36].

Although building energy efficiency is improving, this sector still falls disappointingly short of meeting its full potential. Even when a building owner or manager goes through the process of an audit and retrofit, results can be inaccurate and inconsistent, especially when compared across an entire portfolio. There are many reasons for this shortfall, but it essentially comes down to two factors: people and tools. The people factor is real; the diligence of the audit team and the skills of the retrofit installers can change the results of an energy retrofit drastically. But for now, let’s talk about the tools [37]. In order to be effective and pervasive, audit tools must improve.
1.5 Remote Measurements for Improved Auditing

It may be possible to streamline residential energy auditing with automated measurements, e.g., measurements that can be conducted at low cost and at-scale. If this could happen, when combined with the approach of Badr et al. [26], it might be possible to for energy auditing to access all residences (and buildings).

Tools such as infrared (IR) imagery, which gives qualitative heat loss information for a building, might be used to achieve this automated or data-driven energy auditing. Many researchers and building auditors are not satisfied with the qualitative nature of IR thermal imaging, and many efforts are made to turn the grey-scale values in these images to temperatures. This is called IR thermography. Achieving a temperature measurement from an IR greyscale value involves an understanding of the physics of thermal radiation, transmission through the atmosphere, the camera’s operation, and understanding optical processes that can cause errors. This process is vulnerable to many sources of error. First, an IR camera collects significant background radiation and reflected radiation that is mixed with the desired emitted radiation from the surface of interest. The background and reflected radiation depend on weather conditions and the orientation and temperatures of objects near the surface of interest. Second, generating a temperature estimate from a raw IR camera measurement requires knowledge of the emissivity of the surface being imaged, which is generally unknown and which can be affected by the age and condition of the surface. These sources of error cause the uncertainty for a thermal image derived temperature to be greater than the difference in temperature between the surface and outside ambient air temperatures [38].
Even if an accurate surface temperature measurement can be made remotely for a building, there are many additional sources of error involved in estimating envelope properties, such as R-value, from this measurement. First, the building’s thermal capacitance makes it extremely difficult to use a single point in time measurement to predict an R-value. To interpret a single temperature measurement, many researchers ignore transient effects or assume that the building was at thermal steady-state at the time of the measurement. Others attempt to use weather data for times immediately prior to the measurement, along with a thermal model for predicting heat-exchange through the envelope, in order to use a single surface temperature measurement to infer R-value. Regardless of the method, modeling assumptions about wind conditions, interior temperatures, infiltration, and other factors introduce many sources of error into the process of estimating R-value. These errors are so big that a previous researcher, Goldstein, had concluded that it would be impossible to accurately estimate the R-value of walls from a single point in time measurement [39].

1.6 Overview and Scope of Approach

The approach used here seeks to overcome some of the obstacles to IR imaging to enable its use in automated energy auditing. Three separate options are considered. First, an effort is made to accurately identify surface emissivity and temperature using multi-spectral IR imaging. This approach relies on the idea that different building surfaces have unique spectral emissivity patterns which can theoretically be used to identify the surface. Chapter 2 addresses the theoretical description of this idea, along with simulation results. Chapter 3 documents an experimental approach to validate the viability of this approach.
The results will show that the signal-to-noise ratio of multispectral cameras compromise the ability to use this approach for emissivity estimation.

Due to the experimental difficulty of the multi-spectral approach outlined in Chapter 3, and its large sensitivity to noise, an alternative approach for determining the surface emissivity is outlined in Chapter 4. This approach relies on visual imagery of exterior surfaces, basing emissivity estimation on the perceived color and texture of the surface to estimate the emissivity. This manual approach is a significant retreat from the automated approach described in Chapter 3, but there was little alternative since multi-spectral IR data is unavailable. Although tedious, the manual approach for estimating surface emissivity allows for improving the surface temperature and subsequent R-value measurements.

With some estimate of the exterior temperature capable of being made if the surface emissivity can be accurately identified, the second and much bigger obstacle to IR imaging being used to estimate the R-value of envelope components (walls, windows, roofs) is the time-varying nature of weather and the thermal capacitance offered by envelope components. The surface temperature of an envelope component is dependent not just on the current exterior temperature, but also on the exterior temperature for many hours preceding a thermal imaging event. Two approaches are posed in Chapter 5 to account for the dynamics of the envelope component subject to the transient weather conditions preceding the imaging. The first relies upon development of a dynamic physical model of an envelope component that was calibrated against single point in time thermal imaging measurement of the surface temperature of an envelope component. The modeled envelope R-value and thermal capacitance were tuned in order to predict an exterior wall temperature
equal to the measured surface temperature from the thermal imaging given the historical weather conditions up to 48 hours previous to the measurement. The results will show the qualitative value of this approach, but also show that the ability to predict the R-value from this approach is not possible.

A second approach is proposed that uses the temperature derived from aerial thermal imaging (which inherently has a large uncertainty) along with building geometrical data and energy consumption data. Data mining approach linear model (LM) and random-forest regression tree (RF) models are developed based upon this data and a small sample of residences for which the R-value (of the ceiling) is known. The developed model is then applied to the remainder of the houses to predict the ceiling R-value. The predictions using this approach, as will be seen in Chapter 5, are strikingly good.
CHAPTER II
MULTI-SPECTRAL IMAGING POTENTIAL FOR SURFACE
DETERMINATION AND TEMPERATURE MEASUREMENT

2.1 Abstract
Remote thermal imaging of buildings is notable for providing interesting but generally qualitative images of buildings. A recent study showed that if accurate measurements of exterior surface temperatures could be obtained from single-point-in-time-imaging, then it would be possible to infer envelope R-values and thermal capacitances with reasonable accuracy. This research seeks to answer the question, “How can we make possible reasonably accurate measurements of the external temperatures from at-scale remote imaging?” Without knowledge of the emissivity of the exterior surfaces, accurate thermal assessment is seemingly impossible. Here, we exploit the unique spectral characteristics of the most common exterior building surfaces using multi-spectral imaging. Four to five images of exterior surfaces in the 1-5 micron range, where the spectral emissivity of different building materials changes most, is posed. The pattern of the emission can be correlated to various envelope component surface spectral emissivities. A neural network pattern matching algorithm is used to ‘find’ the surface type. Then, with known emissivity, the surface temperature can be inferred from the magnitude of the emission. Theoretical results indicate that temperature error in measuring the surface
temperature in using this approach can be less than ±1°C. This error is sufficient for identifying envelope R-values based upon the research posed by Salahaldin and Hallinan [1]. Most exciting is the prospect of this technique for effectively measuring building R-values at scale via fly-over or drive by imaging.

2.2 Background

2.2.1 R-Value from Temperature Measurements

Extracting meaningful auditing information from single-point in time temperature measurements is difficult. For example, an envelope R-value can be estimated considering steady-state conditions according to the following equation:

\[ R = \frac{\dot{Q}}{\Delta T} = \frac{(T_i - T_s)}{(T_s - T_\infty)} \]  

(6)

where \( \dot{Q} \) is the estimable convective heat transfer to or from the exterior surface based upon the measured surface temperature \( T_s \) and air temperature \( T_o \). The convection coefficient \( h_0 \) can be estimated using correlations for common building geometries and known wind speed, and the interior wall surface temperature \( T_i \) may also be measured or known. However, the time constant associated with most envelope components (walls, ceilings) is on the order of hours, and such a steady-state determination is generally associated with large error.

Many researchers, however, have reported results using this steady-state assumption. For example, Grinzato et al. utilized thermal imaging and air temperature measurements at a specified distance from the interior side of a wall to measure the heat transfer through the wall [40]. From this, they were able to estimate the R-value. Ham and
Golparvar-Fard likewise estimated the building R-value from thermal imaging using again a steady state thermal analysis [41]. They then coupled the imaging with computational heat and flow analysis to infer local variation in R-value. This approach was quite good in predicting the R-value; but has no hope of success at scale.

None of the efforts to date which have used thermal imaging to calculate R-value have reported the transient weather conditions prior to the imaging. All thermal imaging practitioners understand the influence that prior historical weather information has on the surface temperature. Both exterior and interior surface temperatures are not in phase with the outside temperature. For example, a simulation with the ASHRAE-1052 Version 1.0 transient building thermal analysis toolkit, reveals significant transient effect. Figure 4, for example, shows the transient exterior and interior surface temperature transient after a step change in outdoor temperature [42]. It is clear from the figure that the exterior temperature takes more than 20 hours to reach steady-state [42]. If the R-value is higher and/or the thermal capacitance is larger, even longer transients are observed. A steady-state interpretation of thermal images therefore can only be valid if the outside and inside temperatures are steady over a period of at least a day or more.
Figure 4. Temperature transient of a low R-value wall for a step change in exterior temperature and constant interior temperature predicted from ASHRAE 1052 V 1.0 [42]

Goldstein et al., in assessing the potential of thermal imagery to estimate U-values for building envelopes using a quasi-steady-state model for the buildings and external measurements of temperature, first required quasi-steady-state external weather conditions, at least for 3-4 hours prior to measurement. Further, they restricted the temperature difference inside and outside to 10 degrees. They then validated their thermography results to other independent measurements of U-value, using thermohygrometer and notional results. They found a standard deviation from 10-20% between their measured U-values and the actual values, and the largest errors were found in roof and glazing measurements [39]. These researchers also did a sensitivity analysis to elucidate errors using their approach. They found that the accuracy of the U-value measurement is most sensitive to a changing outdoor temperature (e.g., non-steady-state conditions) and the assumed emissivities for the building surface, which are not known exactly. The authors studied which effects had the most impact on error, and ranked them as first order effect or higher order effects. The errors in the values of emissivity and background radiation were discerned to have the strongest effect on the accuracy of the surface temperature
measurement. An overestimate of surface emissivity will lead to an underestimate of the surface temperature, for example. Radiation from nearby objects can reflect from the surface of interest, increase the measured IR intensity, and lead to a surface temperature overestimation. Surface temperature measurement errors such as these can then lead to errors in predicting R-value. For example, the MIT researchers showed that if the emissivity value is off by 0.5%, then the predicted R-value can be as much as 40% to 50% in error. The time varying inside and outside air temperatures, and interior and exterior heat transfer coefficients also contribute to the error [39]. Goldstein concluded that estimating the R-value from thermal imaging was not possible [39].

Building on the MIT work, Alshathsati et al. attempted to address one of the largest sources of error found by the MIT researchers, which is associated with a changing outside surface temperature for the building [1]. Alshathsati et al. used the previous 48 hours of weather and solar data to reduce the error in this variable by developing a transient model of the building. A genetic algorithm-based approach was used to find the envelope component R-value and thermal capacitance which minimizes the error between the predicted external surface temperature at the measurement time from the dynamic model and the measured surface temperatures. The results show that this inverse model methodology is capable of accurately estimating envelope thermal characteristics over a realistic spectrum of envelope R-values and thermal capacitances present in a sample of typical homes in Dayton, Ohio. With an assumed thermal image accuracy of ±5°C, thermal characteristics are predicted with a maximum error of respectively ±20% and ±14% for high and low R-values respectively when the standard deviation of outside temperature over the previous 48 hours is approximately 5°C [1]. Errors of less than ±5% are realized
when the standard deviation in outside temperature prior to the imaging is less than 1.3 °C [1]. Highly problematic, however, they showed that a 5% error in specifying the surface translates to an error in predicting the R-value of 18%.

2.2.2 Objectives

In this context, the following seeks to investigate the feasibility of measuring the emissivity of exterior surfaces of walls and roofs in an automated fashion to overcome the error in measuring the surface temperature via infrared imaging, and thus the R-value of the envelope component.

The following presents a theoretical basis for potentially inferring the surface emissivity from multi-spectral imaging of surfaces.

2.2.3 IR Thermography

Accurate surface temperature measurements are required in order reduce the error for an approach like Alshatshati’s. An IR thermography measurement, \( I \), from a surface is approximately proportional to the emitted spectral radiance, integrated over the wavelength band of sensitivity for the thermal camera.

\[
I \propto \int \frac{C_1 \varepsilon(\lambda)}{\lambda^5 \left[ e^{\frac{C_2}{kT \lambda}} - 1 \right]} d\lambda
\]  

(7)

This equation ignores the effects of reflected or transmitted radiation from the surface, or instrument noise. In this equation, \( C_1 \) and \( C_2 \) are known constants, \( T \) is the true surface temperature, \( \lambda \) is wavelength, and \( \varepsilon(\lambda) \) is the spectral emissivity. With the goal of inferring \( T \) from the measurement, \( I \), the emissivity must be known. However, exact
determination is difficult, although it is around 0.9 for many building surfaces in the far infrared spectrum, e.g., the wavelength range where thermal images takes place.

For aerial IR imaging, raw intensity values $I$ can be converted to temperature through the following process, which is similar to the process developed by Schott [31]. Several ground targets with known temperatures $T_1, T_2, ..., T_N$ are measured during a flyover. The corresponding raw intensities are given by $I_1, I_2, ..., I_N$. Predicted radiance $R_1, R_2, ..., R_N$ from these known targets is generated with Plank’s law [32].

$$ R_i = \frac{\varepsilon C_1}{\lambda^5 \left[ e^{\frac{C_2}{\lambda T_i}} - 1 \right]} $$

This formula approximates the radiance by taking the wavelength to be the center of the IR camera’s wavelength band. The targets are chosen such that their common emissivity $\varepsilon$ is known and is constant over the wavelength band. A linear regression is performed to create a model $R(I) = \beta_0 + \beta_1 I$. Plank’s law is then solved for temperature, to give the following.

$$ T(I) = \frac{C_2}{\lambda \ln(\frac{\varepsilon C_1}{\lambda^5(\beta_0 + \beta_1 I) + 1})} $$

This provides a calibration for turning raw intensities into temperatures [32]. There are various methods in the literature for estimating emissivity of surfaces. For example, Madding examines several techniques for attaching reference emitters to targets [43]. If the target and reference are at the same temperature, the known emissivity for the reference can be used to find the target emissivity. Alternatively, the target emissivity can be found
if the temperature of the target and reference is the same and is known. It was demonstrated that accuracy of the target emissivity measurement improves if the target temperature was significantly higher than the background temperature, as this condition reduces the deleterious effects of background radiation.

Schott and Wilkinson [31] developed a similar technique for estimating emissivity of roofing material in the 8-14μm band. A large constant temperature cavity was used to reduce the effects of background radiation. The same controlled measurements were carried out with a target and a surface of known emissivity, to estimate the target’s emissivity. The emissivity measurement error was estimated as ± 0.02 [33].

Snyder and Schott noticed a relationship between the line-of-site angle and emissivity [34]. Other researchers have concluded, however, that the viewing angle does not matter until it exceeds a certain value [33].

It is also possible to estimate emissivity using two measurements at different wavelength bands, for example, the 3 -5 micron and 8-12 micron bands [35]. This estimation uses a graybody treatment of the surfaces, such that the emissivity is constant over all wavelengths. In this case, the two separate measurements are influenced by the same surface temperature and emissivity. With some modifications to account for wideband imaging, it is possible to eliminate the temperature and use the two measurements to solve for emissivity.
2.3 Multi-Spectral Emissivity Estimation

Here, a physics-based approach is developed to describe the infrared emission from building surfaces, beginning with Planck’s relationship for blackbody surface emission. The emission from a surface is the product of the blackbody emission at a given wavelength and the surface spectral emissivity at that wavelength. This approach considers a limited number of building materials, each with a unique spectral emissivity pattern. An imager capturing data at several distinct wavelengths theoretically produces a pattern of spectral emission from a surface. The following seeks to show that the resulting pattern that can be used to identify the surface and surface emissivity in the far infrared spectrum where thermal imaging takes place.

2.3.1 Surface Spectral Emissivity

The primary driver for this research is the signature spectral emissivity (and reflectivity) patterns for different kinds of building materials [36]. Figure 5 shows the spectral emissivity for a variety of materials common to walls and roofs. It is clear from this figure that different practical exterior surfaces have unique spectral emissivity patterns.
Figure 5: Spectral emissivities for eight different materials versus wavelength

The 8-12 micron region of the spectrum (termed far infrared) is used for thermal imaging, and a single representative emissivity value (typically 0.9) is used for this range. The spectral emissivities shown in Figure 5 vary significantly over this range, showing the error in emissivity that can result by simply setting the exterior emissivity to 0.9.

The images captured via an infrared camera from high emissivity surfaces will be dominated by the blackbody emission from the surface (not reflected energy), because of the generally high emissivity of the surfaces. Planck’s law [44] provides the spectral emissive power from a surface according to:

\[ E_b(\lambda, T) = \frac{C_1}{\lambda^5 e^{(C_2/\lambda T)} - 1} \left( \frac{W}{m^2.\mu m} \right) \]  \hspace{1cm} (10)

where

\( \lambda \): is wavelength in \( \mu m \).

\( T \): is temperature in Kelvin.
$C_{01} : 3.742 \times 10^8 \left( \frac{W}{\mu m^4 \cdot m^2} \right)$. 

$C_2 : 1.439 \times 10^4 \left( \frac{\mu m}{K^0} \right)$. 

The intensity of emitted light from a material over a specific wavelength range is given by:

$$I (\lambda_0, T) = \frac{1}{2 \Delta \lambda} \int_{\lambda_0 - \Delta \lambda}^{\lambda_0 + \Delta \lambda} \varepsilon(\lambda) E_b (\lambda, T) d\lambda \quad (11)$$

where

\(\varepsilon(\lambda)\) : is the material emissivity.

\(\lambda_0\) : is the center wavelength.

\(\Delta \lambda\) : is the range of wavelengths for the instruments.

Equation (11) can be rewritten for a variable centering wavelength over a given wavelength range, with an assumed constant spectral emissivity over a small \(\Delta \lambda\).

$$I (\lambda_0 \pm \Delta \lambda, T) = \frac{\varepsilon(\lambda_0)}{2 \Delta \lambda} \int_{\lambda_0 - \Delta \lambda}^{\lambda_0 + \Delta \lambda} E_b (\lambda, T) d\lambda \quad (12)$$

where

\(\overline{\varepsilon(\lambda_0)}\) : is the average value of \(\varepsilon(\lambda)\) over the range of wavelengths.

When the surface emissivity is low, the captured image includes significant reflected power as well as emitted power, according to:

$$I (\lambda_0 \pm \Delta \lambda, T) = \frac{1}{2 \Delta \lambda} \int_{\lambda_0 - \Delta \lambda}^{\lambda_0 + \Delta \lambda} \varepsilon(\lambda) E_b (\lambda, T) d\lambda + \frac{1}{2 \Delta \lambda} \int_{\lambda_0 - \Delta \lambda}^{\lambda_0 + \Delta \lambda} \rho(\lambda) E_{background} (\lambda, T) d\lambda \quad (13)$$

where \(E_{background}\) is the background radiative power, and \(\rho(\lambda) = 1 - \varepsilon(\lambda)\) is surface reflectivity. Inclusion of this term would require some estimate of the background.
temperature. For roofs and for isolated building walls, this estimation would be possible. Otherwise it would be a complex undertaking [45].

For the emissivity profiles contained in Figure 5, it would be ideal if the center wavelengths for multispectral imaging could be chosen to maximize the ability to distinguish the materials from one another. However, the choice of wavelengths is dictated by available multispectral imaging sensors. Based on available sensor technology, the infrared spectrum is divided into three practical sub-bands: 3.5 to 4.1 microns, 4.4 to 5.0 microns, and 8-12 microns. For each material, equation (13) can be used to model the images gathered for each sub-band.

### 2.3.2 Wavelength Selection

The choice of a set of center wavelengths $\lambda_1, \lambda_2, \ldots$ would ideally be made based on the spectral emissivity variations in order to optimally separate the multispectral measurements from one another and minimize the possibility of confusing two similar materials. However, practical considerations such as available sensor and filter technology take precedence. IR sensors are available for the mid-wave band (MWIR) of 2-5 microns, and the far-wave band (FWIR) of 8-12 microns. Since most of the spectral emissivity variability illustrated in Figure 6 occurs in the lower wavelengths, it is logical to further sub-divide the MWIR band, in order to measure these variations. Narrowband filters are available for achieving this disaggregation of the signal. A single measurement is collected for the FWIR band, since there is less variability in the emissivities over this band, and because this is the band used for temperature measurements. This logic leads to the center wavelengths organized in Table 1, and illustrated in Figure 6.
Table 1: Center wavelengths and bands for multi-spectral measurements

<table>
<thead>
<tr>
<th>Center Wavelength (µm)</th>
<th>Lower Edge (µm)</th>
<th>Upper Edge (µm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \lambda_1 = 2.5 )</td>
<td>2.0</td>
<td>3.0</td>
</tr>
<tr>
<td>( \lambda_2 = 3.5 )</td>
<td>3.0</td>
<td>4.0</td>
</tr>
<tr>
<td>( \lambda_3 = 4.5 )</td>
<td>4.0</td>
<td>5.0</td>
</tr>
<tr>
<td>( \lambda_4 = 10.0 )</td>
<td>8.0</td>
<td>12.0</td>
</tr>
</tbody>
</table>

Figure 6. Sub-bands for multi-spectral data collection

In Figure 6, the lower MWIR region from 2-5 microns will be further sub-divided into the sub-bands as indicated in Figure 6. This process will thus produce three measurements: \( I_1 \), \( I_2 \), and \( I_3 \), as determined by the equations shown in Figure 6. Because of the variability in the spectral emissivity over this range, we anticipate that these three measurements will serve as a signature that will allow the material to be identified.
The fourth measurement is $I_4$, representing the full emission over the 8-12 micron range. After identifying the surface type and therefore the emissivity from the pattern generated over the MWIR region, this measurement can be used for temperature estimation.

Figure 7 indicates the emissivity variation for the different materials over the three MWIR sub-bands. There is clear difference in emissivity between the different surfaces in this wavelength range.

![Average Material Emissivity at Each Center Wavelength, FWHM=1](image)

**Figure 7.** Average emissivity values for each surface for the three MWIR sub-bands.

Figure 8 and Figure 9 indicate the type of response from each sub-band, at different temperatures, for the different surfaces shown in Figure 7. Figure 8 shows the response at a high temperature of 290 K, and Figure 9 shows the response at a low temperature 260 K.
2.4 Neural-Network Surface Identification and Temperature Measurements

In this section, the methodology for estimating the surface type and temperature from multispectral data is described. The approach taken assumes a realistic range of building surface temperatures, independent of emissivity. Then, the spectral emission from the surface at several sub-bands is estimated using equation (12). The imager is assumed
to capture a signal that will be linearly proportional to the emission. A simulated “data
cube” of imager signals as a function of surface type, temperature, and sub-band is used to
train a neural network to identify surface type (but not temperature) from a single set of
three MWIR emission measurements from an unknown surface at any constant
temperature. Then, with surface type established, the emissivity can be assigned, and the
surface temperature estimated. This requires only the FWIR emission from the 8-12 micron
sub-band. The following details these steps.

The remote thermal measurements should be conducted in the winter, so that there
is a significant difference between the indoor and outdoor temperatures. Buildings that
have good insulation will have exterior surface temperatures close to the outdoor
temperature. Buildings with poor insulation will have an exterior surface temperature close
to the indoor temperature. Therefore, the range assumed for surface temperature for the
Ohio region should be in the range of 10 to 15°C. Fifty samples within this range are used.

A neural network is used to interpret the pattern of emission to determine the
surface type. The type of neural network used in this work is a feedforward network with
one hidden layer. An example of this type of network is illustrated in Figure 10. In the
example, the network accepts two input values, has a “hidden layer” of three neurons, and
has one output neuron. The inputs are multiplied by weights as they are passed to the hidden
layer, and a linear combination of the weighted inputs is formed at each hidden neuron.
The neurons each evaluate function of these linear combinations, called an “activation
function”. The output neurons repeat this process, forming linear combinations of the
results from the hidden layer. This function calculates the output of a neuron from its input.
The neuron outputs are scaled by a different set of weights as they are passed to the output functions [46].

To validate this approach, a small set of material types is considered representing the spectrum of external surfaces seen in the world, and the data are assumed to come from one of these materials. For each material type, wavelength and temperature, equation (14) is used to calculate the theoretical spectral emitted power $I(\lambda, T)$ within the specified narrow wavelength bands. This creates a 3D data structure with temperature along the first dimension, wavelength along with a second and material type along the third dimension. Thus for each material type, we have the spectral emitted power at fixed wavelengths and for surface temperatures over the entire range of surface temperatures expected on roofs and walls. These data can be arranged in different ways and used as inputs to train a pattern matching neural network (NN). The goal will be to use the measured spectral power at several wavelengths as inputs, and surface type and surface temperature as outputs. A trained NN will associate the inputs with specification of the surface type, as shown in

![Example Neural Network Diagram](image)

**Figure 10. Example Neural Network Diagram [46]**
Figure 11. This NN has three inputs, corresponding to the emitted powers in the three MWIR sub-bands, 10 hidden neurons, and one output neuron.

Figure 11. Neural network based model for estimating surface type.

After the surface type and therefore emissivity is identified, the 8-12 micron data is used to estimate surface temperature. This is done in the same way that many IR cameras use. There is a linear relationship between the log of the camera reading and the temperature for the 8-12 micron region. Once the camera is calibrated and an emissivity value for the surface is known, this linear relationship is used to produce a temperature estimate.

The data cube generated according to equation (13) is used to train the NN in order to identify surface type. This process involves creating a data cube with 80 randomly selected temperatures within a specified range, and re-shaping this data cube into an appropriate matrix for use in Matlab’s NN tools. Only the three MWIR sub-bands are used in the training process, because the FWIR data will only be used for temperature
estimation. The training process randomly selects a subset of the data cube for training, and uses the rest of the data to test the trained NN for accuracy.

2.4.1 Temperature Estimation

For the 8-12 micron data, there is a useful linear relationship between the measurement and temperature.

\[ I_k(T) = \int_{8\mu m}^{12\mu m} \varepsilon_k(\lambda) E_b(\lambda, T)d\lambda \]  

(14)

\[ \log(I_k(T)) \approx (\beta_1)T + \beta_{0,k} \]  

(15)

In equations (14) and (15), the subscript \( k \) identifies the surface type, and the raw reading from the IR camera for FWIR range at temperature \( T \) is \( I_k(T) \). Taking the log of this reading gives a line, with slope \( \beta_1 \) and intercept \( \beta_{0,k} \). Note that the slope is not a function of the material type, but the intercept \( \beta_{0,k} \) is. This equation can be solved for \( T \). This step is also a part of the overall block diagram shown in Figure 11. Figure 12 illustrates the linear relationship for the emitted intensity for various surface types as a function of temperature.
Notice in Figure 12 that several of the lines are clustered very close together, which indicates similar emissivities in the 8-12 range for these materials. This means that if the NN makes an identification error, it will not necessarily effect the temperature measurement for these materials.

2.5 Results

2.5.1 Multi-Spectral Surface Signatures

In order for the NN to have the best possible performance for distinguishing the surfaces from one another, the emissivity patterns at the three MWIR wavelengths should be distinct. To measure how distinct the patterns are from one another for the eight surface types considered, the distance between the emissivity vectors for materials $j$ and $k$ at the sub-bands $\lambda_1$, $\lambda_2$, and $\lambda_3$ is computed as follows.
This formula is used to compute the “emissivity distance” between two materials (surfaces), $j$ and $k$. The resulting distance data is summarized in the Table 2 below. On average, the distance between the materials is about 0.72.

The results also indicate that if the wall material is assumed to be known, then it is possible to use a neural network to obtain an estimate of the temperature from the three wavelength intensity measurements.
If two materials in the table have a small distance between their MWIR emissivity vectors, then it is likely that the NN classification may confuse them. In this case, it is important to know the corresponding difference between the FWIR emissivities, since this is the emissivity used in the surface temperature estimation as shown in Table 3 above shows the absolute difference between the FWIR emissivities for each pair of materials.

Some of the materials have very similar FWIR emissivities, such that if the algorithm confuses these two materials, it will have little impact on the emissivity determination at FWIR. For example, wood and terra-cotta tiles have very nearly the same emissivity.

<table>
<thead>
<tr>
<th></th>
<th>Bare Red Brick</th>
<th>wood</th>
<th>Olive Green Gloss Paint</th>
<th>Asphalt Roofing Shingle</th>
<th>White Fiberglass Roofing</th>
<th>Terra Cotta Tiles</th>
<th>Red smooth-faced Brick</th>
<th>Black tar paper</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bare Red Brick</td>
<td>0.0000</td>
<td>0.0104</td>
<td>0.0494</td>
<td>0.0077</td>
<td>0.0012</td>
<td>0.0108</td>
<td>0.0315</td>
<td>0.0084</td>
</tr>
<tr>
<td>wood</td>
<td></td>
<td>0.0390</td>
<td>0.0027</td>
<td>0.0116</td>
<td>0.0004</td>
<td>0.0210</td>
<td>0.0021</td>
<td></td>
</tr>
<tr>
<td>Olive Green Gloss Paint</td>
<td></td>
<td>0.0417</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Asphalt Roofing Shingle</td>
<td></td>
<td></td>
<td>FileSystemFolder</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>White Fiberglass Roofing</td>
<td></td>
<td></td>
<td>FileSystemFolder</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Terra Cotta Tiles</td>
<td></td>
<td></td>
<td>FileSystemFolder</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Red smooth-faced Brick</td>
<td></td>
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<td></td>
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<td>0.0231</td>
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<td>FileSystemFolder</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 3. Absolute difference between average FWIR emissivities for each pair of materials.
2.5.2 Neural Net (NN) Classification Performance

In order to test the NN classification performance, the data cube generated according to equation (11) is first used to train the NN. Eighty randomly selected temperatures within a specified range (260-290 K) are considered. The emission intensity is computed at each temperature at the three MWIR sub-bands. The training process randomly selects 70% of the data cube for training, and uses the rest of the data to test the trained NN for accuracy.

For the eight different surfaces considered, only about 1% of surfaces were misclassified for the test data, which is excellent. However, it should be noted that this result is premised upon the assumption that there is no noise in the spectral emissions from the theoretical surfaces considered. After each data vector is classified, the algorithm then uses the data in the FWIR band for the temperature measurement. The standard deviation for predicting the temperature is about ±0.25 K, which would be tremendous.

The system works well without noise, but its performance breaks down when random errors are added to the training data cube. Randomly generated noise values in the range of ±2% of the intensity values are added to each point in the data cube. When this is processed by the NN, 72% of the surfaces were misclassified. However, this misclassification translated to a standard deviation error in predicting the surface temperature of ±1.3 K. The problem with this is that the greater uncertainty emerges from only ±2% noise in the theoretically measured intensity.
2.6 Conclusions

This work considers using multi-spectral infrared imaging in order to improve the ability to remotely measure surface temperature. The motivation for doing this is to get a more accurate surface temperature measurement, which could then subsequently be used in finding envelope properties for buildings, such as R-values.

The method exploits variability in spectral emissivity for common building surfaces. Most of this variability appears in the MWIR (2-5 micron) range. Therefore, the work proposes to collect three infrared measurements within this range, with these measurements serving as a signature for each material due to the unique spectral emissivity profiles of surfaces.

A NN classification system is trained using simulated MWIR intensity measurements, modeled from Plank’s law and assuming ideal imaging conditions. Eight materials with known spectral emissivities are examined. The trained NN is given an MWIR data vector (3 intensity values) from an unknown surface, and it uses these values to identify the surface. After surface identification, the measurement made at the FWIR range (8-12 microns) is used to estimate the surface temperature, based on the known surface emissivity for the identified material in the FWIR range.

Simulations conducted with the full system indicate that it works well with low-noise conditions, correctly identifying the materials and leading to a surface temperature error standard deviation of about ±0.25 K. Identification breaks down in the presence of noise; increasing the standard deviation in temperature error to ±1.3 K in the case of 2% additive noise. Even with high percentages of misclassifications, the NN may be
identifying a material with similar emissivity in FWIR. Thus, the temperature error is still small; although maybe not small enough to accurately estimate the R-value.

For future work, the current model for I (\(\lambda\)) does not include sources of error, such as background radiation, or error caused by variations in the surface. The model will require modification to incorporate these sources of error. It is also possible to model the physics of the camera more precisely. Also, in the future, rather than using model data, it would be better to use real measurements to train a neural network. Then, the model data can be compared to the real experimental data, to validate the model. This is the subject of the next chapter.
CHAPTER III
MULTI-SPECTRAL IMAGING EXPERIMENTAL VALIDATION

In order to validate the proposed multi-spectral IR approach for surface identification, emissivity determination in the thermal imaging spectrum, and temperature measurement, experiments are necessary. This chapter describes the experiment design, experimental process, and data analysis used in an attempt to validate this approach.

3.1 Experimental Design

Figure 14 illustrates the main components of the experimental set up for collecting multi-spectral data. An FLIR SC6800 MWIR camera, with spectral sensitivity ranging from 2-5 microns, is combined with narrowband IR filters placed in the camera aperture in order to image within 3 MWIR sub-bands: 2-3 microns, 3-4 microns, and 4-5 microns [47], [48]. Within a controlled indoor lab environment, the camera images a 2 ft x 2 ft square wall panel at its focal distance (roughly 3 m from the aperture). The wall panel temperature can ideally be controlled with heating or cooling devices. For each image the camera is directed perpendicular to the wall sample.

A total of six wall panels were created using commonly available building materials. Each wall panel represents a single category of building material, and each has multiple material samples from this category. The categories are asphalt roofing, paint,
stucco, stone, and vinyl. Figure 13 shows photographs of each wall panel that was imaged, with a total of twenty-one different surface materials among the five categories.

![Figure 13. Photographs of the wall panels with sample building materials](image)

For the initial data-collection test, a single IR image for each wall-panel for each narrow band pass filter was taken. For all cases, the panels were at ambient room temperature (70 °F). The emitted energy at this temperature is greater than would be present...
for winter time images. Note that the camera sensor is cooled to about -170 °C; thus it was perceived as capable to image room temperature surfaces.

3.2 Experimental Procedure

For each combination of sample panel and MWIR filter, the following steps were followed.

1. Collect a baseline noise image by covering the camera’s aperture and generating a time-averaged image.
2. Remove the lens cover and place the narrowband filter in the lens holder in front of the camera aperture.
3. Image the target wall panel, integrating over a period of roughly two minutes to improve signal strength.
4. Subtract the baseline noise image from the image of the target wall panel.

Figure 14. Diagram of the experimental set-up for multi-spectral IR data collection
The data was collected under ideal conditions, because the overhead lighting in the lab space was left on, possibly contaminating the imagery with reflected IR radiation; but given the relatively large emissivities of the surfaces imaged, this should have translated to only a small error.

3.3 Data Analysis

The planned approach for analyzing the raw data was to segment the images according to the different samples on the target board. The pixel intensities for each segmented region would be averaged to find a single average intensity value corresponding to each combination of material and wavelength. This data would form a series of MWIR vectors, and a subset of these could be used to train the NN system. The rest of the dataset would be used to test the accuracy of the NN identification. If this worked, then the FWIR emissivity for the identified material could be found from a database of emissivity patterns. Then, this emissivity value could be used to estimate surface temperature using a separate FWIR measurement.

Figure 15 illustrates a processed image collected from the MWIR camera for asphalt shingles using the 4-5 micron narrowband filter. The outline of the square board that the shingles were attached to is visible, along with a metal clamp that shows up as a bright white object to the right. The metal clamp is at the same temperature as the target, but it reflects more IR radiation than the target, which is why it shows up as a bright object.
There were three problems with the image data: first, the images contain high noise levels, which may have been due to the filters blocking too much of the emitted radiation from reaching the camera. The second problem is that the filters, which were smaller than the camera aperture, created circular artifacts, which largely obscure the view of the target. Third, and most importantly, the images taken with the 2-3 and 3-4 micron filters had no or virtually no signal strength. The sensitivity of the camera coupled with the low signal at small MWIR wavelengths (See equation (12)) effectively negated any possibility for this approach to work.
3.4 Conclusions

Due to the noise and artifact problems and the absence of sufficient signal at lower MWIR wavelengths, it was not possible to pursue the multi-spectral imaging approach to estimate emissivity. Perhaps this is a camera that would be more sensitive in the wavelength range from 2-4 microns; however, such a camera would be incredibly expensive. Moreover, one camera could not be used to capture signal over the desired 2-5 micron spectrum desired. Ultimately such a system would be impractical for aerial or drive-by imaging.

As a result, an alternative, visual approach for surface identification and therefore emissivity estimation was posed. Chapter 4 describes this approach.
CHAPTER IV

VISUAL IMAGING FOR SURFACE DETERMINATION

In this Chapter, a visual imaging approach to estimate the surface emissivity is employed. The approach relies on aligning aerial visual imagery with the IR data. Then, manual inspection of each roof in the visual image can be used to classify the roof type, and approximate the emissivity according to the type. Then, this approximated emissivity is used in temperature estimation.

4.1 Visual Determination of Roof Type

Figure 16 below shows two registered aerial views of buildings. The right image in Figure 16 is a high-resolution visual image, which can be zoomed for inspection of any specific building. The left image in this figure shows the IR thermography image of the same neighborhood. Each roof in the visual image is manually inspected, and categorized by its shade. Only roofs that at addresses that are known to have shingle tiles are inspected.

Figure 16. High resolution IR thermography image (left) registered to visual image (right)
Table 4 below illustrates the categories and associated emissivities for the shingle roofs [49]. An image example is shown for each category. From the google earth imagery as shown in Figure 17, the shade of the roof is used to determine the category.

Table 4. Categories and associated emissivities for the shingles roof
4.2 Temperature Estimation

The aerial thermal imaging of the neighborhood in which these houses are located was conducted on December 29th, 2014, at 8:30 PM, completed over a 2 hour period. The imaging was performed from a low altitude aircraft flying at an altitude of 880 m [50]. The average weather conditions during this time were as follows: outdoor air temperature = -3 °C; clear skies; wind direction = 10° North to South; wind speed = 3 m/s; and relative humidity = 78%. An FLIR model SC8303 thermal imaging camera was used for the imaging.

After collecting the data, the sequence of raw images was stitched together with mosaicking software to create the single high-resolution image of the neighborhood, as
shown in the left of Figure 16. Additional software tools were used to segment the roofs in this image, and to identify the address for each roof.

The aerial thermal imagery leads to a single intensity value for each roof, as an average over all of the pixels within the segmented roof region. These values are used to develop a temperature estimate of each roof assuming all the roofs have the same emissivity of 0.889. A large reference area, an artificial turf stadium shown in Figure 18, in the field of view is used in this process [50]. These temperature values are then corrected by using the roof emissivities from observing the asphalt coloring. This modified emissivity is used to create a “corrected” temperature measurement, depends on bias temperature that was determined by Woolpert Company according to the following equation.

\[
\text{Corrected Temperature} = (T_{old} - T_{bias}) \times (\varepsilon / 0.889) + T_{bias} \tag{17}
\]

The parameter \(T_{bias}\) in this equation is one possible source of bias error in the temperature measurement.
For each house, monthly natural gas and electricity meter data is available from the local utilities for the year 2014. Additional house details are available from a local government website [51]. This dataset includes the finished floor area, presence of basement, construction type (wood frame or brick), number of bedrooms, and year built. Maximum occupancy for each residence was provided by the university owning the houses.
CHAPTER V

ESTIMATION OF R-VALUES OF RESIDENTIAL ROOFS VIA AERIAL THERMAL IMAGING USING PHYSICS-BASED AND DATA MINING MODELS

5.1 Abstract

Conventional residential building energy auditing needed to identify opportunities for energy savings is expensive and time consuming. On-site energy audits require quantification of envelope R-values, air and duct leakage, and heating and cooling system efficiencies. There is a need to advance lower cost automated approaches, which could include aerial and drive-by thermal imaging at-scale in an effort to measure the building R-value. However, single-point in time thermal images are generally qualitative, subject to errors stemming from building dynamics, background radiation, wind speed variation, night sky thermal radiation, and error in extracting temperature estimates from thermal images from surfaces with generally unknown emissivity. This work proposes two alternative approaches for estimating roof R-values from thermal imaging, one a physics based approach and the other a data-mining based approach. Both approaches employ aerial visual imagery to estimate the roof emissivity based on the color and type of roofing
material, from which the temperature of the envelope can be estimated. The physics-based approach employs a dynamic energy model of the envelope with unknown R-value and thermal capacitance. These are tuned in order to predict the measured surface temperature at the time of the imaging, given the transient weather conditions prior to the imaging. The data-mining approach integrates the inferred temperature measurement, historical utility data, and easily accessible or potentially easily accessible housing data. A data mining regression model, trained from this data using residences with known R-values, is used to predict the roof R-value in the unknown houses. The data mining approach was shown to be a far superior approach, demonstrating an ability to estimate attic/roof R-value with an r-squared value of greater than 0.88 using as few as nine training houses. The implication of this research is significant, offering the possibility of auditing residences remotely at-scale via aerial and drive-by thermal imaging coupled with utility analysis.

5.2 Background

5.2.1 Motivation

Approximately 40% of world energy consumption and 24% of all CO2 emissions are due to energy use in buildings [4-6]. According to a report from the Intergovernmental Panel on Climate Change (IPCC), CO2 emissions from buildings have doubled from 4 gigatonnes (Gt) per year in 1971 to about 8 Gt per year in 2004, and they are expected to reach 14 Gt per year in 2030 due to expected increases in energy consumption in developing countries [52]. Thus, there is a strong need for energy reduction in all buildings, but especially existing buildings, since these make up the vast majority of the building stock.
Retrofitting older buildings to improve their energy efficiency can be economically as well as environmentally beneficial, with a payback period of less than 3 years in some cases [53]. It was recently reported that up to $1 trillion could be saved in the US over the next decade with energy retrofitting [54].

5.3 Energy Audits

Energy audits are a key step in the process to achieve energy reduction. However, there are a number of impediments to completing these across the entire residential sector. First, is the cost of auditing a home, ranging from $300-$500 [55]. Additionally, there is a dearth of certified auditors; only Approximately 12,000 are certified in the U.S [56], not even close to enough to survey all houses in the country. Second, the technology used to perform an audit, such as door blowers and thermographic cameras, only provide information on efficiency at one point in time, and thus can be sources of uncertainty for the recommendations made. Third, the savings estimates from energy audits are most often over-estimated, and, times, considerably so [54].

5.3.1 IR Thermography for Auditing

It may be possible to streamline residential energy auditing with automated measurements, e.g., measurements that can be conducted at low cost at-scale. If this could happen, when combined with the approach of Badr et al., who used knowledge of building R-values, along with historical utility data and building data to accurately estimate savings and cost effectiveness of energy reduction measures in houses, it might be possible to for energy auditing to access all residences (and buildings) at relatively low cost [26].
Extracting meaningful auditing information from single-point in time thermographic image inferred temperature measurements is difficult. For example, an envelope R-value can be estimated considering steady-state conditions using:

\[
R = \frac{\dot{Q}}{\Delta T} = \frac{(T_i - T_s)}{(T_s - T_\infty)}
\]  

(18)

where \(\dot{Q}\) is the estimable convective heat transfer to or from the exterior surface based upon the measured surface temperature, \(T_s\), and air temperature, \(T_\infty\). The convection coefficient \(h_o\) can be estimated using correlations for common building geometries and known wind speed, and the interior wall surface temperature \(T_i\) may also be measured or known.

Many researchers have explored this problem assuming steady-state or quasi-steady-state conditions. For example, Grinzato et al. utilized thermal imaging and air temperature measurements at a specified distance from the interior side of a wall to measure the heat transfer to the wall \[57\]. Combining these data with surface or internal air temperature measurements allows the overall thermal resistance to be theoretically estimated using Equation (18). Ham and Golparvar-Fard likewise estimated the building R-value from thermal imaging using again a steady state thermal analysis \[55\]. They then coupled the imaging with computational heat and flow analysis to infer local variation in R-value.

Goldstein et al., in assessing the potential of thermal imagery to estimate U-values for building envelopes using a quasi-steady-state model for the buildings and external measurements of temperature, required quasi-steady-state external weather conditions at
least for 3-4 hours prior to measurement. Further, they required that the temperature difference between the inside of a house and outdoors be greater than 10 degrees. They then validated their thermography results to other independent measurements of U-value, using a thermohygrometer and notional results. They found a standard deviation from 10-20% between their measured U-values and the actual values, with the largest errors were found in roof and glazing measurements [39]. These researchers studied which effects had the most impact on error, and ranked them as first order effector or higher order effects. The errors associated with emissivity specification and background radiation were discerned to have the strongest effect on the accuracy of the surface temperature measurement. For example, an overestimate of surface emissivity will lead to an overestimate of the surface temperature. Radiation from nearby objects can reflect from the surface of interest, increase the measured IR intensity, and lead to a surface temperature overestimation. They also documented that transient weather conditions can also significantly impact the error.

The transient nature of the envelope is something well known by thermal imaging practitioners. Both exterior and interior surface temperatures are not in phase with the outside temperature. For example, a simulation with the ASHRAE-1052 Version 1.0 transient building thermal analysis toolkit, reveals significant transient effect. Figure 19, for example, shows the transient exterior and interior surface temperature transient after a step change in outdoor temperature [42]. It is clear from the figure that the exterior temperature takes more than 20 hours to reach steady-state [42]. If the R-value is higher and/or the thermal capacitance is larger, even longer transients are observed.
Figure 19. Temperature transient of a low R-value wall for a step change in exterior temperature and constant interior temperature predicted from ASHRAE 1052 V 1.0 [42]

It is obvious that if the dynamic nature of the weather and the thermal capacitance of the building envelope could be accounted for, one of the largest sources of error in translating exterior thermal images to an R-value estimate could be mitigated. Only a recent effort by Alshatshati et al., which used time-varying weather conditions present in the 48 hours prior to the imaging of an exterior surface and a genetic algorithm optimization to tune an envelope component R-value and thermal capacitance included in a dynamic wall model to predict the measured exterior surface temperature at the imaging time. But, this research, like that posed by Goldstein et al, also pointed to the importance of an accurate surface temperature measurement in order to realize accurate predictions of the R-value. It showed sizable errors if the actual temperature of the surface couldn’t be inferred accurately from thermal images.
5.3.2 Utility Analysis

Utility analysis has proven a cost-effective way to identify high energy consuming buildings and verify savings from retrofits at scale [37]. The basic idea is to correlate energy consumption with external temperature, and perhaps other factors, especially if interval energy data is available for a facility or if the consumption can be disaggregated by energy use categories. Linear regressions have been used to fit monthly utility data with monthly average outdoor temperature since the 1990s, to estimate the sensitivity of energy consumption to outdoor temperature changes [26], [56], [57]. These sensitivities, when applied to typical annual weather consumption data for a site, have yielded estimates of annual weather normalized total, heating, and cooling consumption [58]. However, this approach has not been capable of resolving savings from specific actionable measures. For example, it cannot tell whether the heating or cooling system or controls, or envelope characteristics represent the biggest problem.

5.3.3 Objectives

Recognizing both the promise of automated energy audited of residences and the role that at-scale thermal imaging might have in this process, research is posed to improve the ability to predict R-values from thermal imaging; in this case aerial thermal imaging. Two approaches are posed. The first relies upon a physics based dynamic energy model to account for transient weather conditions prior to the imaging. A second approach, called a data-mining based approach, combines the thermal imaging data, visual imaging of the exterior surfaces, utility analysis results, and easily accessible building geometry data to estimate the R-value. In this approach a data-based model is trained using this data to
predict R-values from a sampling of houses for which the R-value is known. The trained model is then applied to other houses to predict the R-value using the new predictors.

5.4 Data Description

5.4.1 Raw Data

This study is based upon analysis of seventy-nine single-family, detached residences having peaked asphalt shingle roofs located in the Midwest of the US. An energy audit was completed for each of these houses to document the amount of insulation present in the attics and walls, the window types and areas, and heating (natural gas furnaces), cooling, and water heating equipment. The housing set analyzed includes a diversity of houses, with construction years ranging from the early 1900s to current and with square footages ranging from 75.5 to 177.7 m².

Enabling this research effort was an aerial thermal imaging effort of the neighborhood in which these houses are located on December 29th, 2014, at 8:30 PM, completed over a 2 hour period. The imaging was conducted from a low altitude aircraft flying at an altitude of 880 m [50]. The average weather conditions during this time were as follows: outdoor air temperature = -3 °C; clear skies; wind direction = 10° North to South; wind speed = 3 m/s; and relative humidity = 78%. An FLIR model SC8303 thermal imaging camera was used for the imaging.

After collecting the data, the sequence of raw images was stitched together with mosaicking software to create a single high-resolution image of the neighborhood. Additional software tools were used to segment the roofs in this image, and to identify the
address for each roof. The overall post-processed aerial image of the targeted neighborhood is shown in Figure 20 below.

![Aerial thermal image of residential neighborhood targeted](image)

**Figure 20. Aerial thermal image of residential neighborhood targeted**

For each house, monthly natural gas and electricity meter data is available from the local utilities for the year 2014. Additional house details are available from a local government website [51]. This dataset includes the finished floor area, presence of basement, construction type (wood frame or brick), number of bedrooms, and year built. Maximum occupancy for each residence was provided by the university owning the houses.

Visual imagery of the roofs (google earth images) are used to categorize the roofing material and color for each roof in the study. All roofs in this neighborhood were asphalt
shingles. The color categories of the observer roofs and their associated emissivities are summarized in the Table 5 [49].

Table 5. Shingles color vs emissivity

<table>
<thead>
<tr>
<th>Shingles color</th>
<th>Emissivity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ocean Grey</td>
<td>0.885</td>
</tr>
<tr>
<td>weathered Wood</td>
<td>0.917</td>
</tr>
<tr>
<td>Surf Green</td>
<td>0.839</td>
</tr>
<tr>
<td>Aspen Grey</td>
<td>0.828</td>
</tr>
<tr>
<td>Onyx Black</td>
<td>0.967</td>
</tr>
<tr>
<td>Beach wood sand</td>
<td>0.792</td>
</tr>
<tr>
<td>weathered Wood</td>
<td>0.917</td>
</tr>
</tbody>
</table>

5.5 IR-based Roof Temperature Measurement

The aerial thermal imagery leads to a single intensity value for each roof, as an average over all of the pixels within the segmented roof region. These values are used to develop a temperature estimate of each roof assuming all the roofs have the same emissivity of 0.889, and a large reference area (astroturf stadium) in the field of view is used in this process [50]. These temperature values are then corrected by using the roof emissivities from observing the asphalt coloring depends on bias temperature that was determined by Woolpert Company according to the following equation. The correction equation is

$$\text{Corrected Temperature} = (T_{old} - T_{bias}) \times (\varepsilon/0.889) + T_{bias} \quad (19)$$
Figure 21 shows a scatterplot of the identified roof temperatures and the measured roof R-values. The correlation coefficient is -0.89, thus demonstrating a reasonable correlation between the R-value and interpreted temperature; although it is clear that any attempt to estimate the R-value directly from only the roof temperature measurement would be far from perfect.

![Figure 21. Roof R-value measurements versus roof surface temperature measurement for 79 homes](image)

### 5.5.1 Normalized Annual Heating Consumption (NAHC)

The next data-processing step is to determine a normalized annual heating consumption (NAHC) for each house [58]. The natural gas monthly consumption data available for each house is used to do this, since no electricity is used for heating. This measure reflects estimated total heat loss from the house (roof and walls) for a typical weather year in Dayton, Ohio. Because the wall area is typically 3-4 times the roof area, roof heating loss (which determines roof temperature) may not be dominant. The correlation of NAHC with roof R-value is shown in Figure 22, indicating poor correlation.
Table 6 below summarizes the nomenclature used for the data collected and used in the analysis. It also shows how the data was collected. The roof R-value, $R_{\text{roof}}$, was measured for all houses in the study through an on-site energy audit.
Table 6. Predictor variables for data-mining approach.

<table>
<thead>
<tr>
<th>Variable Name</th>
<th>Description</th>
<th>Collection Mechanism</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T_{measured}$</td>
<td>Corrected roof surface temperature ($K$)</td>
<td>From aerial thermal image</td>
</tr>
<tr>
<td>NAHC</td>
<td>Normalized annual heating consumption ($MJ/year$)</td>
<td>From utility analysis of monthly energy data.</td>
</tr>
<tr>
<td>$Y$</td>
<td>Year built</td>
<td></td>
</tr>
<tr>
<td>$N_R$</td>
<td>Total number of rooms</td>
<td></td>
</tr>
<tr>
<td>$N_{BR}$</td>
<td>Number of bedrooms</td>
<td></td>
</tr>
<tr>
<td>$N_{BA}$</td>
<td>Number of bathrooms</td>
<td></td>
</tr>
<tr>
<td>$A_F$</td>
<td>Floor area ($m^2$)</td>
<td></td>
</tr>
<tr>
<td>$I_B$</td>
<td>Indicator variable for presence of basement</td>
<td></td>
</tr>
<tr>
<td>$O_M$</td>
<td>Occupancy maximum</td>
<td></td>
</tr>
<tr>
<td>$A_W$</td>
<td>Wall area ($m^2$)</td>
<td></td>
</tr>
<tr>
<td>$R_{roof}$</td>
<td>Roof area ($m^2$)</td>
<td>From on-site energy audit</td>
</tr>
</tbody>
</table>

5.5.2 Physics-Based Energy Model to Estimate R-Value

In this section, a physics-based energy model approach for estimating the roof R-value based only upon the single point in time measurement of the exterior roof temperature and knowledge of the weather for a two-day period immediately prior to this measurement. The weather data includes wind speed, solar radiation, outdoor air temperature, relative humidity, cloud cover, and cloud height, all collected at half-hour increments [59]. Figure 23 contains a diagram summarizing the model, which uses lumped
parameters to represent the thermal capacitances in the upper level ceiling and attic for each residence. Night sky radiation is also considered in the model, as this can have a substantial impact on exterior surface temperature of the roof. Assumed in the model is that the attic is a triangular air-space with no infiltration, and that the solar radiation has uniform intensity over the exterior roof surface, with an assumed pitch of 15 degrees, typical of the houses in the study. Assumed also is that the initial condition (e.g., 48 hours prior to the imaging time) is represented by steady-state conditions. The model predicts the transient temperatures in each of the thermal masses for the previous 48 hours prior to the imaging measurement.

Figure 23. Dynamic energy model for characterizing the thermal behavior of the attic space (not to scale)
Several quantities in the model are assumed to be known. First, the interior temperature $T_I$ is taken to be a constant, representing the air temperature in the house. This temperature would be potentially knowable from Wi-Fi thermostat temperature schedules. For this study, this data wasn’t available, so an assumed interior temperature of 22.22°C was assumed. Second, the roof thermal resistance, $R_R$, accounting for the serial thermal resistance of the roofing underlayer and shingles, is also assumed known, estimated from known values for typical construction materials (plywood and shingles). The convection thermal resistance at the interior of the ceiling, $R_I$, is taken to be a constant, set per ASHRAE 140-2007 recommendations [60]. The convection thermal resistance between the roof surface and outside air, $R_E$, is derived from the wind speed values at each time increment using heat transfer coefficient correlations [61]. The roof thermal mass $C_R$ is a known constant, estimated from the roof mass and heat capacity value for the roofing materials. The convection coefficients interior to the attic above the insulated surface and at the interior surface of the roof are determinable from the estimations of the top-most insulation and interior roof surface temperatures according to:

$$N_u = 0.15 \cdot R_a^{1.3}$$

(20)

The solar radiant flux is known from measurements collected on-site. Finally, the sky radiation is estimated according to [62]:

$$Q_{sky} = (1 + KC^2) \cdot 8.78 \times 10^{-13} \cdot T_\infty^{5.852} \cdot RH^{0.07195}$$

(21)

where

$Q_{sky}$: Downgoing thermal night sky radiation, $W/m^2$
K : 0.34 for cloud height < 2 km, 0.18 for cloud height between 2km and 5 km, and 0.06 for cloud height > 5km

C : Cloud cover (0.0 for clear sky through 1.0 for totally overcast)

T: Ambient temperature, degrees K

RH: Percent relative humidity

The weather data and sky condition data needed in the model were obtained from National Climatic Data Center (NCDC) historical weather database [63].

The dynamic energy balance for the upper level ceiling and roof are respectively by Equations (22) and (23). In these equations, the terms $dT_C/\, dt$ and $dT_R/\, dt$ are the time rates of change of the upper level ceiling and roof, respectively:

ceiling: \[ dT_C/\, dt = \frac{1}{C_C} (Q_I - Q_A) \] (22)

roof: \[ dT_R/\, dt = \frac{1}{C_R} (Q_A - Q_E) \] (23)

In these equations, the heat flows, $Q_I$, $Q_A$, and $Q_E$ respectively define heat flow rates from the interior to the upper level ceiling, from the ceiling to the attic (and also from the attic to the roof), and from the roof to the exterior. These are written as follows:

\[ Q_I = (T_I - T_C)/[(R_I + R_C/2)/A_C] \] (24)
\[ Q_A = (T_C - T_R)/\left[ \frac{(R_R/2 + R_{AR})}{A_R} + \frac{(R_C/2 + R_{CA})}{A_C} \right] \] \hspace{1cm} (25)

\[ Q_E = (T_R - T_E) * \left[ \frac{(R_R/2 + R_E)}{A_R} \right] + Q_{Sky} - Q_{solar,abs} \] \hspace{1cm} (26)

\[ T_{RE} = T_E + Q_E \frac{A_R}{R_E} \] \hspace{1cm} (27)

In these equations, the thermal resistances \( R_I, R_C, R_R, R_{AR}, R_{CA}, \) and \( R_E \), represent those associated with air below the ceiling, the ceiling, the roof, the air layers in the attic next to the roof and ceiling, and outside air, respectively. Finally, \( Q_{Sky} \) is the radiant heat emitted from the roof, and \( Q_{solar,abs} \) is heat absorbed by the roof from solar radiation.

The unknown quantities in the model are the ceiling thermal resistance, \( R_C \), and thermal capacitance, \( C \). These are estimated per the following logic. Given assumed initial conditions based upon assumed steady-state conditions using the known exterior temperature 48 hours prior to the imaging, the values for \( R_C \) and \( C_C \) are optimally determined to minimize the error between the predicted and measured exterior surface temperature, \( T_{RE} \). A genetic algorithm optimization approach is used to minimize this error. The \( R_C \) value found by this process can then be compared to the measured ceiling thermal resistance to evaluate the accuracy of the prediction.

**5.6 Data-Mining Approach for Estimating the Roof R-Value**

The data shown in Table 6 was defined for each residence in the study. Each observation included the following predictors for the data-mining model included: NAHC, the measured roof temperature measurement, total floor area, wall area, total number of
rooms, number of bedrooms, number of bathrooms, number of floors, presence of
basement and maximum occupancy. The target variable is the measured roof R-value.

Were an aerial thermal imaging approach to be used at scale, the roof R-values
would not in general be known. But, a data-mining approach would require knowledge of
the roof R-values for at least some of the residences to be imaged in order to develop a
data-based model capable of predicting the R-values of the remainder of residences
imaged. Ideally the number of houses needing to be audited to find the R-value should be
minimal; thus, it is important to intelligently select the houses for auditing to guarantee
that houses with high, medium, and low roof R-values would be audited. Two approaches
are posited for identifying these houses. The first approach groups houses according to
NAHC/floor area into low, medium, and high bins and then randomly selects the reference
houses to be audited from these subsets. These houses could be audited prior to the imaging
date. The second approach would look to audit houses after the imaging. It would group
the measured exterior roof temperatures from the collective group of houses imaged into
low, medium, and high bins and then randomly select the reference houses to be audit from
these subsets. Both approaches are considered in this study.

5.6.1 Data-Mining Models

Two types of data-based models were developed: Linear model (LM) and random-
forest regression tree (RF), LM assumes linear relationships between the target variable
and each predictor, whereas the other two machine-learning algorithms can naturally
handle non-linear relationships. Additionally, LM may require regularization to avoid
overfitting the data, but the other methods do not. LM is the fastest approach, although the
datasets in this study are small enough that speed is not an issue.
The RF algorithm is a data-mining classification and regression technique that is based on ensemble learning [63]. During RF training, many decision trees are created, and the mode of the classes for the trees is output. In a RF, a node is divided according to the best predictor from a subset of predictors randomly chosen at that node. The RF approach, although it is counterintuitive, performs very well when compared to many other classifiers, including discriminant analysis, support vector machines and neural networks. RF is robust against overfitting. Here, a convenient RF package within the R programming interface is used. This software package also produces additional information, including: a measure of the importance for each predictor variable, and a measure of the internal structure of the data [64]. An R-squared metric is used to evaluate the effectiveness of these approaches.

5.7 Results

5.7.1 Physics-based Modeling Results

Figure 23 illustrates the predicted exterior surface temperature for one of the houses as a function of time during the 48 hour period before the imaging. Also shown is the exterior temperature and solar flux. The ceiling R-value for this case is pushed to the maximum in order to minimize the error between the predicted and measured exterior temperature at the imaging time (t=48 hr). It is clear that even at the maximum R-value, the predicted exterior roof temperature is greater than the measured roof temperature. There are two possible reasons for this. The roof energy model employs unverifiable assumptions; for example, no air leakage in the attics. This is likely not the case, as wind can cause air flow into and out of the attic spaces through the eaves peripheral to all of the attic spaces present in the houses considered in this study. This airflow would reduce the roof
temperature. The second and likely more important reason for this is that the difference between exterior roof surface and the external environment is quite small regardless of the ceiling R-value. In fact, the difference in the steady-state exterior surface temperature for the high and low R-values is under 2°C. This temperature difference falls well within the uncertainty band of the surface temperature estimated from the aerial thermal images. Plus there is an almost certain bias error associated with the aerial thermal image inferred temperatures associated based upon an unknown sensor temperature for the camera flying at altitude. This would affect the accuracy of the $T_{bias}$ parameter in (17), leading to bias error in the surface temperature estimate. Future experiments point to the importance of measuring the temperature within the camera or on the camera at the time of the imaging and on some select roofs or ground surfaces at locations with known emissivity. Other sources of bias error in the temperature measurement could include reflected and background radiation. However, such a bias error won’t necessarily prevent utilizing the images to infer R-values via a data mining model. The next section presents the data-mining model based results.
Figure 24. Rooftop and ceiling temperatures versus time, found from numerically solving equations (20) and (21) for a sample house

5.7.2 Data Mining Results

The results the data-mining approach are presented in this section. Two methods were used - LM and RF - and their performances are compared. Each method is explored for different training set sizes and sampling methods. These are critical questions, since each house in the training set must be visited in order to make manual measurements of roof R-value, and a plan for selecting the homes to include in the training set is needed. Here, the training set is selected by first binning the homes into low, medium, and high categories based on a selected sorting variable. Two possible sorting variables are studied: the ratio of NAHC to floor area and measured roof surface temperature. Then, the same number of homes is randomly selected from the total set of houses in order to create a training set. The idea of this sampling approach is to obtain a training set that is likely to have roof R-values that span the full range of R-values present in all the homes. For each
combination of data mining algorithm, training set size, and sorting variable, a predictive model is created using the R programming package. Each model is then applied to all the homes in the dataset that were not used for training the model and the R-squared value is reported. Additionally, the results from the Random Forest approach indicate which predictor variables are most important for predicting R-value.

Table 7 shows the R-squared model performance for each combination of algorithm (LM and RF) sorting variable (NAHC/$A_F$ or $T_{measured}$) and training sample size (9, 12, 18, 24, or 30). Based on this table, several conclusions can be made. First, sorting the data according to NAHC/$A_F$ is clearly more effective than sorting according to $T_{measured}$. Second, the LM algorithm produces higher R-square values than the RF algorithm. Interestingly, the LM show very little sensitivity to the training sample size. For this study, only nine homes must be audited to effectively estimate the roof R-value.

### Table 7. R-square performance values for each model, as applied to homes not in the training set.

<table>
<thead>
<tr>
<th>Training Sample Size</th>
<th>RF Algorithm</th>
<th>LM Algorithm</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$NAHC/A_F$</td>
<td>$T_{measured}$</td>
</tr>
<tr>
<td>9</td>
<td>0.35</td>
<td>0.03</td>
</tr>
<tr>
<td>12</td>
<td>0.62</td>
<td>0.45</td>
</tr>
<tr>
<td>18</td>
<td>0.69</td>
<td>0.32</td>
</tr>
<tr>
<td>24</td>
<td>0.75</td>
<td>0.31</td>
</tr>
<tr>
<td>30</td>
<td>0.75</td>
<td>0.30</td>
</tr>
</tbody>
</table>

To further assess the LM model performance, Figure 25 presents the measured and predicted R-values for a training sample size of 9 and based upon NAHC/area sorting. It
is clear from this figure that in general the model predictions are pretty good, if not perfect. The model is however very effective in determining whether the R-value is low, medium, or high. This is a big accomplishment.

![Figure 25. Measured and predicted R-value for sample size of 30 sorting by NAHC sorting](image)

All of the predictor variables listed in Table 6 were used in the LM model development. However, the LM algorithm returns the relative significance of each variable, in terms of a p-value. The model indicates that the measured surface temperature, NAHC, and number of baths were most significant for the model.

### 5.8 Conclusions

The research question addressed in this work is whether roof R-values can be measured remotely at-scale via thermal imaging. The ability to accurately perform such a measurement would lower the cost for home auditing and make it easier to identify buildings that need efficiency retrofits. This research shows that the uncertainty in accurately measuring the roof temperature negates the possibility of utilizing a dynamic
energy model to interpret the inferred temperature to predict the R-value. But, it also shows that there is enough regularity in the thermal images to reasonably estimate the R-value of roofs, especially if energy consumption and geometrical data associated with the residence is included in the analysis.

The drawback of this approach is that it requires knowledge of the ceiling R-value of some of the houses included in the imaging set. In this study, it was shown that only nine of the houses had to be audited to determine the R-value with reasonable accuracy in order to predict the R-value of all other houses imaged at the same time. But a requirement of this approach is that the surveyed houses must be a subset of the imaged houses, e.g., houses imaged under roughly the same weather and flight conditions. If for example, the imaging aircraft moved to a different altitude or the weather changed rapidly, the imaged houses might not be considered part of the same subset. Research will be needed to validate the sensitivity of this approach to varying weather and flight conditions. Also, in this study, the roof emissivities were inferred via manual inspection. This process would need to be automated in order for this approach to be viable at-scale.

The physics-based modeling approach began with many assumptions about the attic structure and its thermal behavior. Key among these is that the house is at a thermal steady-state 48 hours prior to the IR imaging measurement. Weather data for this 48 hour interval, along with a thermodynamic model for the attic space, are used to determine hourly heat transfers through the attic as well as roof surface temperature. The modeled roof surface temperature at the end of the 48 hour period is then compared to the measured temperature, and whether or not the two match depends on the roof thermal resistance and thermal capacitance values chosen for the model. The idea is to search (using the genetic algorithm)
for the combination of resistance and capacitance that creates a match. The resistance value then is an estimate for the roof R-value. The problem with this approach is that it leads to unrealistically high roof R-value estimates. This is likely due to inaccurate modeling assumptions as well as a sensitivity to the difference between the measured roof temperature and outside air temperature. Small errors in the roof temperature measurement can lead to large R-value estimation errors.

The data mining approach proved to be a more reliable way to estimate roof R-value because it did not rely upon making assumptions about the detailed thermal behavior of the attics. It uses the single point in time temperature measurement for the roof surface along with other predictor variables that were not utilized in the dynamic modeling approach. The only assumption made by the data mining approach is that the predictor variables influence the roof R-value in a similar way from house to house. This is a reasonable assumption because the homes were all measured at the same time, have similar construction and type of residents (students), and are in the same neighborhood. Using a subset of the homes, a model is developed (or trained) to search for the connection between R-value and the predictor variables. This model is then validated by applying it to homes not in the training subset. The resulting predicted R-values were found to have low error when comparing them to the measured R-values. Unlike the physics-based approach, this data mining approach is insensitive to bias error in predictor variables (especially roof surface temperature). This is because similar bias error would be present for all of the homes, due to the fact that the data were collected under similar conditions.

As it was conducted in this research, the data mining approach has some limitations. First, the roof emissivities were estimated by manual inspection of visual aerial imagery,
house by house. This cumbersome process would require automation in order to scale the technique effectively. Secondly, all of the data were collected at nearly the same time. Future work with larger areas of study may require the analysis of data collected at different times. This would introduce the need for additional predictor variables, such as time of day, day of week, and weather conditions, and it would make the model construction more complex. Third, the research here only considered one type of dwelling: student rentals with attic spaces. A more general approach would involve categorical variables to describe other types of homes. Finally, future efforts for the data mining approach could benefit from other data that was not available for the present study. For example, if indoor air temperature were available for the homes from wireless thermostats, one would reasonably expect this to strengthen the modeling.
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