Temperature Profile Retrievals with the
NAST-M Passive Microwave Spectrometer

by

Robert Vincent Leslie

B.S., Boston University (1998)

Submitted to the Department of Electrical Engineering and Computer Science
in partial fulfillment of the requirements for the degree of

Master of Science

at the

MASSACHUSETTS INSTITUTE OF TECHNOLOGY

June 2000

© Massachusetts Institute of Technology 2000. All rights reserved.

Author

Department of Electrical Engineering and Computer Science
May 5, 2000

Certified by

David H. Staelin
Professor of Electrical Engineering
Thesis Supervisor

Accepted by

Arthur C. Smith
Chairman, Departmental Committee on Graduate Students
Temperature Profile Retrievals with the
NAST-M Passive Microwave Spectrometer

by

Robert Vincent Leslie

Submitted to the Department of Electrical Engineering and Computer Science
on May 5, 2000, in partial fulfillment of the
requirements for the degree of
Master of Science

Abstract

The National Polar-orbiting Observational Environmental Satellite System (NPOESS) Aircraft Satellite Testbed (NAST) employs a passive microwave spectrometer (NAST-M) with channels in the oxygen absorption bands near 54-GHz and 118.75 GHz. NAST-M has two coregistered total-power radiometers, which were flown on NASA’s high-altitude ER-2 aircraft. The 54-GHz radiometer has a single-sideband receiver with a total of eight channels ranging from 50.2 GHz to 56.2 GHz, and the double-sideband 118-GHz radiometer has six functioning channels with center frequencies from $118.75 \pm 0.8$ GHz to $118.75 \pm 3.5$ GHz. The nadir spatial resolution is 2.6 km from an altitude of 20 km. NAST-M has an antenna reflector that scans $\pm 64.8^\circ$ from nadir and makes 19 measurements with a spacing of 7.5'.

This thesis presents accurate temperature retrievals obtained during WINTEX (WIN-Ter EXperiments, Madison, WI, March/April 1999) using flight data from the NAST-M instrument. A calibration correction was completed after a comparison with the Advanced Microwave Sounding Unit (AMSU-A) passive microwave spectrometer onboard the NOAA-15 satellite. Upper bounds to NAST-M’s sensitivity and accuracy are $< 0.3$ K and $< 1.5$ K, respectfully.

A non-linear statistical/physical temperature profile retrieval technique was implemented with a multilayer feedforward neural network (MFNN). The NAST-M brightness temperature and the aircraft’s altitude are preconditioned (decorrelated, normalized, and biased) and entered into the MFNN to estimate the coefficients of the orthogonal expansion of the temperature profiles. The temperature profile training ensemble of radiosonde data is TIGR, which is segregated into mid-latitude winter profiles. Liebe’s Millimeter-wave Propagation Model (MPM) is used to transform the TIGR profiles into simulated NAST-M brightness temperatures. The rms retrieval errors based on the training and validation sets were $< 2$ K in the mid-troposphere and closer to 3 K at the surface and close to the aircraft.

WINTEX flight data are compared with radiosondes and AMSU-A temperature retrievals. Initial NAST-M/MFNN temperature perturbation images of the lower atmosphere are also presented; they suggest the possible detection of thermal waves on the order of 1 K peak-to-peak with a period of $\sim 20-60$ km.

Thesis Supervisor: David H. Staelin
Title: Professor of Electrical Engineering
Acknowledgments

First and foremost, I would like to thank Prof. Staelin for his guidance, support, and insight. I would also like to thank Bill, Carlos, Junehee, and Phil for patiently answering my endless questions. I appreciate their help. It went beyond the call of duty.

A special thanks goes out to Anne for her love and support, and also for the hours spent proofreading.

Also, I would like to thank the guys at poker night for commiserating and also for letting me win once in awhile.

I would like to dedicate my thesis to my family. They are always there for me.
# Contents

1 Introduction ............................................. 15
  1.1 History ................................................ 15
      1.1.1 NAST Background .................................. 16
      1.1.2 NAST-M ............................................. 16
  1.2 Outline of Thesis ..................................... 17

2 Fundamentals of Temperature Retrievals .................. 19
  2.1 General Remote Sensing Instrumentation ............... 20
      2.1.1 Radiometer ......................................... 20
      2.1.2 Radiometer Performance ............................ 20
      2.1.3 Evaluation of Receiver Sensitivity ............... 22
  2.2 Physics of Thermal Radiation ........................... 24
      2.2.1 Kirchhoff's Law .................................... 25
      2.2.2 Radiative Transfer Equation ....................... 26
      2.2.3 Airborne Microwave FRT ............................ 27
      2.2.4 Spectral Analysis ................................... 29
  2.3 Bayes' Least-Squares Estimation ....................... 30
      2.3.1 Error Criterion ..................................... 30
      2.3.2 Linear Least-Squares Estimator .................... 30
      2.3.3 Statistical Inference ............................... 31
      2.3.4 Linear Regression ................................. 32
  2.4 Inversion Theory ....................................... 33
      2.4.1 Atmospheric Modeling ............................... 34
      2.4.2 Weighting Function Quadrature .................... 34
List of Figures

2-1 A total-power radiometer schematic ........................................... 21
2-2 Receiver power spectral density .................................................. 24
2-3 Geometric layout for plane stratified atmosphere ............................ 27
2-4 Atmospheric transmission at microwave frequencies .......................... 29
2-5 Multilayer perceptron flowchart .................................................. 36
2-6 Single-layer perceptron flowchart ................................................. 36
3-1 Sketch of ER-2 and IFOV ............................................................ 42
3-2 RF front end .................................................................................. 44
3-3 118-GHz filterbank ....................................................................... 45
3-4 Weighting functions for NAST-M ................................................. 46
3-5 An ideal three-point calibration ..................................................... 48
3-6 Noise reduction from calibration count filtering ................................. 52
3-7 Scan pattern illustration .................................................................. 54
3-8 A sample of RTD values on the hot and ambient load ....................... 55
3-9 Hot load weights ............................................................................ 57
3-10 Illustration of calibration corruption and correction ......................... 58
3-11 Range and mean for $\delta T_H$ and $\delta T_A$ .................................... 61
3-12 54-GHz system for March 25th ..................................................... 62
3-13 Linearity of the 118-GHz Channel 8 .............................................. 63
3-14 Improvement of $\Delta T_{rms}$ between 2-pt and 3-pt calibration .......... 66
4-1 Layout for retrieval technique ....................................................... 70
4-2 TIGR month and latitude histogram .............................................. 71
4-3 Scatter plot for air versus water temperatures .................................. 73
<table>
<thead>
<tr>
<th>Section</th>
<th>Title</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>4-4</td>
<td>Scatter plot for air and simulated water temperatures</td>
<td>73</td>
</tr>
<tr>
<td>4-5</td>
<td>TIGR orthogonal basis vectors</td>
<td>75</td>
</tr>
<tr>
<td>4-6</td>
<td>Reconstruction error</td>
<td>76</td>
</tr>
<tr>
<td>4-7</td>
<td>Altitudes of simulations</td>
<td>78</td>
</tr>
<tr>
<td>4-8</td>
<td>Surface emissivities</td>
<td>79</td>
</tr>
<tr>
<td>4-9</td>
<td>MFNN training</td>
<td>86</td>
</tr>
<tr>
<td>4-10</td>
<td>MFNN algorithm results</td>
<td>87</td>
</tr>
<tr>
<td>5-1</td>
<td>Raob comparison over L. Michigan</td>
<td>92</td>
</tr>
<tr>
<td>5-2</td>
<td>Temperature perturbation over L. Michigan</td>
<td>93</td>
</tr>
<tr>
<td>5-3</td>
<td>Raob comparison over Madison, WI</td>
<td>94</td>
</tr>
<tr>
<td>5-4</td>
<td>Temperature perturbation over Madison, WI</td>
<td>95</td>
</tr>
<tr>
<td>5-5</td>
<td>Images over L. Michigan</td>
<td>97</td>
</tr>
<tr>
<td>5-6</td>
<td>Temperature perturbation image using MFNN</td>
<td>99</td>
</tr>
<tr>
<td>5-7</td>
<td>Temperature perturbation image using LLSE</td>
<td>100</td>
</tr>
</tbody>
</table>
List of Tables

3.1 Spectral Description of the NAST-M 54-GHz System .............................................. 42
3.2 Spectral Description of the NAST-M 118-GHz System ............................................. 43
3.3 $\delta T_H$ Correction for the 54-GHz System .......................................................... 60
3.4 $\delta T_A$ Correction for the 54-GHz System ............................................................ 60
3.5 Sensitivities of the NAST-M Instrument .................................................................. 65

4.1 Criterion for Winter Profiles .................................................................................. 71

5.1 WINTEX 1999 NAST-M Flight Summary ................................................................. 90
5.2 National Data Buoy Center .................................................................................... 92
5.3 Data from Buoy 45007 ......................................................................................... 93
5.4 Surface Temperature Comparison ......................................................................... 96
Chapter 1

Introduction

Atmospheric parameters such as temperature and humidity can be retrieved from radiometric observations at the absorption frequencies of the atmospheric constituents. The physical equations governing the relationship between the atmospheric parameters and the radiation can be ill-posed, non-linear, non-gaussian, and therefore difficult to retrieve. Atmospheric profiling is a well-developed science with applications dating as far back as the 1960s [1, 2, 3, 4]. For example, the TIROS-1, which was a polar-orbiting satellite carrying an infrared spectrometer, was launched in 1960. The goal of this thesis is to retrieve temperature profiles of the lower atmosphere with the new WINTEX radiometric data from the NPOESS Aircraft Sounding Testbed-Microwave (NAST-M) passive microwave spectrometer. The platform for the NAST-M instrument is the ER-2 high altitude aircraft and the spectrometer has a spatial resolution of ~ 2 km. NAST-M has eight channels around the 54-GHz oxygen line and six channels around the 118-GHz oxygen line. A multilayer feedforward neural network is used in the retrieval technique, which is a combination of a physical and statistical retrieval.

1.1 History

The work done in this thesis, like all of science and engineering today, built on the effort and work of others. This section briefly introduces the previous work that enabled this thesis to be undertaken.
1.1.1 NAST Background

On May 5, 1994, President Bill Clinton directed the convergence of the Department of Commerce/National Oceanic and Atmospheric Administration’s Polar-orbiting Operational Environmental Satellite (POES) program and the Department of Defense’s Defense Meteorological Satellite Program (DMSP). These two programs became the National Polar-orbiting Operational Environmental Satellite System (NPOESS). The purpose of the convergence was to reduce duplication of efforts in the common goals of the two programs, while satisfying the civil and national security requirements. The National Aeronautics and Space Administration (NASA), through its Earth Observing System (EOS), was also added to provide new remote sensing and spacecraft technologies that could potentially improve the capabilities of the operational system. The Integrated Program Office was established to manage NPOESS. NPOESS utilizes the NPOESS Aircraft Sounder Testbed (NAST) to test infrared and microwave remote sensing instruments before potential use on NPOESS satellites. One of NPOESS’s overall goals is to improve operational weather forecasting. The NAST-M is a passive microwave radiometer that is both an imager and a sounder. The companion instrument of NAST-M is the scanning infrared interferometer (NAST-I). The general purpose of NAST-I/NAST-M is to validate infrared and microwave sounding instruments and retrieval algorithms. The ER-2 measurements obtained during WINTEX are used to validate algorithms being developed to process imaging and sounding data of winter mid-latitude climatology.

1.1.2 NAST-M

Massachusetts Institute of Technology’s Lincoln Laboratories, the Research Laboratory of Electronics, the University of Wisconsin-Madison, and NASA under the sponsorship of the Integrated Program Office developed remote sensing instruments to be tested with NAST. One of these instruments is the NAST-M passive microwave spectrometer, which was designed and built at the Massachusetts Institute of Technology’s Research Laboratory of Electronics [5, 6]. NAST-M had origins in a previous microwave temperature sounder (MTS) and references are in [7, 8]. NAST-M went from the drawing board to having an operational prototype within 18 months and with a budget under one million dollars. The designers include Prof. David H. Staelin, Dr. Philip W. Rosenkranz, Dr. Michael J.
Schwartz, Mr. John W. Barrett, and Mr. William J. Blackwell. NAST-M was the first scanning co-registered 54-GHz and 118-GHz radiometer, and between NAST-I and NAST-M, these instruments were the first high-resolution microwave and infrared combination. The NAST-M also allowed the first three-point calibration with the two onboard loads and the deep-space calibration.

1.2 Outline of Thesis

Chapter 2 covers the fundamentals involved in temperature sounding along with an introduction to neural networks and linear least squares estimators. The fundamentals of temperature sounding include the total-power radiometer and the physics of a generalized atmosphere. Chapter 3 discusses the calibration of the NAST-M instrument. Obviously, a good calibration is necessary for successful retrievals. NAST-M was compared with an operational passive microwave radiometer on the NOAA-15 satellite and with radiosondes. A brightness temperature bias was found between the NAST-M instrument and the AMSU-A instrument and, therefore, a correction was determined for the NAST-M instrument. Chapter 4 describes the retrieval algorithm for inverting the radiative transfer equation. The algorithm transforms the brightness temperatures of the NAST-M instrument into estimated atmospheric temperature profiles; this algorithm utilized a training set developed through software simulation based on a priori information on lower atmospheric profiles (radiosondes). The training set allowed the algorithm's estimator to be developed and then used with the actual radiometric data. Chapter 5 has two case studies in which two portions of separate flights are analyzed. One sample is over Lake Michigan and another is over land, and both were from the WINTEX deployment based in Madison Wisconsin in March 1999. Chapter 6 gives an overview of the results found and also suggests further work that could improve or advance the work in this thesis.
Chapter 2

Fundamentals of Temperature Retrievals

Atmospheric constituents and planetary surfaces emit electromagnetic energy in accordance with Planck’s radiation law. In the microwave region of the electromagnetic spectrum, the power of the emitted ‘thermal radiation’ is directly proportional to the temperature of the constituents. The microwave region lies approximately between 3 GHz to 300 THz. Passive remote sensing uses thermal radiation to determine the temperature profile of the atmosphere.

This paragraph introduces an brief overview of the fundamental concepts of the total-power radiometer and the principals of temperature retrievals. The sensor’s antenna propagates the frequencies that will be used to sound the atmosphere. The necessary frequencies are segregated into different channels. The choice of frequencies used in a particular channel will be explained in Section 2.2.4. The mathematical foundations will be explained under Section 2.2.3. Each channel has a weighting function of the atmosphere defined by the radiative transfer equation. The equation of radiative transfer characterizes the behavior of the radiation within the medium, which is the terrestrial atmosphere. Each channel’s brightness temperature is the integration of the channel’s weighting function times the temperature profile. The weighting functions carve the atmosphere into temperature samples that are highly correlated with one another. This correlation complicates the inversion of the brightness temperature into temperature because the inversion is ill-posed, but the correlation allows the retrieval of more temperature levels than weighting functions. Techniques are
discussed in Section 2.4 for temperature profile inversion.

2.1 General Remote Sensing Instrumentation

2.1.1 Radiometer

A fundamental instrument used in passive remote sensing of atmospheric emission is the total-power radiometer, which uses an antenna to couple the electromagnetic energy to a waveguide. Most of the microwave frequencies used for temperature sounding are difficult to amplify, and the superheterodyne system is used to downconvert the frequencies to an intermediate frequency (IF) so that ‘off the shelf’ RF technology can be used. Then a spectrometer configuration divides the power by frequency. This configuration is implemented by having the IF segregated through a filterbank made up of RF amplifiers, power dividers, and bandpass filters. Each specific passband of a RF filter is called a channel and defines a particular atmospheric weighting function.

After the filterbank, a square law device converts the power incident on the device to a related voltage. A typical square law device is the tunnel diode. The amplification of the voltage before the diode sets the operating point. It is important to set the bias on the diode so that the dynamic range of the input power is within a linear portion of the diode’s square law curve. This assures that the instrument remains linear. The principal purpose of a radiometer is to give a voltage that is proportional to the received power. A schematic is shown in Figure 2-1 from Janssen [9]. It should be noted that the layout only has one filter. A spectrometer would divide the power with a filterbank.

The voltage from each channel is converted to a digital signal, after amplification, by an analog-to-digital converter. Through digital signal processing, the signal is integrated, which is equivalent to a lowpass frequency filter and is expressed as ‘counts.’ Calibration consists of relating the counts to the brightness temperature of the scene. Brightness temperature will be defined in Section 2.2.1.

2.1.2 Radiometer Performance

Attributes of a receiver are the receiver’s sensitivity, spectral response, and directional response [2]. A common receiver sensitivity metric in radio astronomy and remote sensing is $\Delta T_{rms}$ which is in Kelvin s. The $\Delta T_{rms}$ will be investigated further in the next subsection.
for its importance in calibrating radiometric instruments. It should be noted that the $\Delta T_{rms}$ below is idealized. Kraus [10] and Staelin [11] derived

$$\Delta T_{rms} = \frac{V_{out}\text{rms}}{\partial V_{out} \partial T_a} = \frac{T_a + T_r}{\sqrt{B\tau}} \quad [\text{Kelvin}] \tag{2.1}$$

where $V_{out}$ is the output voltage of the total-power radiometer, $B$ is the bandwidth of the channel, $\tau$ is the integration time, $T_r$ is the noise temperature of the receiver, and $T_a$ is the antenna temperature. The receiver noise temperature is internally generated power from the internal components of the receiver. Within the microwave region, it is common to express power in terms of temperature because of the Rayleigh-Jeans approximation. The antenna temperature is

$$T_a(f) = \frac{1}{4\pi} \int_{4\pi} T_b(f, \theta, \phi) G(f, \theta, \phi) \, d\Omega \quad [\text{Kelvin}] \tag{2.2}$$

The antenna temperature integrates or accounts for the brightness temperature $T_b$ over the entire gain pattern of the antenna $G(f, \theta, \phi)$. Therefore, $G(f, \theta, \phi)$ gives the directional response of the radiometer. Scalar feed horns help alleviate spurious signals from the gain pattern’s sidelobes. Spectral response is mainly controlled by the RF filters’ frequency response and the other RF components in the filter bank.
2.1.3 Evaluation of Receiver Sensitivity

A metric for a receiver's sensitivity is the noise equivalent temperature difference, often termed the $\Delta T_{\text{rms}}$. In Hersman and Poe [12], the $\Delta T_{\text{rms}}$ is reduced into its independent components. They present it as $\Delta T_{\text{rms}}^2 = \delta_{sc}^2 + \delta_{cal}^2 + \delta_{gf}^2$. The $\delta_{sc}^2$ is the fluctuation due to scene measurements from an ideal flat power spectral density (Equation 2.1). It is common that the calibration is considered ‘ideal’ by only considering the $\delta_{sc}^2$, but for practical consideration it is not ideal and the calibration estimation causes error $\delta_{cal}^2$. The final noise variance term is from the receiver fluctuations and electronic $1/f$ noise. The total $\Delta T_{\text{rms}}$ can be viewed in a ‘variance’ space with each of these sources of noise as an orthogonal variance that spans the variance space. A superior calibration technique will reduce the total $\Delta T_{\text{rms}}$ with post-flight signal processing. We search for an appropriate calibration technique that would make the $\delta_{cal}^2$ and $\delta_{gf}^2$ as small as possible so that the theoretical $\delta_{sc}^2$ dominates the $\Delta T_{\text{rms}}$. This is examined in more detail in Section 3.2.4.

The lowest limit of $\Delta T_{\text{rms}}$ is $\delta_{sc}^2$, which is repeated here for convenience:

$$\delta_{sc} = \frac{T_a + T_r}{\sqrt{B\tau}}. \quad (2.3)$$

This variance is inherent in a total-power radiometer configuration. The full derivation is discussed by Staelin [11].

There is also a component of the calibration error in the $\Delta T_{\text{rms}}$ that is usually considered zero in the previous analysis. Hersman and Poe [12] extended the representation with a first order approximation, assuming that the scene is the same temperature as the hottest calibration load (worst case scenario):

$$(\Delta T_{\text{rms}})^2 = E[(V_{\text{scene}} - V_{\text{cal}})^2]. \quad (2.4)$$

$V_{\text{cal}}$ is the estimated calibration voltage. It is the output of the total-power radiometer when looking at the calibration load. $V_{\text{cal}}$ has the $\delta_{sc}^2$ added to the measurement variance. If the gain was stable, then we could use each measure of the calibration load during the duration of flight to estimate the counts related to the appropriate brightness temperature of the load. It would greatly reduce the noise from the radiometer because each calibration look is a measurement of a deterministic signal with additive noise. The gain fluctuates slowly with
time. An important parameter to combat the fluctuating gain is the period, $t_c$, between calibration measures. The $t_c$ is chosen so that the gain can be considered constant between calibration measures. Beyond $t_c$ there is still correlation between calibration measures, but it becomes weaker as time progresses. An optimal estimate of $V_{cal}$ can use other calibration measures to reduce the noise in the calibration load counts. This better estimate of $V_{cal}$ is written mathematically as

$$V_{cal} = \sum_k w(t - kt_c) \cdot V(kt_c) \quad k = 0, \pm 1, \pm 2, \ldots$$  \hspace{1cm} (2.5)$$

with the proper constraint that

$$\sum_k w(t - kt_c) = 1,$$  \hspace{1cm} (2.6)$$

with $w(t - kt_c)$ being the weight of the neighboring calibration measures. The final expression of $\Delta T_{rms}$ when considering an imperfect calibration is

$$\Delta T_{rms} = \left( T_a + T_r \right) \sqrt{\frac{1}{B_T} + \frac{1}{B_T} \sum_k w^2(t - kt_c)},$$  \hspace{1cm} (2.7)$$

and the

$$\delta_{cal} = \left( T_a + T_r \right) \sqrt{\frac{1}{B_T} \sum_k w^2(t - kt_c)}.$$  \hspace{1cm} (2.8)$$

The power spectrum of the receiver noise has two primary components. There is a flat component that is due to $\delta_{sc}$, or the fundamental performance of the total-power radiometer. The other component is the gain fluctuation, or $1/f$ noise. This adds to the receiver performance to give a power spectral density similar to Figure 2-2. The calibration technique can be considered a transfer function $H(f)$ of the instrument’s power spectral density $S_r(f)$. This allows the $\Delta T_{rms}$ to be represented as

$$\left( \Delta T_{rms} \right)^2 = \int_0^\infty S_r(f) \cdot H(f) \, df.$$  \hspace{1cm} (2.9)$$

The greater noise spectra at the lower frequencies is the $1/f$ noise and fluctuations in gain. The calibration has an effective filter of $H(f)$ on the receiver’s power spectral density, $S_r(f)$:

$$H(f) = \left| \frac{\sin(\pi f \tau_s)}{\pi f \tau_s} - \frac{\sin(\pi f \tau_c)}{\pi f \tau_c} \sum_k w(t - kt_c)e^{-j2\pi f(t-kt_c)} \right|^2$$  \hspace{1cm} (2.10)$$
\( \tau_s \) and \( \tau_c \) are the integration time for the scene and calibration load respectfully.

The calibration technique is equivalent to a filter that filters out the low frequency noise while at the same time tries to reduce the \( \delta^2_{cal} \) contribution to the \( \Delta T_{rms} \). So it is important to choose \( w(t) \), the weights of the nearby calibration measures, to include as much information as possible for the \( V_{cal} \) estimation while minimizing the \( \delta_{cal} \).

If we separate the noise spectra into the flat portion intrinsic in a total-power radiometer, \( S_i(f) \), and the \( 1/f \) portion that is due to gain fluctuations, \( S_g(f) \), then the \( \Delta T_{rms} \) due to gain fluctuations is

\[
\delta^2_{gain} = \int_{0}^{\infty} S_g(f) H(f) df. \tag{2.11}
\]

The period between calibrations is chosen to filter out as much gain-related noise as possible.

### 2.2 Physics of Thermal Radiation

In order to understand temperature retrievals, the physics behind the retrieval technique must be understood. The physics are also used to form an atmospheric model, which is used to transform temperature profiles into radiances (see Section 2.4.1). The utility of this transformation will be apparent with physical retrievals and in training neural network for retrievals.
2.2.1 Kirchhoff’s Law

The basic element of remote sensing is thermal radiation. Matter emits electromagnetic energy or radiation. A theoretical body of matter that absorbs all incident radiation is called a blackbody. The intensity emitted by a body at uniform temperature $T$ is defined by Kirchhoff’s law:

$$I_f = \alpha_f \cdot B_f(T) \left[ \frac{W}{m^2 \cdot Hz \cdot Ster} \right].$$  \hspace{1cm} (2.12)

The absorption coefficient, $\alpha_f$, that has a value between 0 and 1 and is frequency dependent. A $\alpha_f = 0$ means that the matter neither emits nor absorbs electromagnetic energy, while $\alpha_f = 1$ is the theoretical blackbody. Max Planck derived a radiation formula that relates radiation intensity in units of power per area-hertz-steradian. Planck’s radiation law is as follows

$$B_f(T) = \frac{2h f^3}{c^2 (e^{h f/kT} - 1)} \left[ \frac{W}{m^2 \cdot Hz \cdot Ster} \right].$$  \hspace{1cm} (2.13)

with $T$, temperature in Kelvin; $f$, frequency in Hertz; $h$, Planck’s constant; $k$, Boltzmann’s constant; $c$, speed of light in the medium. The power series expansion $e^x = \sum_{k=0}^{\infty} \frac{x^k}{k!}$ can be approximated when $x \ll 1$ as $e^x = 1 + x$. This approximation is the Rayleigh-Jeans limit and gives

$$B_f(T) = \frac{2kT}{\lambda^2} \left[ \frac{W}{m^2 \cdot Hz \cdot Ster} \right]$$  \hspace{1cm} (2.14)

only when $hf \ll kT$. This is true in the microwave region of the electromagnetic spectrum and at temperatures within 200-300 K.

**Brightness Temperature**

A very common term in passive remote sensing is brightness temperature. Kirchhoff’s law is in units of intensity, and when intensity is expressed in units of temperature, then it is termed brightness temperature. For example, Rayleigh-Jeans law, Equation 2.14, can be rearranged to give the equivalent temperature for a given intensity:

$$T_b = \frac{\alpha_f B_f(T) \cdot \lambda^2}{2 \cdot k} = \frac{I_f \cdot \lambda^2}{2 \cdot k}.$$  \hspace{1cm} (2.15)

This equation is only appropriate if all the conditions for the Rayleigh-Jeans limit are meet.
2.2.2 Radiative Transfer Equation

The radiative transfer equation (or FRT) defines the physics of the thermal radiation reaching the airborne antenna. More in-depth explanations can be found in [13, 14]. The atmosphere and surface emit thermal radiation that is coupled to the antenna. The RTE is defined from a position above a surface. The exchange of radiation in an incremental piece of the atmosphere in between the surface and antenna is

\[ dI_f = dI_{\text{emission}} + dI_{\text{extinction}}. \]  \hspace{1cm} (2.16)

The \( dI_{\text{extinction}} \) comes from Lambert’s law, which states

\[ dI_{\text{extinction}} = -\alpha_f \cdot I_f \, ds. \]  \hspace{1cm} (2.17)

The \( \alpha_f \) is the absorption coefficient and it should be noted that we are neglecting the scattering coefficient. The \( dI_{\text{emission}} \) is from Kirchhoff’s law, which is restated here:

\[ dI_{\text{emission}} = \alpha_f \cdot B_f \, ds. \]  \hspace{1cm} (2.18)

In Figure 2-3, the geometry is illustrated. The distance along the \( s \) can be approximated to \( z \cdot \sec(\theta) \) The optical depth is defined as

\[ \tau(z) = \int_z^{z''} \alpha_f(z) \, dz. \]  \hspace{1cm} (2.19)

Putting Equation 2.17 and Equation 2.18 into Equation 2.16 results in

\[ \frac{dI_f}{ds} = \alpha_f [B_f - I_f]. \]  \hspace{1cm} (2.20)

Multiply both sides by \( e^\tau(z) \), integrating from a point \( z' \) to \( z'' \) results in

\[ I_f(z'') = I_f(z') \cdot e^{-\tau(z') - \tau(z'')} \cdot \sec(\theta) + \int_{z'}^{z''} \sec(\theta) B_f(z) e^{-\tau(z) - \tau(z'')} \cdot \sec(\theta) \alpha_f(z) \, dz. \]  \hspace{1cm} (2.21)
2.2.3 Airborne Microwave FRT

The next step is to determine the intensity the sensor will see in airborne applications. The first step is to transform Equation 2.21 into brightness temperature defined in Equation 2.15. The position at the surface is set to zero \((z' = 0)\) and \(\tau(z'') = 0\):

\[
T_b = T_{b_{\text{surf}}} e^{-\tau(0) \sec(\theta)} + \int_{0}^{z''} T(z) e^{-\tau(z) \alpha_f(z) \sec(\theta)} \, dz. \tag{2.22}
\]

Equation 2.22 only accounts for the thermal radiation from surface and intervening atmosphere. In reality, two additional sources need to be added. They are the downwelling radiation and cosmic background radiation that reflects off the surface and makes it back to the sensor. Therefore the complete microwave RTE is

\[
T_b = T_{b_{\text{surf}}} + (1 - \varepsilon_s) T_{b_d} [e^{-\tau(0) \sec(\theta)}]. \tag{2.23}
\]

The \(\varepsilon_s\) is the surface emissivity. \(T_{b_{\text{surf}}}\) is the portion in the integral that was stated in Equation 2.22, and \(T_{b_d}\) is

\[
T_{b_d} = T_{\text{cosmic}} e^{-\tau(0) \sec(\theta)} + \sec(\theta) \int_{0}^{z''} T(z) \alpha_f(z) e^{-\tau(0) - \tau(z) \sec(\theta)} \, dz. \tag{2.24}
\]
Surface Emissivity

The surface emissivity defines the amount of power that is absorbed by the surface. Radiation incident to the surface is either reflected or transmitted. This can be seen in this relationship between emissivity, \( \varepsilon_s \), and reflectivity, \( \rho_s \):

\[
\varepsilon_s + \rho_s = 1. \tag{2.25}
\]

Emissivity can be derived from use of Maxwell’s equations and the refractive index of the two materials at the boundary \([15, 16]\). In this application, the boundary is the atmosphere and the earth. In thermal equilibrium, the amount of radiation absorbed is also radiated and therefore,

\[
T_{b_{\text{surf}}} = \varepsilon_s \cdot T_{\text{surface}}. \tag{2.26}
\]

Two major classifications for practical terrestrial surface emissivities are ‘absorbers’ and ‘scatterers.’ Many of the surfaces encountered in remote sensing have high emissivity and therefore absorb a large portion of the incident radiation at microwave frequencies, but also emit this same portion of thermal radiation. Examples are vegetation and moist soil. The other classification is scatterers. These surfaces do not absorb as much and therefore they are reflective. Some examples of scatterers are water, ice, and snow.

Weighting Functions

To see the sounding that is accomplished by temperature sounders, it is necessary to introduce the idea of atmospheric weighting functions. Taking Equation 2.23 and combining the integrals at nadir gives:

\[
T_b = \varepsilon_s T_{\text{surf}} e^{-\tau(0)} + \rho_s T_{\text{cosmic}} e^{-2\tau(0)} + \int_0^{\tau''} \alpha_f(z) \left(1 + \rho_s e^{-[\tau(0) - \tau(z)]} \right) e^{-\tau(z)} T(z) \, dz. \tag{2.27}
\]

Everything within the integral except the temperature profile can be placed in a weighting function.

\[
W(z) = \alpha_f(z) \left(1 + \rho_s e^{-[\tau(0) - \tau(z)] \sec(\theta)} \right) e^{-\tau(z) \sec(\theta)}. \tag{2.28}
\]
If $\alpha_f$ is great enough to ignore the contributions of the surface and cosmic background, then Equation 2.27 can be written as a Fredholm integral equation of the first kind:

$$T_b = \int_0^{z''} W(z)T(z) \, dz.$$  \hspace{1cm} (2.29)

This is the principal equation of temperature profile sounding.

### 2.2.4 Spectral Analysis

This section explains which frequencies are chosen within the microwave spectrum for temperature sounding. The shapes of the weighting functions are determined by the absorption coefficient (see Equation 2.28). Weighting functions looking into the atmosphere from high altitudes are somewhat gaussian in shape, with the peak of the gaussian distribution determined by the absorption coefficient. As the transmittance decreases, the altitude of the peak of the gaussian curve increases. Figure 2-4 is a graph of the transmittance within the microwave region of the spectrum using the U.S. 1976 standard atmosphere. In order to get a variety of weighting functions in the atmosphere, the channel's passbands must lie near one or more absorption lines. From the figure, it is seen that the best places for temperature sounding are near the $O_2$ lines around 60 GHz and the single line at 118 GHz. Oxygen is a
molecule that is uniformly mixed in the terrestrial atmosphere. The filter passbands of the total-power radiometer are chosen near the oxygen absorption lines.

2.3 Bayes’ Least-Squares Estimation

Bayesian methods of estimation uses a priori information when choosing the optimal estimator. The probability density function of the desired random variable, \( p_x(X) \), may be known and the estimator can therefore use this information. If a random variable \( Y \) can be measured that has a relationship to \( X \) such as \( Y = g(X) \), then the joint probability density function, \( p_{y|x}(Y, X) \), is also used to estimate \( X \).

2.3.1 Error Criterion

The Bayesian framework takes the expected value of a cost function in order to determine the performance of an estimator. The performance criterion is established to benchmark the estimator with its error in estimating the variable. The error is the difference between the estimated and the actual values. There are many options on how to look at the error. A few examples are the minimum absolute value (MAE), maximum a posteriori (MAP), or the minimum mean-square error (MMSE). The next section deals with the criterion of minimizing the mean-square error which is also called the least-squares criterion:

\[
\hat{Y}(X) = \arg \min_{\hat{a}(\cdot)} E[(Y - \hat{a}(X))^2].
\]  

(2.30)

2.3.2 Linear Least-Squares Estimator

The optimal estimator that estimates \( Y \) based on \( X \), with the MMSE criterion, is

\[
\hat{Y}_{MMSE} = E[Y|X_1 = x_1, \ldots, X_L = x_L] = \int_{-\infty}^{\infty} y \cdot p_{y|x}(y|X) dy.
\]  

(2.31)

\( X \) is a vector of given realizations of the random variables. It can be difficult to determine the complete statistical characterization of the relationship between \( X \) and \( Y \). Also, the relationship between \( X \) and \( Y \) may be nonlinear. To help get around these two shortcomings, an estimator will have an additional constraint that it is an affine function of the measured random variables:

\[
\hat{Y}(X) = \alpha + \beta^T \cdot X.
\]  

(2.32)
One technique for finding the minimum of Equation 2.30, with Equation 2.32 in the place of \( \hat{a}(X) \), is to take the derivative with respect to each coefficient and set it equal to zero. For example,

\[
\frac{\partial}{\partial \alpha} E[(Y - \alpha - \sum_i \beta_i X_i)^2] = 0
\]

\[
-2(E[Y] - \alpha - \sum_i \beta_i E[X_i]) = 0
\]

that gives the solution:

\[
\alpha = E[Y] - \sum_i \beta_i E[X_i].
\]

A similar approach to the other coefficients allows the formation of a set of equations called the normal equations:

\[
\text{Cov}_X \cdot \beta = \text{Cov}_{XY}.
\]

The suboptimal estimator is the linear least-squares estimator:

\[
\hat{Y}(X) = E[Y] + \text{Cov}_X^{-1} \cdot \text{Cov}_{XY} \cdot (X - E[X]).
\]

### 2.3.3 Statistical Inference

A practical consideration when using a LLSE is determining the covariance matrix. The sample variance is an estimator of the population variance, which converges to the true variance when there are enough samples, \( N \). The sample variance is

\[
S_x^2 = \frac{\sum_{i=1}^{N} (x_i - M_x)^2}{N},
\]

with \( M_x \) being the sample mean:

\[
M_x = \frac{\sum_{i=1}^{N} x_i}{N}.
\]

The expected value of the sample mean is the mean of \( X \) and the variance of the sample mean is \( \frac{\sigma_x^2}{N} \). As \( N \) goes to infinity, the variance of the estimator goes to zero. The sample variance has an expected value:

\[
E[S_x^2] = \frac{N - 1}{N} \sigma_x^2,
\]
which also gives the true variance of $X$ when $N$ is large. Another important inference is the sample covariance:

$$S_{xy}^2 = \frac{\sum_{i=1}^{N} (x_i - M_x)(y_i - M_y)}{N}. \quad (2.41)$$

### 2.3.4 Linear Regression

Linear regression is a statistical technique for determining a linear relationship between two variables. The linear relationship is actually affine with a slope and intercept as the two parameters to define the linear relationship. Often the data is in ordered pairs $(x_i, y_i)$, which are samples of the relationship between the random variable $Y$ and $X$. If the given variable is $X$ (called the regressor variable), then the response variable is $Y$. Multivariate linear regression has slope parameters for each regressor variable. $X$ is assumed to be without error and $Y$ has the following relationship with $X$:

$$y_i = \alpha + \beta \cdot x_i + \epsilon_i. \quad (2.42)$$

$\epsilon_i$ is the error from experimental measurements or random variations. If each ordered pair holds equal validity in representing the linear relationship (equal variance and independent), then a linear system can be formed:

$$y_N = A \cdot p, \quad (2.43)$$

where

$$y_N = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_N \end{bmatrix}, \quad A = \begin{bmatrix} x_1 & 1 \\ x_2 & 1 \\ \vdots & \vdots \\ x_N & 1 \end{bmatrix}, \quad p = \begin{bmatrix} \hat{\alpha} \\ \hat{\beta} \end{bmatrix}. \quad (2.44)$$

Equation 2.43 can be rewritten in the more familiar expression of

$$A \cdot x = b. \quad (2.45)$$

In the linear regression situation, we have an overdetermined system. Therefore, Equation 2.45 can be solved in a manner that satisfies Equation 2.30, which is choosing an error criterion that minimizes the mean square error between the estimator and the response.
variable. Minimizing $E[(x - \hat{x})^2]$ is the same as using the least squares approximation. From linear algebra, the familiar form is

$$\hat{x} = (A^T \cdot A)^{-1} \cdot A^T \cdot b.$$ \hspace{1cm} (2.46)

Therefore the least squares solution or the linear regression is

$$\hat{\beta} = \frac{N \cdot \sum_{i=1}^{N} x_i y_i - \left( \sum_{i=1}^{N} x_i \right) \left( \sum_{i=1}^{N} y_i \right)}{N \cdot \sum_{i=1}^{N} x_i^2 - \left( \sum_{i=1}^{N} x_i \right)^2} = \frac{S_{xy}}{S_x^2},$$ \hspace{1cm} (2.47)

$$\hat{\alpha} = \frac{\sum_{i=1}^{N} y_i - \hat{\beta} \sum_{i=1}^{N} x_i}{N} = M_y - \hat{\beta} \cdot M_x.$$ \hspace{1cm} (2.48)

The LLSE estimator (Equation 2.37) and least squares approximation (Equation 2.46) are the same thing with one important difference. The linear regression is the statistically infered form of the LLSE estimator based on a finite training data set.

### 2.4 Inversion Theory

If given a relationship $y = T(x)$ and $T(\cdot)$ is a transformation operator, then the range is $Y$ and the domain is $X$. The forward problem is the calculation of $y$ when given $x$, while the inverse problem is the calculation of $x$ when given $y$. In temperature retrievals, the transform is shown in a simplified manner by Equation 2.29. The physical relationship between the domain (temperature profile) and the range (brightness temperatures) is defined by the weighting function, $W(z)$. Inversion theory is the broad study of the retrieval of the domain from a transformation when given the range of the transformation.

In general, the weighting functions are not invertible nor linear. The weighting functions have a high degree of correlation and this causes instability in the inversion. This means that a small error in $y$ can cause the estimation of $x$ to have gross errors. Non-linearities are also present from surface emissivities and water vapor in the atmosphere.

The inversion techniques can be generalized into two different categories. The older technique is the physical retrieval, which uses the knowledge of the physics of the atmosphere and makes an atmospheric model. A limitation of a physical retrieval is the amount of information ‘seen’ by the instrument weighting function. The physical retrieval uses only
the knowledge of $W(z)$, while the information within $W(z)$ does not span the function space of $T(z)$. Added information from this 'hidden' information space can be found in the statistics of $Y$ and $X$. The second category, called statistical retrievals, also uses statistics in the retrieval technique.

2.4.1 Atmospheric Modeling

In the microwave spectrum, the atmospheric model is the radiative transfer equation of Section 2.2.2. This model assumes clear (no clouds), non-scattering, vertically stratified atmosphere. The absorption coefficient is modeled with a line-by-line model called the Millimeter-wave Propagation Model (MPM). Liebe and Liebe et al. developed the model [17, 18, 19, 20, 8]. The line-by-line model accounts for the absorption lines of the molecular constituents pertinent to the frequencies of interest. The primary molecules within the microwave spectrum are oxygen, $O_2$, and water vapor, $H_2O$. Depending on the pertinent frequencies of the radiometer, the absorption coefficient is calculated from the known absorption lines. The absorption coefficient is a function of the height above the surface, water vapor profile, pressure profile, and temperature profile. Then the brightness temperature from Equation 2.23 is solved with the calculated absorption coefficient.

2.4.2 Weighting Function Quadrature

To improve the stability of the radiative transfer equation inversion, the atmosphere below the radiometer is discretized. This discretization defines the vertical resolution of the temperature retrieval. A limitation of microwave temperature sounding is the small number of channels. Unlike infrared temperature sounders with thousands of channels, the microwave sounders transform from brightness temperature to atmospheric temperature is under constrained because there are only ten known variable that must estimate 30 or so temperature variables. Applying numerical quadrature to the Fredholm integral equation of the first kind gives:

$$\int_a^b h(y) \, dy = \sum_{j=1}^m w_j h(y_j), \quad (2.49)$$
where \( m \) is the number of quadrature abscissas, and then applied to Equation 2.29 it becomes:

\[
\mathbf{T}_b = \mathbf{W}\mathbf{T}, \quad \mathbf{T}_b = \begin{bmatrix} T_{b_1} \\ T_{b_2} \\ \vdots \\ T_{b_n} \end{bmatrix}, \quad \mathbf{T} = \begin{bmatrix} T_1 \\ T_2 \\ \vdots \\ T_m \end{bmatrix}.
\]  

(2.50)

\( \mathbf{W} \) is the matrix from the quadrature approximation of \( \int_0^{z''} W(z)T(z) \, dz \), where \( n \) is the number of channels. From Equation 2.50, it is easier to see the application of linear algebra.

In the microwave case, with few channels, the system is underconstrained and there are infinite number of solutions. While in the infrared case, the system is overdetermined. The fundamental linear algebra techniques to estimate \( \mathbf{T} \) can be found in Strang [21, 22].

### 2.4.3 Linear Statistical Inversion

One of the two retrieval techniques that will be used for retrievals of the NAST-M instrument is the linear statistical retrieval. The fundamentals are explain in Section 2.3. In order to determine the first and second order statistics of Equation 2.47 and 2.48, a collection of temperature profiles are transformed into brightness temperatures by the FRT equation. From these related data sets, the \( \alpha \) and \( \beta \) parameters statistically inferred. The linear statistical inversion will be compared to the neural network inversion, of the next section, to evaluate how the non-linear neural network retrieval compares with a linear retrieval.

### 2.4.4 Neural Network Inversion

An artificial neural network can compensate for the non-linearities of the retrieval. A brief introduction to neural networks is given here, but for a more in-depth source see Haykin [23] and Lippmann [24]. Neural network inversion is a mixture of statistical inversion and physical inversion. There are several types of neural networks and the most common type for pattern recognition is the multilayer feedforward neural network (MFNN).

#### MFNN Architecture

The neural network used in temperature retrievals is typically a multilayered feedforward network. It is called feedforward because it does not have feedback loops in the architecture.
The fundamental unit of a MFNN is called a single-layer perceptron, which is a function of weighted inputs. A column of perceptrons make up a layer, while one or more layers make up a multilayer perceptron (See Figure 2-5) [23, ch. 6]. Figure 2-6, shows the flowchart of a single-layer perceptron. The quantitative relationship is:

\[ y_i = F\left(\sum_{j=1}^{N} w_{ji}x_j + \beta_i\right). \] (2.51)
The activation function, \( F(\cdot) \), can be any monotonically increasing function. The most common activation function is the following logistic sigmoid function:

\[
F(x) = \frac{1}{1 + e^{-x}},
\]

(2.52)

The activation function used in this thesis is called the hyperbolic tangent sigmoid:

\[
F(x) = a \cdot \tanh(b \cdot x) = \frac{2a}{1 + e^{-b \cdot x}} - a
\]

(2.53)

The asymmetric activation function can improve the performance of the training algorithm [23, ch. 6.7]. The layer in the middle is called a hidden layer. Controlling the number of neurons in the hidden layer, \( H \) (with \( M = N \)), is a form of dimensionality reduction or expansion, which is explained further in the Section 2.4.5. This ‘mapping’ of dimensions is done with an autoassociative multilayer perceptron [25, 26].

**Training**

The weights and biases in a multilayer perceptron are numerically optimized for pattern recognition by training through the error back-propagation algorithm. The same training set used to determine the parameters of the LLSE are used to train the MFNN. As mentioned before, the training ensemble is a collection of temperature profiles from radiosondes that were entered into a microwave atmospheric model (MPM). The physical aspect of neural network inversion comes from the use of the radiative transfer equation to simulate instrument brightness temperatures. Training a MFNN is a dynamic process compared to the LLSE. LLSE requires the inversion of a few statistically inferred moments, while the back-propagation algorithm is under supervision to find the minimum of an error criterion.

The basic procedure of the back-propagation algorithm starts with one input vector propagated through the network and then the corresponding output is compared with the correct output. The scaled difference is backpropagated through the network, which adjusts the network’s weights and biases. This is done throughout the entire training ensemble until minimization of the mean squared of error between the network’s output and the training set’s output. This is called the Back-Propagation training algorithm [24]. For a derivation of the back-propagation algorithm see Haykin [23, ch. 6.3]. MFNN training is covered in more depth in Section 4.3.2.
2.4.5 Reduction of Dimensionality

With a collection of random variables, there is a chance that some of the same 'information' is shared between variables. In other words, the random variables are correlated. The correlation can be seen in the covariance matrix of the random vector. The off diagonals are zero when the random variables in the random vector are statistically uncorrelated. The principal component transform (PCT) takes the original random variables and forms a new set of random variables that are statistically uncorrelated with each other. Since the new random variables are uncorrelated, their covariance matrix is diagonal. Part of PCT is ordering the new random variables in size of variance. The first PC variable has the greatest variance, while the last PC has the least variance. In special cases, the dimensionality of the original random vector may be reduced because the lowest principal components have such a small variance that they provide almost no new information (or they are useless noise). By removing these principal components, the dimensionality can be reduced to a set of random variables that contain the greatest amount of information.

Principal Component Analysis

The theory behind principal component analysis comes from the Karhunen-Loève expansion. Discrete KL expansion is a Fourier series expansion where the basis vectors are orthonormal. If given a vector of random variables $\mathbf{x}_N$: 

$$
\mathbf{x}_N = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_N \end{bmatrix}
$$

with $\mathbf{A}_{xx} =$ 

$$
\begin{bmatrix}
\lambda_{x_1 x_1} & \lambda_{x_1 x_2} & \cdots & \lambda_{x_1 x_N} \\
\lambda_{x_2 x_1} & \lambda_{x_2 x_2} & \cdots & \lambda_{x_2 x_N} \\
\vdots & \vdots & \ddots & \vdots \\
\lambda_{x_N x_1} & \lambda_{x_N x_2} & \cdots & \lambda_{x_N x_N}
\end{bmatrix}
$$

(2.54)

and once a PCT is performed on $\mathbf{x}_N$, then the principal components are 

$$
\mathbf{x}_{PC} = \begin{bmatrix} x_{PC1} \\ x_{PC2} \\ \vdots \\ x_{PCN} \end{bmatrix}
$$

with $\mathbf{A}_{PC} = Q^T \cdot \mathbf{A}_{xx} \cdot Q$. 

(2.55)
$Q$ has the eigenvectors of $\Lambda_{xx}$ in its columns. The eigenvectors solve:

$$\Lambda_{xx} \cdot x_{\text{eig}_i} = \lambda_i \cdot x_{\text{eig}_i}, \quad 1 \leq i \leq N. \quad (2.56)$$

The eigenvector with the largest eigenvalue has the largest variance (principal component one). If most of variance of the random vector is in the first $n$ principal components, then the last $(N - n)$ principal components could be removed with minimum loss of information.

The principal components are calculated as

$$x_{PC} = Q^T \cdot x_N. \quad (2.57)$$

It is straightforward to take the above equation and find that it is equivalent to Equation 2.55:

$$\Lambda_{PC} = E[(x_{PC} - E[x_{PC}]) (x_{PC} - E[x_{PC}])^T] = Q^T \cdot \Lambda_{xx} \cdot Q \quad (2.58)$$
Chapter 3

NAST-M Calibration

This chapter covers calibration along with applying the calibration to the NAST-M instrument during the WINTEX deployment. Section 3.1 covers the background information on NAST-M and explains the important characteristics of the NAST-M that are used for accurate temperature retrievals in Chapter 4. Section 3.2 is a radiometer calibration introduction and an explanation of the three-point calibration technique. Section 3.3 explains the hardware involved in the calibration of NAST-M. Finally, Section 3.4 has the results and conclusions of the NAST-M calibration.

3.1 Instrument Overview

Currently, the platform of the NAST is the ER-2 high-altitude aircraft, which is a modified U-2 aircraft on loan to NASA from the United States Air Force. NAST flies in a superpod, which lies under one of the wings of the ER-2 aircraft (see Figure 3-1). NAST-M has ports that view both nadir and zenith. The nadir view is for sounding the atmosphere below the aircraft, and the zenith view is used for calibration.

3.1.1 Radiometers

NAST-M has two total-power radiometers called the 54-GHz system and the 118-GHz system. The 54-GHz radiometer has a single-sideband superheterodyne receiver with a local oscillator (LO) frequency at 46 GHz. Table 3.1 is a list of the 54-GHz system's frequencies before and after downconversion, along with the resulting bandwidths. The 118-GHz radiometer is a double-sideband superheterodyne receiver with an LO frequency at
Table 3.1: Spectral Description of the NAST-M 54-GHz System

<table>
<thead>
<tr>
<th>Chan.</th>
<th>RF (GHz)</th>
<th>IF (MHz)</th>
<th>BW (MHz)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>50.21-50.39</td>
<td>4210-4390</td>
<td>180</td>
</tr>
<tr>
<td>2</td>
<td>51.56-51.96</td>
<td>5560-5960</td>
<td>400</td>
</tr>
<tr>
<td>3</td>
<td>52.6-53</td>
<td>6600-7000</td>
<td>400</td>
</tr>
<tr>
<td>4</td>
<td>53.63-53.87</td>
<td>7630-7870</td>
<td>240</td>
</tr>
<tr>
<td>5</td>
<td>54.2-54.6</td>
<td>8200-8600</td>
<td>400</td>
</tr>
<tr>
<td>6</td>
<td>54.74-55.14</td>
<td>8740-9140</td>
<td>400</td>
</tr>
<tr>
<td>7</td>
<td>55.335-55.665</td>
<td>9335-9665</td>
<td>330</td>
</tr>
<tr>
<td>8</td>
<td>55.885-56.155</td>
<td>9885-10155</td>
<td>270</td>
</tr>
</tbody>
</table>
Table 3.2: Spectral Description of the NAST-M 118-GHz System

<table>
<thead>
<tr>
<th>Chan.</th>
<th>LSB (GHz)</th>
<th>USB (GHz)</th>
<th>IF (MHz)</th>
<th>BW (MHz)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>114.75-115.75</td>
<td>121.75-122.75</td>
<td>3000-4000</td>
<td>1000</td>
</tr>
<tr>
<td>2</td>
<td>115.95-116.45</td>
<td>121.05-121.55</td>
<td>2300-2800</td>
<td>500</td>
</tr>
<tr>
<td>3</td>
<td>116.45-116.95</td>
<td>120.55-121.05</td>
<td>1800-2300</td>
<td>500</td>
</tr>
<tr>
<td>4</td>
<td>116.95-117.35</td>
<td>120.15-120.55</td>
<td>1400-1800</td>
<td>400</td>
</tr>
<tr>
<td>5</td>
<td>117.35-117.75</td>
<td>119.75-120.15</td>
<td>1000-1400</td>
<td>400</td>
</tr>
<tr>
<td>6</td>
<td>117.75-118.15</td>
<td>119.35-119.75</td>
<td>600-1000</td>
<td>400</td>
</tr>
<tr>
<td>7</td>
<td>118.15-118.45</td>
<td>119.05-119.35</td>
<td>300-600</td>
<td>300</td>
</tr>
<tr>
<td>8</td>
<td>118.45-118.58</td>
<td>118.92-119.05</td>
<td>170-300</td>
<td>130</td>
</tr>
<tr>
<td>9</td>
<td>118.58-118.68</td>
<td>118.82-118.92</td>
<td>70-170</td>
<td>100</td>
</tr>
</tbody>
</table>

118.75 GHz. Table 3.2 lists the passbands for the 118-GHz system. Both radiometers follow a similar configuration as in Figure 2-1, with the exception that NAST-M is a spectrometer. Figure 3-2 is a block diagram for the front end, which goes from the scalar feed horn to the radiometer’s receivers. After the front end, a filterbank separates the frequencies into channels using the IF filters. Then the tunnel diode detectors convert the IF signals to a voltage level. The 118-GHz filterbank block diagram is shown in Figure 3-3.

### 3.1.2 Weighting Functions

The spectral response defines the weighting functions of the NAST-M and is implemented by the IF filterbank. Figure 3-4 plots the weighting functions when the U.S. 1976 standard atmosphere is used in the radiative transfer simulation code (FRT). The surface emissivity was set to one. The high correlation between weighting functions is easily seen. The higher the correlation between weighting functions, the more the inversion becomes unstable. A compromise between stability and correlation is chosen when the weighting functions of a sounder are designed. The mathematical formula and purpose of defining the weighting function is described in Section 2.2.3.

### 3.1.3 Reflector Scan Pattern

An important consideration for an imaging radiometer is a method for controlling the field of view. NAST-M has a scanning reflector that gives the radiometers the ability to image a swath that extends to the right and left of the aircraft, not just at nadir. The scanning also
Figure 3-2: The RF front end of the NAST-M instrument
Figure 3-3: 118-GHz filterbank for the NAST-M instrument
allows onboard loads to be viewed during the calibration process. The 54-GHz and 118-GHz scalar feed horns are fixed facing the rotating reflector, and the reflector’s motor and encoder are controlled by the onboard flight computer. The reflector rotates 360 degrees in approximately 5.1 seconds. A total of 25 pauses are made when the instrument takes a measurement. These measurements, or ‘spots,’ are divided between the target and the calibration loads. The scan starts at zenith with two measurements through the skypipe, and then the reflector’s orientation moves to the hot load for another two measurements. The onboard calibration loads are detailed in Section 3.3. The next 19 spots are off the nadir and range from +/- 64.8 degrees from nadir. When the cruising altitude is 20 km, these inclinations give a swath width that is approximately 50 km both port and starboard. At nadir, the horizontal spatial resolution is 2.6 km, while at the largest scan angle, it increases to 20 km. To end the scan pattern, two measurements of the ambient calibration load are taken.

A practical problem with radiometers is constantly changing gain. The active RF components and extreme environmental conditions in which the instrument is required to per-
form are the principal sources of the fluctuations. The periodic views of the calibration loads are designed to alleviate this problem by recalibrating the instrument at every scan. During the time between calibrations, we can assume that the gain fluctuations are linear or at least monotonic. This assumption allows simple interpolations between calibrations to determine the gain and baseline at a particular time during the scan. The calibration design is described in Blackwell [5].

3.2 Calibration

Calibration of NAST-M involves correctly changing the raw A/D converter's counts to target brightness temperature. This section explains the technique and necessary background to calibrate the NAST-M. A new opportunity with the three calibration loads allows a three-point calibration with a weighted least squares solution.

3.2.1 General Calibration

In general, calibration involves finding the most accurate and concise method to correct the raw measurement data. For this calibration, the objective is measurement of the target brightness temperature, with the ‘target’ being the atmospheric brightness temperature within the antenna pattern. Due to the design of a total-power radiometer, the counts are related to the brightness temperature in an affine manner (assuming instrument linearity), but the gain and baseline (slope and y-intercept) are unknown and constantly changing.

We estimate the gain and baseline from the calibration load measurements. Typically, only two calibration loads are used, which is the minimum information needed to determine a gain and baseline. The simple formulas are:

\[
\text{gain} = \frac{T_H - T_A}{C_H - C_A}, \quad (3.1)
\]

\[
\text{baseline} = T_A - \text{gain} \cdot C_A \quad (3.2)
\]

where \(T_H\) and \(T_A\) are the hot and ambient load temperatures and \(C_H\) and \(C_A\) are the hot and ambient load radiance counts. In an ideal instrument, there would be no instrument noise and the calibration load brightness temperature would be known exactly. Therefore, we would have no error in the gain and baseline calculations, and calibration would be very
straight forward.

3.2.2 Three-Point Calibration

NAST-M has three calibration loads and therefore can use a three-point calibration. Figure 3-5 illustrates the fundamental relationship of an ideal three-point calibration. The resistive thermal devices (RTD) from the onboard loads give the temperature of two calibration points, and an estimation of the zenith-view brightness temperature comes from the radiative transfer equation (RTE). The three radiances are coupled with their related brightness temperatures to give three calibration points in which the linear relationship between counts and brightness temperature can be determined.

When there are three-points with noise, then there is a risk of all three-points not lying on a straight line. In linear algebra terms, the $A$ matrix (from Equation 2.43) has a solution in the two-point case but has no solutions in the overconstrained case. The technique of linear regression determines the gain and baseline that minimizes the mean squared error between estimated brightness temperature and actual brightness temperature for the three
calibration points.

In statistical terms, the variable that is estimated is called the response, and the variable that is used to estimate the response is called the predictor. In this case, the counts are the predictor, and the brightness temperature is the response variable.

\[
\hat{T}_b = b_0 + g_0 \cdot C
\]

\(\hat{T}_b\) is the abbreviation for the estimated brightness temperature. Linear regression of counts to brightness temperature is greatly complicated by the fact that both the predictor and response have noise. Most rudimentary linear regression literature deals only with noise in the measurement of the response, not the predictor. Weisberg [27, p. 76] warns that care must be taken when trying to remove the noise in the predictor. If the application of the regression will use noisy inputs, which is true in this case because of the instrument noise, then it is better to do a linear regression with the noisy predictors than with noise-free predictors. The noise statistics for each of the calibration loads are not the same. The \(\Delta T_{rms}\) that is intrinsic to radiometers is dependent on the target's temperature. Therefore, the noise variance is greater for the calibration loads with a higher temperature. The zenith view, which has a brightness temperature that is approximately \(3\) \(K\) for the transparent channels, would have the least noise variance. Unfortunately, another error is introduced in the measurement of cosmic background radiation because the actual temperature profile above the aircraft is unknown. The U.S. 1976 standard atmosphere is used in the RTE model to estimate the brightness temperature seen through the zenith view. The hot load at \(~ 334\) \(K\) has the highest noise variance, followed by the ambient load \(~ 240\) \(K\). Standard linear regression assumes the noise in the predictor variables are equal for each sample point. To circumvent this difficulty, weighted-least squares is used instead of the usual least squares solution. Weighted-least squares normalize the noise in each sample point before calculating the slope and y-intercept. Least squares estimation is the estimation that minimizes the expected value of the error in the estimate squared. The nature of total-power radiometers causes the noise on the regressor (counts) to be unequal for each calibration load. This is easily seen from Equation 2.1 because the temperature of each load, \(T_a\), is different. The technique of weighted least squares can correct the error introduced by the unequal noise
variance. When a system is overdetermined, the linear least squared solution is:

\[ x = (A^T A)^{-1} A^T b, \]  

(3.4)

which comes from

\[ A^T Ax = A^T b \quad \text{or} \quad Ax = b. \]  

(3.5)

Weighted least squares does a matrix multiplication of a weight matrix before a least square solution is found.

\[ WAx = Wb \quad \text{or} \quad A^T W^T WAx = A^T W^T Wb \]  

(3.6)

Now the solution is:

\[ x = (A^T W^T WA)^{-1} A^T W^T Wb = (A^T CA)^{-1} A^T Cb \quad \text{with} \quad C = W^T W. \]  

(3.7)

The optimal weight matrix \( C \) is the inverted covariance matrix of the error. The error is \( e = b - Ax \), and the error covariance matrix is \( V = E[ee^T] \). A mathematical proof can be found in Strang [28, p. 144].

A thoughtful approach to the error covariance matrix starts with a simple noise analysis of the calibration regression. In the ideal case again, where there is no instrument noise, RTD noise, and the instrument is linear, the error would be zero. Nothing would hamper the regression, and \( A \) is invertible. With the addition of instrument noise and RTD noise, the regression becomes:

\[
\begin{bmatrix}
C_s + v_s & 1 \\
C_A + v_A & 1 \\
C_H + v_H & 1
\end{bmatrix}
\begin{bmatrix}
\hat{g} \\
\hat{b}
\end{bmatrix} =
\begin{bmatrix}
T_s + \epsilon_s \\
T_A + \epsilon_A \\
T_H + \epsilon_H
\end{bmatrix}
\]  

(3.8)

where \( v_A \) is the additive noise of the radiometer, and \( \epsilon_A \) is the additive noise of RTDs that is on the ambient load. The noise on the zenith view calibration brightness temperature, \( \epsilon_s \), is different than the other two loads. This noise represents the error in the simulation that arises from assuming the standard atmosphere above the aircraft. For any particular flight to which the calibration is applied, the \( \epsilon_s \) is a bias resulting from the difference between the actual temperature profile above the aircraft and the standard atmosphere. After pulling
out the noise and replacing the matrixes and vectors with a symbol, Equation 3.8 becomes:

\[(\mathbf{\tilde{A}} + \mathbf{Y}) \cdot \mathbf{x} = \mathbf{T} + \epsilon\]  (3.9)

\(\mathbf{\tilde{A}}\) is the counts without instrument noise. After some algebra, the error is:

\[e = \mathbf{T} - \mathbf{\tilde{A}} \cdot \mathbf{x} = \mathbf{gv} + \epsilon\]  (3.10)

The RTDs are filtered before calibration, and the \(\mathbf{gv}\) term dominates. The variance of \(\mathbf{gv}\) is the \(\Delta T_{rms}\) at that particular calibration load's temperature. The error between calibration points is independent and uncorrelated. Therefore, the error covariance matrix is:

\[
V = \begin{bmatrix}
(\Delta T_{sky_{rms}})^2 & 0 & 0 \\
0 & (\Delta T_{ambient_{rms}})^2 & 0 \\
0 & 0 & (\Delta T_{hot_{rms}})^2
\end{bmatrix}
\]  (3.11)

### 3.2.3 Calibration Noise Reduction

The \(\Delta T_{rms}\) that is contributed by practical calibration techniques can be reduced by filtering (averaging) the calibration radiances. The calibration noise is the noise induced by finite averaging times and by gain fluctuations that affect the total-power radiometer (Section 2.1). The radiometer adds the \(\Delta T_{rms}\) to the measurement of the calibration loads and, therefore, introduces error. Even though the instrument gain varies with time, there is still a correlation between the different calibration measurements. Using this correlation can reduce the calibration noise variance.

Each channel has different \(1/f\) noise, which defines the amount of correlation between calibration measurements. If the systems were ideal (no gain variations), then the filter could be square and as long as practical, in order to reduce the instrument noise. The instrument is not ideal, and a triangular filter was chosen because it showed the best performance per length and was the most simple to implement. A routine was devised to determine the optimal length for each of the channels. The routine consists of simply plotting the \(\Delta T_{rms}\) for various filter lengths and choosing the length that is closest to the minimum. The \(\Delta T_{rms}\) is calculated from the estimated (calibrated) hot load's brightness temperature during a flight. The \(\Delta T_{rms}\) was calculated on a portion of the flight after the aircraft was
at altitude and the loads had time to reach an equilibrium. Four channels are shown in Figure 3-6. There are two from each radiometer with an opaque and transparent channel. As the filter length increases, the $\Delta T_{rms}$ should initially decrease as the noise is averaged, but as the correlation decreases, only noise is added, and the $\Delta T_{rms}$ consequently increases. The figure clearly shows a minimum where the optimal filter length lies. To ease numerical computation, and because all channels reached a minimum at approximately the same filter length, a filter size of seven was used for all channels on both radiometers.

3.2.4 Calibration Technique

To deal with the issues explained in the last section, a calibration procedure was devised. First, the aircraft rolls are removed from the zenith view radiance data. Next, all the calibration counts are filtered in order to reduce the calibration noise variance. Each spot during the flight has a time stamp from the flight computer, which is used to interpolate every calibration spot during the flight to a nadir-viewing spot. Then a gain and baseline are determined from the interpolated calibration values for each spot during the flight. The
technique used to determine the gain and baseline is weighted-least squares estimation, which normalizes the noise variance in the calibration measurements to reduce the error in the regression. The procedure is enumerated for convenience:

1. Removal of aircraft rolls from calibration counts
2. Filtering of calibration counts
3. Interpolation of calibration counts
4. Weighted Least Squares estimation of gain and baseline

The aircraft typically makes 'race track' circuits as part of a routine flight plan, and this will introduce rolls in the flight data. Rolls can affect the zenith view brightness temperature because the tilted skypipe view is offset from zenith. The offset increases the amount of atmosphere the skypipe views before deep space and can miscalibrate the opaque channels. The inertial navigation system (INS) from the ER-2 aircraft gives roll, pitch, and yaw data for each flight. For the calibration, the zenith view radiances corresponding to times when the aircraft is in a roll (generally > ±2°, but sometimes flight dependent) are removed and then replaced with interpolated data.

The next step, after removing the rolls of the aircraft, is to filter the radiance data with a triangular filter. Instead of simply filtering with a triangular filter, the numerical method in MATLAB will filter the data to have zero-phase shift. The method starts with the counts of the three calibration loads filtered with a square filter. Then the counts are reversed in time, and the reversed counts are again filtered by the same length square filter. To finish the filtering routine, the output of the second filtering is time-reversed. Therefore, the output has zero-phase distortion, and the equivalent filter's shape is a triangular filter.

The filtered and interpolated variables are regressed to determine the coefficients that define the linear relationship between radiances and brightness temperatures. Figure 3-7 illustrates the scan pattern explained in Section 3.1.3, where S, H, and A signify a skypipe, hot, and ambient radiance, respectfully. Time proceeds with the sequential scan number. It can be seen that the nadir spots lie between two calibration 'sets.' These sets are a collection of the three calibration points. The two observations of the same calibration load are averaged together to reduce the instrument noise. The sets of calibrations are then linearly interpolated to each nadir spot between the calibration measurements. The filtering,
coupled with the linear interpolation, defines the $H(f)$ in Equation 2.10. While the choice of filter length and interpolation scheme may not be optimal, the results were comparable with the optimal Peckham filter and easier to implement for this application [29].

3.3 Calibration Hardware

This section explains the hardware related to the calibration of the NAST-M instrument. Three issues are resolved. The first is the weighting of the RTDs on the hot load and the second is the spillover on the 54-GHz system. Last is the test of the linearity of the NAST-M instrument.

3.3.1 Calibration Loads

NAST-M is configured with three calibration loads. It is standard on satellites to have a calibration load that looks out to deep space where the target is the cosmic background radiation. The brightness temperatures for each channel are calculated by simulations (RTE). The other calibration points are two onboard targets called calibration loads. The loads are made with iron-filled epoxy, which changes the permeability of the epoxy in order to match the impedance of the epoxy as closely as possible to the impedance of the atmosphere. The reflector-facing surface of the epoxy has a grid pattern of pyramids that reduce reflections of the microwave radiation. The augmented epoxy, along with the
pyramids, make the calibration load a matched load. All of the effort put into the loads is to make the loads as close to an ideal black body as possible in order to assume the brightness temperature is the same as the physical temperature of the loads. The loads were then covered with styrofoam in an attempt to stabilize the exchange of heat between the load and ambient air.

**Hot Load Weights**

The hot load is heated during flight to approximately \(334\, K\), and situated on the hot load are resistive thermal devices (RTDs) that measure the temperature at a specific location on the load. The hot load has temperature gradients because the load cannot be completely insulated from the ambient temperature during flight. The gradients between RTDs on the loads are shown in Figure 3-8. The other onboard load is not temperature-controlled during flight. At altitude, the temperature of the ambient load is around \(240\, K\) and the gradients are not as much of a concern. The ambient load is constructed similar to the hot load, but without heaters.
The seven RTDs are averaged together to find the temperature to use in the calibration. It is difficult to determine the proper weights for the seven RTDs which give the correct brightness temperature of the hot load. The first step in determining the proper weight of the RTDs was to find an accurate temperature of the hot load. The two-point calibration mentioned in the first section of this chapter was used to calibrate the brightness temperature of the hot load. With this estimated hot load temperature, a pseudoinverse is used to find the weights for the hot load RTDs because the linear relationship is underconstrained:

\[ T_H = \sum_{i=1}^{7} x_i \cdot T_i = Tx \]  

where \( T \) is a row vector of the RTD's temperatures (filtered) at a particular scan and \( x \) is the weight vector of the RTDs. The weights themselves are not the critical parameter, but the temperature that the weights give affects the calibration. The calibration procedure uses the ambient load and the zenith view to determine the gain and baseline. The zenith view has the complication that the temperature profile above the aircraft is unknown. A transparent channel, which is only marginally affected by the temperature profile above the aircraft, was used to determine the hot load brightness temperature. To avoid the spillover problem on the 54-GHz system (explained in the next section), a transparent 118-GHz system is used for the ambient calibration point. Figure 3-9 shows the calculated weights for six WINTEX flights. The three weights on top correspond to March 15th, March 20th, and March 21st and the bottom three weights are March 29th, March 31st, and April 1st. The event that changed the weights is believed to be a change of the reflector's belt, which broke on the March 26th flight. This is evidence that the position of the reflector on the encoder shaft is related to the corruption of the ambient load, even with the 118-GHz antenna pattern. This issue is discussed more in the next section. The top weights gave a hot load temperature of around 335.5 K, and the lower weights were around 334 K. It is much more reasonable to believe the hot load temperature of 334 K than 335.5 K, because the RTD that is around 335.5 K is located on the back of the calibration load. The other RTDs are located on the sides or on the face of the load and, therefore, closest to the portion of the hot load that the reflector views.
3.3.2 Antenna Pattern Sidelobes

The NAST-M’s radiometric data was compared with the atmospheric model briefly described in Section 2.4.1 and a satellite-based microwave radiometer (AMSU-A). AMSU-A is an operational passive-microwave radiometer onboard the NPOESS’s NOAA-15 weather satellite. AMSU-A has several matching weighting functions for potential comparison with NAST-M when there is an AMSU overpass. The comparison showed a bias between the 54-GHz system’s brightness temperature and the AMSU-A and simulated 54-GHz system’s brightness temperature. From laboratory experiments, it was found that the antenna pattern of the 54-GHz system has frequency-dependent sidelobes that receive radiation from sources other than the calibration loads. The experiments determined that, on average, 3 percent of the antenna pattern spilled off the calibration load. The calibration corruption had two major contributors. The sources are the radiation that leaks in from the zenith view and the radiation that comes through the open-nadir window of the pod. Laboratory experiments with the instrument determined a rough percentage of spillover for each channel. These percentages were further broken down into percentage from the zenith view and
the percentage from the nadir window. Due to the complexity of quantifying the exact spillover percentage and the unknown radiation corrupting the calibration measurement, a simple ‘correction’ is made to the calibration load temperatures. Figure 3-10 illustrates the correction. The calibration loads are corrupted by either a much colder zenith view radiance or a generally colder nadir radiance. The nadir radiance is always colder than the hot load, while the ambient load can be corrupted by temperatures close in range because the nadir scene radiances can range from $\sim 210 - 290 \, K$. The corruption causes the counts to be lower, and the corrupted counts are shown as $\tilde{C}$. The RTDs are obviously unaffected by the corruption, and the temperature of the loads are no longer the temperature that the calibration measures. A correction is needed to realign the linear fit at the proper slope, and a procedure was devised to determine a $\delta T_h$ and a $\delta T_a$, which corrects the absolute accuracy of the calibration.

The forward radiative transfer (FRT) model was key in allowing another calibration point. This allowed the corrupted hot and ambient loads to be uninvolved in the calculation of the correction. A calibration point is gained from the spaceborne AMSU-A radiometer.
An iterative statistical/physical retrieval technique [30] is used to retrieve the temperature profile beneath the satellite. The AMSU-retrieved profile is then used with the NAST-M FRT to simulate the radiances of the NAST-M instrument. These simulated radiances are coupled with the counts from the nadir spot. The line in Figure 3-10 is found with the zenith and nadir simulated radiances along with the corresponding uncorrupted counts.

A critical part in determining the correction is to simulate the nadir and zenith view's brightness temperature. It is difficult to estimate or predict the surface emissivity, therefore a portion of the flight that could be modeled was chosen in the simulation of nadir brightness temperature. The particular corrections determined in this thesis are for the WINTEX deployment of NAST. During WINTEX, a number of the flights had flight plans that flew over one of the Great Lakes. The portions of the flights over the lakes gave the opportunity to use the Klein-Swift seawater surface emissivity model [31]. The emissivity model is for a specular surface, and the salinity was set close to zero to account for the freshwater lakes. Clear skies are also a necessity in order to avoid the difficulty of modeling the clouds. GOES-8 (Geostationary Operational Environmental Satellite) infrared images during the flight give a good indication of whether clouds are present during the time the ER-2 spends over the lake. After searching the WINTEX flights for the criteria of clear skies and a lake surface, the next step was to find the closest NOAA-15 overpass both spatially and temporally. The National Data Buoy Center records water temperatures in various regions of the United States. This allowed an accurate water temperature of the lake to be added in the RTE model. These strict requirements yielded only three flights, which were March 15th, March 25th, and March 29th. Ideally, every flight would have its own correction, but instead the three corrections were split by whether it was before or after the belt change. Before the belt change during WINTEX, the corrections are averaged between March 25th and March 15th. Any flight after March 26th will use the corrections from March 29th.

Table 3.3 and Table 3.4 show the corrections for the three flights, and Figure 3-11 is a plot of the mean correction for all three flights with the bars denoting the range of the corrections. Finally, Figure 3-12 is an example of the effect of the corruption and the subsequent correction. The figure contains the nadir and neighboring views for all eight channels of the 54-GHz system. March 25th is shown because it was one of the three flights that met the clear air and lake overpass requirements. This allowed the flight brightness temperature to be compared with simulated brightness temperature. The * in the figure
Table 3.3: $\delta T_H$ Correction for the 54-GHz System

<table>
<thead>
<tr>
<th>Chan.</th>
<th>Mar. 15</th>
<th>Mar. 25</th>
<th>Mar. 29</th>
<th>AVG</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>3.0337</td>
<td>3.3347</td>
<td>3.1851</td>
<td>3.1842</td>
</tr>
<tr>
<td>2</td>
<td>2.7427</td>
<td>3.7766</td>
<td>2.7749</td>
<td>3.2596</td>
</tr>
<tr>
<td>3</td>
<td>1.0976</td>
<td>1.8739</td>
<td>0.8627</td>
<td>1.4858</td>
</tr>
<tr>
<td>4</td>
<td>3.1929</td>
<td>3.9802</td>
<td>3.0959</td>
<td>3.5866</td>
</tr>
<tr>
<td>5</td>
<td>-3.1717</td>
<td>-2.6265</td>
<td>-3.1620</td>
<td>-2.8991</td>
</tr>
<tr>
<td>6</td>
<td>-1.8511</td>
<td>-1.4230</td>
<td>-1.4951</td>
<td>-1.6371</td>
</tr>
<tr>
<td>7</td>
<td>1.5595</td>
<td>2.4401</td>
<td>2.2651</td>
<td>1.9998</td>
</tr>
<tr>
<td>8</td>
<td>0.0404</td>
<td>2.2098</td>
<td>3.2173</td>
<td>1.1251</td>
</tr>
</tbody>
</table>

Table 3.4: $\delta T_A$ Correction for the 54-GHz System

<table>
<thead>
<tr>
<th>Chan.</th>
<th>Mar. 15</th>
<th>Mar. 25</th>
<th>Mar. 29</th>
<th>AVG</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1.3381</td>
<td>1.5257</td>
<td>0.5602</td>
<td>1.4319</td>
</tr>
<tr>
<td>2</td>
<td>1.7246</td>
<td>2.4093</td>
<td>0.9573</td>
<td>2.0670</td>
</tr>
<tr>
<td>3</td>
<td>2.4227</td>
<td>3.3057</td>
<td>1.7053</td>
<td>2.8642</td>
</tr>
<tr>
<td>4</td>
<td>3.3555</td>
<td>3.8078</td>
<td>2.4196</td>
<td>3.5817</td>
</tr>
<tr>
<td>5</td>
<td>1.6397</td>
<td>1.8968</td>
<td>0.7681</td>
<td>1.7682</td>
</tr>
<tr>
<td>6</td>
<td>1.6856</td>
<td>1.6021</td>
<td>0.8767</td>
<td>1.6438</td>
</tr>
<tr>
<td>7</td>
<td>2.1983</td>
<td>2.1834</td>
<td>1.5558</td>
<td>2.1908</td>
</tr>
<tr>
<td>8</td>
<td>1.9699</td>
<td>2.1727</td>
<td>2.0679</td>
<td>2.0713</td>
</tr>
</tbody>
</table>
is the brightness temperature averaged for approximately one hundred scans at the labeled scan angle. The \( \circ \) is the simulated brightness temperature from the RTE. The surface emissivity, surface temperature, temperature profile (both temporally and spatially) were matched as best as they could from buoy data, modeling, and satellite coverage. After the correction (average of the March 25\(^{th}\) and March 15\(^{th}\) flights), \( \Delta \) is the same averaged brightness temperature as in the \( \ast \) average. The absolute accuracy is probably not this good for the flights before March 26\(^{th}\). Due to the lack of conditions that can be accurately modeled, only a rough idea of absolute accuracy can be assumed for other flights.

### 3.3.3 Instrument Linearity

A criterion that is key to applying linear regression to calibration is linearity. If the instrument has a non-linear relationship between input power and voltage, then the linear regression will introduce error that could possibly be avoided with a non-linear regression. The IF components of the instrument were tested for linearity to help validate the use of linear regression. A frequency synthesizer entered a single frequency into the filterbank, and
Figure 3-12: 54-GHz system for March 25th before and after correction; *=uncorrected, △=corrected, and ○ FRT of AMSU-A retrieval
the corresponding voltage count out of the A/D converter was recorded. The synthesizer frequency entered the system after the receiver and before the RF amplifiers. Figure 3-13 shows a channel tested for linearity. The time-varying gain required a different approach to the input power level. Only four input powers were tested in order to reduce the time between measurements. Sixteen measurements were taken for each input power to reduce the instrument noise. The top of Figure 3-13 shows the scatter plot with a least-squares line for the 118-GHz channel 8. To get a better idea of the linearity, the difference between the regression and the data points is plotted in the lower plot of Figure 3-13. The temperature difference was on the order of 0.5 K, which is within the sensitivity range and satisfactorily shows enough linearity for our purpose.

Figure 3-13: Linearity of the 118-GHz Channel 8
3.4 Results and Conclusions

The final calibration results are presented in this section for the WINTEX deployment. It should be noted, most likely, that the corrections for WINTEX will not apply to other deployments, yet the work done in this chapter can be applied to other deployments. The parameters such as the filter length for calibration noise reduction and the weights on the hot load should follow over to other deployments. These values should not be taken for granted, and should be doubled checked. The spillover problem is strongly related to the antenna reflector’s position, and the corruption cannot be accurately calibrated out due to the number of uncertainties involved. The reflector assembly shifts position on the shaft of the encoder whenever the motor belt is replaced. In order to avoid the loss of data, the belt is routinely replaced. Impending a better solution, the belt breaks during flight on the average of once every four flights. A look at Table 3.4 for March 29th shows that the ambient load correction decreased after the belt change, which may be evidence that the reflector’s position improved after the March 26th flight and that the lower weights in Figure 3-9 are the appropriate weights for the hot load. In the future, an exhaustive study must be undertaken to quantify and eventually remove the corruption from the onboard calibration loads. This will require extensive laboratory measurements and innovative measurement techniques.

Sensitivity

In Section 2.1.2, the general performance of a radiometer was introduced. One parameter was the instrument sensitivity or $\Delta T_{rms}$. There are several techniques for measuring the sensitivity of the instrument. One is to simply calculate the sensitivity from the receiver temperature, target temperature, bandwidth, integration time, and calibration error approximation. A different, but straightforward method, involves calibrating the counts and finding the standard deviation based on the calibrated brightness temperature on the calibration loads. It is important to pick a portion of a flight in which the instrument has had enough time to reach an equilibrium. Table 3.5 presents the root-mean-square variations of the hot load calculated using the second method. The hot load is the ‘worst case’ scenario since no practical targets will be greater than the hot load temperature.

An argument for the three-point calibration is the reduction of $\Delta T_{rms}$. When a two-point calibration is used, the gain and baseline are sensitive to the calibration noise. The
Table 3.5: Sensitivities of the NAST-M Instrument

<table>
<thead>
<tr>
<th>Chan.</th>
<th>54-GHz System</th>
<th>118-GHz System</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.1879</td>
<td>0.1922</td>
</tr>
<tr>
<td>2</td>
<td>0.1274</td>
<td>0.2436</td>
</tr>
<tr>
<td>3</td>
<td>0.1084</td>
<td>0.2066</td>
</tr>
<tr>
<td>4</td>
<td>0.1474</td>
<td>0.2679</td>
</tr>
<tr>
<td>5</td>
<td>0.1248</td>
<td>0.1528</td>
</tr>
<tr>
<td>6</td>
<td>0.1754</td>
<td>0.6080</td>
</tr>
<tr>
<td>7</td>
<td>0.2321</td>
<td>0.8930</td>
</tr>
<tr>
<td>8</td>
<td>0.1528</td>
<td>1.1545</td>
</tr>
</tbody>
</table>

calibration noise is from the instrument when it views the calibration load. If a three-point calibration is used, the extra calibration point is used to minimize the mean square error between all three points. This reduces the effects of the calibration noise on the gain and baseline. Figure 3-14 illustrates the improvement between a two-point calibration and a three-point calibration for the NAST-M instrument. The * data points are the $\Delta T_{rms}$ calculated by the method described above, and for a level portion of flight, the standard deviation was calculated on flight data that was calibrated with the two-point calibration. In order to accentuate the benefit of the three-point calibration, the calibration counts were not filtered with a triangular filter. Consequently, both calibrations will feel the full effect of instrument noise on determining the gain and baseline. The benefit is apparent from Figure 3-14, but when the filtering of the calibration counts is returned to the calibration technique, the improvement is negligible ($\sim 0.005 K$). The three-point calibration does not significantly improve in $\Delta T_{rms}$ when the calibration radiances are filtered.

**Absolute Accuracy**

Another parameter of instrument calibration is the absolute accuracy or bias. Section 3.3.2 on the antenna beam spillover suggested a need and method for improving the absolute accuracy of NAST-M. This section helps quantify the overall accuracy of the two radiometers. After the correction is applied in Figure 3-12, the absolute accuracy is generally within 0.25K, but this is misleading. The simulated 54-GHz radiances are not ground truth. Error arises from the time and spatial difference between the AMSU retrieval and the aircraft’s position and the absolute accuracy of AMSU. Another source of error is the inaccuracy of the surface emissivity model. The Klein-Swift model is widely used, but was originally intended for use only up to X band (12.8 GHz). Recently, an improved model was published [32], which could improve the accuracy of the RTE.
Figure 3-14: Improvement of $\Delta T_{\text{rms}}$ between 2-pt and 3-pt calibration
The 54-GHz system clearly needs the correction, and it can be safely assumed that the absolute accuracy after the correction is implemented is $< 1.5 K$. As for the 118-GHz system, the absolute accuracy is contingent on whether the flight is before or after the belt replacement. There is enough evidence to show that the reflector’s position corrupted even the 118-GHz system before belt replacement. Therefore, a correction, just like the 54-GHz’s, can be implemented. The severity of the corruption is not as profound, and this leads to a possible second solution. An advantage of the three-point calibration over the two-point calibration is the inclusion of more uncorrupted information into the calibration. The zenith view improves the absolute accuracy of the three-point calibration as can be expected. Even though the corrected two-point calibration also uses the zenith view, the three-point calibration is less dependent on the accuracy of the RTE and surface model. The correction applied to the two-point calibration uses the surface model to calculate the brightness temperature from the radiosonde data, and any error introduced by the radiosonde and surface model goes into the correction. The three-point calibration also has the error introduced by assuming the 1976 standard atmosphere in the calculation of the zenith brightness temperature. The advantage of the three-point is the distance in temperature from the typical target temperatures. An error at $77 K$ in the gain and baseline calculation has less effect at the target temperatures around $260 K$ as opposed to the errors at the brightness temperature of the radiosonde over water at $\sim 210 K$. The advantage can be visualized as a level arm (a straight curve determined by the gain and baseline), where the radiosonde error moves the arm at the midpoint which is close to the target temperature as opposed to the end of the lever arm where the zenith view moves the lever arm (the ambient load locks the center into place).
Chapter 4

Retrieval Algorithm

The specific algorithm for the NAST-M that transforms nadir-viewing brightness temperatures into a temperature profile is discussed in this chapter. For this thesis, the retrieval, analysis, and development concentrates on mid-latitude winter profiles, with the purpose of retrieving profiles from the WINTEX deployment. The actual WINTEX retrievals are done in Chapter 5. In Section 4.4, the results of the retrieval technique are presented along with a comparison to a linear statistical retrieval.

4.1 Overview of Algorithm

The retrieval converts 15 inputs to 26 outputs. Figure 4-1 is a flowchart of the retrieval. The 15 inputs are the eight channels of the 54-GHz system, six channels of the 118-GHz system, and the pressure at the aircraft’s altitude. The three most opaque 118-GHz channels are unusable because of LO leakage from the receiver. The radiometric inputs to the retrieval are normalized, decorrelated, and biased. These preconditioned inputs are then entered into the inversion component of the retrieval algorithm, for which a neural network is the principal technique, while the LLSE is used as a benchmark. The specific type of neural network is the multilayer feedforward neural net, or MFNN. The fundamentals of a MFNN are explained in Section 2.4.4.

The other half of Figure 4-1 consists of the orthogonal expansion of the temperature profile, and the choice of the orthonormal basis and discretization is explained in Section 4.3.2. The MFNN estimates the coefficients of the orthonormal basis instead of the temperatures because the coefficients can reduce the architecture of the MFNN. A MFNN that has a sim-
pler architecture with fewer weights and bias can be easier to train and requires a smaller training ensemble.

4.2 Training Set

The LLSE and the MFNN both need a collection of input-output data so that a statistical relationship between the input and output can be determined. With the LLSE, the I/O data is used to determine the optimal parameters to reduce the mean squared error (Section 2.3). For the MFNN, the idea is similar, but finding the optimal parameters (the strength of the weights and bias) is done in a more dynamic fashion.

4.2.1 Ensemble of Temperature Profiles

The first step in forming a training set is collecting an ensemble of the appropriate outputs, such as a collection of temperature profiles. One particular temperature and humidity ensemble is called TIGR [33], which uses a collection of radiosondes from the mid-seventies to late eighties. TIGR is an acronym for TOV (TIROS Operational Vertical Sounder) Initial Guess Retrieval and contains temperature, water, and ozone profiles for a multitude of
climates and seasons. The TIGR ensemble consists of 1761 profiles, and each profile contains forty pressure levels between the surface and 0.05 millibar. Since WINTEX retrievals are concerned with only a mid-latitude winter, the radiosondes are separated by month and latitude. Only 430 TIGR profiles meet the requirements of a mid-latitude winter profile. Table 4.1 breaks down the requirements, and Figure 4-2 gives a histogram of the months and latitudes that were found in the qualified winter TIGR profiles. The instrument was not designed to sound above the aircraft; therefore, a truncated portion of the pressure levels of TIGR will be used in the retrievals. With the height of the aircraft at a nominal 54 mb, twenty-five pressure levels and the surface temperature are attempted to be retrieved.

The TIGR ensemble has surface temperatures for each of the profiles, but this is the surface air temperature and care should be taken when using the TIGR surface temperature. The water surface emissivity model (in Section 4.2.3) needs a surface temperature in order
to calculate the dielectric constant. The dielectric constant is used in the calculation of the reflectivity at the dielectric boundary. Even with the exclusion of the polar profiles, many of the surface temperatures in the TIGR ensemble are below freezing and are inappropriate to be put into the water dielectric constant model. In the hope of modeling a relationship between the water temperature and the frigid surface air temperature, a brief study was made of the buoy data on Lake Michigan and Lake Superior. The National Data Buoy Center collects data from many points in North America for nautical and academic uses. The buoys of interest are on the Great Lakes, and they measure water temperature and air temperature with a resolution of 0.1°C and an accuracy of ±1°C. Figure 4-3 is a scatter plot of the data collected from three buoys on the Great Lakes in 1998. The full collection of 1999 buoy data is unavailable at this time, but a scatter plot of March 1999 data overlaps the 1998 data. Two lines are regressed to represent the correlation between the air temperature and water temperature. If the surface air temperature is below 280 K, then the lower curve’s slope and baseline are used to calculate the corresponding water temperature. A random variable was then added that had a normal distribution, zero mean, and a standard deviation of 3 K. A routine in the code prevents the water temperature from falling below freezing. A similar procedure is used if the temperature is above 280 K, but instead, a regression of the upper curve (with standard deviation of 4 K) is used. Figure 4-4 shows the resulting relationship between the TIGR’s surface air temperature and the simulated water temperature.

4.2.2 Orthogonal Expansion

The ensemble of temperature profiles in TIGR can be expressed in an orthogonal expansion of orthonormal basis functions:

\[ T(z) = \int_0^\infty c(k) \cdot \phi(k, z) \, dk. \]  

(4.1)

With TIGR already being discrete samples of the atmosphere, a more appropriate expansion is:

\[ T(z_i) = \sum_{k=1}^N c_k \cdot \phi_k(z_i) \]  

(4.2)

with \( i \) distinguishing the different pressure levels from 1 to \( N \). \( \phi_i \) are orthonormal and complete. The different \( T(z_i) \) can be thought of as random variables and, therefore, orthog-
Figure 4-3: Scatter plot of the relationship between lake surface air temperature and water temperature

Figure 4-4: Scatter plot of the relationship between lake surface air temperature and simulated water temperature
onality is defined by correlation. The eigenvectors of the covariance matrix are a natural orthonormal collection of basis vectors. The use of the covariance matrix's eigenvectors is not new and has been utilized by other retrieval techniques [25, 34]. There are two advantages of projecting the profiles onto the eigenvectors of the covariance matrix. One is the fact that the profiles can be represented with a set accuracy, but with fewer variables. This allows simplification of the computation requirements of the MFNN because the MFNN has fewer weights and bias and, therefore, less training is required and a smaller training set will suffice. The other advantage is the conversion of the retrieval from being underdetermined to overdetermined. The inversion is no longer ill-posed and, therefore, less vulnerable to measurement errors.

The new variables are the coefficients of expansion, $c_k$, in Equation 4.2. The covariance matrix of the temperature at the different pressure levels has rank $N$. The coefficients are determined by projecting the profile onto the eigenvector:

$$c_k = \phi_k \cdot T(z) = \phi_k^T T(z).$$

(4.3)

Even though the rank of the covariance matrix determines the number of eigenvectors, all $N$ eigenvectors are not needed to reproduce the temperature profile. The projection of the profiles onto the eigenvectors of the covariance matrix is also called principal component analysis, except that the eigenvectors are ordered in descending order of variance, as mention in Section 2.4.5.

The first eigenvector, related to the first principal component, is the lowest spatial frequency variation in the temperature profile. After looking at the NAST-M weighting functions in Figure 3-4 and the FRT equation (Equation 2.29), it is apparent to see how the transformation from temperature to brightness temperature will blur the temperature profile. As a result, the high-frequency variations in the temperature profile are unretrievable and, therefore, fewer eigenvectors are needed to reproduce the temperature profile. No more information is gained by adding additional eigenvectors because the information in the brightness temperatures do not contain those degrees of freedom. Figure 4-5 is a plot of the first eight eigenvectors of the covariance matrix used to retrieve the WINTEX temperature profiles. It should be noted that the x-axis is on a logarithmic scale. The covariance matrix is calculated from the winter TIGR temperature profile ensemble mentioned earlier.
Figure 4-5: The TIGR profile orthogonal basis vectors
Figure 4-6: The TIGR Profile reconstruction error (rms) with eight eigenvectors

in the chapter. The reconstruction error (rms) when limited to the first eight eigenvectors is shown in Figure 4-6.

4.2.3 Forward Radiative Transfer Model

Now that the output of the training set is defined, a collection of inputs must be simulated to correspond with the outputs. This will finish the development of the training set that will train the MFNN or determine the optimal coefficients in a LLSE. A software routine written in MATLAB code simulates the radiances that would be measured by the NAST-M radiometers. The code simulates the forward radiative transfer equation (FRT, Equation 2.23) by calculating the clear-air brightness temperature for each NAST-M channel from an entered temperature and humidity profile. Nadir spots are simulated for each of the 4300 temperature profiles in the winter TIGR ensemble (from 10 different surface parameters and altitudes for each of the 430 profiles).

An important parameter in the FRT is the absorption coefficient (Equation 2.17). It
should be noted that clear air is assumed and no attempt to model clouds is made. The absorption coefficients are calculated by the Liebe MPM, which is briefly explained in Section 2.4.1. Another consideration is the directional response of the scalar feed horn. The simulation code calculates the brightness temperature for a pencil-thin beam, and an antenna pattern must be modeled. The brightness temperature that the antenna views is defined by Equation 2.2 and modified in a numerical approximation:

\[ T_{ch\text{sim}} = \int f \int \pi T_b(f, \theta) \cdot G(\theta) \, d\theta \, df = \sum_j \sum_\theta T_b(f_j, \theta_i) \cdot G(\theta_i) \, d\theta \, df \, [\text{Kelvin}]. \]  

(4.4)

The antenna gain pattern \((G(f, \theta, \phi))\) of the scalar feed horn is approximated by a gaussian distribution in the software simulation. The gaussian distribution determines the weights for the twenty-one angles that are calculated within the antenna gain pattern. The filter-bank design controls the spectral response, and the pertinent frequencies are critical in the computation of the brightness temperature. In the laboratory, the passband characteristics of the NAST-M are measured and then used in a lookup table for the simulation software code.

In the simulations, a particular TIGR profile had three different random variables that affected the brightness temperature. The first variable is the altitude of the aircraft. Even though NAST is a testbed for satellite systems, the aircraft is not at the same altitude as a Polar-orbiting Observational Environmental Satellite (POES). The aircraft typically cruises at an altitude near the tropopause (20 km or 54 millibar). Fluctuations in the altitude have the most effect on the opaque channels because the peaks of their weighting functions are closest to the aircraft (see Figure 3-4). Figure 4-7 is a histogram of the altitudes for all of the 4300 simulated brightness temperatures.

Another variable is the surface emissivity, which is modeled for either land or water. The surface emissivity defines the fraction of incident energy absorbed by the surface and, therefore, the fraction of energy emitted because thermal equilibrium is assumed. The specular surface emissivity of water is frequency dependent, and each simulated water surface had two emissivities that relate to the two different radiometers. The distribution of surface emissivities is bimodel with one peak near 0.95 and the other around 0.55 for the 54-GHz system or 0.7 for the 118-GHz system. The equation for the specular reflection coefficient
of a dielectric boundary [16, p. 229] is:

\[ R_\perp = \frac{\eta_w \cos(\theta_w) - \eta_a \cos(\theta_a)}{\eta_w \cos(\theta_w) + \eta_a \cos(\theta_a)} \]  \hspace{1cm} (4.5)

\[ R_{\parallel} = \frac{\eta_a \cos(\theta_a) - \eta_w \cos(\theta_w)}{\eta_a \cos(\theta_a) + \eta_w \cos(\theta_w)} \]  \hspace{1cm} (4.6)

with \( \eta_w \) and \( \eta_a \) are the intrinsic impedance of water and air respectfully, \( \theta_w \) and \( \theta_a \) are the angles from the normal of the air-water boundary. The power reflection coefficient for a TE and TM wave are:

\[ \Gamma_\perp = |R_\perp|^2 \quad \text{and} \quad \Gamma_{\parallel} = |R_{\parallel}|^2 \]  \hspace{1cm} (4.7)

The intrinsic impedance of water, \( \eta_w \), is calculated as per the Klein-Swift model [31], and the \( \theta_w \) is determined from Snell’s law:

\[ k_w \cdot \cos(\theta_w) = k_a \cdot \cos(\theta_a). \]  \hspace{1cm} (4.8)

The Klein-Swift dielectric model is rated up to 12.8 GHz, and a new study at the higher frequencies was recently published. Cruz-Pol and Ruf [32] did a comprehensive study of
two surface emissivity models along with improved versions of each. Their results showed a 2.72 K bias in the Klein-Swift model using the 1993 Liebe atmospheric absorption model at 37 GHz.

Difficulties arise when determining the correlation between the air and water surface temperature as mentioned in Section 4.2.1. The 430 winter TIGR profiles are divided into two categories. One category is the profiles that could be used for water and land, and the other category is profiles that could be exclusively used for land. The difference between the land and land/water profiles is determined by the surface air temperature of the profile. If the surface air temperature is below 268 K, then the profile would exclusively be used for land profiles. The rationale for this comes from historical data from the National Data Buoy Center, where the mean air-water surface temperature difference is rarely below $-5^\circ C$ on either Lake Michigan or Lake Superior during March and April. After a reflectivity was calculated, a random fluctuation is added that is uniformly distributed between ±10 percent of the Klein-Swift modeled emissivity.

Each of the 430 winter TIGR profiles had ten simulated brightness temperatures, where the surface emissivity, surface temperature, and altitude were different. For the water/land
profiles, four of the brightness temperatures are modeled over water and six are modeled over
land. The simulated brightness temperatures over water use the derived relationship from
Section 4.2.1 between air and water temperature. Figure 4-8 is a histogram of the training
set's simulated surface emissivities. The land emissivities are uniformly distributed, but each
of the ten simulations of a particular profile had different bounds on the uniform distribution.
The land emissivities for a particular profile was broken down into one simulated brightness
temperature within a range of 0.8 to 0.85, then the next one was between 0.85 to 0.9 and so
on in increments of 0.05. The last two surface emissivities ranged between 0.9 to 1 and 0.95
to 1. The plateau distribution is apparent in Figure 4-8. This made sure that each profile
in the ensemble had a range of surface emissivities. The lower emissivity peaks, related to
the water emissivity, are not uniformly distributed even though the random perturbation
had a uniform distribution because the surface temperature also determined part in the
emissivity. The exclusively land profiles have a simple correlation coefficient of one between
air and soil temperature but also included a normal random fluctuation with a standard
deviation of 4 K.

4.3 Multilayer Feedforward Neural Network

This section covers the main issues when developing a MFNN to retrieve temperature pro-
files. The MFNN method starts by finding the best architecture, and proceeds with success-
ful training of the MFNN. The two main topics covered below are the MFNN architecture
and training, which is followed by the results.

4.3.1 Architecture

For pattern classification, the standard architecture is the feedforward neural network
(MFNN). Feedforward neural networks are briefly described in Section 2.4.4 and thoroughly
in Haykin [23]. A paper by Churnside et al. [35] tested various feedforward architectures in
retrieving temperature profiles with a ground-based microwave radiometer. Frate et al. [25]
followed the paper by estimating the coefficients of the expansion instead of the tempera-
ture profile. Their findings show that the best results come from a MFNN with one hidden
layer of hyperbolic tangent neurons with approximately twice as many neurons as inputs
within the hidden layer. Once again, the Frate paper used results from a seven channel
ground-based microwave radiometer.

Using the results from Frate and Churnside as a basis, the final architecture chosen for NAST-M retrievals agree with their previous work. The Planck’s equation (Equation 2.13) at microwave frequencies has little error when linearized, but some sources of non-linearity come from surface emissivity and the non-jointly gaussian statistics of the atmosphere. This argument can support the need of only one hidden layer, and the MFNN should show improvement over the LLSE in retrieving the surface temperature. The final number of hidden layer neurons is 34, which is roughly twice the number of inputs. Going beyond 34 neurons yielded no improvement in the MSE of the retrieval. Therefore, the expression for one of the coefficients of expansion is:

\[
    y_i = \sum_{j=0}^{34} w^{ij} \cdot \Phi_j \left( \sum_{k=0}^{12} w^{kj} \cdot \bar{T}_{bk} + w^{13j} \cdot P_n \right).
\] (4.9)

The \( \bar{T}_{bk} \) is the preconditioned NAST-M brightness temperature and \( P_n \) is the normalized aircraft pressure. To ease the training of the MFNN, the input data is linearly transformed. The brightness temperatures are orthogonalized, normalized, and shifted. The transform is:

\[
    \bar{T}_b = \Lambda^{-1/2} \cdot Q^T \cdot (T_b - M_{T_b}).
\] (4.10)

\( \Lambda \) is a diagonal matrix of the eigenvalues from the brightness temperature's covariance matrix (Cov\(T_b\)), and \( Q \) has the eigenvectors of the Cov\(T_b\) matrix in its columns. The subtraction of the mean brightness temperatures (\( M_{T_b} \)) shifts the brightness temperatures, and the orthogonalization occurs with the matrix multiplication of the orthonormal matrix \( Q \). The normalization is the normalization of the variance through the matrix multiplication of \( \Lambda^{-1/2} \) [36]. The pressure at the aircraft’s altitude is not included in the orthogonalization of the brightness temperatures, and had the mean aircraft pressure from simulations (Figure 4-7) and was normalized to have unit variance. Two of the fifteen decorrelated preconditioned variables are removed with the intent of removing instrument noise. These two PCs are the lowest two, or in other words, the PCs of the highest frequency components.
4.3.2 Training

The neural network is implemented by a mathematical software package called MATLAB (Version 5.3.0), which was created by MathWorks, Inc. The general MATLAB software utilizes an additional package called the Neural Network Toolbox [37]. The general training routine for a MFNN is the backpropagation algorithm, and MATLAB has several optimization techniques for minimizing the error criterion. The optimization techniques are reviewed.

LLSE and MFNN share the common goal of minimizing a cost function. The LLSE uses a priori statistics to regress the input to the output in a Bayesian manner, while the MFNN are actively ‘trained’ by optimizing an error criterion. The most common error criterion is the mean squared error (MSE), but other options exist such as the minimum absolute error (MAE). When estimating principal components, the estimator’s coefficient outputs have different ranges, and an attempt to normalize the outputs before the MSE is calculated was implemented. The results of the normalized MSE showed no improvement over the MSE.

To decrease the time required to train a MFNN, proper initialization and data preconditioning are a necessity. The advantages of preconditioning come from manipulating the error surface to allow the numerical optimization to work faster and potentially more successfully [36, p. 51]. When a MFNN is created in MATLAB, there are several ways to initialize the weights and biases. This initialization is simply the first guess, admittedly a poor one, at the weights and biases. Most optimization techniques need to start at some value. MATLAB allows several techniques for weight and bias initialization, and the most successful is a random choice of values between -1 and 1 [23, p. 162]. The activation function of choice is the hyperbolic tangent, which has a limited output range and can be saturated by the inputs. Thus, normalizing and shifting the input data, along with random initialization, can avoid saturation and therefore ease training.

The fundamental training method for the MFNN is the Back-Propagation Algorithm. The BP algorithm starts with a forward pass of the training set, and then the estimated output is subtracted from the correct output. This error, \( e_n \), in some weighted fashion, is added to the present weights. A derivation of the error back-propagation algorithm can be found in Haykin [23, p. 142], but, in general, it could not be shown to converge [p. 153]. The error criterion can be viewed as a multidimensional surface with a dimension for each
weight or bias. For a typical MFNN used for temperature retrievals, there are hundreds of dimensions. The derivatives of the multidimensional error surface with respect to each weight and bias are set to zero and then a numerical optimization technique attempts to find the root.

The simplest is the gradient descent numerical optimization. Gradient descent is a fundamental technique that takes the next ‘guess’ for the weights in the negative gradient direction on the error surface.

\[ w_{n+1}^{ji} = w_n^{ji} - \eta \cdot g(w_n^{ji}) \quad \text{or} \quad \Delta w_n^{ji} = -\eta \cdot g(w_n^{ji}) \quad (4.11) \]

Where \( \Delta w_n^{ji} \) denotes the change in the weight from neuron \( i \) to neuron \( j \) on the \( n^{th} \) vector of the training set, and the gradient is:

\[ g(w_n^{ji}) = \frac{\partial}{\partial w_n^{ji}} \frac{1}{2} \sum_j e_n^j. \quad (4.12) \]

The parameter \( \eta \) is termed the learning rate and controls the relative size of the weight correction. Large learning rates can cause the solution to overshoot the absolute minimum, while a small learning rate prolongs the convergence to the solution. Another training parameter that can be included in gradient descent is momentum \( (m) \):

\[ \Delta w_n^{ji} = m \cdot \Delta w_{n-1}^{ji} - (1 - m) \cdot \eta \cdot g(w_n^{ji}) \quad (4.13) \]

Momentum helps ‘push’ the iterative solution out of local minima and has an effect similar to that of a lowpass filter. The more advanced Newtonian methods use the Jacobian matrix of the gradient and, therefore, more information. The Jacobian matrix is the second derivative matrix (Hessian matrix) of the error surface. With hundreds of weights and biases, the Hessian is computationally intensive for use with the computers at hand. Even with the techniques devised to get around the full computation of the Hessian matrix, the family of Newtonian numerical optimizations is avoided in this application. There is another type of numerical optimization offered in the MATLAB Neural Network Toolbox. They are the conjugate gradient methods, which have higher performance than the gradient descent without the computation of the Newtonian. The method is similar to the gradient descent,
but with a beneficial addition:

\[
\Delta w_n^{ji} = \eta \cdot d_n \quad \text{with} \quad d_n = -g(w_n^{ji}) + \beta_n \cdot d_{n-1}. \quad (4.14)
\]

The parameter \( \beta \) is:

\[
\beta_n = \frac{g_n^T(g_n - g_{n-1})}{g_{n-1}^T g_{n-1}}. \quad (4.15)
\]

The advantage of conjugate gradient is that it chooses a direction that is orthogonal to all previous directions. This prevents the solution from getting trapped in long valleys of the error surface (instead of hundreds of weights, imagine there are only two). Gradient descent would slowly travel back and forth in the valley, while conjugate gradient will point to the minimum of the valley and therefore converge faster. For a more thorough explanation of the math behind the conjugate gradient method, see Strang [28, Ch. 5].

After the training set is formed, the MFNN initialized, and numerical optimization algorithm is chosen, there are two ways to implement the back-propagation algorithm. The first way is to enter an input vector from the training set and then back-propagate the correction to the weights and biases. The other way is to enter all the vectors of the training set and take the average of the error from a particular output before back-propagating the correction. This is called batch training, and the first method is termed incremental training. Incremental training has an advantage if the process is stochastic, which is not the case during training of a MFNN in this thesis. In Haykin, it is shown that the \( \Delta w^{ji} \) calculated through incremental training is the averaged estimate of the \( \Delta w^{ji} \) calculated through batch training [23, p. 151].

Proper simulation of instrument noise is important for proper MFNN training. Instrument noise for this application is not considered in the MATLAB Neural Network Toolbox, and the MATLAB code had to be modified to handle instrument noise in temperature retrievals. The FRT software simulates noiseless radiances, so that the noise can be added during training. In batch training, all of the vectors in training set are passed through the neural net before the average error is calculated. Each epoch should have a different realization of the instrument noise statistics. Changing the noise every epoch helps avoid over training to a specific realization of the noise.
4.4 Results

The most successful MFNN is trained with a conjugate gradient method using batch training. MATLAB has several conjugate gradient methods, which varies the method of calculating the parameter $\beta$ or is a hybrid of the Newtonian method. In the particular conjugate gradient method that I used, the orthogonality was restarted if the orthogonality between gradients was small [37, p. 5-24]:

$$|g_{n-1}^T g_n| \geq 0.2 \| g_n \|^2.$$  \hfill (4.16)

Most of the conjugate gradient methods also have a line search routine. Once the direction is chosen by the conjugate gradient technique, the software searches along that direction for the minimum of the error surface. The best line search routine is the ‘Golden Rule’. The ‘Golden Rule’ routine takes gradually increasing steps in the direction given until the error increases. In order to avoid regularization of the MFNN, the training routine stops training after the validation set does not improve after 1500 epochs. This is called the early stopping method because the software monitors the validation MSE and once the MSE stops improving, then MFNN could be over training. Usually the number of epochs in the early stopping technique does not have to be as large as 1500, but the simulated instrument noise ‘clouds’ the validation error and can prematurely stop the training if the noise mistakenly gives a good MSE for one epoch. Figure 4-9 is an example of the training record of a MFNN. The validation set is the top curve and the validation set consisted of 30 of the 430 winter TIGR profiles or 300 of the 4300 training vectors. The computation burden for training this MFNN was 815 Gflops. Figure 4-10 is a comparison of the rms retrieval error of the MFNN and LLSE, but also has the $a$ priori variations of the winter TIGR ensemble. The rms retrieval error is a standard metric for measuring the success of a retrieval technique. Error in Figure 4-10 is calculated from the training set and validation set and the $a$ priori rms contains all of the winter TIGR profiles.
Figure 4-9: MFNN training results of the training set and validation set (top curve)
Figure 4-10: MFNN-LLSE algorithm comparison along with the a priori standard deviation of the winter TIGR profiles (error calculated from the training and validation set)
Chapter 5

NAST-M WINTEX Retrievals

This chapter gives the results of the temperature profile estimations using NAST-M data and the retrieval algorithm from the previous chapter. The first two retrievals are centered around two particular flights during the WINTEX field deployment of the NAST instruments. The WINter EXperiment (WINTEX) was deployed from Madison, Wisconsin from March 15, 1999 to April 2, 1999 to define the measurement requirements for the next generation of the National Polar-orbiting Observational Environmental Satellite System (NPOESS). The purpose of WINTEX is to validate atmospheric soundings observed across polar frontal systems. The ER-2 flew from southern Wisconsin northward across Canada deep into the cold Arctic air mass behind the cold front and also southwest to the ARM CART site. For validation purposes, sorties were matched with weather balloon observations which were launched by the National Weather Service and also locally by the University of Wisconsin. Sorties included flights over Lake Michigan and Lake Superior, which were helpful for validation purposes. Table 5.1 is a log of the WINTEX sorties and also contains information about the performance of the NAST-M instrument during the deployment.

5.1 WINTEX Retrievals

The cumulated effort of this thesis is to have the first temperature retrievals with the NAST-M instrument from the WINTEX flights. Radiosondes and a temperature retrieval technique with a different instrument (AMSU-A) are compared with the NAST-M retrieval for validation purposes. The AMSU-A retrieval technique is an iterative statistical and
Table 5.1: WINTEX 1999 NAST-M Flight Summary

<table>
<thead>
<tr>
<th>Date</th>
<th>Flt. Calibrated</th>
<th>Start</th>
<th>Raobs</th>
<th>Weather</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>[Hours]</td>
<td>[UTC]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3/15</td>
<td>4:50</td>
<td>18:07</td>
<td>0</td>
<td>scat. clouds</td>
<td>ferry fit.</td>
</tr>
<tr>
<td>3/18</td>
<td>3:15</td>
<td>19:00</td>
<td>2</td>
<td>partly cloudy</td>
<td>eng. fit</td>
</tr>
<tr>
<td>3/19</td>
<td>0:35</td>
<td>20:58</td>
<td>0</td>
<td>clear</td>
<td></td>
</tr>
<tr>
<td>3/20</td>
<td>6:00</td>
<td>21:00</td>
<td>0</td>
<td>partly cloudy</td>
<td>WI, Canada</td>
</tr>
<tr>
<td>3/21</td>
<td>4:40</td>
<td>21:58</td>
<td>0</td>
<td>scat. clouds</td>
<td>L. Michigan</td>
</tr>
<tr>
<td>3/25</td>
<td>4:20</td>
<td>22:30</td>
<td>1</td>
<td>clear</td>
<td>L. Superior</td>
</tr>
<tr>
<td>3/26</td>
<td>5:30</td>
<td>20:58</td>
<td>5</td>
<td>mostly clear</td>
<td></td>
</tr>
<tr>
<td>3/29</td>
<td>3:30</td>
<td>22:58</td>
<td>3</td>
<td>clear</td>
<td>L. Michigan</td>
</tr>
<tr>
<td>3/31</td>
<td>2:00</td>
<td>16:00</td>
<td>3</td>
<td>clear</td>
<td>WI</td>
</tr>
<tr>
<td>4/1</td>
<td>5:00</td>
<td>21:28</td>
<td>3</td>
<td>mostly clear</td>
<td>CART site</td>
</tr>
</tbody>
</table>

5.1.1 WINTEX Retrieval over Lake Michigan

The first comparison is an average of 60 nadir-viewing spots over Lake Michigan on March 29, 1999. The ER-2 is at a cruising altitude of 19.3 km (0:28 UTC) over the southern part of the lake and approximately a half an hour later the NOAA-15 satellite has an overpass (0:52 UTC). The spatial position of the ER-2 ranges from 42.3777–42.9335°N and 87.3643–87.5688°W, while the AMSU-A retrieval is at 42.796°N and 87.044°W. Another temperature profile reference for comparison is a radiosonde launched off the coast of Lake Michigan at Sheboygan, WI. The radiosonde was launched at 87.71667°W, 43.71667°N, and at an altitude of 700 m. The balloon burst at 86.693°W, 43.393°N, and at 21,724 m (44.2 mb). The launch time was at 00:15 UTC on March 30, 1999 and lasted one hour and twenty-six minutes. Figure 5-1 is a plot of the four retrievals on the left and then the difference between the three microwave retrievals and the radiosonde are on the right. The greatest discrepancies are at the low levels of the atmosphere that have the greatest temporal and spatial difference. The AMSU-A retrieval and NAST-M retrievals are within the retrieval error of the retrieval algorithm (Figure 4-10). The NAST-M retrievals are sixty nadir scans averaged together, while AMSU-A is one 50 km spot using the retrieval technique mentioned above. Radiosondes are typically rated with a 1 K accuracy. Figure 5-2 is approximately three and half minutes of the flight with the mean radiance at each pressure level removed. The data shown in the figure has been expanded by interleaving interpolations between
every spot, working recursively twice. For example, the twenty-six vertical temperatures are interpolated to one hundred and one temperatures. This perturbation plot shows that most if not all of the retrieved temperature profile is within the retrieval error of the retrieval algorithm. The largest perturbation lies near the surface and at the tropopause.

5.1.2 WINTEX Retrieval over Madison, WI

A similar comparison that was done over Lake Michigan was repeated over land in Wisconsin on March 31, 1999. On this particular day a warm air front past over Wisconsin toward Lake Michigan. From the airport that the ER-2 was stationed, a radiosonde was launched at the beginning of the flight. The launch time was at 16:07 UTC on March 31st at 89.333°W, 43.133°N, and an altitude of 278 m. The radiosonde’s balloon exploded an hour and forty five minutes after launch at 87.887°W, 43.443°N, and an altitude of 22,024 m. The weather moved the weather balloon approximately 150 km northwest of Madison, WI to the middle of the Lake Michigan’s western coastline. Figure 5-3 has two NAST-M retrieval techniques and the radiosonde data on the left and the differences of the NAST-M retrieval techniques and the radiosonde on the right. The retrieval had the usual difficulties at the surface and at the tropopause, but there is approximately a 2.5 K bias in the mid-troposphere and just above the tropopause. It is unclear whether this is a bias in the retrieval, but it is much more likely that the retrievals are within the tolerances. The retrieval error is ~ 2 K and the radiosonde has an accuracy of ~ 1 K. Also, the weather was turbulent and could easily cast doubt on the validity of the radiosonde. Figure 5-4 is a strip of nadir-viewing retrievals that were used to calculate the average profile in Figure 5-3. These retrievals were interpolated in the same fashion as the March 29th data. The rms fluctuations in the image are within the retrieval error of the MFNN retrieval technique.

5.2 Surface Temperature Comparison

An interesting result of the retrievals were the success at measuring surface skin temperature on March 29, 1999. A buoy in the lower part of Lake Michigan was continuously monitoring the air and water temperature. Some technical information and the location of the buoy is given in Table 5.2, and at the time of the aircraft overpass, the buoy data is tabulated in Table 5.3. This can be considered ground truth for the different microwave retrieval
Figure 5-1: Temperature retrieval comparison over Lake Michigan on March 29, 1999

Table 5.2: National Data Buoy Center

<table>
<thead>
<tr>
<th>Site elevation</th>
<th>177.0 m above mean sea level</th>
</tr>
</thead>
<tbody>
<tr>
<td>Site location</td>
<td>42.68 N 87.03 W (42°40'20&quot;N 87°01'19&quot;W)</td>
</tr>
<tr>
<td>Air temp. height</td>
<td>4 m above site elevation</td>
</tr>
<tr>
<td>Sea temp. depth</td>
<td>0.6 m below site elevation</td>
</tr>
<tr>
<td>Water depth</td>
<td>164.6 m</td>
</tr>
</tbody>
</table>

45007 - S MICHIGAN 43NM East Southeast of Milwaukee, WI
Figure 5-2: Vertical temperature perturbation over Lake Michigan on March 29, 1999

Table 5.3: Data from Buoy 45007

<table>
<thead>
<tr>
<th>Year</th>
<th>Month</th>
<th>Day</th>
<th>Hour [UTC]</th>
<th>Pressure [mb]</th>
<th>Air Temp. [°C]</th>
<th>Water Temp. [°C]</th>
</tr>
</thead>
<tbody>
<tr>
<td>1999</td>
<td>03</td>
<td>29</td>
<td>23</td>
<td>1022.6</td>
<td>5.6</td>
<td>3.5</td>
</tr>
<tr>
<td>1999</td>
<td>03</td>
<td>30</td>
<td>00</td>
<td>1022.8</td>
<td>5.2</td>
<td>3.5</td>
</tr>
<tr>
<td>1999</td>
<td>03</td>
<td>30</td>
<td>01</td>
<td>1023.3</td>
<td>4.8</td>
<td>3.5</td>
</tr>
</tbody>
</table>
Figure 5-3: Temperature retrieval comparison over Madison, WI on March 31, 1999
Figure 5-4: Vertical temperature perturbation over Madison, WI on March 31, 1999
Table 5.4: Surface Temperature Comparison

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>NAST-M/LLSE</td>
<td>278.6937</td>
<td>279.6035</td>
<td>~ 00:30</td>
<td>~ 42.5 N 87.4 W</td>
</tr>
<tr>
<td>NAST-M/MFNN</td>
<td>277.5307</td>
<td>277.8884</td>
<td>~ 00:30</td>
<td>~ 42.5 N 87.4 W</td>
</tr>
<tr>
<td>AMSU-A/ISP</td>
<td>273.186</td>
<td>267.65</td>
<td>00:53</td>
<td>42.796 N 87.044 W</td>
</tr>
<tr>
<td>Buoy 45007</td>
<td>278.15</td>
<td>276.65</td>
<td>00:30</td>
<td>42.68 N 87.03 W</td>
</tr>
</tbody>
</table>

techniques and, therefore, become a basis for comparison. Table 5.4 has the two NAST-M retrievals, the AMSU-A iterative retrieval, and the buoy data. The MFNN was the most successful at estimating the buoy water temperature and was a close second for the surface air temperature.

5.3 Temperature Imagery

The retrieval technique from Chapter 4 was designed for nadir profiling, but the limb effects are marginal at angles close to nadir. This allows some imaging of the atmosphere both vertically and horizontally. Figure 5-5 is an image over Lake Michigan on March 29th of the temperature perturbation both vertically and horizontally. Only the three closest spots to nadir on the right and left are shown with nadir. In these images, only one point has been interpolated between spots. Before interpolation, the image was convolved with a spatial filter in the horizontal direction. The filter was a three-by-three matrix with uniform weights of one ninth. The edges were padded with scans that were further from nadir but then only the center seven spots were kept. The spatial filtering attempts to reduce the noise of the retrieval and hopefully expose the atmospheric temperature changes. Figure 5-5 is of interest because there is a gradual decrease in temperature (1 K) in the mid-troposphere and yet there is an increase of one Kelvin above the tropopause. The portion shown in the figure was approximately twelve minutes of flight that roughly converts to a 150 km stretch. The swath width shown is approximately 20 km at the surface.

Another image that may possibly be atmospheric temperature gradients is in Figure 5-6. Instead of five different altitudes, three are shown from the March 31st flight over the Iowa and Wisconsin border. Most of the horizontal variation of the temperature perturbations can be explain as either retrieval error or calibration error. Yet a distinguishing atmospheric feature would transgress several scans or form distinct temperature cells within the atmo-
Figure 5-5: Temperature perturbation images at various altitudes over Lake Michigan on March 29, 1999
sphere. There may potentially be a temperature cell in Figure 5-6. Just before 16.84 UTC, an upside down ‘V’, which is hotter than the surrounding atmosphere, starts forming at 13 km and works it way down to 4.5 km. As a comparison a simple LLSE retrieval was done on the same radiometric data with the same colorbar limits. The LLSE estimator did not attempt any principal component transformations or orthogonal expansion of the temperature profiles. The LLSE simply estimated the temperature profiles from the calibrated brightness temperatures. The ‘V’ is faintly visible, but is distinguishable in the LLSE retrieval. The basis for both figures is the use of the same training set. If the calibration and instrument noise has been successfully removed, then the images suggest the possible detection of thermal waves on the order of 1 K peak-to-peak with a period of 20-60 km.
Figure 5-6: Retrieved temperature perturbation images on March 31st using a MFNN with PCA
Figure 5-7: Retrieved temperature perturbation images on March 31st using a LLSE
Chapter 6

Conclusion and Further Work

The work began with calibrating a passive microwave spectrometer in order to retrieve temperature profiles using the data from the WINTEX deployment in Madison, Wisconsin. After the fundamentals in Chapter 2, Chapter 3 addressed the issues of calibrating NAST-M instrument. The instrument sensitivity was quantified to less than $0.3 \, K$ and the absolute accuracy is less than $1.5 \, K$.

Chapter 4 designed a retrieval technique utilizing orthogonal expansion, principal component analysis, and neural network pattern classification. The retrieval technique was benchmarked in the simulation domain with a LLSE statistical estimator, which showed improvement on the order of $0.25 \, K$ throughout the atmosphere. In Chapter 5, the MFNN retrieval technique and calibration technique were united for retrievals of flight’s during the WINTEX deployment. The retrievals were compared with radiosondes and with another microwave radiometer, and showed agreement within the accuracy of the instruments for both water and land surfaces. To finish the thesis, temperature images hoped to show atmospheric temperature gradient in the first imaging of small temperature fluctuations with only a microwave radiometer. The results were inconclusive, yet showed promise. Overall, the WINTEX temperature retrievals agreed with NAST-M training simulations and calibration results from Chapter 3. The next section reviews the potential future work from the conclusion of this thesis.
Further Work

The calibration is complete for the WINTEX deployment, but the calibration does not cross over to the other deployments. Unfortunately, the shifting of the antenna reflector between belt replacements can change the spillover on the calibration loads. A comprehensive study of the antenna pattern should be undertaken. This can involve accurately measuring the spillover on the calibration loads after the antenna reflector’s position has been optimized or even the complete characterization of the antenna pattern at all pertinent frequencies. If the sidelobes are as large as we believe, then future upgrades could improve the present antenna system. In either event, calibration corrections must be tabulated for the previous deployments or for any deployments in the near future.

Another calibration technique may have a simple and robust solution to the missions that are corrupted. After extensive laboratory measurements of the corruption, and an optimal position is determined for the reflector, an ‘iterative’ approach may be the best. The approach consists of doing a first run calibration, even though the onboard loads are corrupted. Then take the first ‘guess’ of the brightness temperature of the corruption and the percentages of spillover into the next calibration of the instrument by correcting the load brightness temperatures. This technique could alleviate the need of a radiosonde, AMSU overpass, clear air, and water surface in order to find an accurate correction. From the first stage calibration, the NAST-M instrument, for both radiometers, has an absolute accuracy that is less than 1.5 K. This assumes that the adequate corrections are found. The 118-GHz needs the correction only for the flights before the belt change. I did a dry run with this technique and failed to obtain the same results as the corrections in Chapter 3. With effort and more accurate modeling of ground truth radiances (better surface model) then the ‘iterative’ technique could prove very useful.

There are several areas to continue to develop the retrieval aspect of this thesis. The most obvious is to make a global retrieval technique and use the data collected from the Convection And Moisture Experiment (CAMEX-3) in Patrick Air Force Base, Florida from August 6 to September 23, 1998 or Wallops 2000 in Wallops Island, Virginia. Another improvement would be a retrieval technique that is no limited to the nadir spot.

The simulation is very important in developing a training set and the surface emissivity model should be evaluated further to determine the error introduced by the Klein-Swift
model. Other models may be more appropriate, especially at the frequencies of the 118-GHz system. The error introduced from the surface model will effect the calibration and retrieval.

In Chapter 5 there was some imaging with the spots closest to nadir, but the retrieval did not account for limb darkening and more can be done. Initially, there was an attempt to train the MFNN with an additional variable which was the cosine of the scan angle, but I believe I encountered problems because the estimation from brightness temperature to atmospheric temperature was not ‘one-to-one’. This means that there were two or more inputs that were trained to give the same output. When a MFNN is trained, it is similar to a LLSE in the sense that it has fixed weights, but it does have non-linear activation functions which are absent in a LLSE (for a first order). The point is that those fixed weights can not have two inputs give the same outputs. There is a possibility, if the architecture is large enough, that the MFNN finds a very similar outputs for two different inputs, but that must be investigated further.

The MFNN gave reasonable estimations for temperature profiling when compared with a LLSE, but the MFNN was not benchmarked against any previously published MFNN estimation techniques. One MFNN that could be used for comparison is Cabrera’s MFNN which he used in humidity profile retrievals [36, 38]. Another way to determine the success of the non-linear MFNN is to compare it with another non-linear estimator. In particular, a LLSE that uses higher order powers of the observed radiance. For example, for a one channel instrument with a radiance $R$ the non-linear retrieval using a LLSE is:

$$\hat{T} = a_0 + a_1 \cdot R + a_2 \cdot R^2 + \ldots$$ \hspace{1cm} (6.1)

A non-linear LLSE should match the retrieval error of the MFNN, and if it does better then the MFNN could be improved.

The NAST platform can not reach the same altitude as a POES, so the aircraft altitude is added to the retrieval technique. Once the microwave instrument is on board a satellite, it will no longer have to worry about the instrument’s altitude because it will be above the atmosphere. Until the instrument has the advantage that it is over the atmosphere, the aircraft’s pressure is entered into the retrieval technique in an attempt to reduce error in the retrieval. The success of the aircraft’s pressure in the retrieval should be tested and
analyzed. A better surface emissivity model was mentioned earlier in the section, and a more thorough investigation into the effects of the surface emissivity is needed in developing the training set.

When the flight data was applied to the retrieval techniques developed in Chapter 4, there was a noticeable change in the retrievals when there was a transition between land and water. Ideally, the temperature retrieval should be not be effected by changes in the surface emissivity, but when the flight data had a lake among a land strip or an island within a water strip, the retrieval had a dramatic temperature perturbation at the location of the emissivity change. The lake or island should realistically have a different temperature profile near the surface, but the perturbations introduced were well above the surface and discounted as false. The problem may arise from the limited expansion of the TIGR profile. There are only eight uncorrelated degrees of freedom when the orthogonal expansion is limited to the eight eigenvectors. Another explanation maybe the limited training set which would need to become more representative of real flight data. This problem related to the surface emissivity brings about the need of a surface effect filter. A principal component analysis of simulated brightness temperature where the all of the profiles would have two simulated brightness temperatures. The first would be at the low end of the emissivity scale at 0.5 and the other would be at 1. The difference between the two emissivities would be taken for each profile. The collection of brightness temperature perturbations induced by the change in surface emissivity would be used to calculate the covariance matrix. The temperature perturbation covariance matrix would be the basis for a principal component analysis. The filter would be a principal component transform into the ‘surface emissivity induced temperature perturbation’ domain, where the first principal component would be removed. Then the filtered data is transformed back into the brightness temperature domain, where it is entered into the preconditioning part of the retrieval algorithm. The purpose of the emissivity filter is to remove the effects of the surface emissivity while minimizing the loss of information. On a similar note, the number of brightness temperature PCs should be optimized in order to maximize the signal to noise ratio. Presently, twelve of the fifteen brightness temperature principal components were entered into the MFNN.

Another test of the retrieval technique would be to simulate an atmosphere and analyze the retrievals. The simulated atmosphere may consist of collecting a subset of similar profiles and filtering the temperature levels with a gaussian filter to introduce correlation.
between neighboring profiles. After calculating the brightness temperatures of the correlated temperature profiles, the resulting retrievals could be analyzed.
function [Tb, X] = calibnastm3pt(x, rtdf, t, tspot, nav, rtdW, HEIGHT, CORR)

% usage [Tb X] = calibnastm3pt(x, rtdf, t, tspot, nav, rtdW, HEIGHT, CORR)
% This script calibrates NAST-M data for both radiometers
% with three calibration points.
% x    -> counts 17x25xr (17 channels, 25 spots, r scans)
% rtdf -> rtd temperatures 29xr (29 rtd's, r scans)
% t    -> time stamp of scan
% tspot -> time stamp of each spot in seconds
% nav is structure array
%     nav.d  ER-2 navigation data
%     nav.t  navigation time stamp
% rtdW  -> structure array
%   rtdW.H hot load rtd index
%   rtdW.A ambient load rtd index
% Height -> height of aircraft
% CORR   -> structure array
%      CORR.TH hot load correction
%      CORR.TA ambient load correction

siz = size(x);
% Hot load weights
load hot_load_weights.mat

% Ambient Load weights
WgtA=[0.2;0.2;0.2;0.2;0.2];

% select the appropriate rtd for each calibration load
Thl=(rtdf(:,rtdW.H(:,1))*w); %[rx1]
Tal=(rtdf(:,rtdW.A(:,1))*WgtA);

% get correction parameters and correct RTD's

corrTh=CORR.TH;
corrTa=CORR.TA;
Th=Thl*ones(1,17);
Th(:,:)=Th(:,:)-(corrTh*ones(1,length(Th)))';
Ta=Tal*ones(1,17);
Ta(:,:)=Ta(:,:)-(corrTa*ones(1,length(Ta)))';

% usual altitude of the aircraft is 20 km
if exist(' HEIGHT ')~=1,HEIGHT=20,end;

% determine the brightness temperature that the zenith view should
% see above the aircraft.
ln=length(rtdf);
[Tb118,Tb54]=skytb(HEIGHT);
Ts=ones(ln,17)';
Ts1=[Tb54(:,1)' Tb118(:,1)'];
for i=1:17,
   Ts(i,:)=Ts(i,:).*Ts1(i)';
end;
Ts=Ts';
clear x_;  

% Remove zenith radiance data during aircraft rolls and replace  
% with interpolated data.  
% clean_sky_rad shifts x to x_ -> [rx17x25]  
x_ = clean_sky_rad(x,nav,t);  

% take mean of the two calibration spots  
Ch = mean(x_(:,:, [3:4]), 3); % [rx17x1]  
Ca = mean(x_(:,:, [24:25]), 3);  
Cs = mean(x_(:,:, [1:2]), 3);  

% filter counts to reduce instrument noise  
Chf = filtfiltcol(ones(1,4)/4,1,Ch);  
Caf = filtfiltcol(ones(1,4)/4,1,Ca);  
Csf = filtfiltcol(ones(1,4)/4,1,Cs);  

% interpolate RTD and simulation temperatures to all spots  
Thi = interp1(t,Th,tspot(:,));  
Tai = interp1(t,Ta,tspot(:,));  
Tsi = interp1(t,Ts,tspot(:,));  

% interpolate radiances to all spots  
th = mean(tspot([3:4,:]));  
Chi = interp1(th,Chf,tspot(:,));  
ta = mean(tspot([24:25,:]));  
Cai = interp1(ta,Caf,tspot(:,));  
ts = mean(tspot([1:2,:]));  
Csi = interp1(ts,Csf,tspot(:,));  

% prepare Weighted Least Square Estimation of linear parameters  
b = zeros(3,siz(1),siz(3)*25);
\[ b(1,:,:)=Tsi(:,:,1); \]
\[ b(2,:,:)=Tai(:,:,1); \]
\[ b(3,:,:)=Thi(:,:,1); \]

\[ A=\text{ones}(3,2,siz(1),siz(3)*25); \]
\[ A(1,1,:,:)=Csi(:,:,1); \]
\[ A(2,1,:,:)=Cai(:,:,1); \]
\[ A(3,1,:,:)=Chi(:,:,1); \]

\% optimal weight matrix \( C \)
\[
\text{load NASTM\_noise\_std.mat} \\
\text{for } z=1:17, \\
C(:,:,z)=\text{diag}(\text{std\_NASTM}(:,z)^{-2}); \\
\text{end}
\]

\[ X=\text{zeros}(2,siz(1),siz(3)*25); \]
\[ \text{for } i=[1:siz(3)*25], \]
\[ \quad \text{for } j=[1:siz(1)], \]
\[ \quad X(:,j,i)=\text{inv}(A(:,:,j,i)'*C(:,:,j)*A(:,:,j,i))*A(:,:,j,i)*C(:,:,j)*b(:,j,i); \]
\[ \quad \text{end;} \]
\[ \text{end;} \]
\[ \text{for } i=1:17, \]
\[ x_2(:,i)=\text{reshape}(x(i,:),\text{length}(x)*25,1); \]
\[ \text{end} \]

\[ Tbl=\text{squeeze}(X(1,:,:))'*x_2 + \text{squeeze}(X(2,:,:))'; \]

\[ Tbl'=Tbl'; \]
\[ \text{for } i=1:17, \]
\[ \quad Tbl(i,:)=\text{reshape}(Tbl(i,:),25,\text{length}(x)); \]
\[ \text{end} \]
fprintf('
 Three-point Calibration is complete.

')

function [Tb118,Tb54]=skytb(H,RAOB)
% usage: [Tb118,Tb54]=skytb(H,RAOB)
% H = height of aircraft
% RAOB = optional raob
% Used to figure out the brightness temperature that
% the chimney on the NAST-M should see from the 1976 U.S. Standard atmosphere.

LO_54GHz = 45.995;
LO_118GHz = 118.7595;
fprintf('
 Using LO freq. from Mar. 27, 1999 for Sky Tb simulation.

');
[F54, p54, F118, p118] = nastm_passband_load(LO_54GHz, LO_118GHz);

if exist('RAOB')~=1,
load /usr/users/michael/matlab/dat/stdatm3.mat
RAOB=std76;
end

L=length(RAOB);
if exist('H')~=1,H=20,end %height of aircraft
H1=max(find(RAOB(:,1)<=H));
H2=min(find(RAOB(:,1)>=H));

fprintf('Calculating absorption coefficients at 118-GHz ...
');
ab118=o2absraob(RAOB,F118)+abh2oraob(RAOB,F118);
fprintf('Calculating absorption coefficients at 54-GHz ...
');
ab54 = o2absraob(RAOB,F54)+abh2oraob(RAOB,F54);

sec = 1;
reflect = 0; %NaN
Ts = 0; %NaN

[Tbup_118, Tb_118] = radtranup_wjb(RAOB,ab118,sec,Tcosmic(118.75),reflect,Ts);
[Tbup_54, Tb_54] = radtranup_wjb(RAOB,ab54,sec,Tcosmic(50.3),reflect,Ts);

Tb118_1 = p118*squeeze(Tb_118(:,1,H1));
Tb54_1 = p54*squeeze(Tb_54(:,1,H1));

Tb118_2 = p118*squeeze(Tb_118(:,1,H2));
Tb54_2 = p54*squeeze(Tb_54(:,1,H2));

G = (Tb54_2 - Tb54_1) ./ (RAOB(H2,1) - RAOB(H1,1));
B = Tb54_1 - G .* RAOB(H1,1);
Tb54 = G .* H + B;

G = (Tb118_2 - Tb118_1) ./ (RAOB(H2,1) - RAOB(H1,1));
B = Tb118_1 - G .* RAOB(H1,1);
Tb118 = G .* H + B;

function [x_, nav_] = clean_sky_rad(x, nav, t)
% usage [x_, nav_] = clean_sky_rad(x, nav, t)
%
% When using the sky pipe, I replaced the counts at the aircraft rolls
% with interpolated data. This nullifies the calibration looks taken at
% that time.
% makes nav_ if not present

    nav_ = nav.d([29 30 9 10 23 24 8 32 6 7],:);'
    nav_(:,2) = nav_(:,2)/1000;
    nav_(:,6) = -nav_(:,6);
    nav_ = interp1(nav.t, nav_, t);

% find points where the aircraft rolled.
% should be visually determined by looking a nav_ data for that particular flt.

    roll = find(abs(nav_(:,4))>1);

% find the index that does not contain rolls.
    siz = size(x);
    noroll = [1:length(x)];
    noroll(roll) = [];

% replace the counts where there are rolls with zeros then interpolate.
    x_ = shiftdim(x,2);
    xt = [1:length(x)];
    for i = [1 2],
        % changed only the skypipe radiances
        for j = [1:siz(1)],
            % changed all channels
                for k = [roll],
                    x_(:,k,i) = 0;
                end;
            x_(:,j,i) = interp1(noroll, x_(:,noroll,j,i), xt);
        end;
    end;
Appendix B

MATLAB Neural Network Code

function [satigr, Ts, lat, long, date] = satigr_read

% [satigr, Ts, latitude, longitude, date] = satigr_read;
% satigr reader 2/21/00

NUM_TITLE = 25;
NUM_PROFILES = 1761;

fprintf('
Opening satigr information file...

')

fid = fopen('/usr/users/share/data/radiosonde/satigr.txt');
for i = 1:NUM_TITLE,
    line = fgetl(fid);
    disp(line);
end
pres = [0.05 0.09 0.17 0.3 0.55 1 1.5 2.23 3.33 4.98 7.43
        11.11 16.6 24.79 37.04 45.73 56.46 69.71 86.07 106.27 131.2
        161.99 200 222.65 247.9 275.95 307.2 341.99 380.73 423.85
        471.86 525 584.8 651.04 724.78 800 848.69 900.33 955.12 1013];

fclose(fid);
fprintf('Preparing variables...
');

Tsurf = zeros(NUM_PROFILES,1);
T = zeros(40,NUM_PROFILES);
dh2o = zeros(39,NUM_PROFILES);

fid = fopen('/usr/users/share/data/radiosonde/satigr.dat');

for i = 1:NUM_PROFILES
    num(i) = fscanf(fid,'%f',1);
    lat(i) = fscanf(fid,'%f',1);
    long(i) = fscanf(fid,'%f',1);
    date(i) = fscanf(fid,'%f',1);
    T(:,i) = fscanf(fid,'%g',40);
    Ts(i) = fscanf(fid,'%g',1);
    h2o = fscanf(fid,'%g',40);
    ozo = fscanf(fid,'%g',40);
    dh2o(:,i) = fscanf(fid,'%g',39);
    sundn = fscanf(fid,'%g',39);
    fgetl(fid);
    clear ozo h2o sundn
    fprintf('Finished reading profile %d\r', i);
end
fclose(fid);

H=std76mb(pres);
fprintf('Converted pressure to altitude.\nHeight is in kilometers.\n');

fprintf('Calculating water vapor density... ');
thick=diff(fliplr(H).*1000);
dh2o1=1e7.*fliplr(dh2o);
h2o=zeros(39,NUM_PROFILES);
for j=1:NUM_PROFILES,
    h2o(:,j)=dh2o1(:,j)./thick';
end
h2o=[zeros(1,NUM_PROFILES); fliplr(h2o)];
fprintf(' done \n');

satigr=zeros(4,40,NUM_PROFILES);
satigr(1,:,:)=fliplr(H) *ones(1,NUM_PROFILES);
satigr(2,:,:)=flipud(T);
satigr(3,:,:)=fliplr(pres) *ones(1,NUM_PROFILES);
satigr(4,:,:)=flipud(h2o);

fprintf(' \nLoading of TIGR ensemble is complete. \n\n')

% ********************************************************************
% this code separates winter profiles from the TIGR ensemble

% TIGR seems to have three date formats
% 4, 6, or 8 digits

if exist('satigr')~=1.
    [satigr, Ts, lat, lon, date_tigr] = satigr_read;
end

D1_index=find(date_tigr<9999);
D2_index=find (date_tigr<999999 & date_tigr>=10000);
D3_index = find(date_tigr > 1000000);

% four digit date year:month

date1 = date_tigr(D1_index);
date1s = num2str(date1);
mon1 = str2num(date1s(:,[3 4]));
yr1 = str2num(date1s(:,[1 2]));

% 6 digit date day:month:year

date2 = date_tigr(D2_index);
date2s = num2str(date2);
day2 = str2num(date2s(:,[1 2]));
mon2 = str2num(date2s(:,[3 4]));
yr2 = str2num(date2s(:,[5 6]));

% 8 digit date hr:day:month:year

date3 = date_tigr(D3_index);
date3s = num2str(date3);
hr3 = str2num(date3s(:,[1 2]));
day3 = str2num(date3s(:,[3 4]));
mon3 = str2num(date3s(:,[5 6]));
yr3 = str2num(date3s(:,[7 8]));

% I'm interested in Winter mid-latitude profiles
% For winter, must check if in N or S hemisphere.

month = zeros(1, length(satigr));
month(D1_index) = mon1;
month(D2_index) = mon2;
month(D3_index)=mon3;

winter_index=find(((month==12 | month<=4) & lat>30 & lat<65) | (month>=6 & month<=9 & lat<-30 & lat<-65));

winter_index(136)=[]; % removed as a bad humidity profile
ocean_index=find(((month==12 | month<=4) & lat>30 & lat<65 & Ts>268) | (month>=6 & month<=9 & lat<-30 & lat>-65 & Ts>268));

% ************************************************************
% script to take TIGR profiles and simulate NAST-M brightness temperatures.
%
if exist('satigr')~=1,
load satigr-ML.mat
end

ANGLES_TO_AVERAGE = 11; % for each spot, average over this many pencil beams
%
% load passband characteristics of NASTM radiometer
if exist('F54')~=1,
LO_54GHz = 45.995;  % from 27mar99;
LO_118GHz = 118.7595;
[F54, p54, F118, p118] = nastm_passband_load(LO_54GHz, LO_118GHz);
end
%
% antenna pattern simulation
beamwidth = 7.5;  % degrees, FWHM
sigma = beamwidth/2/sqrt(2*log(2));  % std dev value to create FWHM = beamwidth
% +/- 4 sigma should account for 99.99 percent of power
% 4 sigma = 4*beamwidth/2/sqrt(2(log(2))) degrees

sigma4 = 4 * sigma;

% average over angles

angles_to_avg = linspace(-sigma4,sigma4,ANGLES_TO_AVERAGE);
d_angle = mean(diff(angles_to_avg));
mts_beam = normpdf(angles_to_avg,0,sigma);
mts_beam118 = ones(size(F118,2),1) * mts_beam;
mts_beam54 = ones(size(F54,2),1) * mts_beam;

fprintf('
Calculation of antenna pattern is complete.
')

fprintf('Starting to calculate nadir spot for each profile ...\n\n');

% Initialize surface parameters and angles within antenna pattern

No_Profiles=1761;

Tb118up = zeros( length(F118), ANGLES_TO_AVERAGE, 40 );
Tb54up = zeros( length(F54), ANGLES_TO_AVERAGE, 40 );
Tb54=zeros(8,8,No_Profiles);
Tb118=zeros(9,8,No_Profiles);
SEC = sec( angles_to_avg / 180 * pi);
refl118=zeros(3,11);
refl54=zeros(3,11);

load /usr/users/vleslie/THESIS/MATLAB/SIM/satigr_wint_index2.mat
emissivity=zeros(14,No_Profiles);
pressure=zeros(10,No_Profiles);
Tsurf=zeros(10,No_Profiles);

% cite Chapter 2 by Philip Rosenkranz from the book: Atmospheric Remote Sensing by Microwave Radiometry; John Wiley and Sons, Inc. New York 1993
% editor Michael A. Janssen
for i=1:No.Profiles,
if sum(i==winter_index),
fprintf('Calculating absorption coefficients at 118-GHz for TIGR profile \
profile \%g...i);
ab118=o2absraob(squeeze(satigr(:,i))',F118)+abh2oraob(squeeze(satigr(:,i))',F118);
fprintf('Calculating absorption coefficients at 54-GHz ...\n');
ab54=o2absraob(squeeze(satigr(:,i))',F54)+abh2oraob(squeeze(satigr(:,i))',F54);

if sum(i==ocean_index),
    for k=1:10,
    % ten different surface emissivities are calculated for each potential ocean TIGR profile
    % randomly choose an aircraft height(pressure) from a uniform distribution
    pressure(k,i)=unifrnd(std76km(20.25),std76km(19));
    fprintf('\nAltitude = %g',std76mb(pressure(k,i)));
    perc=unifrnd(32/36,40/36);
    if k>=5,
        em_min_oc=[0.95 0.9 0.85 0.8 0.95 0.9];
        em_max_oc=[1 0.95 0.9 0.85 1 1];
        emissivity(k+4,i)=unifrnd(em_min_oc(k-4),em_max_oc(k-4));
        fprintf('\nEmissivity of land = \%g
',emissivity(k+4,i));
    end
    for j = 1:(ANGLES_TO_AVERAGE/2+1)
        fprintf('Calculating radiative transfer
        for angle: \%g\r', asec(SEC(j))/pi*180);
        if k<=4,
            if Ts(i)<=280,
                for a=1:1000,
                    Tsurf(k,i)=(1/24).*Ts(i)+normrnd(264.8,3);
                    if Tsurf(k,i)>273,break,end
                Tsurf(k,i)=(1/24).*Ts(i)+normrnd(264.8,3);
            end
        end
    end
end
end
else,
    for a=1:1000,
        Tsurf(k,i)=0.954.*Ts(i)+normrnd(10.88,4);
        if Tsurf(k,i)>273,break,end
    end
end

[refl118h, refl118v] = ref(dilec2(118.75,Tsurf(k,i),0.002),asec(SEC(j)));
% to compute reflectivity
    refl118 = refl118h .* cos(asec(SEC(j))).^2 + refl118v .* sin(asec(SEC(j))).^2;
[refl54h, refl54v] = ref(dilec2(50.3,Tsurf(k,i),0.002),asec(SEC(j)));
% to compute reflectivity
    refl54 = refl54h .* cos(asec(SEC(j))).^2 + refl54v .* sin(asec(SEC(j))).^2;
refl118a(k,j)=perc*refl118;
refl54a(k,j)=perc*refl54;
if j==6,w=1;else,w=2;end
[Tb118up(:,j,:)] = w.*radtranup_wjb(squeeze(satigr(:,:,i))', ab118, SEC(j),
    Tcosmic(118.75), refl118a(k,j), Tsurf(k,i));
[Tb54up(:,j,:)] = w.*radtranup_wjb(squeeze(satigr(:,:,i))', ab54,SEC(j),
    Tcosmic(50.3), refl54a(k,j), Tsurf(k,i));
else
    Tsurf(k,i)=Ts(i)+normrnd(0,4);
if j==6,w=1;else,w=2;end
[Tb118up(:,j,:)] = w.*radtranup_wjb(squeeze(satigr(:,:,i))', ab118, SEC(j),
    Tcosmic(118.75), (1-emissivity(k+4,i)), Tsurf(k,i));
[Tb54up(:,j,:)] = w.*radtranup_wjb(squeeze(satigr(:,:,i))', ab54,SEC(j),
    Tcosmic(50.3), (1-emissivity(k+4,i)), Tsurf(k,i));
end
if k<=4,
    emissivity(k,i)=(1-refl54a(k,6));
    emissivity(k+4,i)=(1-refl118a(k,6));
fprintf('
Emissivity 54 = %g
',(1-refl54a(k,6)));  
fprintf('Emissivity 118 = %g
',(1-refl118a(k,6)));  
end

for d=1:3,
    alt=[23 24 25];
    Tb_54(:,d)=p54 * trapz(mts_beam54 .* squeeze(Tb54up(:,:,alt(d))), 2) * d_angle;
    Tb_118(:,d)=p118 * trapz(mts_beam118 .* squeeze(Tb118up(:,:,alt(d))), 2) * d_angle;
end

[Tb_54e,Tb_118e]= rndpreslog(Tb_54,Tb_118,satigr,pressure(k,i));

    Tb54(:,k,i) = Tb_54e;
    Tb118(:,k,i) = Tb_118e;;
end

else

    for k=1:10,
    % eight different surface emissivities are calculated for each exclusively land TIGR profile

    % randomly choose an aircraft height(pressure) from a uniform distribution
    pressure(k,i)=unifrnd(std76km(20.25),std76km(19));
    fprintf('
Altitude = %g
' ,std76mb(pressure(k,i)));

    em_min=[0.95 0.9 0.85 0.8 0.95 0.9 0.85 0.8 0.9 0.9 ];
    em_max=[1 0.95 0.9 0.85 1 0.95 0.9 0.85 1 1 ];
    emissivity(k,i)=unifrnd(em_min(k),em_max(k));
    fprintf('
Emissivity land = %g
',emissivity(k,i));

    Tsurf(k,i)=Ts(i)+normrnd(0,4);
for j = 1:(ANGLES_TO_AVERAGE/2+1)
    fprintf('Calculating radiative transfer for angle: %g\r', asec(SEC(j))/pi*180);
    if j==6,w=1;else,w=2;end
    [Tb118up(:,j,:)] = w.*radtranup_wjb(squeeze(satigr(:,:,i))', ab118, SEC(j),
    Tcosmic(118.75), (1-emissivity(k,i)), Tsurf(k,i));
    [Tb54up(:,j,:)] = w.*radtranup_wjb(squeeze(satigr(:,:,i))', ab54,SEC(j),
    Tcosmic(50.3), (1-emissivity(k,i)), Tsurf(k,i));
end
for d=1:3,
    alt=[23 24 25];
    Tb_54(:,d)=p54 * trapz(mts_beam54 .* squeeze(Tb54up(:,:,alt(d))), 2) * d_angle;
    Tb_118(:,d)=p118 * trapz(mts_beam118 .* squeeze(Tb118up(:,:,alt(d))), 2) * d_angle;
end
[Tb_54e,Tb_118e]= rndpreslog(Tb_54,Tb_118,satigr,pressure(k,i));
    Tb54(:,k,i) = Tb_54e;
    Tb118(:,k,i) = Tb_118e;
end % ocean_index
end % win tex_index

if sum(i==[1:50:No_Profiles]),
    save tigr_Tb_wint.nn5800.mat Tb54 Tb118 emissivity pressure Tsurf winter_index ocean_index
end

end % tigr_index
save tigr_Tb_wint.nn5800.mat Tb54 Tb118 emissivity pressure Tsurf winter_index ocean_index
fprintf('\nFinished Winter TIGR profiles.\n');
% code to massage simulation code into NN format

load /usr/users/vleslie/THESIS/MATLAB/SIM/tigr_Tb_wint_nn5800.mat

% simulation variables
% Tb18 9x10x1761
% Tb54 8x10x1761
% Tsurf 10x1761
% emissivity 14x1761
% pressure 10x1761
% winter_index
% ocean_index

g=1761-length(Tsurf);
Tsurf=[Tsurf zeros(10,g)];

load /usr/users/vleslie/THESIS/MATLAB/DATA/satigr ML.mat

% satigr 4x40x1761
% Ts 1x1761

for k=1:8,
    Tb54a(k,:)=Tb54(k,:);
end

for k=1:9,
    Tbl18a(k,:)=Tbl18(k,:);
end

Tba=[Tb54a;Tbl18a];

p_index=find(Tba(1,:)==0);
Tempz=[];
for z=1:1761,
    Tempz=[Tempz satigr(2,:,z)'*ones(1,10)];
end

Tba(:,p_index)=[];
Tempz(:,p_index)=[];
em_index=find(Tb18(1,1,:)==0);
emissivity(:,em_index)=[];

pres_wint=pressure();
pres_wint(p_index)=[];

surface=[];
for z=1:1761,
    surface=[surface Ts(z)*ones(1,10)];
end
sur=reshape(surface,10,1761);
surfoc=surf(1:4,ocean_index);
surface_w=surface;
surface_w(p_index)=[];

Tsurf_w=Tsurf();
Tsurf_w(p_index)=[];
Tsuroc=Tsurf(1:4,ocean_index);

Temp_wint=Tempz;

Tb_wint=Tba;
emis_wint=emissivity;

save /usr/users/vleslie/THESIS/MATLAB/SIM/winter_Tb_T_pr4.mat Tb_wint
pres_wint Temp_wint p_index winter_index ocean_index satigr emis_wint
Tsurf_w surface_w

% ****************************
% script used to find natural orthogonal vectors of the TIGR ensemble of
% temperature profile.

% read in tigr ensemble
load /usr/users/vleslie/THESIS/MATLAB/SIM/winter_Tb_T_pr4.mat
% Tb_wint  17xr
% pres_wint  rx1
% Temp_wint  40xr
% emis_wint  12xr
% p_index   1xr  index into 6(surf. emis.)*1761(TIGR profiles) which
%           were not used
% winter_index 1xw  index to winter profiles in TIGR
% ocean_index 1xo  index to potential ocean profiles within winter_index
% satigr  4x40x1761

% take the pertinent temperatures into a variable
% These are the pressure levels under the aircraft.
temp=[Tsurf_w';Temp_wint(1:25,:)];

% determine the mean of each pressure level
Tmean=mean(temp,2); %[25x1]

% create 'mean matrix'
siz=length(temp);
Tmean_m=Tmean*ones(1,siz); %[25x#ofprofiles]

% Determine deviation of each tigr profile from the mean.
Tdif = temp - Tmean.m;

% determine the covariance matrix of Tdif
B = cov(Tdif');  \%[25x25]

% find the eigenvalues and eigenvectors of B
[Evec Eval] = eig(B);

% resort in descending value (PCA)
[Evals, Ev_index] = sort(diag(Eval));
Evals = flipud(Evals);
Ev_index = flipud(Ev_index);

% choose the first 8 eigenvectors for reconstruction.
ord = 8;
NOV = Evec(:, Ev_index(1:ord));

% determine the coefficients of expansion from TIGR ensemble.
C = NOV' * Tdif;
C_wint = C;
NOV_wint = NOV;

save /usr/users/vleslie/THESIS/MATLAB/SIM/winter_Tb_T_pr4.mat
Tb_wint pres_wint Temp_wint p_index winter_index ocean_index
satigr emis_wint Tsurf_w surface_w C_wint NOV_wint Tmean

% **************************************************************
% This script creates, initializes, and trains a MFNN.
% %
% % Training routine is cgb with new noise every epoch
% % -> input is normalized, orthogonalized, and shifted
%
global std_NASTM INPUT A PC Imn index LATENT min_e max_e

% load simulated brightness temperature from TIGR profiles
if exist('Tbwint')~=1,
    load /usr/users/vleslie/THESIS/MATLAB/SIM/winter_Tb_T_pr4.mat
end

% load noise statistics of NASTM instrument
load NASTM_noise_std.mat
% std_NASTM 3x17

% inputs are 14 NAST-M channels and the pressure at aircraft's altitude
[prs_n,meanprs,stdprs]=prestd(pres_wint);
INPUT=[squeeze(Tb_wint(1:14,:));prs_n];
Tb=[squeeze(Tb_wint(1:14,:))];

% training set targets are determined by Temp_exp.m
OUTPUT=[C_wint];

% find the eigenvectors of Ctb+Cn
Imn=mean(Tb,2); %[14x1]
siz1=length(INPUT);
Imn_m=Imn*ones(1,siz1); %[14x#ofprofiles]
Idif=Tb-Imn_m;
Ctb=cov(Idif'); %[15x15]
Cn(1:14,1:14)=diag(std_NASTM(2,1:14).^2);
[PC,LATENT,explained]=pcacov(Ctb+Cn);

% normalize training set
A=[1:12]; % only 12 of the 14 PC are kept
Tb_n=diag(LATENT(A).^(-0.5))*PC(:,A)'*(Tb-Imn*ones(1,length(INPUT)));


INPUT_n=[Tb_n;prs_n];

% split up TIGR into training set and validation set
6:100:3000 7:100:3000 8:100:3000 9:100:3000 10:100:3000];
train_index=[1:4300];
train_index(val_index)=[ ];

% create new virgin feedforward neural network
% NOTE: traincgb_noi is modified training routine with
% a new noise realization every epoch.
PR=minmax(INPUT_n);
nnet=newff(PR,[34 8],{ 'tansig','purelin' },'traincgb_noi');

% set pertinent initialization parameters and reinitialize
nnet.layers{2}.initFcn = 'initwb';
nnet.layers{1}.initFcn = 'initwb';
nnet.inputWeights{1}.initFcn='rands';
nnet.layerWeights{2,1}.initFcn = 'rands';
nnet.biases{2}.initFcn='rands';
nnet.biases{1}.initFcn='rands';
nnet=init(nnet);
nnet.IW{1}=0.5.*nnet.IW{1};

% set pertinent training parameters
nnet.trainParam.max_fail=1500;
nnet.trainParam.show = 100;
nnet.trainParam.epochs = 80000;
nnet.trainParam.goal = 8.5;
nnet.trainParam.searchFcn = 'srchgo1';
nnet.trainParam.minstep = 1e-8;
nnet.trainParam.time = inf;
nnet.performFcn='\texttt{mse}';

\% prepare early stopping validation set
validation.P=[\texttt{INPUT(:,val\_index)}];
validation.T=[\texttt{OUTPUT(:,val\_index)} ];
test.P=\texttt{INPUT(:,val\_index)};
test.T=\texttt{OUTPUT(:,val\_index)};
index.T=train\_index;
index.V=val\_index;

\% train MFNN
\texttt{flops(0)}
[nnett,tr]=\texttt{train(nnet,INPUT(:,train\_index),OUTPUT(:,train\_index),[],[],validation,test)};
flp=\texttt{flops}
Bibliography


