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THESIS

**ANALYZING THE MARS RECONNAISSANCE
ORBITER/SHALLOW RADAR SOLAR RADIO BURST
CANDIDATES FOR SUBSURFACE SOUNDING**

by

Andreas Z. Casillas

June 2023

Thesis Advisor:
Second Reader:

Sean T. Peters
Christopher Gerekos,
University of Texas Institute for Geophysics

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**ANALYZING THE MARS RECONNAISSANCE ORBITER/SHALLOW RADAR
SOLAR RADIO BURST CANDIDATES FOR SUBSURFACE SOUNDING**

Andreas Z. Casillas
Ensign, United States Navy
BS, United States Naval Academy, 2022

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requirements for the degree of

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Approved by: Sean T. Peters
Advisor

Christopher Gerekos
Second Reader

Frank A. Narducci
Chair, Department of Physics

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ABSTRACT

Solar radio bursts (SRBs) are radio emissions that arise from the complex interaction between energetic electrons and the background plasma. SRB emissions can have a significant impact on the space weather environment and thus on the capabilities, performance, and longevity of our space-based systems. Currently, space-based SRB observations have been dependent on solar observatories such as WIND, STEREO-A, and STEREO-B. Recently, the use of the Mars Reconnaissance Orbiter (MRO) subsurface sounder Shallow Radar (SHARAD) has been proposed as a potential additional solar radio waves observatory, with initial observations focusing specifically on type III bursts due to having an identifiable characteristic shape. As SHARAD was not originally designed for observing solar radio emissions, the objective of this research is to analyze which physical or systematic properties influence the detection of SRBs in SHARAD data, to determine the potential and limitations of using SHARAD as a solar radio-observatory. These properties include (1) MRO orientation, (2) MRO-Solar observatory orientation, and (3) SRB peak power output. Analyzing SRBs detected by MRO/SHARAD would enhance our understanding of SRB propagation physics and the space weather environment, and thus allow us to more effectively manage our space-based systems. In addition, we highlight the potential use of these bursts as a source for subsurface radio sounding for future terrestrial and Mars missions.

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List of Acronyms and Abbreviations

FFR	Fixed Frequency Receiver
GNSS	Global Navigation Satellite System
GP	Gonio-Polarimetric
GPS	Global Positioning System
HF	High Frequency
HFR	High Frequency Receiver
ICRF	International Celestial Reference Frame
LFR	Low Frequency Receiver
MARSIS	Mars Advanced Radar for Subsurface and Ionosphere Sounding
MRO	Mars Reconnaissance Orbiter
NAIF	Navigation and Ancillary Information Facility
NASA	National Aeronautics and Space Administration
PCA	Principal Component Analysis
RAD1	Radio Receiver Band 1
RAD2	Radio Receiver Band 2
sfu	Solar Flux Unit
SHARAD	Shallow Radar
SPICE	Spacecraft, Planet, Instrument, C-Matrix (Camera-Matrix), and Events
SRB	Solar Radio Burst
STEREO	Solar Terrestrial Relations Observatory

STEREO-A Solar Terrestrial Relations Observatory (Ahead)

STEREO-B Solar Terrestrial Relations Observatory (Behind)

SVM Support Vector Machine

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CHAPTER 1:

Introduction

1.1 Solar Radio Bursts and the Effects on the Space Weather Environment

Solar radio bursts (SRBs) are radio emissions that arise from the complex interaction between energetic electrons and the background plasma produced by the Sun [1]. SRBs come in various types occurring over a range of frequencies and observable variability in amplitude [2]. SRBs are bright and commonly occurring solar events that deviate significantly from the ambient noise of a quiet Sun at meter and decameter wavelengths. Due to the increase in amplitude, SRB emissions (e.g., shock waves, solar energetic particles, and coronal mass ejections) can have a significant impact on the space weather environment and thus on the capabilities, performance, and longevity of our space-based systems [3].

Our space-based systems are necessary for both commercial and military operations and SRBs have shown to cause significant disruptions in their performance. One of the most noticeable disruptions SRBs have on space systems is the interference of the processes performed by the Global Positioning System (GPS). In December of 2006, a series of three bursts were seen to have saturated all RSTN L band radiometers, as the Owens Valley Solar Observatory recorded the bursts to have peaks in upwards of 10^6 solar flux units (sfu) [4]. Solar flux units ($1 \text{ sfu} = 10^{-22} \text{ W/m}\cdot\text{Hz}$) are used as a measurement of the flux density of radio emission energy propagating from the Sun as it is received back at Earth [5]. Similarly, in September of 2011, a burst in excess of 10^5 sfu was recorded to cause some disruption to the GPS network [6] and even smaller bursts around 20,000 sfu were reported to have an impact on GPS [7]. According to Giersch et al., there appears to be a threshold of 10^5 sfu that causes a definitive degradation on the global navigation satellite system (GNSS) and lesser effects occurring at spectral flux densities below that [8]. Type III SRBs, the burst of interest for this study, have been recorded to have spectral flux densities ranging from around 10^3 to 10^6 sfu within the high frequency (HF) range, well within the range to disrupt GPS networks orbiting Earth. As these SRBs can be a source of detrimental interference, the strength of these signals has also allowed them to be detected by active

radars. Furthermore, there is interest in using SRBs as a potential source for passive radars.

1.2 Solar Observatories and the Mars Reconnaissance Orbiter

In November of 1994, the National Aeronautics and Space Administration (NASA) launched the WIND spacecraft with the primary objective of “providing complete plasma, energetic particle, and magnetic fields for magnetospheric and ionospheric studies” and “to investigate basic plasma processes occurring in the near-Earth solar wind” [9]. In October of 2006, NASA launched the Solar Terrestrial Relations Observatory (STEREO, shown in Figure 1.1[b]), one trailing ahead of Earth’s orbit (STEREO-A), and the other trailing behind (STEREO-B) [10], in order to “study the structure and evolution of solar storms as they emerged from the Sun” [11]. In previous studies, these systems have provided insights into solar propagation physics; however, they are limited in their ability to study the effect of solar propagation physics with regards to planetary bodies.

In August of 2005, NASA then launched the Mars Reconnaissance Orbiter (MRO), shown in Figure 1.1[a], as a multipurpose spacecraft to study the Martian surface, atmosphere, and probe underground in order to gain more information of the distribution and history of Mars’ water, whether frozen, liquid or vapor [12]. MRO is equipped with the Shallow Radar (SHARAD) instrument that is designed to look for a variety of dielectric contrasts (e.g., water, carbon dioxide deposits, etc.) in various states of matter approximately within the first kilometer of Mars’ crust [13]. SHARAD operates as an active radar instrument but contains the potential for novel passive applications [14] and more recently as a potential solar observatory [15].

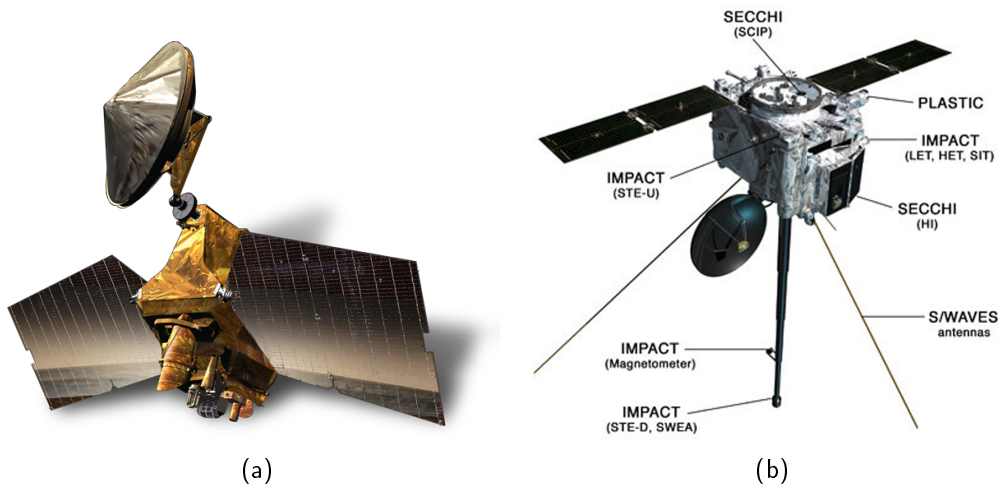


Figure 1.1. (a) The Mars Reconnaissance Orbiter (MRO) was launched in 2005 in order to study the Martian surface; (b) the Solar Terrestrial Relations Observatory (STEREO) was launched a year later in 2006 in order to study solar events. Source: NASA [10], [12].

1.3 Active and Passive Radar Sounding

As an example of active radar sounding, the Mars Advanced Radar for Subsurface and Ionosphere Sounding (MARSIS), a low-frequency active radar on the Mars Express spacecraft, is being used to observe the presence of possible liquid water trapped in the ice caps on Mars [16]. Similar observations have been carried out on Earth and radar data collected above the polar ice sheets were processed through a combination of qualitative (the morphology of the bedrock) and quantitative (the reflected radar peak power) analyses [17], [18]. Roberto Orosei, the principal investigator of the MARSIS radar program, also notes that MARSIS has a radar footprint of approximately three to five kilometers, but does not provide a high spatial resolution. This low spatial resolution significantly limits the ability for MARSIS to discriminate the presence of sub-glacial water bodies, as shown in Figure 1.2, from the shape of the basal topography [19]. To unambiguously detect liquid water at the Martian poles, a quantitative estimation of the permittivity of the basal material must be accounted for in order to determine the strength of the radar echo [16].

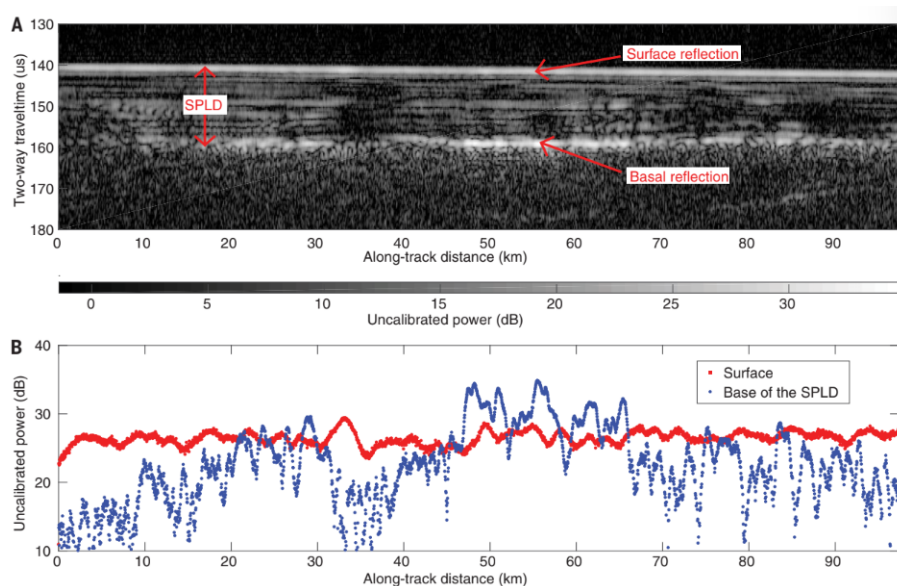


Figure 1.2. MARSIS data showing surface and basal reflection with unverified composition. Source: Orosei et al. [16].

Active radar is composed of both transmit and receive windows whereas passive radar only has a receive window for recording a signal of opportunity at the source. Passive sounding has been successfully demonstrated terrestrially and has been proposed on other planetary bodies, such as Mars, Europa, and Jovian moons (i.e., Io). Research into passive sounding using ambient radio noise vice traditional passive radar that uses anthropogenic signals (FM, GNSS, etc.) is a relatively recent endeavor and requires further study. Benefits of passive radar include lower resource loads as there is no energy required to transmit a high-power signal. In addition, there are potentially lower cost requirements as the transmitting equipment would not need to be transported with future spacecraft. By using Type III SRBs as a passive source, the objective would be to record a reliable ambient source for detecting reflections off planetary surfaces to reduce cost and power consumption. However, one of the main challenges of passive sounding is the spatial coherence resolution and an adequate determination of what properties of Sun-observing spacecraft, known as solar observatories, and spacecraft observing solar phenomena around planets must be to provide the most promising results.

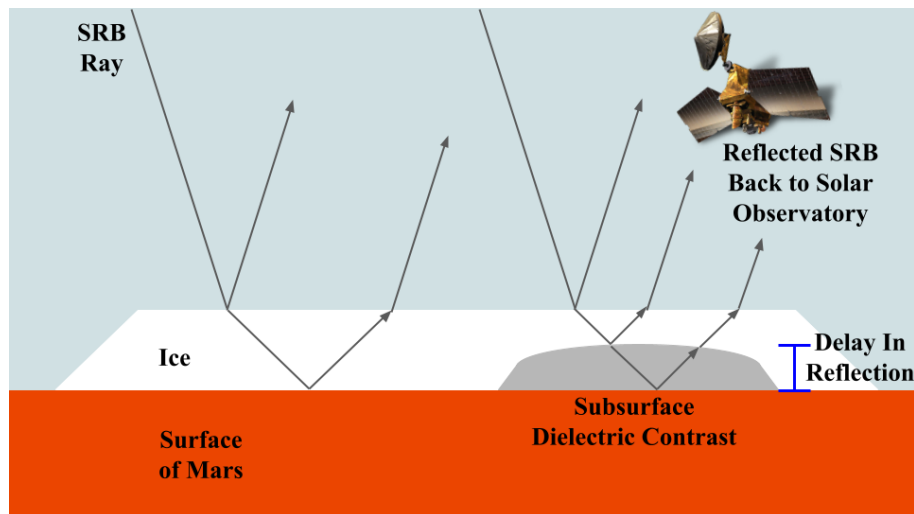


Figure 1.3. Radar sounding, whether active or passive, operates to understand the composition of a surface; in this example, the active MARSIS and SHARAD radar systems are interested in exploring the Martian surface and subsurface. In the case of passive sounding using SRB events, a burst would propagate from the Sun and reflect directly off an unimpeded surface. When the burst comparatively propagates through a medium, such as an ice layer, the burst loses some energy as there is a component of transmission and attenuation through the ice resulting in a delay in reflection back to a detecting instrument. At a solar observatory, a direct incoming wave from the Sun can then be cross-correlated with reflected waves off the surface and reveal features of said surface.

1.4 Motivation

For this research, the intended use of these solar observatories when placed in conjunction with MRO/SHARAD is to study both solar bursts and solar phenomena from the perspective of burst propagation physics and from the perspective of the Martian surface as potential means for future subsurface sounding missions. This is a novel application of SHARAD as it was primarily designed to study the geology of Mars using active radar in order to survey the Martian surface in search for subsurface dielectric contrasts such as water. The properties of the aforementioned solar observatories and MRO/SHARAD spacecraft that may lead to better understanding of SRBs and their relation to passive subsurface sounding on Mars are the orientation of the MRO spacecraft, true anomaly difference between MRO

and STEREO or WIND, and the peak solar power recorded by MRO after being reflected off the surface of Mars. Previous efforts have looked at MRO/SHARAD to use passive means for subsurface sounding of water by investigating SRBs. Although initial attempts of similar research were unsuccessful, the authors noted that one could still potentially use MRO/SHARAD for studying the burst characteristics directly [14], [15].

1.5 Thesis Organization

The objective of this thesis is to conduct a statistical analysis of solar observatory and MRO properties such as the (1) spacecraft orientation, (2) true anomaly difference, and (3) the SRB peak power output during Type III solar radio burst events to better understand SRBs and solar propagation physics and to improve the potential for subsurface sounding through the Martian surface. The following thesis is comprised of four additional chapters. Chapter II offers a more detailed discussion of solar radio bursts and the specifications of the environment and instruments used to conduct this research. Chapter III discusses the data collection process and observations made based solely from the initial geometry of the spacecrafts. In Chapter IV a detailed analysis of the statistical techniques used and the performance of such models is provided. Finally, in Chapter V a summary of the results found is provided alongside potential improvements for future work.

CHAPTER 2:

Fundamentals of SRBs and Spacecraft Properties

2.1 Solar Radio Bursts Types

SRBs can range from Type I to Type V depending on their observed dynamic spectrum [20]. For example, a Type II burst (shown in Figure 2.1[a] and [b]) is commonly seen in conjunction with solar flares and has shorter pulse durations, while a Type IV burst (shown in Figure 2.1[b]) is strongly correlated with large solar flares of longer durations. For Type III SRBs (shown in Figure 2.1[a] and [c]), electrons are accelerated ($v \approx 0.03$ to 0.3 c) from active regions of the Sun and travel outward along magnetic field lines to lower electron density areas within the interplanetary medium. As the electrons are traveling along this path, rapid oscillations of the electron density, known as Langmuir waves, are then partially converted into radio emissions [21], which can be detected by solar observatories. In this research and previous complementary work, Type III SRBs are the focus of observation for three main reasons: (1) they tend to propagate early in the rise of impulsive solar flares [2], (2) they have a distinct shape [15], and (3) are broadband enough to be seen in the hectometric wavelength range, and likely the decametric range as well. These factors are beneficial as they allow for tailor-made algorithms to be formulated in order to find and research Type III SRBs.

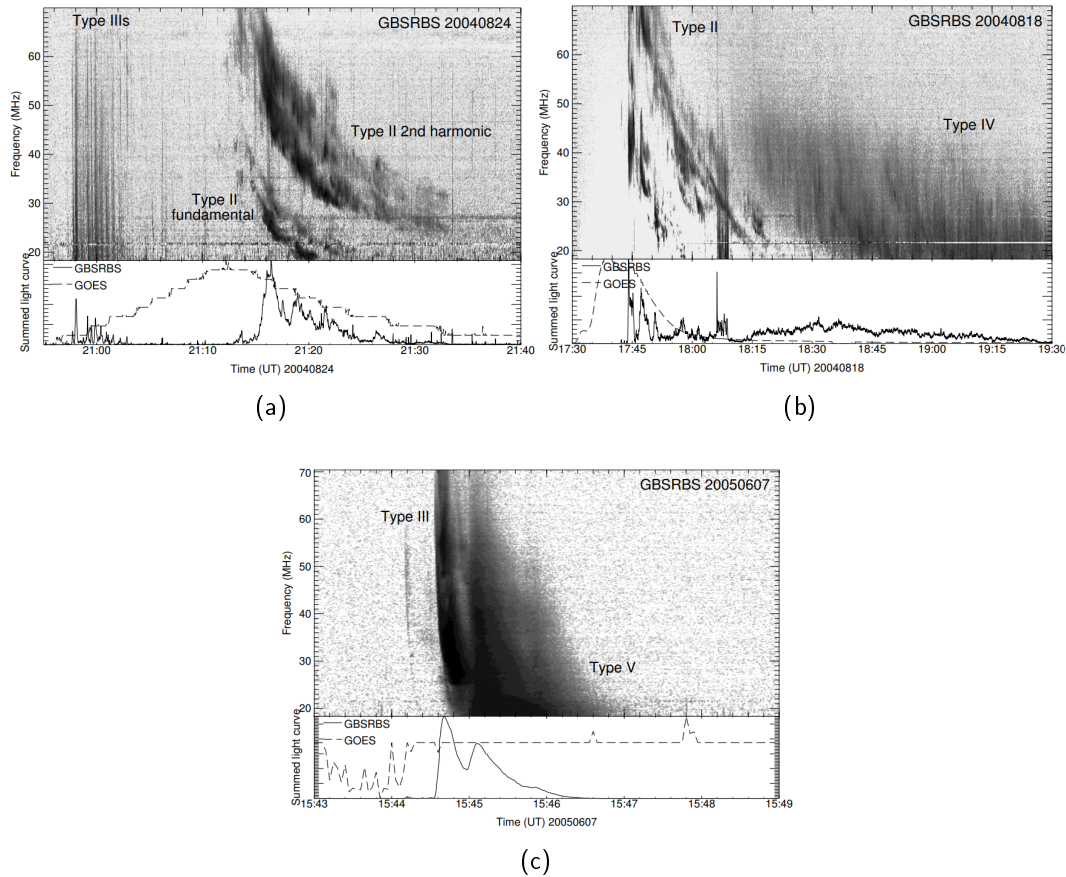


Figure 2.1. The radio spectra shown were acquired through the Green Bank SRB Spectrometer in West Virginia to compare and study the different phenomena of SRB types. (a) This spectra recording on 24 AUG 2004 shows a Type III burst at 21:00:00 and two variants of a Type II burst occurring at 21:15:00. (b) This spectra recording on 18 AUG 2004 again shows a Type II burst occurring at 17:32:00 due to the background noise level beginning to drop but also a Type IV burst propagating for the duration of the recording. (c) The spectra recording on 07 JUN 2005 shows a Type III burst at 15:44:30 which proceeds a Type V burst that lasts for a short time 15:45:00 to 15:46:30. Source: White [2].

In order to visualize what the frequency content looks like over a given time frame, spectrograms are used to do so for any given SRB event. The purpose of using these spectrograms is to observe the dynamic solar spectrum in the frequency range of interest (~13-27 MHz)

and detect Type III bursts based on their characteristic spectrum shape. These spectrograms are produced by applying a Fast Fourier Transform to a time signal [22] and expressed on a plot of time (on the x-axis) versus frequency (on the y-axis) with the power expressed through a color scale. The spectrograms, shown in Figure 2.2 and 2.3, are produced by cross-correlating a reference SHARAD signal with the measured signal being propagated from the Sun. In Figure 2.2, examples of spectrograms recorded by MRO (Figure 2.2[a]) and STEREO (Figure 2.2[b]) of a type III SRB exemplifies the significant difference in temporal resolution between the spacecraft. In Figure 2.3[a], an example of a range-compressed spectrogram is shown and displays the delay in the return signal (τ) that is reflected from Mars. For strong enough bursts, a reflection can be seen as shown by the horizontal line seen at around $100 \hat{\text{A}}\mu\text{s}$. The horizontal lines seen on the frequency spectrogram are products of electromagnetic interference and their complete effect on the collection of SRBs is unknown and a topic of interest for future research. In addition, for the spectrograms shown in Figure 2.2 the power is denoted in decibels (dB); however, due to discrepancies in the antenna beam pattern of SHARAD, the power collected is uncalibrated due to not being characterized on the ground as it is large in size and operates at long wavelengths [23] and causes some uncertainty with the values shown. Determining the power scale is also a subject of future work as it will allow for the most accurate values of SRB power.

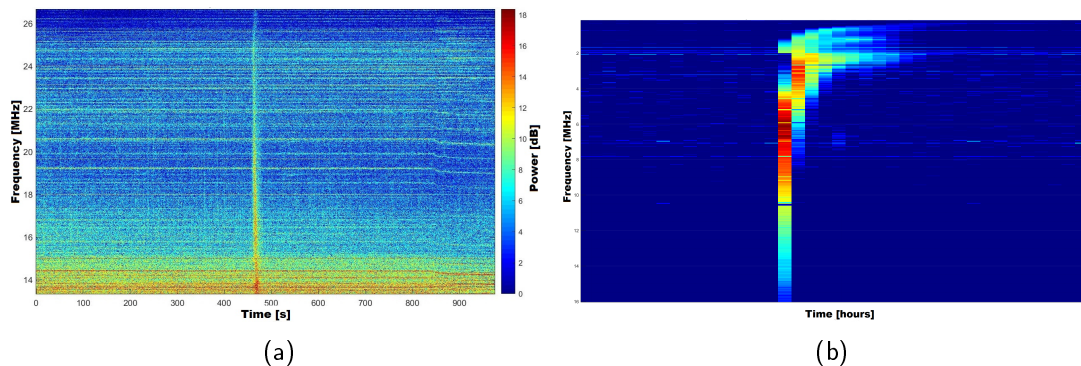


Figure 2.2. (a) Example of a SHARAD product occurring on 22 DEC 2011 from the time of 13:44:03 to 14:00:19 and (b) is an example of a STEREO-A calibrated product of the same Type III SRB. The frequency axis is inverted for the STEREO products. The SHARAD product has the advantage of higher temporal resolution allowing for the signal to be more accurately deconvolved to expose the SRB signal. Source: Gerekos et al. [15].

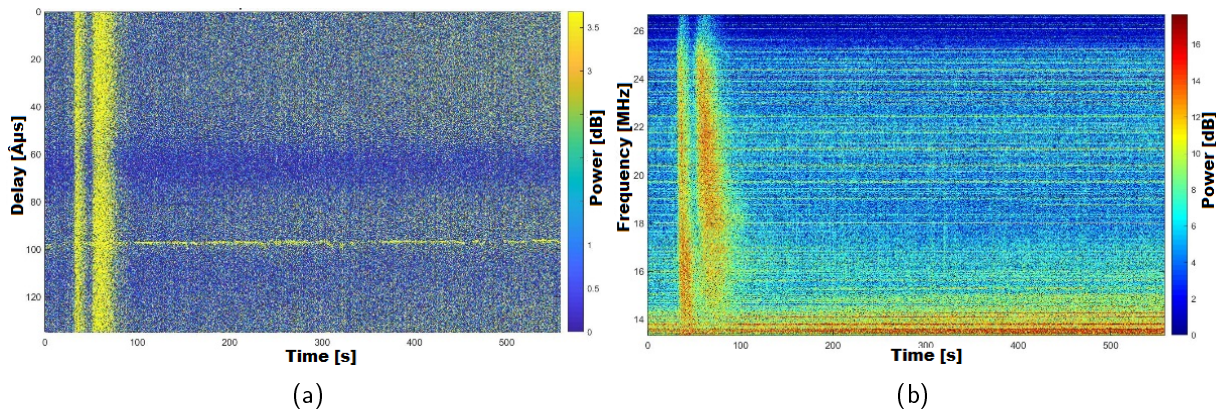


Figure 2.3. (a) Example of the range compressed experiment data record (EDR) signal coming from SHARAD with the delay ($\hat{\mu}s$) expressed on the y-axis, time (s) on the x-axis, and power (dB) on a color-scale. (b) Example of the power spectrogram of the same burst coming directly from the Sun occurring on 30 DEC 2020 with the frequency (MHz) on the y-axis, time (s) on the x-axis, and power (dB) on a color-scale. Source: Gerekos et al. [15].

2.2 Solar Mission Specifications

Each of the spacecraft used to observe SRBs (WIND, STEREO, and MRO) are equipped with instruments that operate within Type III SRB frequency propagation ranges. The WIND spacecraft is equipped with two radio receivers covering 2 separate frequency bands. The WIND radio receiver band 1 (RAD1) has a frequency range of 20–1040 kHz with a bandwidth of 3 kHz. Additionally, the WIND radio receiver band 2 (RAD2) has a frequency range of 1.075–13.825 MHz with a bandwidth of 20 kHz [24]. Each STEREO solar observatory is equipped with a low frequency receiver (LFR) rated for 2.5–160 kHz, a high frequency receiver (HFR) rated for 125 kHz–16 MHz, and a fixed frequency receiver (FFR) rated for 30 or 32 MHz [21]. The emitted chirp of SHARAD, equipped on MRO, operates in a frequency range of 15–25 MHz and the receiver is sensitive to frequencies of 13.3–26.7 MHz. Furthermore, MRO/SHARAD orbits at an altitude of 300 kilometers above Mars' surface [25] allowing the observation of prominent Type III SRBs as they propagate up to approximately 27 MHz.

Table 2.1. SHARAD Instrument Parameters

	Frequency Range (Transmit/Receive)	Vertical Resolution	Horizontal Resolution (along track × cross track)	Penetration Depth
SHARAD	15–25/13.3–26.7 MHz	~7.5 m*	0.3–1 km × 3–7 km	~0.1–1 km

*10 MHz Bandwidth

Adapted from: Seu et al. [25].

Additionally, the receivers on the STEREO/Waves instruments are designed to have direction finding capabilities, also known as gonio-polarimetric (GP) capabilities. The receiver inputs that are observed consist of the direction of arrival, polarization state, and the flux of the observed electromagnetic wave and are retrieved quasi-instantaneously, as listed by Cecconi et al. [21]. However, they note that receiver inputs do not consider any propagation effects (such as refraction and diffusion) as GP techniques can measure only the direction of the local wave vector.

2.3 Reference Frame Discussion

For this thesis, the collection and analysis of solar observatory properties has initially been in reference to an assumed general solar spatial frame. However, after further analysis of the data collected, it is more accurately represented in reference to what is known as the J2000 reference frame, modeled in Figure 2.4[a]. As defined by the Navigation and Ancillary Information Facility (NAIF), under the direction of NASA’s Planetary Science Division, a reference frame is “an ordered set of three mutually orthogonal (possibly time-dependent) unit-length direction vectors coupled with a location called the frame’s ‘center’ or ‘origin’” [26]. The location of the center of a reference frame is concurrent with the origin of the frame which is defined as (0, 0, 0). While the center of a given frame does not hold a significant role in the specification of celestial states, it can be used in computing light time to centers of non-inertial frames. In this thesis, internal frames are utilized whereas non-inertial frames are useful for fixed-body and dynamic frame analysis. An inertial frame

is defined as being non-rotating with a non-accelerating origin. An example of this would be the J2000 reference frame [26].

The J2000 frame is defined by its basis on the Earth's equator and equinox. These are determined by observing the motion of Earth and other complementary celestial parameters. The term J2000 is in reference to the zero epoch of the ephemeris time system, which was initialized on 01 JAN 2000 (12:00:00). The International Celestial Reference Frame (ICRF), a frame that is similar to the J2000 frame modeled in Figure 2.4[b], is defined slightly differently as it includes the locations of 295 extragalactic radio sources. The biggest difference between the two is that of a small rotational offset of less than 0.1 arc seconds, but since it is such a small deviation J2000 and ICRF are utilized interchangeably. All data collected used to determine burst candidates that is in reference to the J2000 frame is also in reference to the ICRF [26].

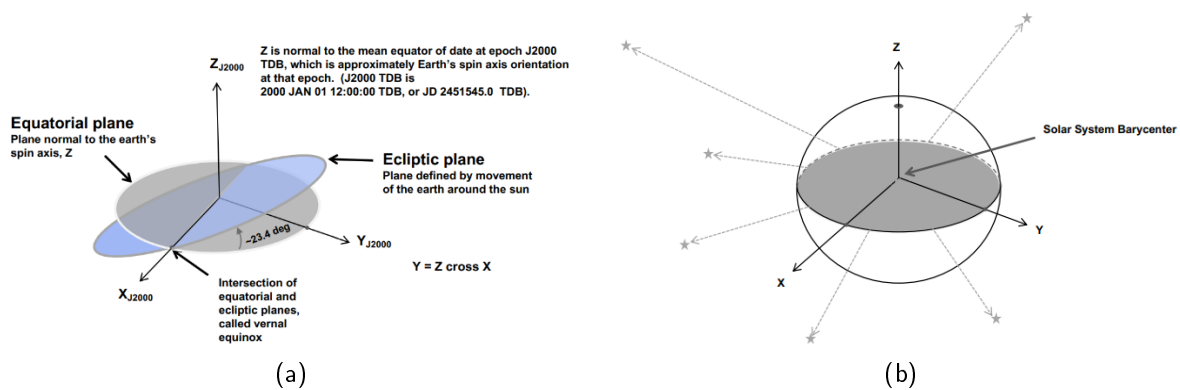
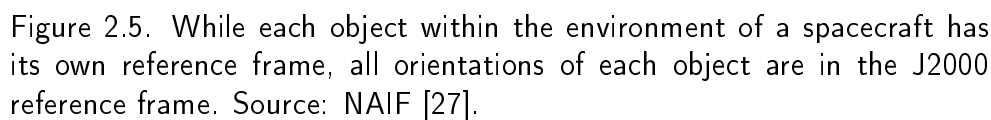


Figure 2.4. (a) The J2000 frame is comprised of an equatorial plane and an ecliptic plane that sits at about a 23.4 degree offset. (b) The ICRF frame is different in the case that it is not defined by the equatorial and ecliptic planes but by extragalactic radio sources throughout space. Source: NAIF [27].

The center of this reference frame is with respect to the Sun as it will be described as a fixed celestial body. There is a potential limitation in analyzing with slight difference in reference frames as it may not provide a completely accurate description of the orientation and position of the solar observatories. Future work may look into the complete significance of a general solar reference frame and the J2000 reference frame.



All properties for the solar observatories are collected through an algorithm designed by NAIF known as Spacecraft, Planet, Instrument, C-Matrix (camera-matrix), and Events, or SPICE [27]; in addition, SPICE data that is in reference to the J2000 reference frame is also in reference to ICRF. SPICE has the ability to compute observation geometry properties at any given time, which is useful in finding the orientation of the solar observatories. SPICE data is stored in various kernels that can be exploited by users and passed through user geometry programs (via MATLAB, Python, etc.) in order to get the desired geometry properties that can then be analyzed, in this case for the use of a statistical analysis.

13

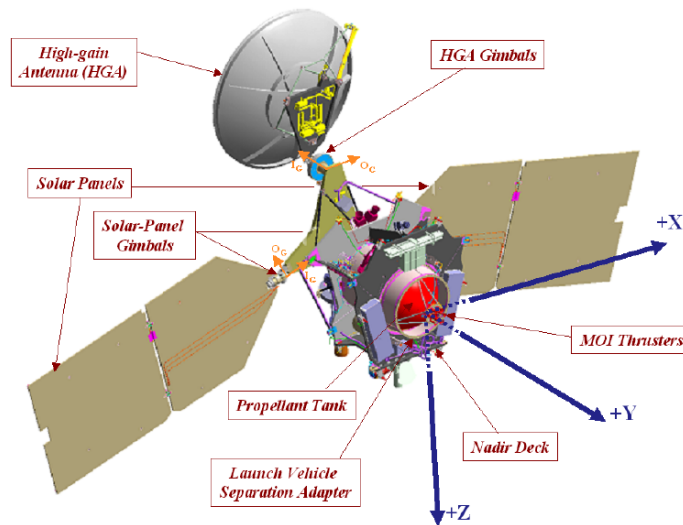


Figure 2.6. MRO with yaw (along the Z-axis), pitch (along the X-axis), and roll (along the Y-axis) defined. Source: Tung-Han You [28].

are represented in the J2000 reference frame and have the Z-axis of MRO co-aligned with the center of Mars. The second property that will be looked at is the MRO-Source angle as it is the angle between either WIND, STEREO A/B, and MRO with the Sun as the origin; this is also referred to as the true anomaly difference. For this analysis, the position vector and the X-axis of MRO are both within the same plane that contains the Z-axis and velocity vector of MRO that are oriented with respect to the center of Mars [23]. Describing freely moving crafts such as MRO are commonly oriented in this manner when placed in a three-dimensional space as it provides a more accurate definition of the position of said craft.

CHAPTER 3:

Observing Geometrical Effects on Burst Detection

3.1 Data Collection Process: Determining Bursts Candidates

A modified version of this section was submitted as: Christopher Gerekos, Gregor Steinbrügge, Immanuel Christopher Jebaraj, Andreas Casillas, Elena Donini, Beatriz Sánchez-Cano, Mark Lester, Jasmina Magdalenic, Sean T. Peters, Andrew Romero-Wolf, and Donald D. Blankenship, “Observation of solar radio burst events from Mars orbit with the Shallow Radar instrument,” to *ApJ Letters*, May 2023 [3].

In order for SRBs to be classified as a burst by MRO/SHARAD, a candidate must be verified through the following conditions in order to reject solar prominences due to interference or instrument malfunction. First, by using a 3-step fuzzy logic algorithm developed by Gerekos et al., the shape of a Type III burst must sufficiently match a set of predetermined conditions used to test for the flatness and asymmetry of the peak of a given burst as well as the high frequency content. One of the conditions for a burst to occur is that there must be a significant amount of energy above the noise floor detected at a minimum frequency of 10 MHz, which can also then be observed by other solar observatories. From this process, STEREO-A detected 5676 bursts, STEREO-B detected 4340 bursts, and WIND detected 3538 bursts; in total these 13554 bursts are suitable for SHARAD to detect [3]. Second, the time of arrival of a burst at Mars (t') must be predicted. Additionally, there is a time of detection at Mars (t) and delay in signal (τ). The supposed time of arrival at Mars (t') must fall between the start and stop time of a given SHARAD product, meaning that SHARAD must be turned on. Thus, to predict the time of arrival the difference in radial distance, with respect to the Sun between MRO and a given solar observatory, is measured with the equation,

$$t' = t + \tau$$

$$t' = t + (|x_M - x_S| - |x_W - x_S|)c^{-1}$$

$$t' = t + (r_M - r_W)c^{-1}. \quad (3.1)$$

x_M , x_S , and x_W represent the position of a given solar observatory (STEREO A, B, or WIND) while r_M and r_W are the radial distances from the Sun. The final step is to ensure that the Sun is not occulted by Mars as it is seen from MRO at t' . After these conditions are applied, only 226 SHARAD candidates and 179 SHARAD products were deemed viable for analysis within the conditions that have been set [3].

3.2 Histogram Analysis of True Anomaly Difference and MRO Axial Dynamics

A modified version of this section was submitted as: Andreas Casillas, Sean T. Peters, Gregor Steinbrügge, Elena Donini, Immanuel Christopher Jebaraj, Jasmina Magdalenic, Andrew Romero-Wolf, Donald D. Blankenship, Christopher Gerekos, “A Preliminary Statistical Analysis of Type-III Solar Burst Detections in Mars Reconnaissance Orbiter (MRO) Shallow Radar (SHARAD) Data,” International Geoscience and Remote Sensing Symposium (IGARSS), Accepted 2023.

This portion of the study begins by establishing a basis for burst detection by analyzing each property individually. This is first done by organizing burst candidates within a normalized one-dimensional histogram which describes the frequency of which they occur at varying angles, as well as when they are classified as either a YES or NO burst. A YES classified burst is defined as an SRB event in which the conditions in Section 3.1 (significant energy above the noise floor is detected, the SHARAD instrument is enabled, and MRO is not occulted by the Sun) are met as well as a burst truly occurring at the Sun and is recorded. Alternatively, a NO classified burst is defined as a candidate that meets the same conditions and should be receiving a burst but does not record one during the time that MRO/SHARAD is enabled.

Burst detection can be influenced by true anomaly difference, the angle between MRO and

STEREO/WIND with the Sun as the origin. As seen in Figure 3.1[a], a noticeable trend emerges as there are more YES classified bursts when the true anomaly difference is low. This region occurs most frequently in the provided data set between the angles of 0° and 80° . Due to this, it shows that when MRO is in close proximity to a STEREO or WIND observatory, the likelihood of a Type III burst detection increases. This is supported by the understanding that as a burst propagates from a specific sector of the Sun, it can be better seen by both MRO and STEREO/WIND thus performing as a double confirmation of that burst occurring and being reflected off the surface of Mars. NO classification is more likely to happen when MRO (and subsequently Mars) approach 180° which would place both entities on the other side of the Sun opposite of STEREO or WIND, completely out of view.

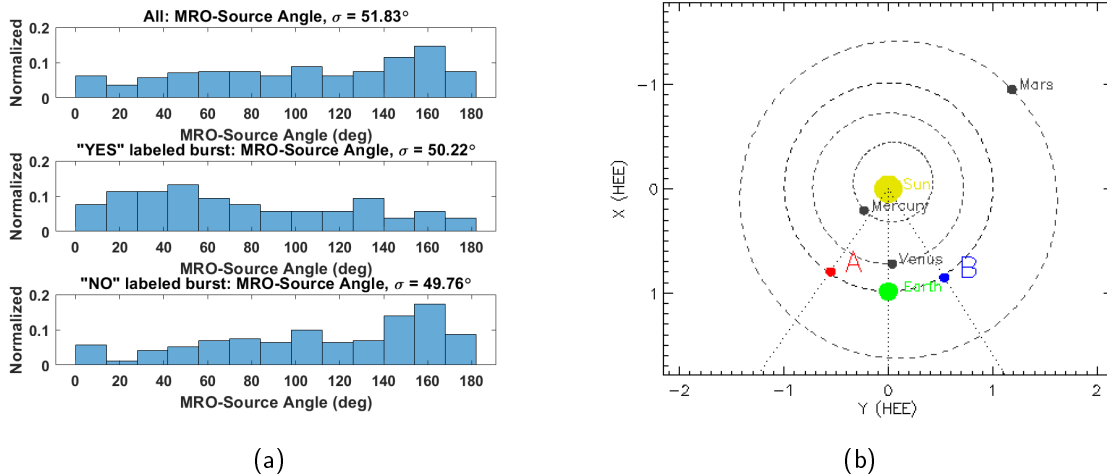


Figure 3.1. (a) Normalized histogram of the true anomaly difference (MRO-Source angle) for all candidates, YES classified candidates, and NO classified candidates. All histograms have a bin width of 14. (b) Example of how true anomaly difference is viewed as the angle between MRO, which orbits Mars, and either STEREO-A, STEREO-B, or WIND (not shown) with the Sun as the origin. Source: Thompson [29].

Burst detection also is significantly impacted by the effect of the pitch, roll, and yaw properties of MRO. When observing the pitch axis in the first column of Figure 3.2, a majority of YES classified bursts occur when the pitch angle is high, being above 0° . The highest density of these bursts are within the range of 20° to 80° , with a total standard

deviation of 32.11° . Conversely, bursts appear to more likely to be classified as NO (as seen from MRO) when the pitch angle is low, ranging from -60° to -15° , with a total standard deviation of 31.01° .

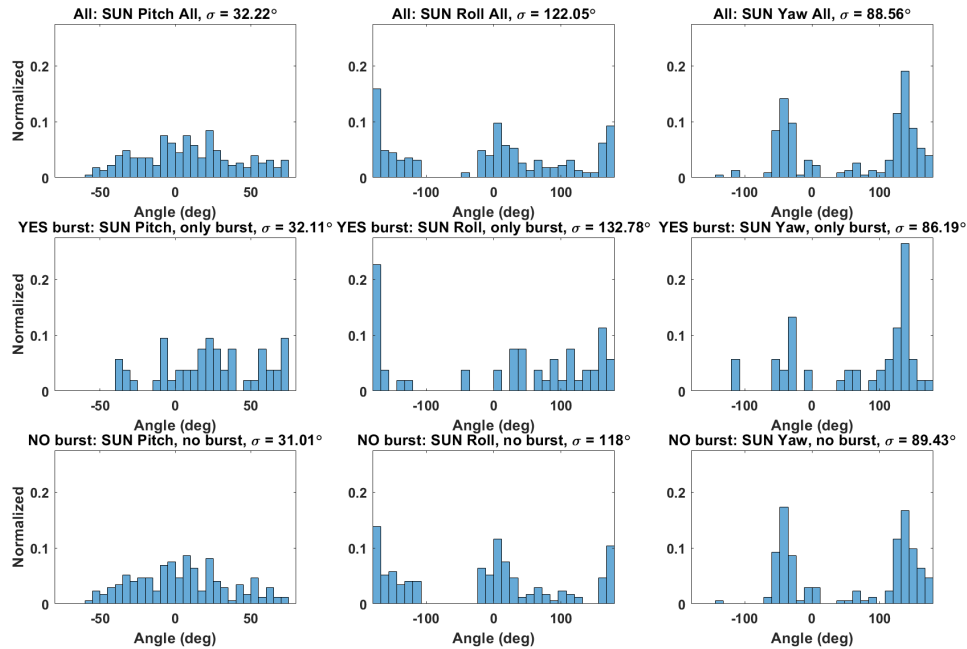


Figure 3.2. A 3x3 normalized histogram grid displaying the frequency of SRB occurrence for the yaw, pitch, and roll angles. Each is displayed for all bursts, YES classified bursts, and NO classified bursts. The histograms have a bin size of 12.

When observing the roll axis in the second column of Figure 3.2, there are two distinct groups of roll angles where candidates are collected. The first section of candidates ranges from -180° to -100° and the second section ranging from -25° to $+180^\circ$. For both classes, YES and NO, this large spread in candidate data results in large standard deviations of 132.78° and 118.0° respectively. It is difficult however to observe a significant qualitative distinction between the YES and NO classification groupings as the standard deviation is so large and the classes occupy the same regions with similar patterns. However, what can be observed is that the NO classified bursts appear to be dominate slightly more at the roll origin of 0° and occur more frequently within the first section of candidates. In addition,

the YES classified bursts slightly occur more frequently at the far end of -180° and in the second section of candidates (between -25° to $+180^\circ$); however, it is difficult to determine burst detection solely based on the roll angle.

Similar to the roll axis, two sections of yaw angles (shown in the third column of Figure 3.2) emerge when observing burst candidates. The first section centers around -50° and the second section centers around $+150^\circ$. The YES classified bursts have a standard deviation of 86.19° and the NO classified bursts have a standard deviation of 89.19° . Here, it is more difficult to determine any dependence of yaw angle on burst classification as the YES and NO classes appear to happen within the same sections and with similar frequency. Within the population of candidates along the yaw axis, there are slightly more NO classifications around -50° and more YES classifications around $+150^\circ$ however, this may change with an increase in candidate population size.

When analyzing the position of MRO with respect to STEREO or WIND and the yaw, pitch, and roll properties of MRO individually it is possible to see the beginnings of what angles are most prevalent to burst detection. A significant dependence trend emerges when the true anomaly difference is low as the number of YES classifications are more prominent when MRO and STEREO/WIND are oriented in such a way. Observation of the pitch angles also provides a strong dependence when setting a distinction between YES and NO classifications. The yaw and roll axes are similar as there is a pattern of two groups emerging but it is difficult to determine whether or not is altering the yaw and/or roll will positively or negatively affect MRO when detecting SRBs. These ambiguities along with analyzing the single property histograms, highlight the need for comparative analysis between the properties which is the focus of the following section.

3.3 Comparative Scatter Plot Analysis of True Anomaly Difference and MRO Axial Dynamics

By comparing each of the properties of MRO (true anomaly difference, yaw, pitch, and roll) more insight can be gained as to how the addition of a second property dimension alters SRB classification analysis. By observing the pitch vs. true anomaly difference scatter plot in Figure 3.3[a], the YES classified bursts tend to populate most frequently when the true anomaly difference is below 100° and when the pitch angle above 0° . In addition, when

observing the yaw vs. true anomaly difference scatter plot (shown in Figure 3.3[b]), the pattern of two main groups of burst candidates emerge once again along the yaw angles of -50° and $+150^\circ$; again, more YES classified bursts are seen in the yaw figure when the true anomaly difference is small. To highlight next, a unique result was obtained when scattering the roll vs. true anomaly difference (as shown in Figure 3.3[c]). Three main groups of burst candidates are observed in this roll vs. true anomaly difference scatter plot: the first from -180° to -100° , the second from -25° to $+50^\circ$, and the third from $+150^\circ$ to $+180^\circ$. In addition, it is highlighted that there are nearly zero YES classifications when the roll angle is between -180° to 0° and when the true anomaly difference is between 90° to 180° . This region forms a well-defined array of angles where a NO burst classification can be inferred.

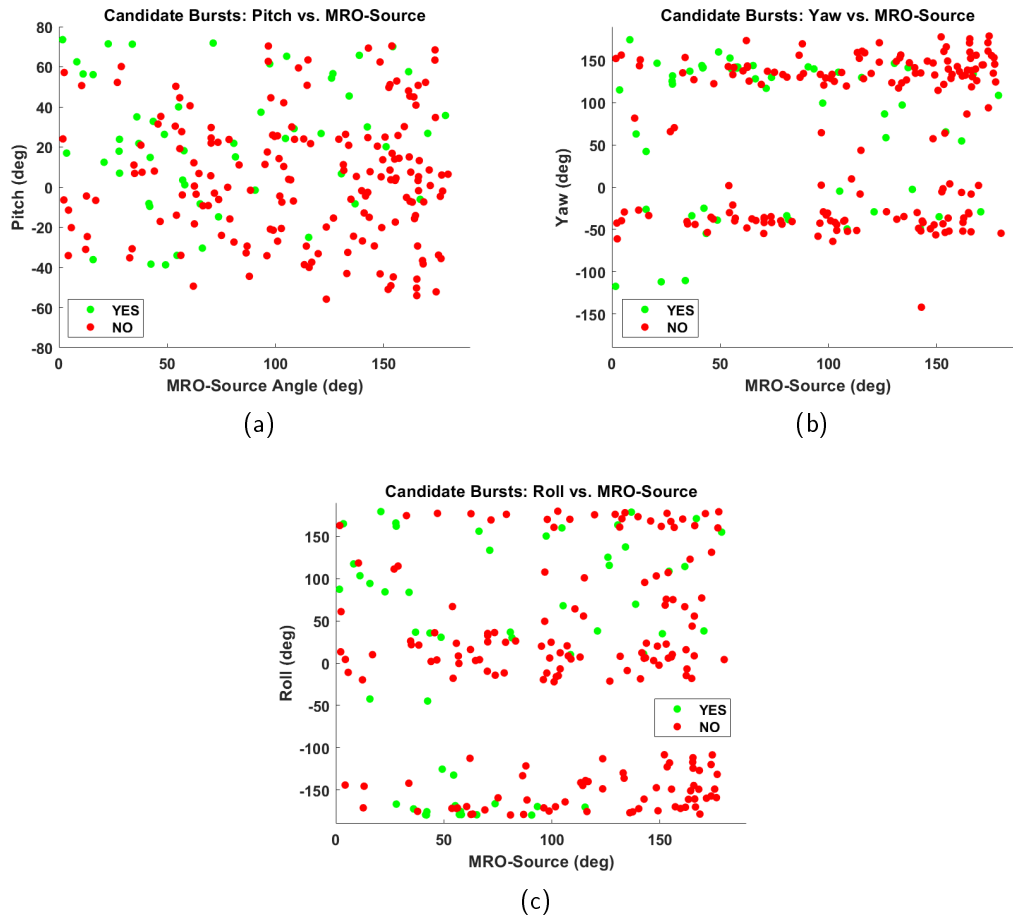


Figure 3.3. Distribution of burst candidates, YES or NO, when plotted along either the (a) pitch vs. true anomaly difference, (b) yaw vs. true anomaly difference, or the (c) roll vs. true anomaly difference. For the initial scatter plots the green markers indicate YES classifications and red indicate NO classification.

As each axial property is scattered in relation to the other axial properties, similar patterns that were discovered previously through the histograms (Figures 3.1[a] and 3.2) and scatter plots (Figure 3.3) emerge, once again strengthening the previous conclusions. In Figure 3.4, burst classification can be observed between two axial properties and covers a portion of the perspective of MRO and can provide a second dimension to improving burst classification that was initially analyzed through histograms and true anomaly difference comparison.

Viewing MRO from the roll-pitch orientation, a greater percentage of YES classified bursts are observed when the roll of MRO is high, $\pm 100^\circ$, and the pitch angle is above the origin of 0° . Viewing MRO from the pitch-yaw orientation also confirms that more YES classified bursts are made when the pitch angle is high as approximately 75% of the currently YES classified bursts are above a pitch degree angle of 0° . Additionally, viewing MRO from the roll-yaw orientation highlights two main groups of labeled bursts: the first when the roll angle is low (occurring between -180° to -100°) and the yaw angle is high (occurring between $+100^\circ$ to $+180^\circ$), and the second when both the roll and yaw angles span from around -50° to $+180^\circ$. While there are a few YES classified burst outliers in the three scatter plots, in general there is a potential pattern of pitch angle dependence on YES vs. NO classification. While there appear to be unique scatter patterns of the plots (either the S shapes of the roll vs. pitch and pitch vs. yaw plots or the grouping of the roll vs. yaw plot) the actual regions of positive burst detection could be confirmed with a larger population of SRB candidates. This will in turn require further analysis to positively relate accurate burst detection with respect to each MRO axial property and could be done by computationally analyzing the current data set.

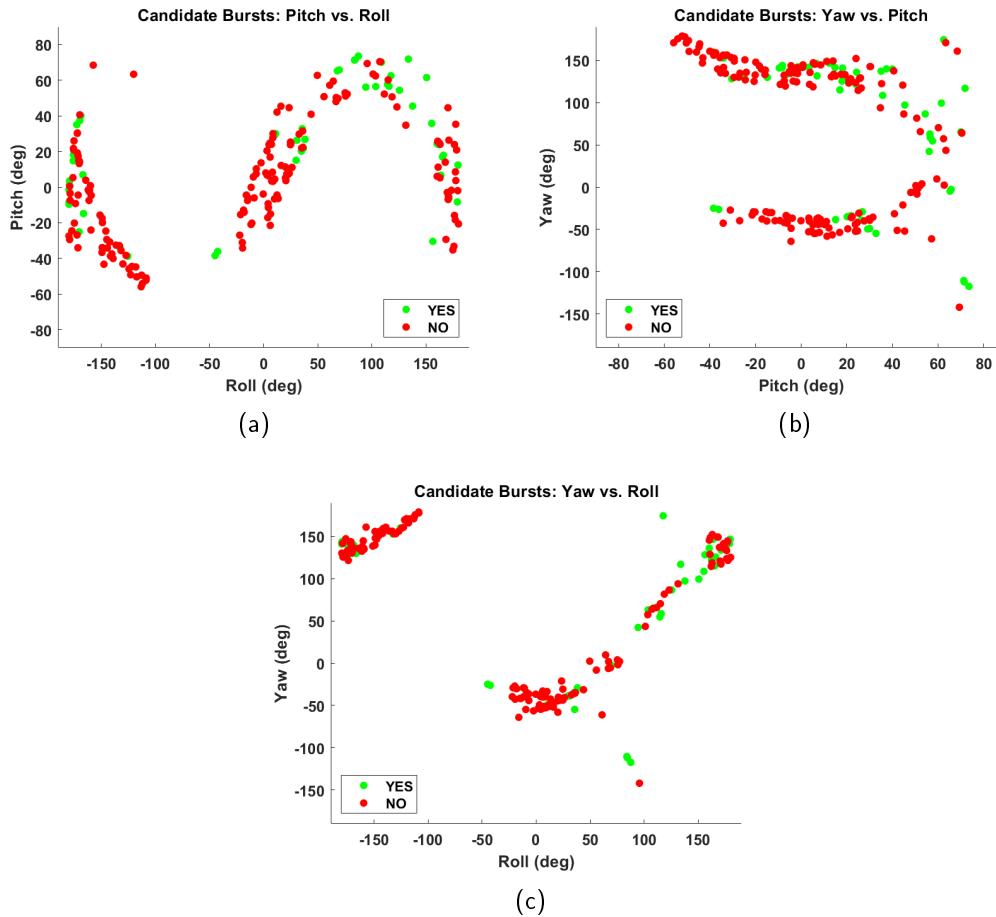


Figure 3.4. Distribution of burst candidates, YES or NO, when plotted along either the (a) pitch vs. roll axes, (b) yaw vs. pitch axes, or the (c) yaw vs. roll axes.

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CHAPTER 4:

Statistical Analysis for SRB Classification

4.1 Performance of Two-Dimensional Logistic Regression

A modified version of this section was submitted as: Andreas Casillas, Sean T. Peters, Gregor Steinbrügge, Elena Donini, Immanuel Christopher Jebaraj, Jasmina Magdalenic, Andrew Romero-Wolf, Donald D. Blankenship, Christopher Gerekos, “A Preliminary Statistical Analysis of Type-III Solar Burst Detections in Mars Reconnaissance Orbiter (MRO) Shallow Radar (SHARAD) Data,” International Geoscience and Remote Sensing Symposium (IGARSS), Accepted 2023 [30].

One of the main goals of this thesis is to analytically classify a burst with the properties provided thorough MRO/SHARAD. One of the binary classification algorithms that is utilized in order to do so is known as a two-dimensional logistic regression which takes the form of a linear classifier. A logistic regression algorithm is defined as a discriminative classifier as it only segregates two properties based on a combination of inputs but does not have the capability to decipher the exact differences between them and generate an original event [31]. For example, the logistic regression algorithm separates between the classes, YES and NO, but cannot provide the exact qualities of a Type III bursts in order to recreate a hypothetical ideal burst. As the algorithm provides a boundary between the classes the probability of the classification of an event depends, in addition to being within the linear boundary, on the distance to this boundary [32]. By using a logistic regression algorithm, the ability to determine the most important properties becomes more systematic and highlights what indicators provide the best probability for the event of a burst occurring.

The two-dimensional logistic regression algorithm was applied (attached in Appendix A [33]) to the scatter plots in order to systematically assign a binary classification of the SRB candidates. When analyzing the plain-view scatter plots it is only possible to generalize amongst the patterns seen, whereas the two-dimensional logistic regression algorithm was able to perform slightly above visual inspection, however not perfectly. Through this process, the predictive model becomes more explicit. Additionally, the accuracy that is obtained is

derived from how well the model can then reproduce the labeled data. The choice of a 0.5 threshold, a natural condition, is made due to the model providing a continuous output range [0–1] and the threshold having to convert the continuous output into a binary classification from 0 (pure NO) to 1 (pure YES). Note when analyzing qualities that lie above the 0.5 threshold, this is indicative of where there is more likely for a YES classification to be made and vice versa.

Through the two-dimensional logistic regression products shown in Figure 4.1 it is possible to again conclude that a low true anomaly difference is a reasonable indicator of burst classification; however, as will be seen in the next section this is not useful as the sole indicator. When observing Figure 4.1[a], it is shown that when high pitch angles (0° to $+80^{\circ}$) are coupled with low true anomaly difference (0° to 100°) the model classifies candidates as YES with an upwards of 0.8 certainty and a total accuracy in the model of 77.9%. In Figure 4.1[b], the model suggests that bursts are best classified as YES when the yaw angle is high (0° to $+180^{\circ}$) and the true anomaly difference is low (-180° to 0°), with a lower certainty tending towards 0.5 and the model results in a 75.7% accuracy. For the roll vs. true anomaly difference in Figure 4.1[c], the model suggests that burst candidates are best classified as YES when the roll angle is high (0° to $+180^{\circ}$) and the true anomaly difference is low (0° to 45°) with again a certainty approaching 0.5. In addition, the roll vs. true anomaly difference model has the highest accuracy in the model compared to all of the two-dimensional logistic regressions with an accuracy of 78.3%.

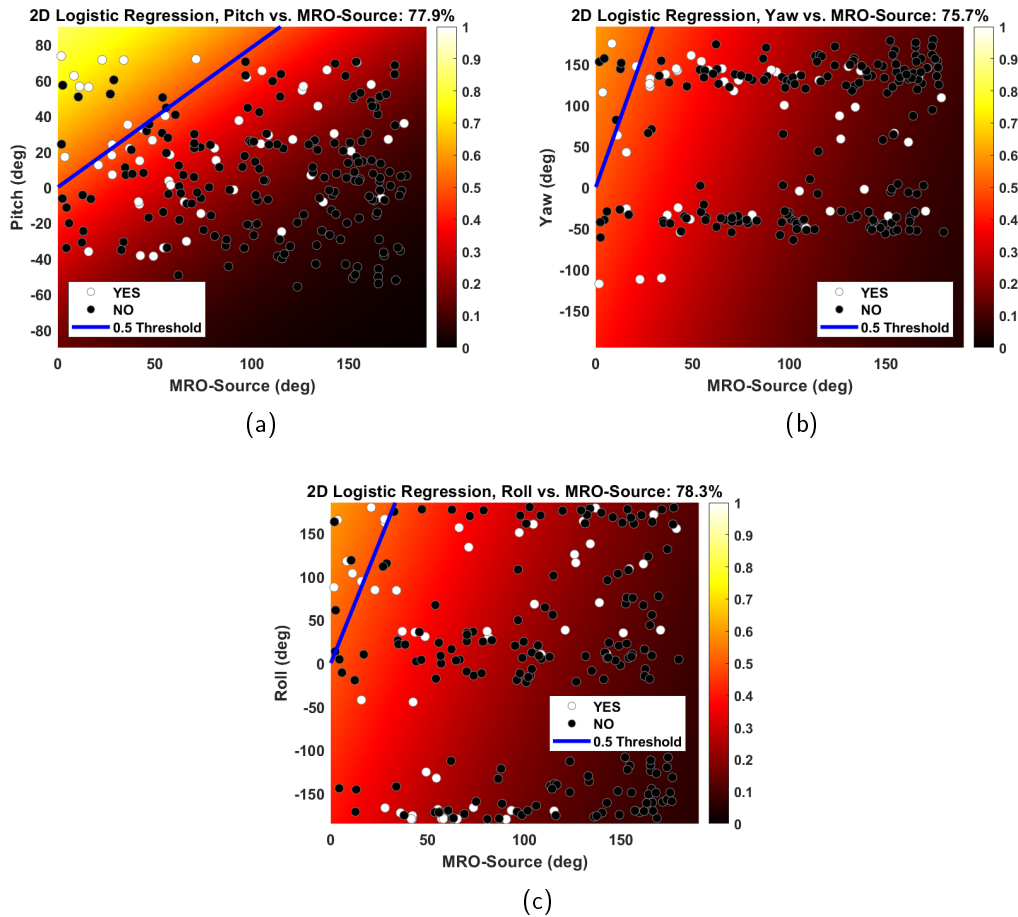


Figure 4.1. Two-dimensional logistic regression was applied to (a) pitch vs. true anomaly difference, (b) yaw vs. true anomaly difference, and (c) roll vs. true anomaly difference.

By performing the logistic regression algorithm on axial orientation angles against the other orientation angles, the model results in slight lower accuracies compared to the models in Figure 4.1. Applying this logistic regression algorithm to the pitch-roll plot in Figure 4.2[a] exhibits that a YES classification is expectedly made in the region of high roll and high pitch angles (0° to $+180^{\circ}$ and $+60^{\circ}$ to $+80^{\circ}$, respectively) but only with approximately a 0.5 certainty. This does not provide insight into which angles a candidate may be most susceptible to burst detection in addition to not encompassing YES classified candidates at lower angles reasonably enough. Conversely, the algorithm reasonably sequences the NO

classified bursts within the lower roll and pitch angles (100° to -180° and -60° to -20° , respectively). This highlights the conditions where it is expected not to see positive burst candidates, however this is an example of possible selection bias within the methodology as just because the observed angles do not result in a YES classification it cannot accurately be implied that a burst did not occur at all and that it was just not detected. Overall, the two-dimensional logistic regression is able to process and classify YES burst candidates with an accuracy of 77% through the pitch and roll angles. The logistic regression algorithm is also prone to possible false negative classification as even when pure YES classified bursts are present in a region primarily populated with NO classified bursts, the model does not account for those YES candidates well enough due to the restrictive parameters set by binary requirements. This is also shown throughout other logistic regression plots even as the properties analyzed change.

When observing the yaw-pitch plot in Figure 4.2[b], there is a slight improvement in the 0.5 certainty threshold but still results in similar conclusions that were derived from the yaw-pitch scatter plot. The region of the plot of high pitch angle and low yaw angle (10° to $+80^{\circ}$ and -180° to $+25^{\circ}$, respectively) maximized at approximately 0.65 which is a slight improvement compared to the pitch-roll scatter plot but not by a significant margin. Overall, the yaw-pitch two-dimensional logistic regression produces a classification accuracy of 77%.

When observing the yaw-roll plot in Figure 4.2[c], the logistic regression is limited by the same lapses in classification as the two previous plots. As the yaw angle is low (-180° to 0°) along any roll angle, the algorithm produces a region where a burst may occur with an upwards of 0.75 certainty. This however is not an entirely reasonable determination as it excludes a large portion of currently assigned bursts that are populated below the 0.5 threshold. Overall, the yaw-roll two-dimensional logistic regression produces a classification accuracy of 51.3%.

Similarly to the logistic regression models in Figure 4.1, these models produce reasonable ranges of MRO axial orientation angles where bursts should not be expected. With all three of these models, it is difficult to draw complete conclusions on which properties are most relevant to YES burst classification as many of the positive YES bursts are well below the 0.5 threshold. In addition, the Figure 4.1[b] performs in slight opposition from what was concluded by Figures 4.2[b] and [c], where when the yaw angles were modeled against

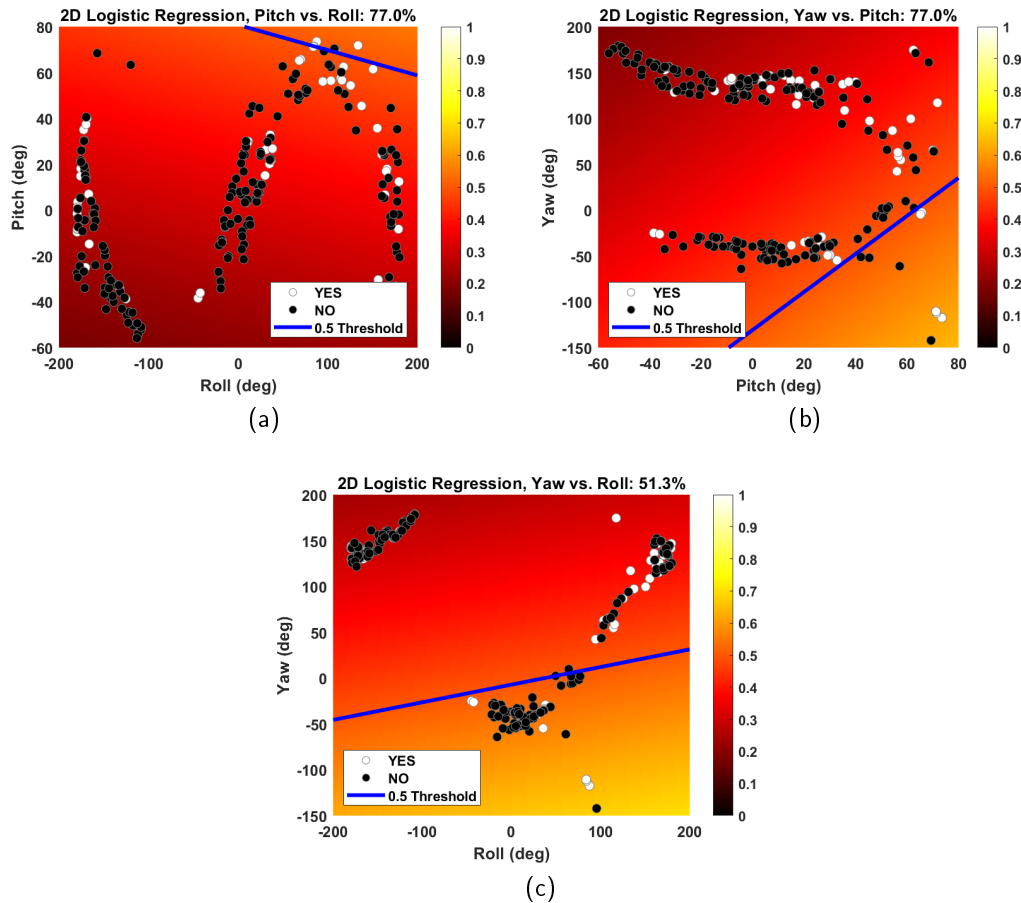


Figure 4.2. Two-dimensional logistic regression was applied to each of the axial comparisons (a) pitch vs. roll, (b) yaw vs. pitch, and (c) yaw vs. roll.

the true anomaly difference, it suggests that high positive angles lead to YES classification whereas when modeled against the other MRO orientation angles, pitch and roll, suggest that low yaw angles lead to YES classification. That is to say, analysis into burst classification could be improved even further by increasing the number of properties compared.

4.2 Performance of Multivariate Logistic Regression

A modified version of this section was submitted as: Christopher Gerekos, Gregor Steinbrügge, Immanuel Christopher Jebaraj, Andreas Casillas, Elena Donini, Beatriz Sánchez-Cano, Mark Lester, Jasmina Magdalenic, Sean T. Peters, Andrew Romero-Wolf, and Donald

D. Blankenship, “Observation of solar radio burst events from Mars orbit with the Shallow Radar instrument,” to *ApJ Letters*, May 2023 [3].

The next step in order to potentially support the conclusions made by the histograms, scatter plots, and two dimensional logistic regression, a multivariate logistic regression algorithm is applied (attached in Appendix B [34], [35]). By exploring a multivariate approach, all of the properties of MRO/SHARAD are compared to one another simultaneously and ranked by the weight of importance for MRO/SHARAD to detect a burst. This process is known as principal component analysis (PCA) which assigns a score to each feature vector (i.e., weights each property) while also reduces the size of the dimension space observed by eliminating redundancy in the column space [36].

The column vectors in Table 4.1 are representative of the component coefficients for each of the properties. To start, the coefficients (or the weights) are computed using the MATLAB PCA function, and defining the data matrix as [true anomaly difference, yaw, pitch, roll]. Multiplying the data matrix by each column of the component weights would provide the corresponding component vectors. Based on the coefficients of the first order PCA decomposition, the yaw (0.9480) and pitch (0.8220) orientation of MRO results in the two most important components for classifying a burst. Additionally, the PCA coefficients provide the result that the roll (0.0690) of MRO is less important in the classification of these burst candidates when utilized in the first two components.

Table 4.1. Principal Component Analysis Coefficients

PC	True Anomaly Difference	Yaw	Pitch	Roll
1	-0.1416	0.9480	-0.2764	0.0690
2	-0.5346	0.1206	0.8220	0.1262
3	0.6038	0.1111	0.2578	0.7461
4	0.5741	0.2573	0.4261	-0.6501

The percentage of the data variance (shown in Table 4.2) that can be explained by the associated principal components and is known as the percent variability. The first three components (the summation of 43.62%, 25.29%, and 17.38%) can explain 86.29% of all

the variability within the original data, and for all four components, 100% of the variability within the data. This logic follows as the first two components maintain the ability to explain 68.91% of all the variability in burst classification. This suggests there is not a significant amount of redundancy between the properties and that a stronger classification can be made with three components. With this understanding, by using the first three principal components together, 86.29% of the variability in burst classification can be made.

Table 4.2. Percent Variability in the Data Explained by Principal Components

Component	(%)
1	43.6184
2	25.2920
3	17.3810
4	13.7086

It can then be confirmed by analyzing the correlation matrix (shown in Table 4.3), which shows low correlation across all properties, that each of the properties used are able to perform SRB classification independently but can be improved when used together without being dependent on each other. First, the correlation matrix shows that the true anomaly difference has very weak correlation, less than 0.12, with the MRO yaw property, and even weaker anticorrelations with the pitch (-0.064) and roll (-0.0015). While the pitch and roll angles are slightly correlated, at 0.4441, the true anomaly difference is completely decorrelated with the orientation of MRO resulting in weak correlations/anti-correlations around 0.3-0.4 between other orientation angles.

Table 4.3. Correlation Matrix of Feature Vectors

	True Anomaly Difference	Yaw	Pitch	Roll
True Anomaly Difference	1.0000	0.1233	-0.0640	-0.0015
Yaw	0.1233	1.0000	0.3473	-0.2978
Pitch	-0.0640	-0.3473	1.0000	0.4441
Roll	-0.0015	-0.2978	0.4441	1.0000

Finally, the multivariate logistic regression shown in Figure 4.3 was performed using the PCA feature vectors to then classify the bursts based on an array of threshold values. This analysis shows that the accuracy of classification currently maximizes at 0.792 when using all four feature vectors ($n = 4$). Secondly the accuracy of classification degrades with a decreasing number of components. This again signifies the importance of utilizing all four properties for analyzing burst detection capabilities. As a modest detection accuracy of SRB candidates can be obtained, even with a single PCA component, these results also suggest that the one-dimensional histograms are a relevant and useful tool for determining preferential solar radio burst detection conditions for MRO/SHARAD. However, a larger set of burst candidates and different potential MRO properties may increase, whether separate or in conjunction to the ones currently studied, may improve these results.

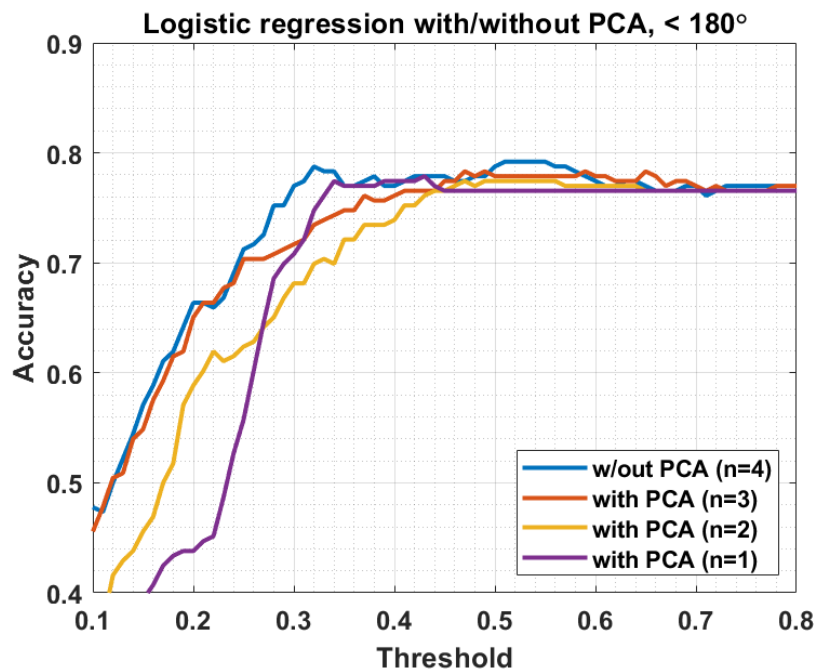


Figure 4.3. Multivariate logistic regression with and without principal component analysis (PCA). As the number of properties component increases, the accuracy of the algorithm maximizes at 0.792 when the threshold value is set between 0.51 to 0.535.

CHAPTER 5:

Conclusion

5.1 Summary of Results

The purpose of this study was to examine and determine which properties described by the MRO/SHARAD spacecraft (yaw, pitch, roll, true anomaly difference with respect to STEREO or WIND) would lend to positive burst classification as passively observed at Mars. The histograms of individual properties, comparative scatter plots between properties, and the two-dimensional logistic regression of those plots showed potential as initial tools in SRB classification, however when used individually these tools did not provide much confidence in the accuracy of those classifications. By using a multivariate approach, this showed that SRB classification is a process that will require the aggregation of multiple properties. By using the multivariate logistic regression model, the first two most principal components for burst classification showed to be the yaw and pitch angles of the MRO spacecraft. The most significant components, which covers 86.29% of the variability in burst detection, is a product of using any combination of three principal component vectors that were analyzed. The addition of another property increases the accuracy of burst classification. Finally, the correlation between the properties is not significant. The MRO axial angles (yaw, pitch, and roll) have weak correlations between each other (0.3-0.4) with the pitch and roll angles being the most correlated, however slightly (0.4441). The true anomaly difference is very weakly correlated (<0.12) to the axial angles. Improving our understanding of SRB detection by MRO/SHARAD would enhance our understanding of SRB propagation physics and the space weather environment, and thus allow more effective management of our space-based systems. Additionally, these SRBs could serve as a potential source for subsurface passive radio sounding for future terrestrial [37] and Mars missions [14].

5.2 Future Works

5.2.1 Improvement of Properties

In order to further refine the classification algorithms, this research highlights the need for additional burst data and properties to determine when bursts are present. The three properties to study next would be:

1. The peak power recorded by SHARAD as the power recorded would need to be calibrated with respect to the power recorded by STEREO or WIND thus allowing for an accurate observation of SRB strength both before and after reflection from the Martian surface,
2. The antenna sensitivity as SHARAD was not properly parameterized when it was built [25] and by studying this further it may allow for an accurate understanding of the antenna orientation in space and burst resolution when observing candidates, and
3. The source spread of the burst since SRBs undergo wave propagation effects within the interplanetary medium [38], and the apparent size of the source is predicted to be significant (1° to 6°) for a HF radar.

5.2.2 Processing Techniques

In both disciplines of statistics and physics, logistic regression is one of the most commonly used tools for discrete data analysis [32]. In the case of a statistical analysis of burst detection, it provided an initial base case in determining what properties of MRO/SHARAD are most predictive of SRB burst detection. While the multivariate approach is most optimal for large data-sets, one of the limitations of using this technique for this study is that the size of the overall data-set was only 226 samples. These statistical algorithms can be further improved to become more efficient, accurate, and standard with increasing amount of data.

The limitations of using these algorithms have shown that there is a limit to the maximum accuracy that can be determined with the given properties. This is coupled with the issue that when the classification boundary moves, the accuracy of classification drops. This may be alleviated if the classification boundary was altered from a linear boundary function to a polynomial function or cluster boundary, which is the scope of a future study. This also opens the potential for the addition of machine learning, such as support vector

machines (SVMs), to better assess boundary conditions and improve classification accuracy.

SVMs are useful as they are able to determine the most effective hyper-plane, shown in Figure 5.1, in order to separate all of the data into each of the assigned classes. The quality of a hyper-plane is set by the size of the margin between the two classes. The margin is also then defined as the “maximal width of the slab parallel to the hyper-plane that has no interior data points.” [39], [40] By using SVMs, the boundary conditions of burst classification can be improved and allow for better separation of the bursts.

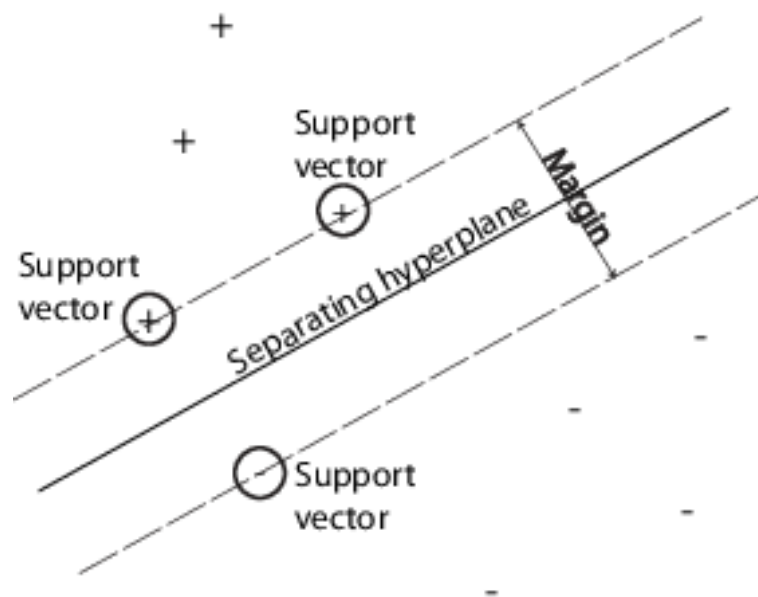


Figure 5.1. Example of the SVM separating hyper-plane and margin. Source: MathWorks Inc. [41].

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APPENDIX A: MATLAB Code for Two-Dimensional Logistic Regression

Code was adapted from Dr. Kendrick Kay, PhD (University of Minnesota) script found at:
<https://www.cmrr.umn.edu/~kendrick/statsmatlab/MatlabExamples4.pdf>

The Yaw vs. Pitch plot in Figure 4.2[b] is used as a demonstration in this script:

```
% plot of the candidates and filled in as 1 or 0
figure();clf
h1 = scatter(sunpitchyes,sunyawyes,50,'w','filled'); % white
      dots for 1
hold on,
h2 = scatter(sunpitchno,sunyawno,50,'k','filled'); % black
      dots for 0
set([h1 h2],'MarkerEdgeColor',[.5 .5 .5]); % outline dots in
      gray
xlabel('Pitch (deg)'),
ylabel('Yaw (deg)'),
title('Candidate Bursts: Yaw vs. Pitch')
legend('YES','NO','location','NorthWest')

% Variables and then the 1 or 0 for classication
x1 = [sunpitchyes;sunpitchno];
x2 = [sunyawyes;sunyawno];
y = [ones(length(sunpitchyes),1);zeros(length(sunpitchno),1)
    ];
threshold = 0.5;

% define optimization options
```

```

options = optimset('Display','iter','FunValCheck','on','
    MaxFunEvals', ...
    Inf,'MaxIter',Inf, 'TolFun',1e-6,'TolX',1e-6);

% define logistic function (this takes a matrix of values
    and
% applies the logistic function to each value)
logisticfun = @(x) 1./(1+exp(-x));

% construct regressor matrix
X = [x1 x2];
X(:,end+1) = 1; % we need to add a constant regressor

% define initial seed
params0 = zeros(1,size(X,2));

% define bounds
paramslb = []; % [] means no bounds
paramsub = [];

% define cost function (negative-log-likelihood)
% here, the eps is a hack to ensure that the log returns a
    finite number.
costfun = @(pp) -sum((y .* log(logisticfun(X*pp')+eps)) +
    ...
    ((1-y) .* log(1-logisticfun(X*pp')+eps))));

% fit the logistic regression model by finding
% parameter values that minimize the cost function
[params,resnorm,residual,exitflag,output] = ...
    lsqnonlin(costfun,params0,paramslb,paramsub,options);

% compute the output (class assignment) of the model for

```

```

    each data point
modelfit = logisticfun(X*params') >= threshold;

% calculate percent correct (percentage of data points
% that are correctly classified by the model)
pctcorrect = sum(modelfit==y) / length(y) * 100;

% visualize the model
% prepare a grid of points to evaluate the model at
ax = axis;
xvals = linspace(ax(1),ax(2),100);
yvals = linspace(ax(3),ax(4),100);
[xx,yy] = meshgrid(xvals,yvals);

% construct regressor matrix
X = [xx(:) yy(:)];
X(:,end+1) = 1;

% evaluate model at the points (but don't perform the final
% thresholding)
outputimage = reshape(logisticfun(X*params'),[length(yvals)
length(xvals)]);

% visualize the image (the default coordinate system for
% images
% is 1:N where N is the number of pixels along each
% dimension.
% we have to move the image to the proper position; we
% accomplish this by setting XData and YData.)
h3 = imagesc(outputimage,[0 1]); % the range of the logistic
% function is 0 to 1
set(h3,'XData',xvals,'YData',yvals);
colormap(hot);

```

```

colorbar;

% visualize the decision boundary associated with the model
% by computing the 0.5-contour threshold of the image
[c4,h4] = contour(xvals,yvals,outputimage,[threshold
    threshold]);
set(h4,'LineWidth',3,'LineColor',[0 0 1]); % make the line
    thick and blue

% send the image to the bottom so that we can see the data
    points
uistack(h3,'bottom');

% send the contour to the top
uistack(h4,'top');

% restore the original axis range
axis(ax);

% report the accuracy of the model in the title
title(sprintf('2D Logistic Regression, Yaw vs. Pitch: %.1f%%
    ',pctcorrect));
legend_string = strcat(num2str(threshold),' Threshold')
legend('YES','NO',legend_string,'location','SouthWest')

```

APPENDIX B:

MATLAB Code for Multivariate Logistic Regression

```
% Example code of multivariate logistic regression shown in
    Section 4.2

% Without and With PCA for dimension reduction

X2 = [sourceangle_final,sunyaw, sunpitch, sunroll];

% normalize data by subtracting mean and dividing by
    standard deviation
for i = 1:4
    X2(:,i) = (X2(:,i)-nanmean(X2(:,i)))/sqrt(nanvar(X2(:,i)
        ));
end

[coeff,score,latent,tsquared,explained] = pca(X2);%,'
    VariableWeights','variance') % PCA
wcoeff = coeff
coefforth = diag(std(X2))\wcoeff

x2 = [score(:,1) score(:,2) score(:,3)]; % take first three
    (of 4)

[B,dev,stats] = mnrfits(x2,y); % logistic regression
pihat2 = mnrfits(B,x2); % evaluate regression
pihat_new2 = 1 - pihat2(:,1);

threshold_test = 0.1:0.01:0.9;
```

```

for ii = 1:length(threshold_test)
    predicted_Burst2 = pihat_new2>threshold_test(ii);
    number_wrong2 = sum(abs(predicted_Burst2-isBurst));
    fraction_error2 = number_wrong2/length(isBurst);
    logregaccuracy3(ii) = 1-fraction_error2;
end

figure();clf
plot(threshold_test,logregaccuracy3),xlabel('Threshold'),
    ylabel('Accuracy'), xlim([min(threshold_test) max(
    threshold_test)])
title(['Logistic regression with ',num2str(size(x2,2)),'
    variables with PCA'])
ylim([0.4 0.9])
xlim([min(threshold_test) 0.8])

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% logistic regression with PCA (n=2 of 4)

x2 = [score(:,1) score(:,2)]; % take first two (of 4)

[B,dev,stats] = mnrfits(x2,y); % logistic regression
pihat2 = mnrfits(B,x2); % evaluate regression
pihat_new2 = 1 - pihat2(:,1);

threshold_test = 0.1:0.01:0.9;

for ii = 1:length(threshold_test),
    predicted_Burst2 = pihat_new2>threshold_test(ii);
    number_wrong2 = sum(abs(predicted_Burst2-isBurst));
    fraction_error2 = number_wrong2/length(isBurst);
    logregaccuracy2(ii) = 1-fraction_error2;

```

```

end

figure();clf
plot(threshold_test,logregaccuracy2),xlabel('Threshold'),
     ylabel('Accuracy'), xlim([min(threshold_test) max(
         threshold_test)])
title(['Logistic regression with ',num2str(size(x2,2)), '
        variables with PCA'])
ylim([0.4 0.9])
xlim([min(threshold_test) 0.8])

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% logistic regression with PCA (n=1 of 4)

x2 = [score(:,1)]; % take first one (of 4)

[B,dev,stats] = mnrfits(x2,y); % logistic regression
pihat2 = mnrfits(B,x2); % evaluate regression
pihat_new2 = 1 - pihat2(:,1);

threshold_test = 0.1:0.01:0.9;

for ii = 1:length(threshold_test),
    predicted_Burst2 = pihat_new2>threshold_test(ii);
    number_wrong2 = sum(abs(predicted_Burst2-isBurst));
    fraction_error2 = number_wrong2/length(isBurst);
    logregaccuracy1(ii) = 1-fraction_error2;
end

figure();clf
plot(threshold_test,logregaccuracy1),xlabel('Threshold'),
     ylabel('Accuracy'), xlim([min(threshold_test) max(
         threshold_test)])

```

```

title(['Logistic regression with ', num2str(size(x2,2)), '
      variables with PCA'])
ylim([0.4 0.9])
xlim([min(threshold_test) 0.8])

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Plot all together: w/out PCA (n=3), with PCA (n=2), with PCA
% (n=1)

figure();clf
plot(threshold_test, logregaccuracy4),
hold on,
plot(threshold_test, logregaccuracy3),
plot(threshold_test, logregaccuracy2),
plot(threshold_test, logregaccuracy1),
legend('w/out PCA (n=4)', 'with PCA (n=3)', 'with PCA (n=2)', '
      with PCA (n=1)', 'location', 'SouthEast')
title(['Logistic regression with/without PCA, < ', num2str(
      angularseplimit), '\circ'])
ylim([0.4 0.9])
xlim([min(threshold_test) 0.8])
xlabel('Threshold'), ylabel('Accuracy'),

```

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