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Realistic texture in simulated thermal infrared imagery

Jason T. Ward

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Realistic Texture in Simulated Thermal Infrared Imagery

by

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A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the Chester F. Carlson Center for Imaging Science Rochester Institute of Technology

2008

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Realistic Texture in Simulated Thermal Infrared Imagery

by

Jason T. Ward

Submitted to the
Chester F. Carlson Center for Imaging Science
in partial fulfillment of the requirements
for the Doctor of Philosophy Degree
at the Rochester Institute of Technology

Abstract

Creating a visually-realistic yet radiometrically-accurate simulation of thermal infrared (TIR) imagery is a challenge that has plagued members of industry and academia alike. The goal of imagery simulation is to provide a practical alternative to the often staggering effort required to collect actual data. Previous attempts at simulating TIR imagery have suffered from a lack of texture—the simulated scenes generally failed to reproduce the natural variability seen in actual TIR images. Realistic synthetic TIR imagery requires modeling sources of variability including surface effects such as solar insolation and convective heat exchange as well as sub-surface effects such as density and water content.

This research effort utilized the Digital Imaging and Remote Sensing Image Generation (DIRSIG) model, developed at the Rochester Institute of Technology, to investigate how these additional sources of variability could be modeled to correctly and accurately provide simulated TIR imagery. Actual thermal data were collected, analyzed, and exploited to determine the underlying thermodynamic phenomena and ascertain how these phenomena are best modeled. The underlying task was to determine how to apply texture in the thermal region to attain radiometrically-correct, visually-appealing simulated imagery. Three natural
desert scenes were used to test the methodologies that were developed for estimating per-pixel thermal parameters which could then be used for TIR image simulation by DIRSIG. Additional metrics were devised and applied to the synthetic images to further quantify the success of this research. The resulting imagery demonstrated that these new methodologies for modeling TIR phenomena and the utilization of an improved DIRSIG tool improved the root mean-squared error (RMSE) of our synthetic TIR imagery by up to 88%.
Acknowledgements

None of this would have been possible without the support and dedication of numerous people. I would especially like to thank my committee members. Dr. John Schott helped guide my research and was an invaluable source of information. Dr. David Messinger contributed valuable ideas and provided clarity to various subjects. Dr. Emmett Ientilucci stepped-in to help solidify the committee at only a moment’s notice and contributed constructive reasoning for several processes. Dr. Harry Gross provided outside expertise about the problem domain and potential research avenues. Finally, Dr. Joseph DeLorenzo took time out of his schedule to serve as the outside reader and provided alternative perspectives.

In addition to my committee, I need to thank Niek Sanders and Scott Brown for all of their assistance with DIRSIG—a critical component to my research. I am also grateful to my Air Force officer-peers who helped me along in various capacities during my time at RIT. My hat’s off to all of you! Lastly, I cannot forget to thank Cindy Schultz, who kept me on the straight-and-narrow and was a constant source of encouragement.
Dedication

This dissertation is dedicated to my wife, Ally, and son, Royce, without whom this effort could never have come to fruition. Your faithful love and support have made all the difference in my life.
DISCLAIMER

The views expressed in this dissertation are those of the author and do not reflect the official policy or position of the United States Air Force, Department of Defense, or the United States Government.
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1.1 Introduction

Remote sensing has advanced enough as a discipline that one may now classify it as a technology. A myriad of broad definitions for remote sensing exist, however in this endeavor, remote sensing is defined as the detection and quantification of electromagnetic energy (\textit{i.e.}, photons) emanating from distant objects made of various materials. The goal of remote sensing is to successfully identify and classify remote objects by type, substance, and/or spatial distribution. To achieve this goal
utilizing airborne or space-based sensors is known as overhead remote sensing.

Platforms carrying remote sensors are launched into and above the atmosphere in order to monitor the earth from overhead. The earth radiates thermal energy primarily due to heating by solar irradiation and internal heat flow. Remote sensors which measure this emitted radiation in the thermal region of the electromagnetic spectrum can produce imagery indicative of scene object temperatures due to their material properties and insolation histories. Thermal infrared (TIR) imagery is useful at all times of the day to monitor changes or detect anomalies but is especially useful at night or in areas where there is little to no solar activity in order to view otherwise irresolvable scenes. TIR images are usually formed using sensors based on airborne (or space-based) platforms in the 3-5 µm (Mid-Wave Infrared Region or MWIR) and 8-14 µm (Long-Wave Infrared Region or LWIR) wavelength regions. The 5-8 µm portion of the spectrum is not normally used for imaging due to the high levels of photon absorption by the constituent molecules of the atmosphere in this region.

TIR images are created by spatially and spectrally quantifying the photons that are detected by a sensor which is sensitive to photons in the TIR. The LWIR image shown in Figure 1.1 is a good example of the end result of this process. One can see the different types and consistencies of concrete resulting in areas of differing temperatures. The taxiway lane lines are prominent due to their thermal properties resulting in the painted concrete having a higher observed temperature. Numerous thermally-induced phenomena make this type of imagery useful in many kinds of applications. However, the tremendous effort required to collect actual TIR data is extremely expensive. One alternative to actually building and flying systems is to use synthetic imagery to test new algorithms or data exploitation methods. In addition, synthetic imagery can provide complete control over all of the variables in
1.1. Introduction

Figure 1.1: LWIR Image (Courtesy of RIT Wildfire Airborne Sensor Program).

a scene and can be used to help develop sensor requirements. This research effort uses a simulation system developed at the Rochester Institute of Technology (RIT) called the Digital Imaging and Remote Sensing Image Generation (DIRSIG) model to provide radiometrically-correct, synthetically-textured TIR imagery, where the term ‘textured’ refers to an image’s spatial and spectral in-class variability.

DIRSIG is a complex synthetic image generation application that can produce simulated imagery from the visible (VIS) out through the TIR regions of the electromagnetic spectrum [Schott et al. 1999]. DIRSIG calculates self-emitted radiances by using emissivities and surface temperatures which are predicted by a passive
thermodynamic model known as THERM [Brown and Schott 2000]. In the reflective portion of the spectrum, DIRSIG has multiple techniques for providing texture variability in synthetically-generated images. However in the TIR there are additional sources of variability that must be correctly modeled, to include surface effects such as solar insolation and convective heat exchange as well as sub-surface effects such as density and water content.

This research effort utilized DIRSIG to investigate how these additional sources of variability could be modeled in order to provide radiometrically-accurate, simulated TIR imagery. The importance of radiometric accuracy becomes apparent when one wants to exploit TIR imagery for purposes other than presentations. Algorithms for the purposes of target detection and tracking, anomaly detection, or even basic classification mapping may not perform realistically if the underlying radiometry is incorrect. An overview of the overall scope of this research project follows in the next section.

1.2 Scope

This research effort primarily considered the texture of synthetic imagery in the LWIR region, defined for this purpose as 8-14 µm. Several commercial vendors have already spent decades successfully building real-time IR products that are functional but not necessarily radiometrically-correct. Their proprietary methods were not accessible, and as such the plan behind this research was to utilize THERM to provide the necessary thermodynamic calculations based on the material properties, scene geometry, and prevailing weather conditions.

It is important to understand that this research did not purport to modify or improve the underlying thermodynamic model, its purpose was to realistically
implement algorithms that provide texture to synthetic TIR images based on the outcome of THERM. The algorithms developed using THERM and subsequently implemented in DIRSIG were only tested on the models and associated materials provided by the modeling group, and as such may not function properly if applied to vastly different scene objects or at wavelength regions not previously considered. The materials modeled included natural desert scene classes such as sand, soil, asphalt, and salt flats. The spatial scale of the images used is in the 2-3ft Ground Sample Distance (GSD) range. Higher resolution GSDs impact the fidelity of the terrain mapping. Emissivity variation is contingent upon the fidelity of emissivity measurements of various scene objects.

In addition, this research did not delve into sensor effects such as detector calibration, sensor noise, or spectral smile. The deliverables for this project included the texturing algorithms, code implementation and testing, and calculation of appropriate metrics. An overview of the research objectives adapted from the original proposal appears in the next section.

1.3 Objectives

This section highlights the main objectives as adapted from the original research proposal. Each objective had a number of tasks assigned which were designed to lay out a path by which each research milestone was to be attained. Once again, the overarching goal of this research was to investigate how realistic TIR texture in synthetic images could be achieved.

1. Investigate the effects of material properties and scene geometry upon observed temperatures.
(a) Devise methods to represent thermodynamic properties and different aspects of scene geometry in the TIR model.

(b) Discover how to use THERM to manipulate thermodynamic material properties in order to mimic real-world image phenomena.

(c) Determine which properties produce the largest changes in temperature in order to optimize thermal parameter mapping based upon those variables which most significantly affect temperatures.

Design a series of algorithms to estimate the thermodynamic parameters in order to provide radiometrically-correct, realistic texture in synthetic TIR imagery.

(a) Ensure the estimated parameters are not ‘overfitted’ (i.e., varying abnormally).

(b) Discover methods for pre-determining thermal parameters that can be estimated using techniques in the visual portion of the electromagnetic spectrum.

(c) Optimize the parameters to produce images with the smallest root mean-squared error (RMSE) with the observed brightness temperatures over a diurnal period in calibrated TIR imagery.

Implement a per-pixel, thermodynamic and scene geometry parameter selection algorithm.

(a) Test the algorithm on natural desert scenes with model materials consisting of sand, gravel, soil, asphalt, and salt flats.

(b) Compare simulated images with real data taken of the same scene at different points during the diurnal cycle.
(c) Define and demonstrate a procedure to implement the approach inside of DIRSIG.

1. Develop a series of test metrics to determine whether the texture of synthetically generated TIR images adequately matches the texture of actual TIR data collected over Trona, CA.

2. Calculate the necessary statistics and compute corresponding metric scores to determine the best texture method.

3. Define a generalizable approach for texture generation in the TIR. This is to include a graceful degradation of the proposed approach to deal with less than complete data sets.

All of these objectives were achieved through the course of this research and will be described in complete detail in the following chapters.

1.4 Dissertation Overview & Organization

The theoretical basis of TIR imaging is described in Chapter 2. This chapter also reviews texture and associated metrics. This background information is followed by the research approach in Chapter 3. The results of this effort are presented in Chapter 4. Finally, Chapter 5 provides some observations and recommendations for future efforts, to include algorithm enhancements and additional areas of research.
This chapter provides the background information and context within which this research effort took place. Section 2.1 begins with a succinct summary of the physics of TIR imagery collection. Section 2.2 illustrates the three methods of heat transfer and how each is modeled. Section 2.3 defines important thermodynamic properties and describes their measurement. Section 2.4 discusses the creation and analysis of texture within imagery. Finally, Section 2.5 relates the current state of the art of texture in synthetic TIR imagery and motivates the need to model the additional sources of variability in the TIR.
2.1 Thermal Infrared Imagery

Infrared remote sensing in the MWIR and LWIR portion of the electromagnetic spectrum makes use of sensors which are sensitive to infrared radiation emitted from various sources (which will be discussed in depth in Section 2.2) located on the earth’s surface as shown in Figure 2.1.

![Figure 2.1: Sources of Thermal Emission [CRISP 2006].](image_url)

As discussed in Chapter 1, most thermal remote sensing occurs in two atmospheric windows, the MWIR and LWIR, where atmospheric absorption is at a minimum. Space-based sensors commonly reduce these windows of the spectrum to 3-5 µm and 10.5-12.5 µm respectively, while airborne platforms often use the full 8-14 µm region in the LWIR. None of these windows transmit 100% of the emitted radiation because water vapor and carbon dioxide absorb some of the energy going through the atmosphere, while ozone is known to absorb in the 9-10 µm interval. The actual transmittance through these windows is shown in Figure 2.2. Note that solar reflectance can contaminate the 3-4 µm MWIR region during daylight hours.
and should be taken into consideration.

![Figure 2.2: Atmospheric Transmission [Short 2006].](image)

Thermal IR images are produced by airborne or space-based scanning systems as shown in Figure 2.3. The particular configuration shown is for a line-scanning device, but similar configurations exist for framing arrays. For remote sensing in the LWIR, one traditionally uses a detector composed of an alloy of mercury-cadmium-telluride (HgCdTe) that acts as a photoconductor in response to incoming photons that have a wavelength between 8-14 \( \mu \text{m} \). Mercury-doped germanium (Ge:Hg) can also be used in this interval, although it is broadly-effective all the way down to about 2 \( \mu \text{m} \). Other alloys such as Gallium arsenide (GaAs) can be used to create strained-layer superlattice structures for specific LWIR-sensing applications, but these techniques will not be discussed here. Over the MWIR interval, indium-antimony (InSb) is the alloy commonly used [Committee on New Sensor Technologies 1995].

Efficient operation of these detectors requires onboard cooling to temperatures
Figure 2.3: Diagram of a TIR Scanning System [Sabins 1997].
between 30-77 K, depending on the detector type. This temperature range is maintained either with cooling agents such as liquid nitrogen or helium in a Dewar vessel, or for some spacecraft designs, with radiant cooling systems that take advantage of the cold vacuum of outer space. Detectors utilize this cooling to improve their signal-to-noise (S/N) ratio to a level at which they have a stable signal response. The signal, itself, is an electrical current relating the changes in detector resistance to the proportion of incident radiant energy. This proportion is calibrated using sources at different temperatures near the extremes that one can expect from the targets in order to provide a correction function [Short 2006].

In this research effort, we use remotely-sensed TIR images taken by the RIT Wildfire Airborne Sensor Program (WASP) framing array sensor package. WASP is a high-performance multi-spectral camera system built from Commercial Off-the-Shelf (COTS) products that includes Visible, SWIR, MWIR, and LWIR bands. The cameras’ detectable portions of the IR bands are shown in Figure 2.4.

WASP has three Indigo Phoenix™ IR cameras and one Terrapix™ visible imager mounted in a pivoting gimbal assembly as shown in Figures 2.5a and 2.5c. This entire assembly looks down through a hole in the bottom of the host air-
craft (currently a Piper Aztec plane). WASP also has an inertial measurement unit shown as Figure 2.5b in order to determine the exact position and orientation of the imagers and aircraft when each image is captured.

![Figure 2.5: (a) WASP Camera Layout, (b) Inertial Measurement Unit, (c) Gimbal Assembly][1]

The three IR imagers acquire 640x512 12-bit images that are 638 KB in size. The Terrapix™ acquires 2048x2048 raw images using a high-performance Kodak charge-coupled device (CCD) over roughly the same area on the ground. The IR cameras can be sampled simultaneously at a maximum rate of four frames per second. The GSD of the IR cameras is approximately 3m when the sensor is flown at 10,000 ft. The images shown in Figure 2.6 are an example of how the simultaneous nature of frame capture in the three different IR cameras shows the apparent contrast in phenomena between these bands. The emissivities of natural objects such as the grass on the football and baseball fields varies between IR bands and manifests itself at vastly different brightness temperatures\(^1\).

This section has shown how IR imagery is captured and given examples of the types of imagery that will be used to create models by which thermal texture can

---

\(^1\) *Brightness temperature* is defined as the temperature that a blackbody would need to have in order to emit radiation of an observed intensity at a given wavelength [Darling 2007].
2.2. Heat Transfer

The subject of heat transfer must be well understood if one is to have any success modeling remote sensing and imaging in the TIR. The prediction of surface temperatures of objects is handled by thermal models that utilize material thermodynamic properties and meteorological conditions for their computations. In actual remote sensing, objects absorb and emit energy in concert with the surrounding surfaces, while convection and conduction also serve to transfer heat from objects to other objects and their surrounding environments.

Heat transfer refers to the exchange of energy between objects and their environments due differences in temperature. The three mechanisms of heat transfer are conduction, convection, and radiation. Figure 2.7 shows an analogy of a barn on fire and uses the three methods of heat transfer to contrast the differences between methods.

In Figure 2.7, consider the water (W) to be analogous to heat and assume the...
people represent a heat transfer medium. In Case 1, the hose directs water from (W) to the barn (B) independently of the medium. This is comparable to thermal radiation in a vacuum or in most gases. In Case 2, a bucket brigade delivers water from (W) to (B) by going through the medium, just as heat is transfered via conduction (assuming the brigade is rigid). In Case 3, a runner carries water from (W) to (B). This macroscopic movement is analogous to convection. The subsequent sections will describe each mechanism for heat transfer in more detail and explain how each method can be modeled.

Figure 2.7: Barn Fire Analogy of the Three Modes of Heat Transfer [Lienhard(IV) and Lienhard(V) 2005].
2.2. Heat Transfer

2.2.1 Radiation

Radiation is the method of heat transfer in which energy is emitted due to the temperature of an object. Any object at a temperature above absolute zero will radiate energy. A perfect radiator, or blackbody, is the concept of an ideal material (surface or cavity) that perfectly absorbs and then re-radiates all incident electromagnetic flux. Therefore, the blackbody does not permit any transmittance or reflectance but rather emits the absorbed energy at the maximum possible rate per unit area. The amount of this radiant energy varies with both temperature and wavelength(s).

In 1901, Max Planck derived an expression to describe this radiant energy,

\[ M(\lambda, T) = \frac{2\pi hc^2}{\lambda^5(e^{\frac{hc}{\lambda kT}} - 1)} \left[ \frac{W}{m^2\mu m} \right] \]  

(2.1)

which gives the spectral radiant exitance, \( M \), from a blackbody based on the statistical calculation of the vibrational energy states between the atoms. This calculation (now known as the Planck or blackbody radiation equation) is based on \( h \), an empirically derived value now referred to as Planck’s constant (6.6256 x 10\(^{-34}\) J/sec), \( c \) - the speed of light (2.9979 x 10\(^8\) m/sec), \( k \) - Boltzmann’s gas constant (1.38 x 10\(^{-23}\) J/K), \( T \) - the temperature of interest in Kelvins, and \( \lambda \) - the wavelength of interest in meters [Jacobs 2006]. By selecting temperatures of interest, a set of curves can be generated demonstrating spectral exitance versus wavelength as shown in Figure 2.8. These curves show how the exitance increases with temperature and how the peak value of the function shifts to shorter wavelengths as the temperature is increased.

For instance, if one were to regard the earth’s surface as a blackbody emitter at 300°K, its spectral exitance as a function of wavelength is related by Planck’s blackbody equation and is plotted in Figure 2.8. However, in reality there is no
perfect blackbody and one must approximate using imperfect absorbers. This phenomenon is described using the concept of emissivity, $\varepsilon(\lambda)$, mathematically defined as

$$\varepsilon(\lambda) = \frac{M_{\lambda}(T)}{M_{\lambda,BB}(T)} \quad (2.2)$$

where $M_{\lambda}(T)$ is the spectral exitance from an object at temperature $T$ and $M_{\lambda,BB}(T)$ is the exitance from a blackbody at the same temperature. Thus, the emissivity of an object describes its ability to radiate energy versus that of a blackbody radiator and it can take on unitless values from 0 to 1.

Integrating Planck’s blackbody radiation equation over all wavelengths gives us the total exitance from a blackbody, which is known as the Stefan-Boltzmann equation

$$M = \int_0^\infty M_{\lambda} \mathrm{d}\lambda = \int \frac{2\pi h c^2 \lambda^5}{e^{\frac{hc}{kT \lambda}} - 1} \mathrm{d}\lambda = \frac{2\pi^4 k^4 T^4}{15 c^2 h^3} = \sigma T^4 \quad \left[ \frac{W}{m^2} \right] \quad (2.3)$$
where $\sigma$ is known as the Stefan-Boltzmann constant ($5.67 \times 10^{-8} \frac{W}{m^2K^4}$) [Nave 2005].

Looking once again at Figure 2.8, one notices that the hotter the radiating body, the greater is its exitance over its range of wavelengths, and the shorter is its peak emission wavelength. This relationship between peak wavelength and radiant body temperature is also derived from the Planck equation and is known as the Wien Displacement Law

$$\lambda_{\text{max}} = \frac{A}{T} \ [\mu m]$$ (2.4)

where $\lambda_{\text{max}}$ is the wavelength at maximum exitance, $A$ is the Wien displacement constant (2898 $\mu m^\circ K$), and $T$ is the absolute temperature in Kelvins. For the sun, with a photospheric radiant temperature of about 6000 K, this peak wavelength is in the visible portion of the spectrum at approximately 0.5 $\mu m$. A forest fire’s peak wavelength is around 5 $\mu m$. Peak flux for an object near earth’s ambient temperature of 300$^\circ K$ will occur at approximately 10 $\mu m$ (shown in Figure 2.8). Conveniently this is in the center of an atmospheric transmission window (see Figure 2.2) which is extensively used for studying the thermal characteristics of Earth [Schott 1997].

So far we have only discussed radiation in terms of surface emission. However, each surface is simultaneously absorbing energy from its surrounding environment, complicating the determination of the overall rate of heat transfer. The actual radiant flux from a surface due to radiative heat transfer is

$$q = \int_{0}^{\infty} \epsilon_{\text{surf}}(\lambda)[M_{\lambda BB(\text{surf})}(T) - \epsilon_{\text{surr}}(\lambda)M_{\lambda BB(\text{surr})}(T)] \, d\lambda \ [\frac{W}{m^2}]$$ (2.5)
which using Equation 2.3 and assuming the surround is a blackbody, simplifies to

\[
q = M_\lambda(T) = \varepsilon \sigma (T_{\text{surf}}^4 - T_{\text{surr}}^4) \left[ \frac{\text{W}}{\text{m}^2} \right]
\]  

(2.6)

where \( q \) is the radiant flux density, \( T_{\text{surf}} \) is the temperature at the surface in Kelvins, and \( T_{\text{surr}} \) is the temperature of the surrounding air in Kelvins. Hence, as \( T_{\text{surr}} \) approaches absolute zero, radiation becomes its most efficient as a process of heat transfer away from a surface. Note that due to the spectral nature of Equation 2.6, solar absorptivity will dominate SWIR activity, while a surface’s thermal emissivity will dictate longer-wave emission.

In order to demonstrate the profound effect emissivity has upon the radiant flux leaving a surface, consider Figure 2.9. This figure illustrates the effect of different emissivities on the energy radiated from an aluminum block at a uniform kinetic temperature of 10°C (283 K). The polished shiny surface has a low emissivity leading to very few photons being emitted, while the other half has been painted a dull black with a much higher emissivity and higher resultant radiant temperature. This demonstrates how surfaces of the same object can appear vastly different in imagery just based upon the difference in their emissivities, assuming the surrounding environment allows for normal radiative heat transfer.

### 2.2.2 Conduction

Conduction is the method of heat transfer by which energy is transferred through a medium in direct contact with two objects or surfaces at different temperatures. The medium must be a rigid solid, or a fluid with no circulating currents. If there is no macroscopic movement, then the heat transfer must be at the molecular level. It is known that any molecule at a temperature above absolute zero must be in
motion, and this motion is measured in terms of its internal kinetic energy. To illustrate this method, consider a group of molecules or atoms with high kinetic energy isolated via a thermal insulator from a group at a lower temperature. If the thermal insulator is removed, the atoms will randomly collide with each other and eventually reach an equilibrium temperature. The rate at which the material reaches an equilibrium temperature is a material property known as thermal conductivity. All materials have some degree of thermal conductivity since only a perfect vacuum is an ideal insulator.

We can now quantify the heat transfer rate of conduction (also known as
Fourier’s Law) via

\[ q = -k \frac{dT}{dx} \left[ \frac{W}{m^2} \right] \]  (2.7)

where \( k \) is the thermal conductivity in \( \frac{W}{mK} \), \( dT \) is the temperature difference in Kelvins, and \( dx \) is the distance in meters. The heat flux is actually a vector quantity (i.e., it has a magnitude as well as a direction), and we can express it in three-dimensional form

\[ \vec{q} = -k \nabla T \left[ \frac{W}{m^2} \right] \]  (2.8)

where we can track \( q \) as it flows from high to low temperatures [Martinez 2006].

### 2.2.3 Convection

Convection is heat transfer by the mass motion of a fluid (such as air or water) moving away from the source of heat and carrying energy with it. Convection above a hot surface such as a heater occurs because hot air expands, becoming less dense, and then it rises. As another example, consider cool wind flowing past the earth. The air immediately adjacent to the earth forms a thin, speed-retarded region called a thermal boundary layer. The hotter molecules move into this layer, and then are swept away to where they finally mix into the air further downstream.

In 1701, Isaac Newton considered convective heat transfer and suggested that the cooling would be such that

\[ \frac{dT_{\text{body}}}{dt} \propto T_{\text{body}} - T_{\infty} \]  (2.9)

where \( T_{\infty} \) is the temperature of the oncoming fluid. This statement suggests that
energy is flowing from the body, but if the energy of the body is constantly replenished, then the temperature of the body need not necessarily change. Thus we can rephrase this in terms of

\[ \bar{q} = \bar{h}(T_{body} - T_{\infty}) \quad \left[ \frac{W}{m^2} \right] \]  

(2.10)

where \( \bar{h} \) is the convective heat transfer coefficient average over the surface of the body in \( \frac{W}{m^2K} \). The convective heat transfer coefficient is a function of (and increases with) wind speed and surface roughness. Equation 2.10 is known as the steady-state form of Newton’s law of cooling [eFunda 2006].

It is important to realize that of the three mechanisms of heat transfer, only radiation can transport energy through a vacuum. This form of transport allows the heat from the sun to reach the earth. Energy is conducted beneath the earth’s surface through heat conduction, resulting in physical temperature changes. Also, the fact that the surface is not at absolute zero temperature means that the surface itself will again radiate electromagnetic energy according to Planck’s Law as described in Equation 2.1. It is this electromagnetic radiation that is measured by remote sensing instruments, allowing the study of thermal properties of the earth’s surface [Elachi and van Zyl 2006].

In this section the three methods of heat transfer were discussed and the important equations by which one can model heat transfer among objects were highlighted. However, before one can undertake modeling these heat transfers and corresponding temperature changes, one must understand the thermodynamic properties of materials and the role they play in governing overall temperature change in a scene.
2.3 Thermodynamic Properties

A primary objective in relating thermal responses to temperature changes is the physical relationship between the composition of a material and the surrounding atmosphere of the earth. For a given material, certain thermodynamic properties play important roles in governing the temperature of a body at equilibrium with its surroundings. As described in [Presley 2002], these properties include:

1. **Thermal Conductivity** ($k$): As defined in Section 2.2.2, thermal conductivity describes the rate at which heat passes through a specific thickness of a substance in a direction normal to the surface due to a temperature difference, measured in $\frac{W}{mK}$.

2. **Heat Capacity** ($C$): The measure of the increase in thermal energy, $q$, per degree of temperature rise. It denotes the capacity of a material to store heat in Joules per Kelvin. One calculates heat capacity as the ratio of the amount of heat energy required to raise a given volume of a material by one Kelvin (using a standard temperature of 288.15 K) to the amount of energy needed to raise the same volume of water by one degree. A related quantity, **Specific Heat** ($c$), is defined as being equal to $C/\rho$, (where $\rho$ is the density of the substance) and is given in units of $\frac{J}{gK}$. This property associates heat capacity to the thermal energy required to raise a mass of one gram of water by one Kelvin. Often instead of specific heat, a substance’s heat capacity is calculated because it results in a single number that combines the specific heat and mass density of that material.

3. **Thermal Inertia** ($P$): The resistance of a material to temperature change, indicated by the time-dependent variations in temperature during a full heat-
ing/cooling cycle (*i.e.*, 24-hour day). It is defined as $P = \sqrt{k_c \rho}$, and its units are given in $J/m^2s^{1/2}K$. Since materials with a high thermal inertia possess a strong inertial resistance to temperature fluctuations at a surface boundary, they show less temperature variation per heating/cooling cycle than those with lower thermal inertia.

The following table exhibits some characteristic values of these intrinsic thermal properties. Note that these are only the average values for each property. In reality, the values for these properties vary and are not homogeneous even within the same object. This phenomenon is a major source of the texture that we see in TIR imagery.

<table>
<thead>
<tr>
<th>Thermodynamic Property</th>
<th>Water</th>
<th>Soil</th>
<th>Basalt</th>
<th>Steel</th>
</tr>
</thead>
<tbody>
<tr>
<td>Thermal Conductivity</td>
<td>0.0014</td>
<td>0.0014</td>
<td>0.0050</td>
<td>0.0300</td>
</tr>
<tr>
<td>Specific Heat</td>
<td>1.00</td>
<td>0.24</td>
<td>0.20</td>
<td>0.12</td>
</tr>
<tr>
<td>Density</td>
<td>1.00</td>
<td>1.82</td>
<td>2.80</td>
<td>7.83</td>
</tr>
<tr>
<td>Thermal Inertia</td>
<td>0.038</td>
<td>0.024</td>
<td>0.053</td>
<td>0.168</td>
</tr>
</tbody>
</table>

*Table 2.1: Sample Thermodynamic Property Values [Short 2006].*

This section has laid out the relevant thermal properties necessary to model temperature changes in materials. The thermodynamic properties are critical to modeling the rate and magnitude of temperature change throughout a scene. These are the essential variables that will have to be optimized in our model in order to successfully generate synthetic TIR imagery.

### 2.4 Texture

The ability to render texture in digital images has become important and extremely complex over the past several decades. Texture can be seen in every image, ranging from remotely-sensed images obtained from airborne or satellite platforms to
microscopic images of individual cells or tissue samples within the biomedical community. While texture seems to be an intuitive concept, no one definition for texture is universally accepted; instead, particular applications have developed their own definitions and often utilize their own ad hoc approaches for addressing texture. For the purposes of imagery obtained via remote sensing, texture is the relationship between gray-levels in neighboring pixels which contribute to the overall appearance or visual characteristics of an image. Textural features include the statistical distribution of image intensity (i.e., gray-level) and information about boundaries arising from gray-level gradients [Thomas 1977]. Section 2.4.1 builds working definitions and highlights physical examples of texture and then it demonstrates how texture can be characterized using two dimensions. Section 2.4.2 then explains the methods for analyzing TIR image texture and determining image spatial properties.

2.4.1 Texture Characterization

Texture is an intuitive and naturally-occurring phenomenon in imagery and has been an active field of study since the early 1970s. Through a series of publications, Haralick pioneered an approach to texture quantification through both statistical and structural methods. Haralick stated that image texture has two basic dimensions by which it can be described or characterized. The first dimension describes the primitives from which the image texture is composed, and the second dimension describes the spatial dependence (or interaction) between primitives of an image texture. Thus, the first dimension is concerned with the tonal primitives or local properties, and the second dimension is only concerned with the spatial organization of the tonal primitives. The tonal primitive, itself, is described in terms
2.4. Texture

Image texture can be qualitatively evaluated as having one or more of the following properties: fineness, coarseness, smoothness, granulation, randomness, or regularity. Each of these properties translates into some combination of tonal primitives and the spatial interaction between them. Unfortunately, very few experiments have been conducted to attempt to map semantic meanings with precise properties of tonal primitives and their spatial distributions. However, a texture ‘taxonomy’ has evolved within the literature in order to explore texture characterization. One featured collection is the Brodatz texture database, originally designed for artists as well as engineers [Brodatz 1966]. It is often cited and considered to be one of the most complete representations of different texture types. Although the emphasis appears to be on more biomedical-type imaging textures, there are textures potentially applicable to remote sensing as well as seen in Figure 2.10.

There are also other more recently developed databases with more interesting terrestrial-type textures such as the Visual Texture (VisTex) database, shown in Figure 2.11, created at the Massachusetts Institute of Technology. These include coarse, grainy, fine, periodic, and irregular textures. Of course these adjectives are just qualitative descriptions of the textures; however, they do allow one to understand part of the basic nature of the phenomena behind the texture. Understanding the phenomena providing the variability within textures in the reflective region can help determine correlations with phenomena causing variability in the thermal region.

In order to quantitatively evaluate image texture, first the concepts of tonal and textural features must be explicitly defined. With an explicit definition, one discovers that tone and texture are not independent concepts. They actually exhibit an inextricable relationship to one another just like the relationship between the
photon’s wave-like and particle-like nature. A photon behaves neither solely as a particle nor solely as a wave. Rather, photons possess both particle and wave properties and depending on the situation, the particle or wave properties may predominate. Similarly in an image context, tone and texture are always present,
although at times one can dominate the other and lead one to speak in terms of only tone or only texture. Hence, when one makes an explicit definition of tone and texture, one is not defining two separate concepts, but instead just one tone-texture concept.

The basic interrelationship in the tone-texture concept may be defined as follows: when a small area of an image has little variation of tonal primitives then the dominant property of that area is tone. Likewise, when a small area has a wide variation of tonal primitives, the dominant property of that area is texture. The crucial distinctions become the size of the area, the relative sizes and types of tonal primitives, and the number and placement or arrangement of distinguishable
primitives. As the number of distinguishable tonal primitives decreases, the tonal properties will predominate. In fact, when the small area is reduced to just one pixel, so that there is only one discrete feature, the only property present is simple gray-tone. As the number of distinguishable tonal primitives increases within the area, the texture property will begin to dominate. When the spatial pattern in the tonal primitives is random and the gray-tone variation between primitives is wide, a fine texture results. As the spatial pattern becomes more definite and the tonal regions involve more and more pixels, a coarser texture will result.

In summary, in order to characterize texture one must characterize the tonal primitive properties as well as the spatial interrelationships between them. Therefore, one would expect that methods designed to characterize texture would have parts devoted to analyzing each aspect of texture. However, one will discover that the existing methods tend to emphasize one aspect or another and tend to ignore other aspects.

2.4.2 Texture Analysis

Texture analysis is commonly used to determine the spatial properties of an image. Texture analysis greatly facilitates tasks such as image segmentation and subsequent classification. Image classification is the task of categorizing pictorial data. For purposes of this research, we will only consider image classification using pattern-recognition techniques performed on a per-pixel basis. When searching for meaningful features to describe visual information, it is natural to consider the types of features which we use to interpret pictorial information. Spectral, structural, and textural (or statistical) features are three fundamental pattern elements used in human interpretation of imagery [Haralick et al. 1973]. All three of these ap-
proaches contain numerous mathematical variants for quantifying and analyzing texture. However, since this research will focus on utilizing the statistical method of texture quantification and analysis, this approach will be the main focus for the remainder of this section.

Textures often tend to be random with certain consistent properties. This makes analysis of the statistical properties of an image a very effective method for describing and quantifying texture. First-order gray-level statistics could be compiled using image histograms and computing the moments of intensity such as the mean and the variance. Of course these measures alone do not capture the position of the pixels, and by themselves these first-order statistics only provide information about the coarseness of the texture within the image. Second-order statistics consider the relationship between pixels (i.e., usually neighboring pixels) in an image. Since the aim of this texture analysis is to characterize the stochastic properties of the spatial distribution of gray-levels, it is apparent that there needs to be some simultaneous parametric measure of spatial relationships between pixel gray-levels. This motivated Haralick to use second-order statistics as the framework for developing a *Gray Level Co-occurrence Matrix* (GLCM), which has now become the most well-known and widely-used method to describe texture features [Chen et al. 1998].

The GLCM approach introduced by Haralick rapidly became a prominent tool for applications such as texture feature extraction, image segmentation and classification. GLCM performs well as a texture analysis tool over a broad range of texture types while working very well for finer textures, which are prominent in remotely-sensed imagery. Additionally, GLCM techniques can identify differences between materials as well as differences within a material. Several ad hoc methods have been proposed in order to improve upon the general computational efficiency of
the GLCM method when applied image-wide for purposes of classification [Scanlan 2003]. However, these extensions will not be discussed here in detail since the GLCM in its traditional form is used in this research effort.

In its simplest form, the GLCM approach is a statistical method for capturing the spatial structure of an image in a given bandpass by statistically sampling the way that certain gray-levels occur in relation to other gray-levels. Haralick’s GLCM method assumes an \(N \times N\) pixel image with \(G\) gray-levels. The \(G \times G\) gray-level co-occurrence matrix, \(P_d\), for a displacement vector, \(d = (dx, dy)\), is defined as follows. The entry \((i, j)\) of \(P_d\) is the number of occurrences of the pair of gray-levels \(i\) and \(j\) being a distance \(d\) apart. A more formal definition is

\[
P_d(i, j) = |\{(r, s), (t, v) : I(r, s) = i, I(t, v) = j\}|
\]  

(2.11)

where \((r, s), (t, v) \in N \times N\), \((t, v) = (r + dx, s + dy)\), and vertical bars denote the cardinality of the set. As an example, consider this \(4 \times 4\) image containing three different gray-values (or digital counts):

\[
\begin{pmatrix}
1 & 1 & 0 & 0 \\
1 & 1 & 0 & 0 \\
0 & 0 & 2 & 2 \\
0 & 0 & 2 & 2 \\
\end{pmatrix}
\]

The \(3 \times 3\) gray-level co-occurrence matrix for this image for a displacement vector of \(d = (1, 0)\) is
Here the entry \((0,0)\) of \(P_d\) is 4 since there are four pixel pairs of \((0,0)\) that are offset by \(d = (1,0)\). Notice that this \(P_d\) matrix (known commonly in the literature as a \(P\)-matrix) defined in this manner is not symmetric. The upcoming texture calculations will require a symmetric matrix. This is obtained by computing \(P = P_d + P_{-d}\) [Chen et al. 1998]. Finally, the \(P\)-matrix should be expressed as a probability via normalization. Normalization is the process of dividing by the sum of the values, \(V\),

\[
P_d[i,j] = \frac{V[i,j]}{G^{-1} \sum_{i,j=0} V[i,j]}. \tag{2.12}
\]

The normalized \(P\)-matrix reveals certain properties about the spatial distribution of gray-levels in an image. If the main diagonal of the \(P\)-matrix has most of the high values, then the texture is coarse with respect to \(d\). When the values are dispersed throughout the \(P\)-matrix, the opposite is true and the texture is fine with respect to \(d\).

Most texture calculations use different weighted averages of the \(P\)-matrix. In order to create a texture image using one of Haralick’s texture features, the result of each texture calculation is a single number representing a GLCM window applied to a small portion of the original image, similar to how a kernel is applied to filter an image. This singular number is put in the place of the center pixel of the window, then the window is moved one pixel and the process is repeated. In
this way an entire image is built up of texture values. Intuitively, the edges of the image are somewhat problematic, and some logical scheme must be adapted (e.g., to fill-in edge pixels with the nearest valid texture calculation) [Hall-Beyer 2006].

Haralick had originally proposed 14 useful texture features that can be computed utilizing the $P$-matrix. These texture measures can be grouped according to the purpose of the weights in each. The three groups are measures of contrast, measures of orderliness, and descriptive statistics. The contrast group uses weights related to the distance from the GLCM diagonal. A representative measure from this group is Contrast ($CON$), mathematically defined as

$$CON = \sum_{i,j=0}^{G-1} P_{[i,j]}(i-j)^2$$

which defines contrast as increasing exponentially as values away from the diagonal increase. Dissimilarity and homogeneity are two slightly different measures that are highly correlated with contrast. They will not be formally defined here, since they are not used in this research due to the lack of additional information they provide.

Orderliness measures, in a similar manner to contrast measures, use a weighted average of the computed $P$-matrix values. The weight is constructed in order to relate how many times a given pair occurs. As such a weight that increases with a larger number of occurrences will yield a texture measure that increases with orderliness, and a weight that decreases with a larger number of occurrences yields a texture measure that increases with disorder. Angular Second Moment (ASM) and Entropy (ENT) are the two most common measures of orderliness. ASM is calculated by

$$ASM = \sum_{i,j=0}^{G-1} P_{[i,j]}^2,$$
Notice that ASM possesses a similar form to its alternate definition as a measure of rotational acceleration in physics. Energy is found by simply taking the square-root of ASM. Entropy is a notoriously difficult term to understand. In thermodynamics, entropy refers to the quantity of energy that is permanently lost to heat (i.e., chaos) every time a reaction or physical transformation occurs. Entropy cannot be recovered in order to do useful work. Thus, the term is used to mean irremediable chaos or disorder. Similarly, entropy is defined in information theory as a measure of uncertainty. Entropy is calculated by

\[
ENT = - \sum_{i,j=0}^{G-1} P_{[i,j]} \ln P_{[i,j]}.
\]  

(2.15)

Notice that the maximum value of ENT is 0.5. This maximum is reached when all probabilities are equal (i.e., a random distribution of digital counts in the image). This situation would yield maximum “chaos” or entropy [Hall-Beyer 2006].

The third group of GLCM texture measures consists of descriptive statistics derived from the \(P\)-matrix. These are GLCM Mean, GLCM Variance, and GLCM Correlation (COR). Notice that an image mean, variance, and correlation can easily be calculated, however the GLCM Mean is expressed in terms of the \(P\)-matrix. Therefore, a pixel value is weighted not by the frequency of its occurrence, itself, but rather by the frequency of its occurrence in combination with a particular neighbor’s pixel value. These statistical calculations use the same basic formulas that are in the introductory chapters of every statistics textbook and will not be reiterated at this point. It is the application of basic statistics to the \(P\)-matrix that is of interest.

There are some important practical considerations when using the GLCM texture methodology. Recall that the size of the \(P\)-matrix is determined by the number of gray-levels in the image. If there are too many different gray-levels (i.e., eight or
more), then the $P$-matrices will be sparsely populated and become so large as to be intractable. In such cases it is often useful to first equalize the histogram and then re-quantize the entire image using a smaller number of $2^n$ gray-levels (e.g., from 8-bit data with 256 values to 5-bit data with 32 values) [Jensen 2005].

Another consideration is the size of the GLCM window. This window is usually square with odd-numbered side lengths for practical purposes. The relative size of the window to the objects in the image will determine the usefulness of the texture measure for purposes such as classification. It is expected that different objects will have different characteristic texture measures. In order to facilitate this, the window must be smaller than the object(s) of interest but big enough to include the characteristic variability of the object(s). For example, consider how the texture of a closed-canopy forest is determined by the light and shadow-regions among tree crowns. A window that is covering one tree will not correctly measure the texture of the forest. Similarly, a window covering the entire forest and the fields next to it will not measure the texture of the forest [Hall-Beyer 2006].

It is quite possible to use any of the GLCM texture measures by themselves. However, in terms of classification many of these individual statistics have a peak classification accuracy at a relatively coarse quantization level with a decrease in classification accuracy with increasing gray-levels. In addition, arbitrary selections of re-quantization for these statistics can produce misleading results in terms of classification of textured imagery. A preferable choice of GLCM statistics is the combined use of three fairly independent statistics: CON, ENT, and COR. This statistics set demonstrates the most consistent accuracy in terms of classification over a range of quantization gray-levels [Clausi 2002].

As a practical and visual example of the GLCM methodology, consider Figure 2.12a in which we see a LWIR image taken by the WASP sensor over Trona, CA,
2.5. Thermal Infrared Imagery Simulation

and in Figures 2.12b, 2.12c, and 2.12d we see the CON, ENT, and COR GLCM texture images respectively. For this example, a 5x5 window was used and quantization was performed at the 5-bit level. The co-occurrence shift, \( d \), was X:1, Y:1. Notice how the contrast in Figure 2.12b is high along the roads and in the graded field. The entropy is highest along the roads in Figure 2.12c. Different types of soils show the highest correlation in Figure 2.12d. These three different metrics highlight the different patterns or structures in the image and are independent enough to allow for improved classification. In this research, we will be comparing the results of the CON, ENT, and COR GLCM texture images to quantitatively measure how well our TIR texture algorithm(s) has performed.

This section has demonstrated the overall power and flexibility of the GLCM approach for texture feature analysis. While some authors describe the GLCM approach as cumbersome due to the potentially large quantity of calculations and parameters involved, it is the actual availability of these parameters that makes this methodology adaptive and flexible enough to utilize as a detailed texture feature discriminant for comparing real and synthetic scenes [Scanlan 2003]. This methodology also allows for a comparative performance analysis of different texturing algorithms. The next section will discuss how we will generate the synthetic TIR images for textural comparisons.

2.5 Thermal Infrared Imagery Simulation

Synthetic image generation (SIG) has quickly become a popular and powerful tool in the remote sensing community. The process of effectively modeling the physical world in order to mimic real images requires detailed knowledge of the entire imaging chain. There are many advantages to the use of SIG in the study of imag-
Figure 2.12: LWIR Texture Example Images: (a) Original, (b) CON, (c) ENT, (d) COR.

...ing systems and image analysis. One of the most attractive aspects is that synthetic images with realistic texture can be produced over a range of spatial, spectral, and radiometric performance specifications, providing versatility in the construction of...
realistic scenes. In particular, SIG can be used for the testing and development of algorithms on scenes containing targets of interest over widely-varying scenarios, scene components, and image acquisition conditions as long as the radiometry is preserved. Furthermore, since SIG models are often highly-modularized and composed of sub-models, the identification of weak links in the chain is made easier by the isolation and analysis of individual components of the imaging chain [Schott 1997].

The purpose of this section is to describe the current state of the art of synthetic TIR image generation. The alternative to fully-computerized synthetic imagery is to have some type of hardware in-the-loop, however this research is focused upon methods that rely only on computer algorithms for their output. Specifically, Section 2.5.1 highlights some current models offered by commercial vendors and discusses their potential shortfalls in terms of realistic TIR texture. Section 2.5.2 describes in-detail the DIRSIG model for SIG applications and in particular its current capabilities with respect to synthetic TIR generation.

### 2.5.1 Survey of Commercial SIG Models

Due to the myriad of military applications, SIG model development has been rampant among commercial vendors looking to cater to the needs of Department of Defense customers. The U.S. Army’s Imagery and Geospatial Research Division of the Topographic Engineering Center tracks more than 500 different SIG products from various open sources such as vendor literature, web sites, and live demonstrations [U.S. Army Topographic Engineering Center 2006]. There are approximately a dozen applications whose vendors purport to provide synthetic TIR generation, however none of these products produce high-fidelity TIR simulated im-
agery because they do not modify thermal parameters beyond emissivity on a per-pixel basis.

One of the more advanced products is IRGen™, developed by the Technology Service Corporation. IRGen™ is an IR sensor simulation program that generates 3D TIR databases as viewed by a TIR sensor. Given a user-specified thermal environment, IRGen™ computes the surface temperature of every polygon in the simulated scene. To accomplish this, it uses a first-principles\(^2\) calculation based upon a time-dependent heat transport equation, integrated with a finite-difference time-dependent solution method. The thermal model computes the surface radiance from the surface temperature, emissivity, and reflected radiance terms. The radiance is integrated across the sensor spectral band. The material database contains the thermal and radiative properties of the materials used in the database. The environment model accounts for parameters including time, location, air temperature, wind speed, and sky radiance. The sensor model contains the parameters that specify the properties of the simulated sensor. IRGen™ converts visual textures into gray-scale TIR textures, with the texture modulation dependent solely upon the surface temperature and the sensor’s dynamic range. An example of the output of this process is seen in Figure 2.13. Note the lack of contrast and detail on the surfaces of the ship. This is due to the materials comprising the ship not being allowed to vary thermally and relying on sensor noise to provide realistic texture. Also notice that there is no reflection on the surface of the water from the ship where one would expect a strong ‘halo effect’ to appear.

Another product that has been in development for several years is Vega Prime IR Scene™ by MultiGen-Paradigm Inc. Vega Prime IR Scene™ computes and dis-

\(^2\)First principles approaches imply that to the extent that it is practical, physics-based theories are used to predict higher-level phenomenologies.
2.5. Thermal Infrared Imagery Simulation

plays quantitative sensor images at wavelengths from the VIS through the TIR. Apparent radiance of a scene is computed from the position and orientation of the observer, producing quantitative radiance values for each pixel. The software uses a radiometric equation that contains terms for modeling reflected solar energy, reflected ambient skyshine energy, path emission, scattering, and thermal emittance. The Texture Material Mapper (TMM) is an optional add-on that makes it possible to classify all of the textures by material in a database that includes descriptions in terms of wavelength-dependent reflectance and thermodynamic properties. TMM can classify individual texels (or texture elements) with composite materials comprised of up to three individual materials at user-defined ratios to generate accurate classifications. Figure 2.14, which was generated by Vega Prime IR Scene™ shows a synthetic VIS and TIR image. At first glance, the resulting TIR image seems to have higher fidelity in its texture, however, the ground lacks detail that could only be provided by modeling the thermodynamic changes that occur per
pixel. Important factors such as soil moisture, material thickness, insolation history, and the underground water table all serve to modulate observed brightness temperatures naturally occurring in TIR imagery. This research will endeavor to improve upon the modeling of these TIR-dominating phenomena.

Aechelon Technology has developed a multi-sensor simulation tool called C-Radiant. C-Radiant provides physics-based spectral rendering and controls auto-gain, noise, and special effects. C-Radiant features real-time spectral rendering on a per-texel basis. Radiance is computed with multiple materials per texel, using a surface normal vector for both emissive and reflective components. Computed irradiance is based upon spectral response, sensor altitude and attitude. C-Radiant also computes solar loading in the TIR. This includes per-texel directional computation of the thermal solar/wind cycle load. An example of C-Radiant images
rendered in the VIS and TIR appears as Figure 2.15.

![Figure 2.15: C-Radiant Simulated Imagery: (left) VIS, (right) TIR [Aechelon Technology 2007.]](image)

C-Radiant appears to have reasonable results in terms of providing TIR texture in a synthetic image. However, once again the lack of in-depth thermodynamic modeling leaves the TIR images inadequate in terms of replicating realistic texture. For example, the fields and roads have a lack of in-class contrast. The mixture of classes per texel provides some texture along with the sensor noise modeling, however, additional thermodynamic modeling could be undertaken to fully realize all of the thermal processes contributing to observed TIR phenomena.

CAMEO-SIM is an electro-optic simulation environment developed by Lockheed Martin UK specifically for defense applications. CAMEO-SIM uses a physics-based, radiometrically-accurate synthetic scene generator between 0.3-25 µm. CAMEO-SIM predicts the diurnal variation in temperatures of all materials in the scene based on a weather history defined by the user. Specifically, the model includes the effects of wind speed, solar insolation, thermal shadowing and both natural and forced convection [Lockheed Martin 2007]. However, this model does not solve the 3D heat transfer equation across scene geometries. In order to ad-
dress this limitation, an infrared signature prediction model called MuSES (the Multi-Service Electro-optic Signature code) has been integrated into CAMEO-SIM. The result of this integration can be seen in Figure 2.16.

![CAMEO-SIM Simulated Imagery: (left) VIS, (right) TIR](image)

**Figure 2.16:** CAMEO-SIM Simulated Imagery: (left) VIS, (right) TIR [Curran and Curlee 2006].

MuSES-integrated CAMEO-SIM seems to have the best TIR texture result of current products in industry. However, the advanced thermal interactions that MuSES calculates for the tank are not computationally-feasible for the rest of the scene geometry. The combined CAMEO-SIM methodology uses a scene-wide look-up table of temperature predictions with different orientations and shadow histories. Final temperatures are then computed via interpolation. The TIR texture would be more realistic if detailed thermodynamic modeling could be employed across the entire scene. The research approach delineated in Chapter 3 implements a series algorithms in DIRSIG to address this problem of realistic TIR texture. Background information on DIRSIG and its current texture implementation will be discussed subsequently in Section 2.5.2.
2.5.2 DIRSIG

The initial development of the DIRSIG model was undertaken at RIT in the late 1980s as a simple thermal image rendering program using basic material thermodynamic properties and broadband emissivity values applied to 2D scene elements. Today, the DIRSIG model has evolved into a complex SIG application which produces simulated imagery in the VIS through the TIR regions. The model is designed to produce radiometrically-robust, broadband and hyperspectral imagery. This is accomplished through the integration of a suite of software tools based on a first principles approach utilizing radiation propagation sub-models. A first principles approach is used to decide whether a photon with a certain wavelength will be absorbed or reflected by a material with a specific chemical composition. Another first principles approach is employed using thermodynamic properties to predict surface temperature. These properties can be used as parameters to a set of governing equations that describe the flow of energy into and out of a surface in order to predict its steady-state temperature [Brown 2006]. Figure 2.17 provides examples of DIRSIG renderings in the VIS and LWIR.

Figure 2.17: DIRSIG Simulated Imagery: (left) VIS, (right) TIR.
Notice the VIS image in Figure 2.17 is using a fair amount of texture mapping to achieve its results. This will be discussed further in Section 2.5.2. The LWIR image in Figure 2.17 is lacking realistic texture in a lot of classes. Modeling additional thermodynamic properties such as thermal conductivity and heat capacity as well as providing accurate zenith and azimuth angles could potentially enhance the texture of this LWIR image.

Radiation Propagation

In Section 2.2.1 we defined radiation as a method of heat transfer in which energy is emitted due to the temperature of an object. This section will discuss how photons (especially those at TIR wavelengths) propagate and the mathematics we can use to model this phenomenon. Consider Figure 2.18, which depicts all of the energy paths of a photon whether the source was solar or self-emission. Here we are primarily concerned with paths D, E, F, and H (the self-emitted thermal photons). In the MWIR and LWIR, there are significantly more D- and F-type photons for which to account. DIRSIG uses the following equation (derived in detail in [Schott 1997]) to account for each of these photon sources to accurately model in-band scene radiometry:

\[
L_\lambda = \{E_{s\lambda}^\prime (\cos \sigma^\prime) \tau_1 (\lambda) \frac{r(\lambda)}{\pi} + \varepsilon(\lambda)L_{T\lambda} + F[E_{ds\lambda} + E_{de\lambda}] \frac{r_d(\lambda)}{\pi} \\
+ (1 - F)[L_{bs\lambda} + L_{be\lambda}]r_d(\lambda)\} \tau_2 (\lambda) + L_{us\lambda} + L_{ue\lambda} \left[ \frac{W}{m^2 \cdot sr \cdot \mu m} \right]
\]  

(2.16)

Table 2.2 defines each of the parameters involved. Notice the different types of photons are depicted in Figure 2.18. The radiometry sub-model, which is described in detail in Section 2.5.2, utilizes the physics of radiation propagation to explain sensor-reaching radiances.
Figure 2.18: Radiation Propagation Paths (A: Directly-Reflected, B: Downwelled, C: Upwelled, D: Self-Emitted, E: Emitted Downwelled, F: Emitted Upwelled, G: Multiple-Reflected, H: Background-Emitted & Reflected) [Schott 1997].

**DIRSIG Sub-Models**

Recall from Section 2.5.2 that DIRSIG is modular in design and utilizes numerous sub-models, each responsible for a link in the imaging chain. Several basic sub-models integral to this research are briefly described in the subsequent sections.

**Scene Geometry Sub-Model** The scene geometry sub-model allows the user to provide a 3D description of the synthetic scene. Every object within the scene is generated using an enhanced computer-aided design (CAD) environment. Once
<table>
<thead>
<tr>
<th>Parameter</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>$L_{\lambda}$</td>
<td>Wavelength-dependent total sensor-reaching radiance</td>
</tr>
<tr>
<td>$E'_{\lambda}$</td>
<td>Exoatmospheric irradiance (A-type photons)</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>Angle from target normal to the sun</td>
</tr>
<tr>
<td>$L_{T\lambda}$</td>
<td>Self-emitted radiance from target at temperature $T$ (D-type photons)</td>
</tr>
<tr>
<td>$\tau_1$</td>
<td>Transmission through the atmosphere along sun-target path</td>
</tr>
<tr>
<td>$\tau_2$</td>
<td>Transmission through the atmosphere along target-sensor path</td>
</tr>
<tr>
<td>$F$</td>
<td>Fraction of hemisphere above target that is sky (Shape Factor)</td>
</tr>
<tr>
<td>$r$</td>
<td>Target reflectance</td>
</tr>
<tr>
<td>$\varepsilon$</td>
<td>Target emissivity</td>
</tr>
<tr>
<td>$E_{ds\lambda}$</td>
<td>Downwelled solar irradiance (B-type photons)</td>
</tr>
<tr>
<td>$E_{de\lambda}$</td>
<td>Downwelled atmospheric self-emitted irradiance (E-type photons)</td>
</tr>
<tr>
<td>$L_{bs\lambda}$</td>
<td>Background solar reflected radiance (G-type photons)</td>
</tr>
<tr>
<td>$L_{be\lambda}$</td>
<td>Background self-emitted radiance (H-type photons)</td>
</tr>
<tr>
<td>$L_{us\lambda}$</td>
<td>Upwelled solar reflected radiance (C-type photons)</td>
</tr>
<tr>
<td>$L_{ue\lambda}$</td>
<td>Upwelled self-emitted radiance (F-type photons)</td>
</tr>
</tbody>
</table>

Table 2.2: Summary of Radiometric Parameters.

Objects are drawn to scale using wireframe models such as the one in Figure 2.19, they can be facetized (i.e., segmented into groups of 2D polygons). Detailed objects may contain tens of thousands of individual facets. Each facet may be assigned thermodynamic and optical properties based upon the material of which the facet is comprised. In addition to facetized objects, scene geometry also encompasses
the relative positions of all the objects within the scene referenced to the focal plane of the detector as seen in Figure 2.20. The scene geometry directly affects the amount of radiance observed at each polygon within the scene and greatly affects the resultant texture of objects within images.

Ray-Tracing Sub-Model The ray-tracing sub-model utilizes the scene geometry to render 2D imagery following mathematically-rigorous radiometric and thermal rules. For each pixel in the sensor’s focal plane, a ray is cast into the scene. As the ray encounters facets, an interaction list is produced with help from the radiometry sub-model. Rays are then cast from the encountered facets to the sun in order to determine solar shadowing histories and for current shadowing conditions at the simulation time. Figure 2.21 depicts the ray-tracing methodology used within DIRSIG. Additional rays are cast from the facet into the hemisphere above the target for characterization of the downwelled radiance onto the target.
Radiometry Sub-Model  The radiometry sub-model is responsible for computing the spectral radiance incident from a given path. Depending upon scene geometry, the radiance computation for a given path might include the incorporation of direct sky or sun light and the reflected or emitted components from one or more facets along the path. The details about how these components determine sensor-reaching radiance are described in Section 2.5.2. Utilizing the information passed from the ray-tracer and the thermal sub-model along with MODTRAN [Berk et al. 1988] or FASCODE [Smith et al. 1978], a sensor-reaching radiance is then computed for each pixel in the scene. MODTRAN was developed by the U.S. Air Force to compute atmospheric radiation propagation based upon user inputs. FASCODE is a high-resolution equivalent to MODTRAN. MODTRAN computes transmission as a function of view-angle, upwelled and downwelled spectral radiance as a func-
tion of view-angle, slant path, and range for any given sensor geometry [Schott et al. 2001]. Pre-defined atmosphere descriptions exist in MODTRAN (e.g., ‘tropical’ or ‘mid-latitude summer’) that can be rapidly integrated into a scene. If a more detailed atmospheric description is required, user-supplied radiosonde data can be incorporated [Peterson 2004].

**Thermal Sub-Model** The main purpose of the thermal sub-model is to predict a diurnal temperature per facet. DIRSIG accomplishes this by utilizing a modified version of the Air Force Infrared Image Model (AIRSIM) known as THERM, which was developed by the DCS Corporation for the Air Force in the late 1980s [DCS Corporation 1990]. THERM is a forward-chaining differential thermodynamic model that calculates time-dependent temperatures of objects as influenced by their environment. The model uses a meteorological history to drive its passive slab model which incorporates conventional thermodynamic parameters such as thermal conductivity, heat capacity, and thickness in order to produce surface temperatures [Brown 2006].

As discussed in Section 2.2, several processes of energy exchange (*i.e.*, radiation, conduction, and convection) occur at the interface between an object and its natural surroundings. Some of these processes cause a net absorption of energy by the surface and raise its temperature. Other processes result in a net loss of energy from the surface and tend to lower the surface temperature. Objects have the capacity to store and release heat, hence the past thermal history can be expected to affect the current temperature. However, this depends upon the thermal mass of the radiating surface, as larger masses tend to have more thermal inertia and change more slowly [Balfour 1995]. Of the three modes of heat transfer, radiation from the sun tends to dominate natural scenes during the day. Conduction is more
important in metals, and convection is most active under windy conditions. In addition, condensation and evaporation may also occur.

The THERM model begins with the generalized heat transfer equation

$$\nabla^2 T + \frac{\tilde{Q}_G}{k} + \frac{Q_s A}{AV} = \frac{\rho c}{k} \frac{\partial T}{\partial t} \left[ \frac{^\circ C}{cm^2} \right],$$  \hspace{1cm} (2.17)

where $T$ is the internal temperature of the object in $^\circ C$, $\tilde{Q}_G$ is the rate at which heat is generated internally per unit volume in $\frac{L}{hr \cdot cm}$ ($L \equiv$ Langleys), $Q_s$ is the net rate at which heat is entering through the surface per unit area in $\frac{L}{hr}$, $A$ is the surface area of the object in $cm^2$, $V$ is the volume of the object in $cm^3$, $k$ is the thermal conductivity in $\frac{cmL}{hr \cdot ^\circ C}$, $\rho$ is the mass density in $\frac{g}{cm^3}$, $c$ is the specific heat in $\frac{cal}{g \cdot ^\circ C}$, and $t$ is the time in hours. For reference, a Langley is equal to one $\frac{cal}{cm^2}$. In this lumped parameter method, the thermal conductivity is assumed to be high enough that objects cannot sustain large thermal gradients. Thus the first term of Equation 2.17 is set to zero [Karlekar 2005].

Multiplying both sides of Equation 2.17 by $\frac{kV}{A}$ results in the ordinary differential equation for heat transfer

$$\frac{\tilde{Q}_G V}{A} + \frac{Q_s A}{A} = \frac{\rho c V}{A} \frac{\partial T}{\partial t} \left[ \frac{^\circ C}{cm^2} \right],$$  \hspace{1cm} (2.18)

where the quotient $\frac{V}{A}$ represents a characteristic length, $L_c$, of the object. As previously mentioned, temperatures are calculated separately for each facet of a complete object. Each facet has surface area facing the outside world as well as surface area facing the interior of the object. Thus, the characteristic length is equal to half
of the true thickness of the facet. That is

\[ L_c = \frac{Th}{2} \quad [\text{cm}] \quad , \]  

(2.19)

where \( Th \) is the true thickness of the facet. The term \( \frac{\rho cV}{A} \) in Equation 2.18 controls the rate at which the temperature of the object can react to a given amount of heat input. This term can be interpreted as an object’s thermal mass, \( m_{th} \). It is also convenient to interpret the term \( \bar{Q}_G \) as a self-generated power term that is averaged over the surface area of the facet

\[ Q_G = \frac{\bar{Q}_G V}{A} \quad \left[ \frac{L}{hr} \right] \quad . \]  

(2.20)

Equation 2.18 then can be reduced to

\[ Q_G + Q_S = m_{th} \frac{\partial T}{\partial t} \quad \left[ \frac{L}{hr} \right] \quad . \]  

(2.21)

It is important to note that the term \( Q_S \) represents the rate of heat transfer across the surface of the object—it includes the effects of radiative heat exchange, convection, conduction, and absorption of insolation.

The primary concern with the rate of heat transfer is the specific temperature difference between an object and its environment. Thus it is convenient to express Equation 2.21 as

\[ m_{th} \frac{\partial T}{\partial t} = h_{eff} (T_e - T) \quad \left[ \frac{L}{hr} \right] \quad , \]  

(2.22)

where \( T_e \) is the equilibrium temperature at which \( \frac{\partial T}{\partial t} \) would become 0°C, and

\[ h_{eff} = \frac{Q_G + Q_S}{T_e - T} \quad \left[ \frac{L}{hr^\circ C} \right] \]  

(2.23)
is the heat transfer rate. Due to continually-changing environmental conditions, the equilibrium temperature is a goal that is seldom obtained. It does however provide an excellent benchmark for predicting the actual temperature of the facet [Karlekar 2005].

Equation 2.22 is the combined parameter thermal transient equation that is valid as long as the Biot condition is satisfied. The Biot condition states that the rate of internal conduction due to temperature gradients is high compared to the rate of radiative, convective, and evaporative heat transfer across the facet surface to the environment [Karlekar 2005]. Metallic objects tend to satisfy the Biot condition

\[ Bi = \frac{h_{eff}L_C}{k} \leq 0.1 \]  

because the thermal inertia of the surrounding air exceeds that offered by the metal. However, most natural scene objects do not satisfy the Biot condition and instead behave somewhat like thermal insulators. In this case the assumption that the object cannot sustain large thermal gradients does not hold, and the generalized heat transfer equation (Equation 2.17) needs to be applied throughout the volume of the object.

The heat balance equation establishes the equilibrium temperature toward which an object is being driven at each point in time. It corresponds to the steady state condition of Equation 2.21, in which the differential term is zero. The heat transferred across the surface of the facet includes the effects of radiation, convection, and conduction. Thus it is convenient to recast Equation 2.21 into energy leaving versus energy arriving at the facet

\[ \varepsilon_r \sigma T_e^4 + (h_{conv} + h_{cond})T_e = Q_{ex} + I_v + Q_G \left[ \frac{L}{hr} \right], \]  

(2.25)
where $\varepsilon_t$ is the thermal emissivity of the facet (dimensionless), $h_{\text{conv}}$ is the convective heat transfer rate in $\frac{\text{L}}{\text{hr} \cdot \text{C}}$, $h_{\text{cond}}$ is the conductive heat transfer rate in $\frac{\text{L}}{\text{hr} \cdot \text{C}}$, $Q_{\text{ex}}$ is the effect of external temperatures in $\frac{\text{L}}{\text{hr}}$, and $I_v$ is the effective insolation in $\frac{\text{L}}{\text{hr}}$.

The effects of external temperatures on the facet include the effects of radiation, convection, and conduction and are represented by

$$Q_{\text{ex}} = \varepsilon_t \sigma \left[ F_{f-sky} T_{sky}^4 + (1 - F_{f-sky}) T_a^4 \right] + h_{\text{conv}} T_a + h_{\text{cond}} T_{PP} \left[ \frac{\text{L}}{\text{hr}} \right], \quad (2.26)$$

where $F_{f-sky}$ is the dimensionless fraction of a facet’s surface that is exposed to the sky (usually 0.5), $T_{sky}$ is the effective temperature of the sky which radiates toward the external surface of the facet in °C, $T_a$ is the air temperature in °C, and $T_{PP}$ is the temperature of any precipitation in °C. Note that each facet is assumed to be thermally-independent and exhibit an isothermal surface behavior. Thus, THERM does not calculate the conduction between lateral facets. The effective insolation on a facet is represented by

$$I_v = \alpha_{\text{solar}} F_{f-sky} [ I_d \tau_d + I_D \tau_D \ast \max(0, \cos \theta) ] \left[ \frac{\text{L}}{\text{hr}} \right], \quad (2.27)$$

where $\alpha_{\text{solar}}$ is the dimensionless solar absorptivity, $I_d$ is the diffuse insolation on an exposed surface in $\frac{\text{L}}{\text{hr}}$, $\tau_d$ is the effective transmission of diffuse insolation (dimensionless), $I_D$ is the direct insolation on an exposed surface in $\frac{\text{L}}{\text{hr}}$, $\tau_D$ is the effective transmission of direct insolation (dimensionless), and $\theta$ is the angle between the facet surface normal and sun position in degrees [Karlekar 2005].

The surface geometry of an object is critical to correctly calculating thermal parameters. The surface geometry determines the effective angle of illumination by the sun and the relative amounts of diffuse sky and background irradiance that
are received by each facet. The difference in azimuth between the surface normal of a facet and the position of the sun is given by

\[ \gamma = A_R + \psi - \phi \quad [\text{degrees}] \quad , \]  

(2.28)

where \( A_R \) is the azimuth angle for the object in degrees, \( \psi \) is the azimuth angle of the facet surface normal relative to the object reference in degrees, and \( \phi \) is the azimuth angle of the sun position in degrees. The angle between the facet surface normal and the sun position is given by

\[ \theta = \cos^{-1}[\max(0, \cos(\Sigma) \cos(\beta) + \sin(\Sigma) \sin(\beta) \cos(\gamma))] \quad [\text{degrees}] \quad , \]  

(2.29)

where \( \Sigma \) is the angle between the facet surface normal and zenith in degrees and \( \beta \) is the angle between the zenith and the sun [Karlekar 2005]. These angles are represented pictorially in the example shown in Figure 2.22, where the pixel of interest has an azimuth of 60° and a zenith of 25°, while the solar azimuth is 45° and the solar zenith is 55°.

This series of equations forms the backbone of DIRSIG’s thermal sub-model and controls how DIRSIG utilizes all of the meteorological and thermodynamic parameters shown in Table 2.3. Since most natural backgrounds and many man-made targets have significant thermal inertia, it is important to accurately characterize the meteorological and environmental conditions in the recent past as well as the current acquisition period [DCS Corporation 1990]. DIRSIG computes a 24-hour solar insolation history for each rendered pixel by using the ray-tracer to determine the shadowing condition for each time in the broadband solar insolation history, as depicted in Figure 2.23. Transmissive objects in the solar path
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Figure 2.22: Azimuth & Zenith Angle Example Highlighting Scene Geometry.

<table>
<thead>
<tr>
<th>Location Parameters</th>
<th>Material Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Latitude</td>
<td>Heat Capacity</td>
</tr>
<tr>
<td>Longitude</td>
<td>Thermal Conductivity</td>
</tr>
<tr>
<td>Date</td>
<td>Thickness</td>
</tr>
<tr>
<td>Time (Difference from GMT)</td>
<td>Absorptivity/Emissivity</td>
</tr>
<tr>
<td>Time Interval</td>
<td>Exposed Area</td>
</tr>
<tr>
<td>Time of Sunrise</td>
<td>Self-Generated Power</td>
</tr>
<tr>
<td>Time of Sunset</td>
<td>Zenith &amp; Azimuth Angles</td>
</tr>
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</table>

<table>
<thead>
<tr>
<th>Meteorological Parameters</th>
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<tbody>
<tr>
<td>Direct Insolation</td>
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<td>Diffuse Insolation</td>
</tr>
<tr>
<td>High Noon Transmission</td>
</tr>
<tr>
<td>Air Temperature</td>
</tr>
<tr>
<td>Sunrise Air Temperature</td>
</tr>
<tr>
<td>Peak Air Temperature</td>
</tr>
<tr>
<td>Peak Air Temperature Time</td>
</tr>
</tbody>
</table>

Table 2.3: THERM Inputs [Brown 2006].

attenuate the solar insolation as necessary. When DIRSIG passes-on this insolation history, THERM evaluates the solar shadow history over the previous 24 hours
at 15-minute intervals (and at finer 5-minute intervals in the last hour) in order to determine an accurate temperature prediction per facet. This is accomplished by solving the differential heat balance equation (Equation 2.22) implemented as two nested loops. The first loop computes the equilibrium temperature at each timestep assuming that the surface has no thermal mass. Subsequently, THERM performs a loop through each timestep and accomplishes the forward-chaining to take into account the actual thermal mass in its temperature prediction. This temperature prediction is often described as diurnal temperature variation.

Consider the temperature variation of different class types in Figure 2.24. Notice that the temperature changes most rapidly near sunrise and sunset. The labels IM-
Figure 2.24: Diurnal Temperature Variation for Typical Class Types [Campbell 2002].

$\text{AGE 1}$ and $\text{IMAGE 2}$ represent TIR images taken at different times and a possible range of temperature values for each image. The vertical bars on the right are projections of the corresponding class types on the left. The intersection of any two curves is called the \textit{thermal crossover}, where radiant temperatures are identical for both material or class type. These diurnal curves must be modeled correctly for each corresponding class type in the image. Once THERM successfully calculates temperature variation predictions for each facet, this information is passed to the radiometry sub-model.

Figure 2.25 illustrates the entire interaction between sub-models. The next section will describe the methodology already within DIRSIG to accomplish spatial/spectral texture. This scheme already works well within the VIS/NIR region,
however it breaks down in the TIR due to a lack of thermodynamic modeling of within-class variability.

**Figure 2.25**: Current DIRSIG Sub-Model Interaction [Peterson 2004].

**Current DIRSIG Texture**

Real imagery is known to contain a high degree of spatial and spectral variability which provides texture that is not easily characterized by lower-order statistics. The complexity of this variability challenges target-detection algorithms to successfully separate targets and backgrounds by fitting known statistical or geometrical models. Thus it is important that modeled data contain a sufficient level of variability within any given material. In the VIS/NIR regions, DIRSIG utilizes a large database of reflectance curves for a given material that are presumed to represent possible in-class variations. DIRSIG must be provided with a sample texture image that is assigned to each material class to represent the spatial variation of reflectance for a specific wavelength region. During the rendering process,
a mapping mechanism identifies a pixel that is then used to drive a statistical process using Z-scores to select a spectral reflectance curve from the large database as in Figure 2.26. The selected spectral reflectance curve is then used in all the computations involving that surface for the pixel currently being rendered. This process can be extended by the use of multiple texture maps per class and even modified to use fractions (or mixtures) of classes per pixel as seen in Figure 2.27.

Figure 2.27 illustrates the three current rendering techniques offered by DIRSIG on a portion of Rochester, NY modeled as Megascene 1. Figure 2.27a is obtained using only one panchromatic texture map, while Figure 2.27b increases the number to three broadband maps across the VIS. Figure 2.27c uses fraction maps (a.k.a.,...
mixture maps) to model a spatially-varying linear combination of materials at each location within the scene. Instead of introducing the spatial/spectral variation by modifying the spectral reflectance of a given class as a function of location, fraction maps introduce variation by spatially varying the proportions of materials. This allows each synthetic pixel to be rendered by re-mixing endmembers according to the values in the fraction map. One of the drawbacks of the mixture method is the periodic striping seen in Figure 2.27c. This is an artifact of the noise in the real imagery used to create the mixture maps.

These techniques are known to work well in the VIS/NIR. However, in the TIR the variation in the emissivity of materials is quite small. Thus, these approaches do not introduce sufficient variation or texture in the TIR. In order to improve upon existing texture generation in the TIR, one must consider methods modeling variability that is driven primarily by geometric and thermodynamic inhomogeneities. These thermodynamic inhomogeneities include spatially-varying radiational and convective loading effects and sub-surface variations in material density, water content, etc. Due to these additional sources of variability cited here and in Section 2.5.2, a fundamentally different approach is necessary to model realistic texture in

Figure 2.27: DIRSIG Renderings of MegaScene 1 Using (a) a Single Texture Map, (b) Three Texture Maps, (c) Fraction Maps.
2.5. Thermal Infrared Imagery Simulation

The most comprehensive example so far of using DIRSIG to model scenes in the TIR was undertaken in [Peterson 2004]. This research endeavored to create a synthetic high-fidelity model of a landmine scene being imaged by the Airborne Hyperspectral Sensor (AHI). After solving numerous geometric issues relating to roll correction due to the sensor being mounted on an airborne platform, he proceeded to incorporate the use of a mapping technology widely known as bump mapping. *Bump mapping* allows for a specified two-dimensional surface variation of a given material. In order to accomplish this, a gray-level mapping image is used where the difference in digital counts between neighboring map-image pixels is used to alter the direction of a material’s surface normal vector, as seen in Figure 2.28. For example, any scene built in a computer-aided design (CAD) program would most likely be built on a perfectly flat surface. However, outdoor scenes have natural variations due to changes in elevation, structures, and features in the earth’s crust. Thus, a bump map is used to create the appearance of 3D structure without having to define additional facets. A bump map image is then applied to the earth’s surface. The resulting amount of change in gray-level value between any two bump map image pixels corresponds to a deflection of the earth’s surface normal at that spatial location by a calculated angular amount. DIRSIG allows the scaling or resolution of the map to be determined by a GSD value. Note, using DIRSIG’s bump
mapping feature is also a potential method for introducing brightness temperature change resulting in TIR texture. This would be accomplished by altering the surface normal of facets such that they would receive differing amounts of solar insolation, resulting in perceivable per-pixel changes in temperature.

Peterson used the texture mapping process described previously where DIRSIG statistically chooses from a family of emissivity curves to vary the texture. In addition, he added the bump map shown in Figure 2.29 with a scaling of 0.015 to produce a small (0°-17°) amount of variation in the surface normal of the terrain. A final tweak (i.e., blurring) took place in the form of sensor noise characterization.

![Bump Map Gray-Level Image](image)

**Figure 2.29:** Bump Map Gray-Level Image

An example of the results of Peterson’s efforts is shown in Figure 2.30. Figure 2.30 contrasts Band 25 of an AHI hyperspectral image with a synthetically-derived image of the same landmine scene. The image was taken at 700 ft during the evening. Allowing DIRSIG to statistically choose between emissivity curves brought some additional variability in terms of spectral texture across individual material types. However, spatially the variability is inadequate due to a lack of thermodynamic modeling and the effect of applying the bump map randomly to the scene. Each pixel of the same class received the exact same values for its thermodynamic parameters, thus only the bump map, sensor noise characterization, and statistically-chosen emissivity curves provide the texture seen in Figure 2.30.
This chapter has laid out the background and theory surrounding this research effort. At this point DIRSIG is not able to spatially and temporally vary the thermodynamic material parameters (first defined in Table 2.3) in a matter consistent with what is observed in TIR-radiance imagery. Physics tells us that thermodynamic properties such as thermal conductivity and heat capacity vary enough in nature to cause these phenomena to be observable in TIR imagery. Spatially, the scene geometry tends to be dominated by solar insolation history. Thus, identifying the correct per-pixel azimuth and zenith angles is paramount. However, differences in soil moisture, material thickness, the surrounding weather conditions, and the
underground water table will certainly affect how the thermodynamic properties manifest themselves in modulating the sensed radiance. Temporally, the scene geometry tends to dominate more so, since most of the other variables do not fluctuate as much over time. The next chapter will outline an approach to model these additional causes of variability in the TIR. This approach will include algorithms that will modify the thermodynamic variables using a physics-based first principles methodology to correctly and consistently model the diurnal temperature variation of the various class types found within TIR imagery.
This chapter utilizes the background information and theory from Chapter 2 to describe the approach which was undertaken to address the problem of differences in TIR-radiance from phenomenology seen in the VIS/NIR portions of the electromagnetic spectrum. Section 3.1 gives a graphical overview of the entire experimental process. Section 3.2 first describes a data collection performed at RIT to determine the relative importance of spatial versus temporal variability in LWIR texture. The remainder of Section 3.2 explains the details behind the Trona data collection and calibration. Section 3.3 defines each TIR texture variable and describes
Section 3.4 discusses the methods to estimate each parameter in order to have THERM correctly model temperature variation for various class types. Section 3.5 delineates the ground truth requirements in order to achieve various levels of TIR texture accuracy. Section 3.6 lays out a plan for incorporating a map-manipulation technique inside DIRSIG in order to model the additional TIR variability. Finally, Section 3.7 describes how specific GLCM metrics and in-class rank-order correlation statistics are used to quantify the success of this effort. Note that this chapter is dedicated to describing the approach undertaken in this research, thus all of the results will be discussed in the following chapter.

### 3.1 Experimental Design Overview

The flowchart depicted in Figure 3.1 provides a summary of the experimental process that was followed in this research. Each stage in the flowchart is discussed in detail in a corresponding section of Chapter 3.

### 3.2 Trona Experimental Data Collection

#### 3.2.1 JaTeX Pre-Collection

Before the Trona data collection could be planned, a 24-hour data collection entitled JaTeX (Jake’s Texture eXperiment) was devised to capture both spatial and temporal variability in the LWIR. JaTeX employed the WASP sensor system on a rooftop to stare at a scene (see Figure 3.2) from approximately 1000’ away for 24 hours, performing the same script of tests at hourly intervals in order to determine
the relative importance of temporal factors. The script, as shown in Figure 3.3, was designed to capture changes in texture at specific time intervals of hours, minutes, seconds, and split-seconds (3Hz). An LWIR example image from this collect is shown in Figure 3.2b. After calibrating the imagery utilizing pre-built calibra-
Figure 3.2: JaTeX Data Collection Imagery in (a) VIS (b) LWIR.

Figure 3.3: JaTeX Hourly Script.

tation instruments that were imaged every hour by the sensors, statistical analysis was performed over the 3x3 pixel region depicted in Figure 3.2b for each image acquired during the collect.

The image statistics resulting from the script executed at 6 PM (shown in Table 3.1) are typical of those over the entire 24-hour period. A noise characterization of

<table>
<thead>
<tr>
<th>Type of Area Measured</th>
<th>Digital Counts (14-bit)</th>
<th>°C</th>
</tr>
</thead>
<tbody>
<tr>
<td>Highlighted 3x3 Area (Spatial Variability)</td>
<td>38.4</td>
<td>0.31</td>
</tr>
<tr>
<td>Center Pixel (1 Hz)</td>
<td>8.73</td>
<td>0.07</td>
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<td>Center Pixel (1/60 Hz)</td>
<td>18.9</td>
<td>0.15</td>
</tr>
<tr>
<td>Center Pixel (1/600 Hz)</td>
<td>262.7</td>
<td>2.14</td>
</tr>
</tbody>
</table>

Table 3.1: Sample JaTeX Standard Deviation Statistics.

WASP performed by Pixel Physics in 2003 gave an NEΔT of the LWIR camera of
154 mK [Pixel Physics 2003], meaning that the magnitude of changes in apparent temperature within any 10-minute time interval were within the noise levels of the sensor. This led to the conclusion that temporal variability need not be modeled on a minute- or second-timescale.

### 3.2.2 Trona Collection Overview

The JTeX data collection was a stepping stone for planning the timescale of the Trona data collection. Figure 3.4 is an annotated graphic provided by Google™ Maps that illustrates the flightlines and surrounding area of Trona, CA that were the focus of the data collection for this TIR texture research. Trona is located in southeastern California (see Figure 3.5) at Latitude 35.762°N, Longitude 117.371°W, and it has a hot, arid climate particularly from April-November. The analysis of

![Figure 3.4: Trona, CA Data Collection.](image)
JaTeX allowed for the planning of four Trona data collection flights over the two target flightlines shown in Figure 3.4 at 5 AM, 11 AM, 4 PM, and 5 PM PDT. The WASP sensor (first described in Section 2.1) was mounted in a small Piper Aztec aircraft and flown at heights from 2500’-3500’ over the target areas. Meanwhile temperature and meteorological data for image calibration purposes were taken at a ground site along the eastern flightline. The flightlines were chosen in order to incorporate areas that would most likely provide good texture in the TIR. These areas included the dry salt lake bed, different portions of sandy soil in the area, the vegetative outwash north of Trona, the chemical plant and part of Trona itself. Figure 3.6 depicts some of the local terrain and shows the two calibration pools. Reflectivity and thermal emissivity measurements of various subjects were taken.
using ASD and D&P Instruments field spectrometers, respectively. Figure 3.7 depicts the LWIR portion of a D&P-sampled spectrum of a sand/salt mixture with some small pebbles taken along an access road to the salt flats.
3.2.3 Trona Data Collection

The Trona TIR texture data collection mission resulted in a series of images taken over each flightline at the four imaging times. The GSD of the SWIR, MWIR & LWIR cameras in the imagery with which we are concerned was ~2.5’ at 2500’ AGL (Above Ground Level). The VIS camera took images concurrently with a 0.4’ GSD. The sky had no visible cloud cover, and weather conditions of the local area ranged from 11.7°C at 5 AM to 21.1°C at 5 PM as seen in Table 3.2.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
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</thead>
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<td>13.9</td>
<td>1.1</td>
<td>1016</td>
<td>N 29</td>
</tr>
<tr>
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<td>14.4</td>
<td>0.0</td>
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<td>N 25</td>
</tr>
<tr>
<td>2 AM</td>
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<td>0.0</td>
<td>1017</td>
<td>N 13</td>
</tr>
<tr>
<td>3 AM</td>
<td>10.6</td>
<td>0.6</td>
<td>1017</td>
<td>N 9</td>
</tr>
<tr>
<td>4 AM</td>
<td>11.1</td>
<td>-2.8</td>
<td>1017</td>
<td>N 10</td>
</tr>
<tr>
<td>5 AM</td>
<td>11.7</td>
<td>-4.4</td>
<td>1018</td>
<td>N 13</td>
</tr>
<tr>
<td>6 AM</td>
<td>12.2</td>
<td>-4.4</td>
<td>1018</td>
<td>N 18</td>
</tr>
<tr>
<td>7 AM</td>
<td>9.4</td>
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<td>1019</td>
<td>SW 6</td>
</tr>
<tr>
<td>8 AM</td>
<td>13.3</td>
<td>-4.4</td>
<td>1020</td>
<td>NW 8</td>
</tr>
<tr>
<td>9 AM</td>
<td>15.6</td>
<td>-4.4</td>
<td>1021</td>
<td>N 14</td>
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<td>-4.4</td>
<td>1022</td>
<td>NNE 10</td>
</tr>
<tr>
<td>11 AM</td>
<td>18.3</td>
<td>-4.4</td>
<td>1021</td>
<td>NNE 9</td>
</tr>
<tr>
<td>12 PM</td>
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<td>-5.0</td>
<td>1021</td>
<td>NE 17</td>
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<tr>
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<td>-5.6</td>
<td>1020</td>
<td>NNE 16</td>
</tr>
<tr>
<td>2 PM</td>
<td>21.7</td>
<td>-6.1</td>
<td>1019</td>
<td>NE 13</td>
</tr>
<tr>
<td>3 PM</td>
<td>22.2</td>
<td>-6.7</td>
<td>1019</td>
<td>NNE 9</td>
</tr>
<tr>
<td>4 PM</td>
<td>21.7</td>
<td>-7.2</td>
<td>1019</td>
<td>NE 5</td>
</tr>
<tr>
<td>5 PM</td>
<td>21.1</td>
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<td>Calm</td>
</tr>
<tr>
<td>6 PM</td>
<td>20.6</td>
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<td>1019</td>
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</tr>
<tr>
<td>7 PM</td>
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<td>1019</td>
<td>Calm</td>
</tr>
<tr>
<td>8 PM</td>
<td>13.9</td>
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<td>1020</td>
<td>W 7</td>
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<td>-1.7</td>
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</tr>
<tr>
<td>11 PM</td>
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<td>-1.7</td>
<td>1021</td>
<td>NWW 3</td>
</tr>
<tr>
<td>12 AM</td>
<td>6.7</td>
<td>-4.4</td>
<td>1021</td>
<td>Calm</td>
</tr>
</tbody>
</table>

*Table 3.2:* Weather at Trona on October 18, 2006 (in PDT).
The four missions flown over Trona on Oct 18 resulted in several hundred VIS, SWIR, MWIR, LWIR images. As an example of the variability between images of the same subject in different portions of the spectrum, consider Figure 3.8. Many features are correlated between the two images, however several phenomena present in the VIS as surface features do not appear in the LWIR image, and likewise thermodynamic factors are affecting the LWIR image in ways not perceivable in the VIS.

**Figure 3.8**: Trona WASP Imagery at 11 AM from 2500': (left) VIS, (right) LWIR.

### 3.2.4 Trona Data Calibration

The first step before being able to use a TIR texturing algorithm is to calibrate the obtained imagery from raw digital counts into brightness temperatures. This was accomplished utilizing calibration data taken at the ground station mentioned previously in Section 3.2.2. At the ground station, the resistance (then converted
into temperature) of a warm bath and a separate cold bath of water was measured using two thermistors. A gain and a bias was then calculated for each camera per imaging time. This allowed the imagery to be converted into in-band ground-leaving brightness temperature in °C via a simple linear equation

\[ DC = \text{Gain}(T) + \text{Bias} \quad [\text{counts}] \]

where \( DC \) is digital counts and \( T \) is brightness temperature. Rearranging Equation 3.1 gives us a brightness temperature for which we can solve per pixel

\[ T = \frac{DC - \text{Bias}}{\text{Gain}} \quad [\text{°C}] . \]

Once the imagery has been calibrated it undergoes registration in order to have a “time history” per pixel. Registration with sub-pixel accuracy (see Tables in Chapter 4) was performed manually by selecting tiepoints in the image processing program ENVI (Research Systems Inc.). Rotation, scaling, and translation matrices are then calculated by ENVI and used to register the images. A sample registration of a 5 AM, 11 AM, 5 PM time series of images appears as Figure 3.9. Dead pixels on the CCD are readily apparent in Figures 3.9a and 3.9c. These are a known problem with WASP and can be removed by interpolating values from neighboring pixels.

This section has described the WASP data collection over Trona, CA in detail. The process of image calibration and registration has been illustrated. The next section will provide a methodology for synthetically reproducing these images to include the image texture. It will also be possible to simulate images of the same scene at any other time even under potentially different weather conditions. This will be accomplished by modeling the thermodynamic parameters of the scene.
3.3. *TIR Texture Parameters*

The crux of this research is to create a method to model the underlying physics of each of the thermodynamic material parameters in Table 3.3, such that simulated

**Figure 3.9:** LWIR Registered WASP Imagery (Non-Interpolated) at 2500': (a) 5 AM, (b) 11 AM, (c) 5 PM.

using calibrated and registered imagery.

### 3.3 TIR Texture Parameters

The crux of this research is to create a method to model the underlying physics of each of the thermodynamic material parameters in Table 3.3, such that simulated
brightness temperatures quantitatively match those found in real TIR imagery at various times. In order to understand some of the complexities involved with this

<table>
<thead>
<tr>
<th>TIR Pixel Parameter</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Azimuth Angle</td>
<td>Angle counter-clockwise from true north [degrees]</td>
</tr>
<tr>
<td>Zenith Angle</td>
<td>Declination angle from the outward normal of the Earth [degrees]</td>
</tr>
<tr>
<td>Exposed Area</td>
<td>Fraction of exposure to ambient air</td>
</tr>
<tr>
<td>Solar Absorptivity</td>
<td>Fraction of incident solar energy neither transmitted nor reflected</td>
</tr>
<tr>
<td>Thermal Emissivity</td>
<td>Ratio of energy radiated by a material to energy radiated by a blackbody at the same temperature</td>
</tr>
<tr>
<td>Self-Generated Power</td>
<td>Rate at which heat is generated internally ( \frac{L}{hr.cm} )</td>
</tr>
<tr>
<td>Thermal Conductivity</td>
<td>Ability to conduct heat ( \frac{cm.L}{hr.C} )</td>
</tr>
</tbody>
</table>
| Thickness           | Facet depth \( [cm] \)  
                     \( \text{(**note: characteristic thickness is one half the true thickness since there are both inward- and outward-facing surface areas)} \) |
| Specific Heat       | Energy required to increase the temperature of an object by a certain interval \( \frac{cal.cm^{3}}{g.\circ C} \) |
| Mass Density        | Ratio of the amount of matter in an object compared to its volume \( \frac{g}{cm^{3}} \) |

*Table 3.3: Modeled Thermodynamic Parameter Descriptions.*

...
3.3. *TIR Texture Parameters*

<table>
<thead>
<tr>
<th>TIR Pixel Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Azimuth Angle</td>
<td>0°</td>
</tr>
<tr>
<td>Zenith Angle</td>
<td>0°</td>
</tr>
<tr>
<td>Exposed Area</td>
<td>0.5</td>
</tr>
<tr>
<td>Solar Absorptivity</td>
<td>0.56</td>
</tr>
<tr>
<td>Thermal Emissivity</td>
<td>0.93</td>
</tr>
<tr>
<td>Self-Generated Power</td>
<td>0 $[\frac{L}{hr\ cm}]$</td>
</tr>
<tr>
<td>Thermal Conductivity</td>
<td>50 $[\frac{cm\ L}{hr\ ^\circ C}]$</td>
</tr>
<tr>
<td>Thickness</td>
<td>1 $[cm]$</td>
</tr>
<tr>
<td>Specific Heat</td>
<td>5 $[\frac{cal\ cm^3}{g\ ^\circ C}]$</td>
</tr>
<tr>
<td>Mass Density</td>
<td>1 $[\frac{g}{cm^3}]$</td>
</tr>
</tbody>
</table>

*Table 3.4:* Baseline Thermal Parameter Values of a Sand Pixel.

45° to better display the effect of the solar component in determining temperature. As one might expect, the north-facing pixel stays cooler throughout the 24-hour period. The south-facing pixel is warmer for most of the day, except for the morning when east-facing is warmer and evening when west-facing is warmer. Figure 3.11 demonstrates the change in temperature as a function of the zenith angle of
the pixel. The pixel azimuth angle is set to 225°. Temperatures are largely similar until early evening, when lower profile zenith angles preclude many solar photons from impacting the pixel and subsequently raising its temperature.

![Pixel Zenith Angle Variation (Azimuth = 225°).](image)

Figure 3.11: Pixel Zenith Angle Variation (Azimuth = 225°).

The exposed area of mostly ‘flat’ pixels simulated to be on the surface of the earth does not greatly affect diurnal temperature profiles as seen in Figure 3.12. Notice that a pixel with a lower exposed area will have a slightly higher temperature in the morning since there is less exposed area in which to emit photons. Conversely, in the afternoon pixels with higher exposed area have slightly higher temperatures because there is more ambient air exposure.

The thermal conductivity of materials such as salt and dry sand is low, meaning that heat will not be dissipated to the surrounding earth very quickly. This leads to the higher temperatures seen for these types of materials in Figure 3.13. One common source of higher thermal conductivity is the increase in water content. Although one should note that higher orders of thermal conductivities have
3.3. TIR Texture Parameters

**Figure 3.12:** Exposed Area Variation.

...decreasing returns in terms of lowering daytime temperatures.

**Figure 3.13:** Thermal Conductivity Variation.

Heat capacity is the product of the specific heat and mass density of a material.
The behavior of the diurnal temperature profile will vary in a non-linear fashion with increasing heat capacity as seen in Figure 3.14. There is a median heat capacity at which the temperature changes very little throughout the day. Since the heat capacity indicates the ability of a substance to store heat energy, materials with low heat capacities are greatly affected by the ambient air temperature and are dominated by the solar component (or lack thereof). Moist or saturated sand/soil has greater heat capacity which prevents it from greater temperature swings.

The thickness of a desert sand pixel refers to the depth of the earth at which the physical model is assuming that thermodynamic processes are taking place. As seen in Figure 3.15, an increasing pixel thickness prevents change in the slope of the temperature profile due to the increased thermal inertia resulting from the increased mass.

Solar absorptivity has a straight-forward effect on the diurnal temperature profile of a sand pixel as seen in Figure 3.16. Increasing the solar absorptivity of a
substance will increase its temperature in the daytime due to the solar component while having no effect at night. Notice that solar absorptivity and pixel azimuth
angle have the most profound range of effects on the daytime temperature of a substance. This follows logically when considering the overwhelming amount of energy that can be provided by the solar component.

The final physical thermodynamic parameter to be modeled in DIRSIG is thermal emissivity. Its effect on diurnal temperature is also straightforward as seen in Figure 3.17. Lower emissivities lead to slightly higher diurnal temperature profiles and vice versa is also true. The overall magnitude of temperature change due to thermal emissivity is lower than most of the parameters. However, apparent effects to in-band emission are present with changing thermal emissivity and have great bearing upon perceived brightness temperature.

Armed with the knowledge of each of these DIRSIG TIR parameters, the subsequent sections will describe methods for their estimation. These methodologies will entail separate solutions for some of the parameters using various sources of data. The per-pixel solution for the remaining thermal parameters is estimated us-

**Figure 3.17:** Thermal Emissivity Variation.
3.4 TIR Parameter Estimation

This section defines several approaches whose amalgamation will estimate all of the thermal parameters necessary to simulate the physical processes that affect the brightness temperature of pixels throughout a given scene. These methods can be employed with various amounts of success based upon the types and fidelity of image coverage of the scene of interest.

3.4.1 Brightness-Derived Orientation Mapping (BDOM)

It is unfortunate that we often do not have the ground truth necessary to accurately know the azimuth/zenith of every pixel in a given scene. Digital Elevation Maps (DEMs) published by the U.S. Geological Survey (USGS) and others often have 30m (or even 10m) postings, however this is not good enough to provide reasonable detail at the 2.5’ GSD-level. This is a common problem and our algorithm assumes this lack of ground truth.

In addition, due to the highly undetermined and non-linear aspects of the thermodynamic parameterization space, an ad hoc method is needed for restricting the largest sources of error. As seen in Section 3.3, the per-pixel azimuth and zenith angles have a substantial impact on the brightness temperature profiles of pixels in a TIR image. In order to determine these angles, the 3D shape of the terrain must be recovered from 2D images. This is commonly known as ‘shape from shading’ in the machine vision field. An alternative method is to exploit a binocular disparity, which is the difference in relative positions of corresponding features resulting...
from the spatial separation of two co-located or nearly co-located sensors [Horn and Brooks 1989]. However this type of binocular stereo imaging is not commonly available, and thus will not be included in our TIR texture algorithm.

Another method of assimilating the azimuth/zenith angles is to rely on the variation in brightness (VIS) or brightness temperature (LWIR) and utilize the brightness ratio of multi-temporal images, assuming that first-order changes are due to deviations in the terrain’s surface normal. This methodology will be referred to as Brightness-Derived Orientation Mapping (BDOM) and was developed jointly for this research and that prescribed in [Lach 2008]. Specifically, the two different (but roughly equivalent in principle) procedures for accomplishing this are—1) use the change in per-class brightness ratio from 11 AM to 5 PM images in the VIS to determine azimuth/zenith, or 2) use per-class brightness temperature relative scales at 11 AM and 5 PM in the LWIR to determine azimuth/zenith. The first method is preferable since VIS data of the scene is available and should allow for more accurate scene geometry estimation. The latter method of using the LWIR will not be as successful for azimuth/zenith angle determination because many of the phenomena causing variation in the thermal will be incorrectly attributed to the azimuth/zenith angles during this process.

The first step in BDOM angle estimation is to classify one of the images to serve as a ‘truth’ classification map for both images. This has to be done in-advance because all of the brightness ratios will be scored on a per-class basis. An unsupervised method such as k-means is adequate. The next step is to convert the Red, Green, Blue (RGB) VIS images into panchromatic images for easier brightness ratio comparisons. A common equation for doing this is

\[ Y = 0.3R + 0.59G + 0.11B. \] (3.3)
3.4. TIR Parameter Estimation

Note, this texture algorithm only requires brightness ratios; absolute conversions from RGB to gray-scale depend on the sensitivity response curve of the detector to light as a function of wavelength [Fanning 2007].

Once the images have an individual class and brightness value associated with each pixel, the next step is to use this empirical data to determine the most feasible combination of per-pixel azimuth/zenith angles. This is accomplished using the panchromatic AM and PM images and the classified image. The following pseudocode describes how an azimuth/zenith angle combination will be estimated on a per-pixel basis:

- Start with classified image and panchromatic AM/PM images in order to compare brightnesses
- Calculate sun azimuth/zenith angles
- Assume ‘flat pixel’ brightness to be per-class mean brightness-level
- Define \( \sigma \) as the solar declination angle [rad]
  - \( u_p = [0,0,1] \)
  - \( \sigma_{AM} = \cos^{-1}\left(\frac{u_p \cdot \text{sunAM}}{|u_p| \cdot |\text{sunAM}|}\right) \)
  - \( \sigma_{PM} = \cos^{-1}\left(\frac{u_p \cdot \text{sunPM}}{|u_p| \cdot |\text{sunPM}|}\right) \)
- FOR \( m = 1, \) image size DO BEGIN
  - Calculate target difference angle \( \theta \) using per class ratio (\( B = \) brightness):
    \[
    \frac{B}{B_{flat}} = \frac{\cos \theta}{\cos \sigma}
    \]
  - Test each potential azimuth/elevation combination at 45\(^\circ\)/5\(^\circ\) increments to get closest RMSE match to \( \theta_{AM} \) and \( \theta_{PM} \)
  - **Note: Test potential azimuth angles from 0\(^\circ\)-360\(^\circ\) and zenith angles from 0\(^\circ\)-25\(^\circ\)
  - Return per-pixel closest RMSE azimuth/zenith combination
- END FOR

The key to this algorithm is an assumption that to first order the brightness of a per-class ‘flat pixel’ is only contingent upon where the sun is: \( B_{flat} = E_s\cos \sigma \).
Meanwhile, the brightness difference in the AM/PM image is attributable to first degree by $\cos \theta$: $B = E_s \cos \theta$. Taking the ratio of these two equations results in $\frac{B}{B_{flat}} = \frac{\cos \theta}{\cos \sigma}$. Notice that $\cos \theta$ is a combination of the original $\cos \sigma$ term and the $\cos \theta$ difference. A given AM/PM brightness value could actually be higher than that of a ‘flat pixel’ if that pixel is facing more into the sun. This brightness comparison essentially identifies the most likely azimuth/zenith angle combination to produce the given AM & PM brightness ratios. Figure 3.18 demonstrates how this algorithm works. Figure 3.18a represents the base case in which the pixel is at the mean brightness level for the class and thus the pixel is deemed to be ‘flat’. This means that the pixel zenith is assumed to be 0° (pixel azimuth is irrelevant if pixel zenith = 0° since any value of pixel azimuth will result in the same brightness). Figure 3.18b depicts how a pixel with an azimuth of 155° and zenith of 25° would result in a detectable change in brightness that would be attributed to first degree to the direct-solar $\cos \theta$ term. Note that the sun rises in the East Southeast (ESE) during autumn in Trona, CA. Thus, we would expect this pixel to be significantly brighter in the AM image than the PM image. In addition, a maximum zenith angle of 25° was chosen for this algorithm based on WASP LWIR having a 2.5’ GSD.
and seeing fairly steep ravines in the imagery that were resolvable and could result in somewhat severe zenith angles. Once again, the zenith angle estimation will provide the amount of surface normal deflection for purposes such as determining the degree of solar insolation that a facet receives.

Figure 3.19 depicts an oblique-angle image of a BDOM test scene in which ten pyramids of varying pitch are placed on a flat plate. The pyramid pitch is increased by 5° in each pyramid from the top right to the bottom left. Pyramids that reside next to each other from left-to-right are identical except for their orientation. All facets have the same material assigned to them. The difference in radiance is solely attributable to the sun location. The scene has the same latitude/longitude/altitude as Trona, CA. Some shadows exist due to the height of the pyramids and the sun angle.

Figure 3.20 demonstrates how the BDOM algorithm works on the pyramid test scene generated using the DIRSIG tool. Figures 3.20a and 3.20b are the AM and PM radiance images, respectively, of the test scene. The pixel azimuth and pixel zenith results in Figures 3.20c and 3.20d, respectively, closely match what we know as the input truth previously described in Figure 3.19. Pixel azimuth in Figure 3.20c is exactly correct except in the shadow regions and on the highest-pitch (25°) pyramid.
This behavior is acceptable because we expect there to be very few pixels in natural desert scenes at this steep angle or that are in shadow. Similarly, the pixel zenith
result in Figure 3.20d is excellent except for the 15°, 20°, and 25° pyramids. Here the pixel zenith angles are estimated to be slightly lower—which is an acceptable shortcoming of this algorithm. Once again the shadows will slightly perturb the result.

### 3.4.2 Pixel Exposed Area from the Surround (PEAS)

Once azimuth/zenith angles have been estimated using BDOM, one can determine an exposed area value for the pixel from the geometry of the surrounding pixels. As defined in section 3.3, exposed area is the parameter used to estimate the amount of exposure a material has to the ambient air. For example, the pixel may consist of a material arranged as a horizontal slab that is exposed to the air only through its top-facing surface (i.e., flat natural terrain). In contrast, the pixel may consist of a material that may be a vertical surface such as a wall that is exposed to the air on both sides. In addition to convective loads, this parameter plays a role in the calculation of radiational loading by describing how much of the surface is exposed to the sky. This term is unitless and has a valid range of [-1,1]. Negative values denote surfaces that are exposed on both sides while positive ones denote single-sided surfaces. The values commonly range from 0.25-0.70 (with the addition of a +/- sign to denote the cardinality of sides of the surface).

As shown in Figure 3.21, the PEAS algorithm begins by assigning an exposed area value to the pixel (0.45-0.50) depending upon its slope. Pixels on an incline will start with a lower exposed area value which depends upon the severity of the rise (inclines decrease the amount of ambient air exposure). Then for each of the four directly neighboring pixels, a value up to 0.05 is added or subtracted to the exposed area depending upon whether the neighbor is facing away or toward the
Figure 3.21: Exposed Area from Surrounding Pixels.

given pixel, respectively.

Figure 3.22 shows a practical example using the same pyramid test scene. The pixel azimuth and pixel zenith images in Figures 3.22a and 3.22b, respectively, are the same as in Figure 3.20. The corresponding exposed area values in Figure 3.22c range from $\sim40$-60\% ($\sim0.40$-0.60). Outer edges of the pyramids have lower exposed area values because they are at concave points, while inner edges are at convex points increasing their exposed area. The pyramids of higher pitch are darker because more of the ambient surround is blocked. As before, shadows slightly perturb the final result.
3.4. TIR Parameter Estimation

3.4.3 Abundance-Derived Estimated Solar Absorption & Thermal Emissivity (ADESATE)

At this point, we have estimated values at each pixel for azimuth angle, zenith angle and exposed area using multi-temporal, calibrated VIS images (or TIR images if collocated VIS imagery is unavailable). There are two more parameters that we can fix in order to lower the remaining degrees of freedom in the model. This can be accomplished through the use of mixture (or fraction) maps that will produce mixed, per-pixel, solar absorptivity and thermal emissivity values. These mixture maps can be produced by a process called linear spectral unmixing.

The goal of unmixing is to determine the relative abundance of each material (or endmember) at each pixel location. This process starts by ascertaining the endmembers (defined to be less than the number of spectral bands) of a given multispectral image (in digital counts if no a priori knowledge exists to calibrate radi-

Figure 3.22: PEAS Example: (a) Pixel Azimuth [deg], (b) Pixel Zenith [deg], (c) Exposed Area [%].
ance into reflectance/emissivity). This can be accomplished through the use of an automated process such as RSI ENVI’s Sequential Maximum Angle Convex Cone (SMACC) Endmember Extraction function. These endmembers are then used to linearly unmix each pixel into abundances per endmember. If endmember spectra are generically defined in units of digital counts, then each endmember must be subsequently identified and have appropriate reflectivity and emissivity spectra assigned. Preferably these have been measured in-scene. These assumed endmember spectra are potentially significant sources of error and must be carefully chosen to accurately represent the constituents of the scene.

Once we have obtained an abundance map and assigned a spectrum to each endmember, we can linearly combine them according to

$$r_{eff}(\lambda) = \sum_{i=1}^{3} f_i [r_i(\lambda)]$$  \hspace{1cm} (3.4)$$

in order to find a per-pixel effective reflectivity as a function of wavelength. The same can be done in terms of thermal emissivity via

$$\epsilon_{eff}(\lambda) = \sum_{i=1}^{3} f_i [\epsilon_i(\lambda)]$$  \hspace{1cm} (3.5)$$

to find a per-pixel effective emissivity as a function of wavelength. At this point we can calculate an effective absorptivity by integrating the effective reflectivity and exoatmospheric irradiance as functions of wavelength with the $\cos \theta$ effect

$$SA_{eff} = 1 - \frac{\int_{\lambda_{min}}^{\lambda_{max}} r_{eff}(\lambda) E'_{s}(\lambda) \cos \sigma'/\pi d\lambda}{\int_{\lambda_{min}}^{\lambda_{max}} E'_s(\lambda) \cos \sigma'/\pi d\lambda}$$  \hspace{1cm} (3.6)$$

to result in a mixed, per-pixel effective solar absorptivity. Notice the denominator
3.4. TIR Parameter Estimation

serves to normalize the result. The same process using effective emissivity as a function of wavelength and integrating it with the radiance of a blackbody at 300K (i.e., the earth)

\[ T_{eff} = \frac{\int_{\lambda_{min}}^{\lambda_{max}} \varepsilon_{eff}(\lambda)L_{BB300K}(\lambda) \, d\lambda}{\int_{\lambda_{min}}^{\lambda_{max}} L_{BB300K(\lambda)} \, d\lambda} \]  

(3.7)

results in a mixed, per-pixel effective thermal emissivity. Once again, the denominator serves to normalize the result.

3.4.4 Estimating Remaining Thermodynamic Parameters

Consulting Table 3.3, thus far we have pre-defined the necessary per-pixel values for azimuth angle, zenith angle, exposed area, solar absorptivity, and thermal emissivity. This will greatly aid our estimation effort by narrowing the search space in which the remaining thermodynamic parameters will be found. In addition, we can assign self-generated power equal to zero, as there are no engines or other man-made sources of thermal energy.

The four remaining parameters necessary to invoke THERM (inside of DIRSIG) are the bulk property parameters—thermal conductivity \( k \), thickness \( L_C \), specific heat \( \rho \), and mass density \( c \). Looking at Equation 2.24, we see that thickness and thermal conductivity can be combined into a single parameter \( \frac{L_C}{k} \) for estimation purposes. Similarly, specific heat and mass density are combined into a thermal mass parameter for use throughout DIRSIG. These two terms are combined via a simple multiplication \( \rho \times c \). Both of these combined parameters have realistic ranges of values per material class that we can accept based upon physics and empirical observations. Nonetheless, this algorithm will only provide estimations whose fidelity is mainly a factor of the quantization-level (and any subsequent interpolation) that is employed when implementing this methodology.
Another important consideration is the determination of which temporal TIR truth images are used to estimate the remaining thermal parameters. A combination of three times (i.e., morning, midday, and evening) is the most effective at identifying the diurnal cycle for the different materials and their thermodynamic parameters. If only two separate image times are available, it would be preferable to have an AM and PM image—with which one could still attempt to fit the diurnal profile. More than three truth images may make the estimates slightly more precise at the cost of additional processing time.

The estimation of the remaining thermal parameters requires a flexible algorithm that can be refined as necessary for specific results. This basic algorithm does not employ any optimization in order to more intelligently traverse the search space—rather it cycles through the ranges via a given step size. The steps can be chosen logarithmically or at some fixed interval, depending upon the desired run time. Notice that this ‘nested for-loop’ will require on the order of $n^2$ executions to finish, meaning that each incremental increase in step size will exponentially increase (i.e., by the power of 2) the required execution time. The following pseudocode is used to estimate these parameters on a per-pixel basis using RMSE as the discriminant function:

- Select TIR brightness images to base RMSE function
- Read in pre-estimated thermal parameter maps
- FOR k = 1, image size DO BEGIN
  - FOR i = 1, cardinality of T/TC parameter set DO BEGIN
    * FOR j = 1, cardinality of SH*MD parameter set DO BEGIN
      ; Goal is to compute RMSE for TIR image[k] using i,j
      - Modify map_therm.img to run DIRSIG with current parameters
      - Modify therm.cfg for MappedTherm temperature solver for each imaging time
      - Run DIRSIG with mapped parameters at each imaging time
3.5. Ground Truth Requirements

- Get temperatures from DIRSIG truth files
- Compute RMSE using all imaging times
- If RMSE improved, then save $i,j$ as best estimates
* END FOR
– END FOR

Upon successful implementation of this code, the result will be a 10-band ENVI-style image where each band corresponds to a thermal parameter map. This image is necessary to run DIRSIG and its MappedTherm temperature solver at specific times under various meteorological conditions. The next section will discuss what steps must be taken in order to handle data collections with various amounts of available ground truth.

3.5 Ground Truth Requirements

There are a total of ten (but effectively only eight independent) thermodynamic parameters that must be specified in order to have DIRSIG simulate a TIR pixel. As more types of ground truth data are made available, the resulting TIR texture in DIRSIG-generated synthetic imagery will become increasingly accurate. In order to more readily understand how each parameter can be obtained (and its default estimation method), Table 3.5 provides a degradation of each parameter. The end result of having inadequate ground truth will be an overfitting of the model due to having too many degrees of freedom. Desired synthetic imagery simulated at different image times or under different weather conditions will most likely be much less accurate as the model will be fitted to one particular situation and not
have an overall understanding of the environment and actual underlying values of the thermodynamic parameters.

At this point it would be prudent to discuss the degradation due to having only thermal imagery (i.e., TIR BDOM & PEAS). The critical assumption for determining pixel azimuth and zenith (first introduced in Section 3.4.1)—that we can assume the brightness difference between the AM & PM images is attributable to first degree by $\cos \theta$: $B = E'_{s} \cos \theta$ is no longer valid. In TIR imagery, the emissive term, $\varepsilon(\lambda) L_{T(\lambda)}$, in Equation 2.16 has a profound effect upon image brightness. Furthermore, the thermal phenomena that we are modeling via the bulk thermal parameters in Section 3.4.4 will contaminate our brightness AM/PM difference calculation. Thus, the TIR BDOM & PEAS methodology is inferior to the use of VIS BDOM & PEAS.

This section has described what ground truth is necessary for modeling the various thermodynamic parameters in order to optimally simulate TIR imagery. The next section will describe how the modeling tool DIRSIG can incorporate a series of mapping mechanisms to take all of these new thermodynamic parameters as inputs to an entire scene.
3.6 Thermal Texture Mapping in DIRSIG

Section 2.5.2 described in detail the current state of the art of DIRSIG TIR imagery simulation. Per class inputs for all of the thermodynamic parameters are allowed and utilized in the RitTherm temperature solver. In addition, thermal emissivity and solar absorption are calculated on a per-pixel basis, however there is no mechanism currently for mapping per-pixel thermodynamic materials. In the past there has not been a need for this since there was no algorithm for inverting brightness temperatures and deciphering values for the thermodynamic parameters of in-scene materials. Now we will add this capability and map the optimized parameters on a per-pixel basis as shown in Figure 3.23. The result of this entire

![Diagram](image-url)  

**Figure 3.23:** DIRSIG Flow Diagram Denoting Thermal Parameter Map Inclusion.
methodology should be higher fidelity synthetic TIR images with quantitatively- and qualitatively-improved texture. With this goal in mind, a test plan with quantitative measures of the success of this method will be discussed in the next section.

### 3.7 TIR Texture Algorithm Test Plan & Performance

In order to thoroughly test the TIR texture algorithm, we need a test plan to explain which images will be compared and by what methods. The test plan will begin by selecting three different desert scenes from the Trona data collection. These three scenes each have a 5 AM, 11 AM, & 5 PM image that can be used for parameter estimation and a 4 PM image that will serve as the unbiased ground truth comparison. Each scene will use both the DIRSIG fraction mapping and thermal parameter mapping methods to discover changes in texture. These changes will be measured by both difference images and RMSE images to indicate overall quantitative performance. In addition, regions of interest (ROIs) using the various assumed scene constituents will be defined for use in both types of DIRSIG-generated imagery. These ROIs will be used in conjunction with the GLCM methodology outlined in Section 2.4.2 to further quantify the synthetic texturing of TIR imagery. Specifically, we will rely on the three fairly independent GLCM statistics: CON, ENT, and COR. Once again, this set of statistics is known to be the most consistently accurate over a range of quantization gray-levels. Furthermore, we will use Spearman’s rank-order correlation metric [Lowry 2008], defined as

\[
    r_s = 1 - \frac{6 \sum_{i=1}^{n} d_i^2}{n(n^2 - 1)},
\]

(3.8)
in order to compile per-ROI results. In Equation 3.8, $n$ is the number of pixels being ranked and $d$ refers to the difference in the ranking of each pixel from the original image to the simulated one. Note, all of these metrics will be performed on imagery not used in the parameter estimation process in order to assess unbiased synthetic TIR texture generation.

This chapter has laid out the approach this research effort undertook in order to create a methodology for generating realistic TIR texture in synthetic imagery. We can now vary the thermodynamic material parameters (first defined in Table 2.3) in a matter consistent with what is observed in TIR-radiance imagery. The next chapter will demonstrate the results of having implemented this algorithm as described.
This chapter presents the results of applying the methodology outlined in Chapter 3 to several Trona scenes. Section 4.1 provides the reflectivity and emissivity spectra assigned as the constituent endmembers of the unmixed scenes. Section 4.2 shows the results of simulating a ‘dirt track’ scene at Trona and the corresponding GLCM images. Section 4.3 depicts the same methodology applied to another scene in which an anomalous bump on the desert surface is prominent and referred to as a ‘beetle’. Section 4.4 shows the results of simulating a desert road intersection and the corresponding GLCM images. Finally, Section 4.5 describes a simple sen-
sitivity analysis performed upon the ‘dirt track’ scene, while Section 4.6 delineates the correlation between bulk parameters and the original imagery.

### 4.1 Reflectivity & Thermal Emissivity Spectra

The first step in the ADESATE process from Section 3.4.3 in order to estimate solar absorption and thermal emissivity is to unmix a base image in order to obtain abundances of the underlying constituents or endmembers. Once ENVI’s SMACC Endmember Extraction function is performed on a panchromatic base image (still in DCs), endmembers must be assigned (and assumed to represent all scene constituents).

The reflectivity spectra used in all three of the scenes in Chapter 4 are seen in Figure 4.1. Notice that an absorption feature occurs in all of the spectra around 1.4 µm. The thermal emissivity spectra used in all three of the scenes in Chapter 4

![Figure 4.1: Reflectivity Spectra Assigned As Scene Constituent Endmembers.](image-url)
are seen in Figure 4.2. Notice that the salt and mud spectra are quite similar and

![Emissivity Spectra](image)

**Figure 4.2:** Emissivity Spectra Assigned As Scene Constituent Endmembers.

that all three of the spectra have an average value between 0.92-0.95 which will dominate the per-pixel thermal emissivity calculations in the ADESATE methodology.

This section has provided the spectra representing the endmembers of all three scenes found in Chapter 4. The next section will display results particular to the simulation of the ‘Dirt Track’ scene.

### 4.2 ‘Dirt Track’ Scene Simulation

Figure 4.3 is a high-resolution image of the ‘Dirt Track’ scene and immediate surrounding area. This will be the first scene to which we will apply the entire methodology developed in Chapter 3. The first step is always to register all of the imagery associated with the scene. This is an extremely arduous task as the difference in
resolution between the VIS and LWIR imagery is quite substantial and leads to a myriad of registration problems that are not easily solved by any sort of automatic registration due to the requisite transforms not being affine. As such tie points must be manually selected and mis-registration adds immediate (and often significant) sources of error. Table 4.1 shows the registration accuracy in the ‘Dirt Track’ scene. Notice that the LWIR 11 AM image was the ‘base’ image and was
4.2. ‘Dirt Track’ Scene Simulation

<table>
<thead>
<tr>
<th>Image</th>
<th>RMS Error [Pixels]</th>
</tr>
</thead>
<tbody>
<tr>
<td>VIS 11 AM</td>
<td>0.69</td>
</tr>
<tr>
<td>VIS 5 PM</td>
<td>0.88</td>
</tr>
<tr>
<td>LWIR 5 AM</td>
<td>0.48</td>
</tr>
<tr>
<td>LWIR 11 AM (base)</td>
<td>0.00</td>
</tr>
<tr>
<td>LWIR 4 PM</td>
<td>0.59</td>
</tr>
<tr>
<td>LWIR 5 PM</td>
<td>0.33</td>
</tr>
</tbody>
</table>

Table 4.1: ‘Dirt Track’ Scene Registration Accuracy (to LWIR 11 AM Image).

not warped. The GSD of the LWIR pixels is 2.5’ while the GSD of the VIS pixels is 0.5’. Five control points were used with a first-order polynomial warp and nearest-neighbor re-sampling.

The results of the registration of the VIS AM and PM images can be seen in Figures 4.4a and 4.4b, correspondingly. The abundance image in Figure 4.4c was derived from Figure 4.4a having the SMACC Endmember Extraction algorithm applied and spectra assigned before linear unmixing was performed. Figures 4.4d and 4.4e show the results of the ADESATE process (i.e., solar absorptivity and thermal emissivity). Notice that the regions of high solar absorptivity correctly correspond to the darker regions of the scene and lighter salt patches have lower solar absorptivities. Thermal emissivity varies according to the abundances and their associated spectra assigned during the ADESATE process. Figures 4.4f and 4.4g depict per-pixel azimuth and zenith estimates, respectively. Notice in these two figures how pixels in the upper left corner tilt toward the north. This would seem to indicate that there is a slight incline running from north-to-south along the western edge of the simulated area, which appears to be a makeshift road in higher-resolution imagery.

Figures 4.4i and 4.4j are the combined bulk parameters maps estimated by using the algorithm put forth in Section 3.4.4. Looking at the wide areas of uniformity
in these two figures, we sought to discover what additional level of improvement we might achieve by using a higher-level of quantization when estimating the T/TC and SH*MD parameters. Figures 4.4k and 4.4l depict the results of nearly doubling the number of possible estimates, leading to a slightly improved result at more than three times the processing cost. The level of residual correlation be-
4.2. ‘Dirt Track’ Scene Simulation

tween the combined bulk parameter maps in Figures 4.4i-l and the surface thermal parameter maps in Figure 4.4 is quite low and reaffirms that our physical thermodynamic model is performing reasonably well. However, there is still some level of correlation since our previous estimates of surface thermal parameters included some amount of error for which the bulk parameter estimates must compensate.

Figure 4.5 shows the LWIR results at all of the simulation times. The original and simulated versions of the same imaging time reside next to each other throughout Figures 4.5a-l. Each WASP image is followed by a DIRSIG image simulated using fraction maps (FM), which is then followed by a DIRSIG image simulated using thermal parameter mapping (TPM), and finally by a DIRSIG TPM image that used a higher level of quantization (HQ) in its parameter estimation of T/TC and SH\*MD. Only the 5 AM, 11 AM, & 5 PM images were used in the estimation algorithms. The 4 PM image represents a separate imaging time that can be used to test how well we have truly estimated the physical thermal parameters using the methods described in Chapter 3. The DIRSIG TPM methodology clearly outperforms the prior DIRSIG FM approach. However, the simulated night-time 5 AM image in Figure 4.5c has a reverse-contrast issue. This is because the error function weighs deviations from predicted temperatures at all three imaging times equally, thus errors in the high-contrast 5 PM evening image will receive more attention. A heuristic that penalizes night-time temperature simulation errors more heavily should be employed if night-time simulation will be frequent.

Most of the ‘spottiness’ prevalent in the DIRSIG TPM-simulated images is due to a low level of parameter-estimation quantization and the non-use of any optimization methods. Higher computing resources could be employed to ascertain smoother simulated imagery. In order to test just how much improvement might be achieved, the amount of quantization-levels in the combined parameter esti-
Figure 4.5: ‘Dirt Track’ Scene LWIR Imagery (11-29°C): (a) WASP 5 AM, (b) DIRSIG FM 5 AM, (c) DIRSIG TPM 5 AM, (d) DIRSIG TPM HQ 5 AM, (e) WASP 11 AM, (f) DIRSIG FM 11 AM, (g) DIRSIG TPM 11 AM, (h) DIRSIG TPM HQ 11 AM, (i) WASP 4 PM, (j) DIRSIG FM 4 PM, (k) DIRSIG TPM 4 PM, (l) DIRSIG TPM HQ 4 PM, (m) WASP 5 PM, (n) DIRSIG FM 5 PM, (o) DIRSIG TPM 4 PM, (p) DIRSIG TPM HQ 5 PM.
mation was almost doubled. This led to the slightly better results seen in the far right column of Figure 4.5. Note, this improvement nearly tripled the required processing time, although this methodology could be ported to work on multiple machines simultaneously in order to mitigate this issue.

Figure 4.6 shows the twelve difference images (WASP vs DIRSIG FM, TPM & TPM HQ) for the ‘Dirt Track’ scene. The DIRSIG TPM method shows improvement across-the-board in terms of absolute difference. The difference patterns in the DIRSIG FM images in Figures 4.6a-d are correlated with the in-scene features because the FM method does not precisely estimate individual thermal parameters such as solar absorptivity on a per-pixel basis. Notice in the DIRSIG TPM images that the 5 AM image has the most error of the three imaging times used to simulate the thermal parameters, due to the relatively small thermal contrast range at this imaging time. The dirt track stands out in Figure 4.6e and 4.6g as the most significant (albeit small) source of error. As one might expect, Figure 4.6g has the highest overall amount of error since the 4 PM image was not used in the parameter estimation process and is serving as a ground truth comparison. Comparing Figures 4.6c and 4.6g, the DIRSIG TPM method appears to be superior. The DIRSIG TPM HQ demonstrates an incremental improvement over DIRSIG TPM, especially between Figures 4.6g and 4.6k (the 4 PM image).

Table 4.2 shows the mean absolute error (MAE) between the various images using the different DIRSIG methods. The absolute error at any given pixel is simply the absolute value of the difference in brightness temperatures between corresponding pixels in the original and simulated images. The mean absolute error is equivalent to the mean of the difference images of Figure 4.6. Once again, the 4 PM ground truth image shows a large improvement (50%) in terms of mean absolute error in Table 4.2 and the TPM HQ method shows an even greater improvement.
Figure 4.6: ‘Dirt Track’ Scene WASP vs DIRSIG FM Difference Images [°C]: (a) 5 AM, (b) 11 AM, (c) 4 PM, (d) 5 PM; WASP vs DIRSIG TPM Difference Images [°C]: (e) 5 AM, (f) 11 AM, (g) 4 PM, (h) 5 PM; WASP vs DIRSIG TPM HQ Difference Images [°C]: (i) 5 AM, (j) 11 AM, (k) 4 PM, (l) 5 PM.

The RMSE images in Figure 4.7 tell a more interesting story. The RMSE is computed using all four imaging times (i.e., 5 AM, 11 AM, 4 PM & 5 PM) and its average is

\[
RMSE = \frac{1}{4} \sum_{i=1}^{4} \sqrt{E \left\{ \left( \theta_i(x,y) - \hat{\theta}_i(x,y) \right)^2 \right\}}. \tag{4.1}
\]
### DIRSIG Method

<table>
<thead>
<tr>
<th>Acquisition Time</th>
<th>Mean [°C]</th>
<th>Stan Dev [°C]</th>
</tr>
</thead>
<tbody>
<tr>
<td>FM 5 AM</td>
<td>1.63</td>
<td>0.76</td>
</tr>
<tr>
<td>TPM 5 AM</td>
<td>0.90</td>
<td>0.76</td>
</tr>
<tr>
<td>TPM HQ 5 AM</td>
<td>0.87</td>
<td>0.74</td>
</tr>
<tr>
<td>FM 11 AM</td>
<td>1.12</td>
<td>0.82</td>
</tr>
<tr>
<td>TPM 11 AM</td>
<td>0.79</td>
<td>0.57</td>
</tr>
<tr>
<td>TPM HQ 11 AM</td>
<td>0.71</td>
<td>0.51</td>
</tr>
<tr>
<td>FM 4 PM</td>
<td>1.30</td>
<td>0.93</td>
</tr>
<tr>
<td>TPM 4 PM</td>
<td>0.64</td>
<td>0.57</td>
</tr>
<tr>
<td>TPM HQ 4 PM</td>
<td>0.58</td>
<td>0.51</td>
</tr>
<tr>
<td>FM 5 PM</td>
<td>1.59</td>
<td>1.20</td>
</tr>
<tr>
<td>TPM 5 PM</td>
<td>1.20</td>
<td>0.89</td>
</tr>
<tr>
<td>TPM HQ 5 PM</td>
<td>1.11</td>
<td>0.94</td>
</tr>
</tbody>
</table>

**Table 4.2:** ‘Dirt Track’ Mean Absolute Error.

The DIRSIG TPM RMSE of 1.97°C has clearly outperformed the DIRSIG FM RMSE of 5.93°C over most of the scene, although the dirt track represents a challenge to both. The DIRSIG TPM HQ RMSE of 1.06°C shows another level of improvement over the DIRSIG TPM RMSE. As predicted, higher levels of parameter quantization have delivered additional improvements at the cost of additional computing.
Another important measure of success is how well different classes of pixels in different regions keep their rank-ordering from real to synthetic imagery. In order to compare specific regions of interest (ROIs), consider Figure 4.8. Three regions each of salt, mud, and sand pixels were selected for purposes of textural and rank-order comparisons. These regions are defined in Table 4.3. Table 4.3 displays brightness temperature statistics by region and shows the resulting Spearman rank-order correlation metric that was first introduced in Section 3.7. Notice that most of the regions exhibit overlapping brightness temperature ranges and similar standard deviations. However, the mean brightness temperatures of Salt3 and Sand3 are more than 2°C different. This could easily be a result of misregistration, as this is a common (and often significant) source of error. These errors led to some alterations in the rank-ordering of regions between the two images, providing a reasonably-good (but not excellent) Spearman coefficient of 0.83, meaning that 83% of the variation in rank within the subscene is explained by the simulated subscene.

In terms of texture analysis, Figure 4.9 displays the GLCM CON, ENT, and COR
4.2. ‘Dirt Track’ Scene Simulation

<table>
<thead>
<tr>
<th>Region</th>
<th>Name</th>
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<th>Temp Max</th>
<th>Temp Mean</th>
<th>Temp Stan Dev</th>
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</tr>
<tr>
<td></td>
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<td>21.52</td>
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<tr>
<td>Green</td>
<td>Salt2</td>
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</tr>
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<td></td>
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<td>23.80</td>
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<td></td>
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<td>23.91</td>
<td>1.44</td>
</tr>
<tr>
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</tr>
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<td></td>
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<td>26.79</td>
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<td></td>
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<td>23.73</td>
<td>22.62</td>
<td>0.74</td>
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<td>Sand1</td>
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<td>23.92</td>
<td>23.92</td>
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<tr>
<td>Sea Green</td>
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<td>21.88</td>
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<td>Sand3</td>
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<td>24.84</td>
<td>23.05</td>
<td>1.05</td>
</tr>
</tbody>
</table>

Spearman Rank-Order Coefficient: **0.83**

**Table 4.3:** ‘Dirt Track’ 4 PM ROI Statistics [°C] WASP/DIRSIG TPM and Spearman Rank-Order Correlation Coefficient.

Images for the 4 PM WASP image and the corresponding DIRSIG FM & TPM images. The three GLCM images of the DIRSIG TPM method appear more similar to the original WASP imagery than the DIRSIG FM method. Specifically, the contrast level is higher along the ‘dirt track’ in Figure 4.9g than in Figure 4.9d, and the entropy metric in Figure 4.9h more consistently matches Figure 4.9b than the DIRSIG FM version. Within-class correlation is also better in the DIRSIG TPM image in Figure 4.9i versus that of the DIRSIG FM image in Figure 4.9f.

In order to have a more quantitative sense of the meaning behind these GLCM figures, consider Figures 4.10-4.12. When Haralick first employed the GLCM techniques, he noted that there are some intuitive expectations as to what properties will be represented by textural features. These features ought to be more
readily understood by comparing the range of values by region throughout an image. [Haralick et al. 1973] Figures 4.10-4.12 use the same regions defined in Table 4.3. The CON comparison in Figure 4.10 is of interest. The Salt regions have more similar contrast levels in the DIRSIG TPM image. However, in the Mud regions the DIRSIG FM image is more similar (note that Mud 1T seems to be a significant outlier). Once again in the Sand region the DIRSIG FM image has a more
4.2. ‘Dirt Track’ Scene Simulation

Figure 4.10: ‘Dirt Track’ 4 PM GLCM CON Comparison (R: Real WASP, F: DIRSIG FM, T: DIRSIG TPM).

similar contrast level.

Figure 4.11 depicts the results of the ENT metric for corresponding regions of
the two images. The ENT ranges are slightly lower for more of the DIRSIG FM image regions, but the overall range of randomness is congruent. The results of the
4.2. ‘Dirt Track’ Scene Simulation

COR metric by region are shown in Figure 4.12. Notice that these are all negative correlation values because corresponding pixels tend not to necessarily increase.
in unison (as positive correlation requires). The negative correlation is very high for the DIRSIG FM image, resulting in non-uniform regions that have a speckled appearance—thus the DIRSIG FM image loses much of its contiguousness within regions of the image.

Overall, this scene seems well-suited to this TIR-texture methodology. The improvements of the DIRSIG TPM method over the DIRSIG FM method are readily apparent and hold up well under quantitative scrutiny (i.e., an RMSE reduction of 82%). The next section will discuss the results using the Desert ‘Beetle’ scene.

### 4.3 Desert ‘Beetle’ Scene Simulation

Figure 4.13 is a high-resolution image of the Desert ‘Beetle’ scene and immediate surrounding area. The ‘beetle’ itself looks to be a large mound of mostly sand. This will be the second scene to which we will apply the TIR-texture methodology. Registration of this scene was adequate and Table 4.4 shows the accuracy for each image in the Desert ‘Beetle’ scene. Notice that the LWIR 5 PM image was the ‘base’ image and was not warped. Once again, the GSD of the LWIR pixels is 2.5’ while the GSD of the VIS pixels is 0.5’. In addition, five control points were used with a first-order polynomial warp and nearest-neighbor re-sampling.

<table>
<thead>
<tr>
<th>Image</th>
<th>RMS Error [Pixels]</th>
</tr>
</thead>
<tbody>
<tr>
<td>VIS 11 AM</td>
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</tr>
<tr>
<td>VIS 5 PM</td>
<td>0.42</td>
</tr>
<tr>
<td>LWIR 5 AM</td>
<td>0.11</td>
</tr>
<tr>
<td>LWIR 11 AM</td>
<td>0.41</td>
</tr>
<tr>
<td>LWIR 4 PM</td>
<td>0.15</td>
</tr>
<tr>
<td>LWIR 5 PM (base)</td>
<td>0.00</td>
</tr>
</tbody>
</table>

**Table 4.4:** Desert ‘Beetle’ Scene Registration Accuracy (to LWIR 5 PM Image).
4.3. Desert ‘Beetle’ Scene Simulation

Figure 4.13: Hi-Resolution Desert ‘Beetle’ Scene Surrounding Area (11 AM Image).

The results of the registration of the VIS AM and PM images can be seen in Figures 4.14a and 4.14b, correspondingly. The abundance image in Figure 4.14c was derived from Figure 4.14a having the SMACC Endmember Extraction algorithm applied and spectra assigned before linear unmixing was performed. Figures 4.14d and 4.14e show the results of the ADESATE process for solar absorptivity and thermal emissivity. The ‘beetle’ features prominently in most of the parameter maps and has the high zenith angles in Figure 4.14g that we would expect. The
‘beetle’ azimuth angles in Figure 4.14f are roughly correct but mis-registration has added some error to the BDOM process. The vertical feature perpendicular to the mounds of earth located across the top of the scene is particularly well-represented in terms of pixel azimuth and zenith angles. It can be seen that the azimuth of the east-facing side of the feature is significantly lower than the west-facing side as we would expect from the difference in the VIS AM & PM images. In addition,
the azimuth angles are elevated showing the change in grade along the feature in Figure 4.14g. Notice that the ‘beetle’ appears more prominent in Figure 4.14j. Since that portion of the ‘beetle’ appears to be in shadow in the afternoon, the thermal model tries to match its lower afternoon temperature by assuming the material has a higher heat capacity.

Figure 4.15 shows the LWIR results at all of the simulation times. The original and simulated versions of the same imaging time reside next to each other throughout Figures 4.15a-l. The 5 AM, 11 AM, & 5 PM images were used in the estimation algorithms. Once again, the 4 PM image represents a separate imaging time that can be used to test how well we have estimated the physical thermal parameters using the methods described in Chapter 3. Notice that the night-time 5 AM image does not have the same reverse-contrast issue. This is most likely due to a superior gain/bias DC-to-brightness temperature calibration allowing for nearly perfect estimation of thermal parameters. The challenge of this scene is the ‘beetle’. It is a protruding mound on the order of 20’-across with an unknown elevation change. Even with the existing registration error, the movement of the shadows as the day progresses reveals to the BDOM algorithm how to estimate the pixel azimuth/zenith angles. The lower-temperature shadow regions of the ‘beetle’ appear in the correct geometric areas of the simulated imagery. However, the extent of the shadowed areas is incorrect due to the mis-registration. As with the ‘Dirt Track’ scene in Section 4.2, the DIRSIG TPM methodology clearly outperforms the prior DIRSIG FM approach. The DIRSIG FM approach rapidly breaks down in the presence of elevation changes as scene geometry is not well-represented.

Figure 4.16 shows the eight difference images (WASP vs DIRSIG FM & TPM) for the Desert ‘Beetle’ scene. Once again, the DIRSIG TPM method shows improvement in every image pair. There is a higher amount of correlation to the scene
Figure 4.15: Desert ‘Beetle’ Scene LWIR Imagery (11-29°C): (a) WASP 5 AM, (b) DIRSIG FM 5 AM, (c) DIRSIG TPM 5 AM, (d) WASP 11 AM, (e) DIRSIG FM 11 AM, (f) DIRSIG TPM 11 AM, (g) WASP 4 PM, (h) DIRSIG FM 4 PM, (i) DIRSIG TPM 4 PM, (j) WASP 5 PM, (k) DIRSIG FM 5 PM, (l) DIRSIG TPM 4 PM.
4.3. Desert ‘Beetle’ Scene Simulation

Figure 4.16: Desert ‘Beetle’ Scene WASP vs DIRSIG FM Difference Images [°C]: (a) 5 AM, (b) 11 AM, (c) 4 PM, (d) 5 PM; WASP vs DIRSIG TPM Difference Images [°C]: (e) 5 AM, (f) 11 AM, (g) 4 PM, (h) 5 PM.

geometry in Figures 4.16a-d as the previously-mentioned elevation changes and bulk thermal properties were not estimated. As one might expect, the 4 PM image in Figure 4.16g has the highest amount of error, as the 4 PM image was not used in the parameter estimation process and is serving as a ground truth comparison.

Table 4.5 shows the mean absolute error between the various images using the different DIRSIG methods. Here the 4 PM ground truth image shows only incremental improvement in terms of mean absolute error in Table 4.5. However, consider the RMSE images in Figures 4.17a and 4.17b. As a reminder, the RMSE is computed using all four imaging times (i.e., 5 AM, 11 AM, 4 PM & 5 PM) and its average is computed using Equation 4.1. The DIRSIG TPM RMSE of 0.67°C has again
### Table 4.5: Desert ‘Beetle’ Mean Absolute Error.

<table>
<thead>
<tr>
<th>DIRSIG Method</th>
<th>Acquisition Time</th>
<th>Mean [°C]</th>
<th>Stan Dev [°C]</th>
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<td>11 AM</td>
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<tr>
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</tr>
<tr>
<td>FM</td>
<td>4 PM</td>
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<td>0.86</td>
</tr>
<tr>
<td>TPM</td>
<td>4 PM</td>
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<tr>
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</tr>
<tr>
<td>TPM</td>
<td>5 PM</td>
<td>0.60</td>
<td>0.51</td>
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</table>

Figure 4.17: Desert ‘Beetle’ Scene WASP vs DIRSIG RMSE Images [°C]: (a) DIRSIG FM, (b) DIRSIG TPM.

outperformed the DIRSIG FM RMSE of 5.59°C throughout the scene to include the ‘beetle’. This is in stark contrast to the MAE comparison because the RMSE formula heavily penalizes outliers. Since the DIRSIG FM method does not correct its estimates based upon observed training images, it is more apt to produce outliers and thus have a worse RMSE.

In order to compare specific regions of interest, consider Figure 4.18. Three regions each of sand, mud, and salt pixels were selected for purposes of textural and rank-order comparisons. These regions are defined in Table 4.6. Table 4.6
4.3. Desert ‘Beetle’ Scene Simulation

Figure 4.18: Desert ‘Beetle’ Scene Regions of Interest: (a) VIS-Based Abundances (red=sand, green=mud, blue=salt), (b) WASP VIS, (c) WASP VIS With ROIs Overlaid.

<table>
<thead>
<tr>
<th>Region</th>
<th>Name</th>
<th>Temp Min</th>
<th>Temp Max</th>
<th>Temp Mean</th>
<th>Temp Stan Dev</th>
</tr>
</thead>
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<tr>
<td>Red</td>
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</tr>
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<td>1.07</td>
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<tr>
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<td>Salt2</td>
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<td>25.43</td>
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</tr>
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<td>24.92</td>
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<td>Sand3</td>
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<td>21.97</td>
<td>27.00</td>
<td>24.13</td>
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</table>

Spearman Rank-Order Coefficient: 0.92

Table 4.6: Desert ‘Beetle’ 4 PM ROI Statistics [°C] WASP/DIRSIG TPM and Spearman Rank-Order Correlation Coefficient.

displays brightness temperature statistics by region and shows the resulting Spearman rank-order correlation metric value. The results here are excellent. Brightness
temperature mean values are quite compatible and lead to a Spearman coefficient of 0.92.

In terms of texture analysis, Figure 4.19 displays the GLCM CON, ENT, and COR images for the 4 PM DIRSIG FM image and corresponding DIRSIG TPM image. The contrast level in the DIRSIG TPM image in Figure 4.19g compares quite favorably to the original in Figure 4.19a. The entropy metric in Figure 4.19h also

**Figure 4.19**: Desert ‘Beetle’ Scene GLCM 4 PM Images (5x5 Window, 32-level, d=1,1): (a) WASP Contrast, (b) WASP Entropy, (c) WASP Correlation, (d) DIRSIG FM Contrast, (e) DIRSIG FM Entropy, (f) DIRSIG FM Correlation, (g) DIRSIG TPM Contrast, (h) DIRSIG TPM Entropy, (i) DIRSIG TPM Correlation.
compares well to the original in Figure 4.19b. Finally, the correlation metric in Figures 4.19f and 4.19i does not add much additional information. Note that since all of the correlation is negative, darker values indicate higher negative correlation while brighter values denote non-correlation.

Figures 4.20-4.22 provide a textural analysis by region as defined in Table 4.6. The CON comparison in Figure 4.20 is quite interesting. The Salt and Sand regions of the DIRSIG TPM image have more contrast, however the Mud regions show significantly more contrast in the DIRSIG FM image. Consider that the area identified as Mud in the WASP image should not exhibit nearly as much contrast as the areas dominated by Salt and Sand. This leads to the conclusion that the DIRSIG TPM image has more contrast in the appropriate regions and the contrast level is higher (than the WASP image) in those regions because of the quantization-level.

Figure 4.21 depicts the results of the ENT metric for corresponding regions of the two images. The ENT ranges are slightly higher for most of the DIRSIG FM image regions. The entropy in the Sand region of the DIRSIG FM image is particularly low, most likely due to a lack of variation in that region. Thus, one observes an unusual amount of neighboring sand pixels with similar brightness temperatures, leading to inaccuracies in this area of the DIRSIG FM image. In addition the Salt3 region is an interesting outlier in the WASP image. This low entropy metric is the result of a uniform region of brightness temperatures.

The results of the COR metric by region are shown in Figure 4.22. Once again these are all negatively correlated values. The negative correlation is very high for the DIRSIG FM image in a couple of regions, resulting in highly non-uniform regions that have a speckled appearance—thus the DIRSIG FM image loses some of its contiguousness within regions of the image. The correlation between the WASP and DIRSIG TPM images compares quite favorably.
Overall, between the excellent rank-order correlation and favorable GLCM regional comparisons, the DIRSIG TPM methodology seems to have dealt well with
the Desert ‘Beetle’ and its challenging scene geometry. The RMSE exhibited an 88% improvement and qualitatively the results appear to be a significant improvement.
Figure 4.22: Desert ‘Beetle’ 4 PM GLCM COR Comparison (R : Real WASP, F : DIRSIG FM, T : DIRSIG TPM).

over the DIRSIG FM method. The next section will discuss all of the results using the Desert ‘Intersection’ scene.
4.4 Desert ‘Intersection’ Scene Simulation

Figure 4.23 is a high-resolution image of the Desert ‘Intersection’ scene and immediate surrounding area. This will be the final scene to which we will apply the TIR-texture methodology. The differences in resolution between the VIS and LWIR imagery made registration of this scene more difficult. Table 4.7 shows the RMS
accuracy for each image in the Desert ‘Intersection’ scene. Once again the LWIR

<table>
<thead>
<tr>
<th>Image</th>
<th>RMS Error [Pixels]</th>
</tr>
</thead>
<tbody>
<tr>
<td>VIS 11 AM</td>
<td>0.86</td>
</tr>
<tr>
<td>VIS 5 PM</td>
<td>1.31</td>
</tr>
<tr>
<td>LWIR 5 AM</td>
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<td>LWIR 11 AM</td>
<td>0.29</td>
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<td>LWIR 4 PM</td>
<td>0.20</td>
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<tr>
<td>LWIR 5 PM (base)</td>
<td>0.00</td>
</tr>
</tbody>
</table>

*Table 4.7:* Desert ‘Intersection’ Scene Registration Accuracy (to LWIR 5 PM Image).

5 PM image was the ‘base’ image and was not warped. The GSD of the LWIR pixels is 2.5’ while the GSD of the VIS pixels is 0.5’. In addition, five control points were used with a first-order polynomial warp and nearest-neighbor re-sampling. Notice the high level of RMS-error in the VIS images. After expending much time and effort trying to improve the registration accuracy it was decided that this scene would serve as an example of how well the algorithm could perform after relatively poor registration.

The results of the registration of the VIS AM and PM images can be seen in Figures 4.24a and 4.24b, correspondingly. Once again, the abundance image in Figure 4.24c was derived from Figure 4.24a having the SMACC Endmember Extraction algorithm applied and spectra assigned before linear unmixing was performed. Figures 4.24d and 4.24e show the results of the ADESATE process for solar absorptivity and thermal emissivity. Figure 4.24g has interesting features in two regions. The first region is near the top-right of the image. Several pixels in that region have a high zenith angle. This is due to the BDOM algorithm detecting the change in brightness between Figures 4.24a and 4.24b and estimating a high zenith angle to achieve the change in brightness. This would be accurate if there is some sort of depression on the side of the road. However another possibility is that shadows
from scene geometry may also have contributed to the change in brightness, in which case this higher zenith angle estimate may be incorrect. The second interesting region is the area of higher zenith angle along the portion of the road near the bottom of the image. Once again, if there is a downward grade on the side of the road this will be accurate. However, mis-registration or shadows from scene geometry can also contribute to an incorrect zenith angle estimation. Once again,
the residual correlation between the bulk thermal parameter maps in Figures 4.24i-j and the surface thermal parameter maps in Figure 4.24d-h is low.

Figure 4.25 shows the LWIR results at all of the simulation times. The original and simulated versions of the same imaging time reside next to each other throughout Figures 4.25a-l. The 5 AM, 11 AM, & 5 PM images were used in the estimation algorithms. Once again, the 4 PM image represents a separate imaging time that can be used to test how well we have estimated the physical thermal parameters using the methods described in Chapter 3. Notice that the night-time 5 AM image has the same reverse-contrast issue as the ‘Dirt Track’ scene in Section 4.2. Once again this is because the error function weighs deviations from predicted temperatures at all three imaging times equally, thus errors in the high-contrast 5 PM evening image will receive more attention. Also, the ‘spottiness’ prevalent in all of the DIRSIG TPM-simulated images is due to the low level of parameter-estimation quantization.

The DIRSIG TPM method did not greatly outperform the DIRSIG FM method (at least visually) at simulating this scene for several reasons. The difficulties with registration that were previously mentioned where a significant source of error. The importance of accurate registration should not be underestimated. Also the thermal emissivity (seen in Figure 4.24e) along the road seems rather high. This could be a problem with incorrect material assumptions, as the in-band emissivity in that area may be much lower. In addition the solar absorptivity (seen in Figure 4.24d) may not have been estimated to be low enough. Finally, errors in temperature calibration may have made it impossible for the thermal model to fit a diurnal profile to pixels along the road. Any combination of the above problems would have contributed to the poor simulation results. Further numerical analysis could be undertaken to determine the exact nature of the underlying problem(s).
Figure 4.25: Desert ‘Intersection’ Scene LWIR Imagery (11-29°C): (a) WASP 5 AM, (b) DIRSIG FM 5 AM, (c) DIRSIG TPM 5 AM, (d) WASP 11 AM, (e) DIRSIG FM 11 AM, (f) DIRSIG TPM 11 AM, (g) WASP 4 PM, (h) DIRSIG FM 4 PM, (i) DIRSIG TPM 4 PM, (j) WASP 5 PM, (k) DIRSIG FM 5 PM, (l) DIRSIG TPM 4 PM.
For a more quantitative comparison, consider Figure 4.26, which depicts the eight difference images (WASP vs DIRSIG FM & TPM) for the Desert ‘Intersection’ scene. In Figure 4.26, the DIRSIG TPM method shows modest improvements. The ground-truth 4 PM image in Figure 4.26g indicates that DIRSIG TPM will provide a moderately better estimate for this scene even with the poor registration. The entire road area is particularly difficult for the DIRSIG TPM method.

Table 4.8 shows the mean absolute error between the various images using the different DIRSIG methods. Here the 4 PM ground truth image shows a small improvement in terms of mean absolute error in Table 4.8. However, DIRSIG TPM is clearly better when considering RMSE as in Figures 4.27a and 4.27b. Once again,
### 4.4. Desert ‘Intersection’ Scene Simulation

<table>
<thead>
<tr>
<th>DIRSIG Method</th>
<th>Acquisition Time</th>
<th>Mean [°C]</th>
<th>Stan Dev [°C]</th>
</tr>
</thead>
<tbody>
<tr>
<td>FM</td>
<td>5 AM</td>
<td>1.47</td>
<td>0.64</td>
</tr>
<tr>
<td>TPM</td>
<td>5 AM</td>
<td>0.83</td>
<td>0.66</td>
</tr>
<tr>
<td>FM</td>
<td>11 AM</td>
<td>1.44</td>
<td>0.75</td>
</tr>
<tr>
<td>TPM</td>
<td>11 AM</td>
<td>1.09</td>
<td>0.63</td>
</tr>
<tr>
<td>FM</td>
<td>4 PM</td>
<td>1.89</td>
<td>1.20</td>
</tr>
<tr>
<td>TPM</td>
<td>4 PM</td>
<td>1.65</td>
<td>1.21</td>
</tr>
<tr>
<td>FM</td>
<td>5 PM</td>
<td>1.12</td>
<td>0.96</td>
</tr>
<tr>
<td>TPM</td>
<td>5 PM</td>
<td>0.76</td>
<td>0.63</td>
</tr>
</tbody>
</table>

**Table 4.8:** Desert ‘Intersection’ Mean Absolute Error.

![Figure 4.27: Desert ‘Intersection’ Scene WASP vs DIRSIG RMSE Images [°C]: (a) DIRSIG FM, (b) DIRSIG TPM.](image)

The RMSE is computed using all four imaging times (*i.e.*, 5 AM, 11 AM, 4 PM & 5 PM) and its average is computed using Equation 4.1. The DIRSIG TPM RMSE of 1.05°C has again outperformed the DIRSIG FM RMSE of 5.73°C throughout the scene to include the ‘intersection’. This emphasizes that the TPM algorithms sacrifice accuracy of estimates at some points in the day in order to make more accurate estimates at different times of the day that would otherwise result in larger errors. The DIRSIG FM has no method of compensation and uses no intelligent method to compare estimate errors.
In order to compare specific regions of interest, consider Figure 4.28. Three

![Figure 4.28: Desert ‘Intersection’ Scene Regions of Interest: (a) VIS-Based Abundances (red=sand, green=mud, blue=salt), (b) WASP VIS, (c) WASP VIS With ROIs Overlaid.](image)

regions each of sand, mud, and salt pixels were selected for purposes of textural and rank-order comparisons. These regions are defined in Table 4.9. Table 4.9 displays brightness temperature statistics by region and shows the resulting Spearman rank-order correlation metric value. The mis-registration has negatively affected the results—almost half of the regions have means that are nearly 2°F different, leading to incorrect brightness temperature rankings and a low Spearman coefficient of 0.67. This low coefficient means that users desiring to perform analysis (e.g., target detection) based on this simulated imagery would find it difficult because the brightness temperatures would not have a consistent ordering by region throughout the image.

In terms of texture analysis, Figure 4.29 displays the GLCM CON, ENT, and COR images for the 4 PM DIRSIG FM image and corresponding DIRSIG TPM image. The overall contrast level of the DIRSIG FM image is quite low in Figure 4.29d, while the DIRSIG TPM counterpart in 4.29g has the contrast levels almost reversed from the original WASP image in 4.29a. The entropy and correlation metrics in Figure 4.29 do not appear to significantly match the DIRSIG images. This
result is unsurprising in that the difference images for this scene revealed numerous difficult areas for the DIRSIG methodologies.

Figures 4.30-4.32 provide a textural analysis by region as defined in Table 4.9. The contrast regions in the Salt and Sand are quite similar throughout Figure 4.30 for both DIRSIG FM and TPM. The main difference is in the Mud regions. Here the DIRSIG TPM method utilizes a higher level of contrast. This is once again due to the high quantization-level in parameter estimation, meaning that the ‘speckled’ brightness temperatures result in higher contrast levels.

Figure 4.31 depicts the results of the ENT metric for corresponding regions of the two images. The ENT ranges are quite close and resemble each other well. The randomness between regions of the images is quite comparable. The results of the
COR metric by region are shown in Figure 4.32. Once again all of the regions have negative correlation values. The negative correlation is much higher in most regions of the DIRSIG FM 4 PM image. Thus every pixel has a value vastly different than the next, resulting in an even more ‘speckled’ image than its DIRSIG TPM counterpart.

Overall, applying the DIRSIG TPM texture methodology to mis-registered im-
agery appears to still have some utility, however the rank-order correlation will not be favorable for relying on estimates from images that are poorly registered for
further analysis. In addition, one has observed that incorrect assumptions about the constituent in-scene materials can lay havoc upon the surface thermal param-
Figure 4.32: Desert ‘Intersection’ 4 PM GLCM COR Comparison (R: Real WASP, F: DIRSIG FM, T: DIRSIG TPM).

Parameter estimation processes. The \( \text{RMSE} \) reduction of 82% even after poor registration and potentially-inaccurate material assumptions further supports the DIRSIG
TPM methodology. The next section will present a short sensitivity analysis performed upon the first ‘dirt track’ scene in order to determine the relative impacts of the various thermodynamic parameters.

### 4.5 Sensitivity Analysis

This section uses all of the data associated with the ‘dirt track’ scene first introduced in Section 4.2 in order to have a more quantitative understanding of the relative importance of each of the thermal parameters being utilized in the DIRSIG TPM methodology.

Table 4.10 shows each parameter in order of its RMSE impact upon the simulated scene at 4 PM. This ranking was accomplished by taking each thermal parameter map and setting every pixel equal to the mean of that entire parameter map. Each of these ‘mean-only’ maps were used in-turn with unperturbed versions of the other TPMs in order to execute the DIRSIG simulation tool. The RMSE is calculated using Equation 4.1.

<table>
<thead>
<tr>
<th>Thermal Parameter</th>
<th>RMSE [°C]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Specific Heat * Mass Density</td>
<td>1.51</td>
</tr>
<tr>
<td>Thickness/Thermal Conductivity</td>
<td>1.42</td>
</tr>
<tr>
<td>Solar Absorptivity</td>
<td>0.91</td>
</tr>
<tr>
<td>Pixel Azimuth</td>
<td>0.57</td>
</tr>
<tr>
<td>Exposed Area</td>
<td>0.40</td>
</tr>
<tr>
<td>Pixel Zenith</td>
<td>0.22</td>
</tr>
<tr>
<td>Thermal Emissivity</td>
<td>0.16</td>
</tr>
</tbody>
</table>

**Table 4.10:** ‘Dirt Track’ Scene Thermal Parameter Sensitivity.

Observe that the two combined free parameters are at the top of the list. This means that either these parameters were permitted to vary outside of their actual physical bounds in order to compensate for errors in the surface thermal pa-
4.6 Bulk Thermal Parameter Correlation

This section describes the correlation between the original imagery and the bulk thermal parameter maps that were obtained via the DIRSIG TPM methodology. One application for which knowledge of the level of correlation would be useful is the determination of whether one might be able to use the bulk parameter map estimates in a general sense with other scenes having similar characteristics and statistics. If the correlation were low enough, then the power spectral distribution of the bulk property maps could be perturbed via white noise and the resulting maps could serve as estimates for a scene without training imagery.

Table 4.11 shows the correlation coefficients for each combined bulk parameter on a per scene basis. Notice that in each scene at least one of the parameters has
Table 4.11: Bulk Thermal Parameter Pearson Correlation Coefficients.

<table>
<thead>
<tr>
<th>Scene</th>
<th>T/TC</th>
<th>SH*MD</th>
</tr>
</thead>
<tbody>
<tr>
<td>’Dirt Track’</td>
<td>-0.42</td>
<td>-0.02</td>
</tr>
<tr>
<td>Desert ’Beetle’</td>
<td>-0.02</td>
<td>0.30</td>
</tr>
<tr>
<td>Desert ’Intersection’</td>
<td>-0.07</td>
<td>0.15</td>
</tr>
</tbody>
</table>

a non-negligible correlation with the original image. Thus, if we were to attempt to use this simple filter previously described to introduce variation, we would encounter some problems since these correlation values seem to indicate a level of spatial correlation with the original image. One should consider this carefully if attempting to extrapolate this methodology into something to be applied more generally.

This chapter has focused upon the results of applying the TIR-texture methodology to three separate desert scenes from the Trona data collection. This was accompanied by a quick sensitivity analysis using the ‘dirt track’ scene in order to determine the relative importance of the fidelity of the thermal parameter estimates. The results of this physical thermal modeling process were inspiring, especially the desert ‘beetle’ scene in Section 4.3. The following chapter will discuss the entire research endeavor, drawing final conclusions and making recommendations for future research areas.
Conclusions & Recommendations

This chapter provides a summary of the contributions of this research and makes recommendations for future work. Section 5.1 describes themes for future research endeavors, while Section 5.2 discusses potential methods to enhance computational efficiency in order to better estimate per-pixel thermal parameters in a more rapid manner.
5.1 Future Research Areas

The main thrust of this research effort was to design and implement a detailed methodology as put forth in Chapter 3 in order to realistically simulate texture in synthetic TIR imagery. As such, there are areas of the various algorithms that could be improved and further analyzed in order to ascertain more accurate simulated TIR imagery.

One potential improvement would be the utilization of Light Detection and Ranging (LIDAR) and/or Digital Elevation Models (DEM) of appropriate resolution to improve the pixel azimuth, pixel zenith, and exposed area estimates from the BDOM and PEAS processes. Although this research did not purport that these types of data are widely available at appropriate resolutions, a research endeavor to utilize these with the BDOM and PEAS algorithms could result in more accurate azimuth, zenith, and exposed area estimates.

Another incremental improvement for the bulk parameter and even surface parameter estimation processes would be to consider using the estimates previously computed for the surrounding pixels as a starting point. This would allow for more physically-accurate estimates as parameter values would not change as sporadically and should serve to smooth contiguous regions of the resultant imagery. In addition, some sort of interpolation of the combined thermal parameter values ought to result in more accurate estimates.

One area of significant potential is the use of some sort of heuristic that provides a weighting function to increase the cost of certain errors when estimating parameters. For instance, if one were mostly interested in simulating nighttime TIR imagery, providing a heavy penalty for large RMSE values at night will change the estimates and result in more accurate nighttime imagery.
5.1. Future Research Areas

Registration plays a large role in the overall accuracy of the thermal parameter estimation process (as noted in the desert ‘intersection’ scene). Using imagery at vastly different resolutions makes registration extremely difficult and often inaccurate. Additional research into registration techniques and their employment could greatly increase the overall accuracy of this methodology and result in much-improved DIRSIG TPM imagery.

Endmember determination is another important subject for accurate thermal parameter estimation. Numerous endmember selection algorithms and tools currently exist that could be utilized to more accurately determine the constituents of any given scene. This research used a simple automated endmember extraction tool and had spectra assigned to the identified endmembers. More analysis using different endmember selection tools could greatly effect the accuracy of the assumed abundances and thus contribute to reducing the error through the rest of the TPM process.

This research was undertaken assuming a natural desert setting, however given reasonable urban or forest spectra, there are no overarching assumptions that would preclude the TPM methodology from working in different settings. Additional work could be performed to determine the validity of this methodology in various types of scenes. In addition to locality, acquisition times and quantity should also be considered as logical areas of future research. Due to the complexity of this non-linear problem, there is no straightforward answer for how to best plan a data collection for using this TPM methodology. However, a dimensional analysis could be used to potentially determine the most important acquisition times, while the quantity will probably be driven by the amount of resources that can be allocated.

Finally, given the large set of thermal parameters being used in the estimation
process, additional experimentation may be necessary in order to determine the relative importance of each parameter and how they might be better estimated. A simple sensitivity analysis was performed on the ‘dirt track’ scene in Section 4.2, however this question of the relative importance of thermal parameters is critical to every analyst’s quandary concerning which thermal parameters should have the most resources devoted to them during the modeling process. Furthermore, additional research could be undertaken using only TIR imagery to determine how well this methodology may still perform.

5.2 Computational Efficiency

One consideration for future research is the use of a multi-tasking CPU program such as Condor that can execute the bulk parameter estimation process simultaneously on different portions of a scene using the same pre-determined surface parameter maps. This will become increasingly important as the size of the scene in pixels is increased. If this method were used to estimate the spatial clutter of a large desert scene, this code would need to be executed in parallel on many machines to pare the required processing time. For example, if one wanted to simulate an entire WASP LWIR image (i.e., 640x512 pixels), the scene would need to be divided into smaller sections as a function of known endmember(s) and their associated spectra and then reduced into chunks as a function of desired processing time.

Another important area for consideration is a more ‘intelligent’ traversal of the various search spaces using optimization techniques commonly employed to minimize error functions (e.g., the RMSE function used in this research). Optimization is a large field of research that has numerous well-known techniques for finding the maxima (or minima) of a given (possibly non-linear) function. If reasonable
estimates could be provided to seed an algorithm, then an optimization routine could be utilized to find the optimal value of each thermal parameter.

Finally, potential improvement could readily be ascertained by expending more effort into implementing tighter code. The crux of this research was to find new methods to estimate thermal parameters, and as such the code was only written at the engineering-level and was not optimized for execution speed. Furthermore, any effort to increase the levels of quantization for the various combined bulk parameters would be greatly enhanced by the use of a structured programming environment and modern programming practices.

DIRSIG now has the capability to utilize thermal parameter mapping to generate synthetic TIR imagery of impressive quality. However, the implementation of any of these suggested areas of research would benefit the end user of this methodology and make the resulting imagery even more accurate.


