Processing and Analysis for Radio Science Experiments (PARSE): Graphical Interface for Bistatic Radar

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Abstract

Opportunistic bistatic radar (BSR) observations of planetary surfaces can probe the textural and electrical properties of several solar system bodies without needing a dedicated instrument or additional mission requirements, providing unique insights into volatile enrichment and supporting future landing, anchoring, and in situ sampling. Given their opportunistic nature, complex observation geometries, and required radiometric knowledge of the received radio signal, these data are particularly challenging to process, analyze, and interpret for most planetary science data users, who can be unfamiliar with link budget analysis of received echoes. The above impedes real-time use of BSR data to support mission operations, such as identifying safe landing locations on small bodies, as was the case for the Rosetta mission. To address this deficiency, we develop an open-source graphical user interface—Processing and Analysis for Radio Science Experiments (PARSE)—that assesses the feasibility of performing BSR observations and automates radiometric signal processing, power spectral analysis, and visualization of DSN planetary radio science data sets acquired during mission operations or archived on NASA’s Planetary Data System. In this first release, PARSE automates the processing chain developed for Dawn at Asteroid Vesta, streamlining the detection of DSN-received surface-scatter echoes generated as the spacecraft enters/exits occultations behind the target. Future releases will include support for existing Arecibo data sets and other Earth-based radio observatories. Our tool enables the broader planetary science community, beyond planetary radar signal processing experts, to utilize BSR data sets to characterize electrical and textural properties of planetary surfaces. Such tools are becoming increasingly important as the number of space missions—and subsequent opportunities for orbital radio science observations—continue to grow.

Unified Astronomy Thesaurus concepts: Doppler shift (401); Radar astronomy (1329); Small Solar System bodies (1469); Solar system (1528); Astronomy software (1855)

1. Introduction

Planetary radio science is the analysis of changes in power, frequency, and polarization of the communication signal between the spacecraft and the Earth’s downlink station (often referred to as the link budget analysis) to assess the gravitational, atmospheric, electrical, and textural properties of planetary bodies. This method that primarily uses S- and X-band frequencies to connect the satellites to the ground-based communication systems, and more recently Ka and Ku bands, is increasingly used to reduce uncertainties associated with retrieving surface and subsurface physical parameters by other instruments aboard planetary missions (e.g., Fjeldbo 1964; Eshleman et al. 1977; Asmar & Renzetti 1993; Asmar et al. 2019). The above is accomplished by accurately measuring Doppler shifts of the carrier signal, as well as potential secondary echoes in the telecommunications spectrum received at the downlink antenna. These measured Doppler shifts result from the changes in the spacecraft’s relative velocity with respect to Earth-based downlink stations and are governed by the observation geometry, planetary atmospheric refraction, changes in the signal power and polarization, and the electrical properties and roughness of the target’s surface (e.g., Simpson 1993; Campbell 2002; Simpson et al. 2011; Palmer et al. 2017; Asmar et al. 2019).

Among the different types of radio science data that we aim to analyze, the software tool we present herein focuses on forward-scatter bistatic radar (BSR) observations, which occur at grazing incidence angles when the spacecraft enters and exits from an occultation behind the target body (see Figure 1). By analyzing the radiometric properties of the telecommunications signal as it forward-scatters off the planetary surface, we can characterize the textural and electrical properties of the target body. These occultations inevitably occur for orbital missions, meaning that these BSR experiments can be performed opportunistically, at low risk and low cost to the baseline mission. As the number of orbital space missions increases, so will the prevalence of BSR observations, thus increasing the demand for tools that streamline the processing and analysis of radio science data sets.

Data products that can be retrieved specifically from orbital BSR observations of planetary surfaces include maps of surface radar reflectivity variations (e.g., Palmer et al. 2017), which can be compared to observations by other instruments aboard the spacecraft—such as maps of shallow subsurface hydrogen concentrations, thermal inertia, surface mineralogy, and surface age—to investigate the primary geophysical processes that have shaped the body’s surface at the observing wavelength scale (centimeters to decimeters)—e.g., whether associated with regolith gardening processes, regolith compositional variability, or potential icy volatile occurrence. The analysis performed using these data products informs potential sites of interest for...
volatile exploration and provides an assessment of surface navigability for landing, roving, or sampling activity (Gunnarsson-dottir et al. 2008; ElShafie & Heggy 2013; Rozitis et al. 2020; Heggy et al. 2020).

However, given the complex observation geometries associated with planetary radio science observations—as well as the complexity of generating radio science data products and quantifying their error sources—subsequent processing, analysis, and interpretation are often challenging and time-consuming as opposed to other planetary data sets that provide visual verification tools for data quality analysis, such as optical and spectroscopic imaging. Hence, despite the public availability of such data on the NASA Planetary Data System (PDS) archives or equivalent repositories, planetary radio science data products are only analyzed by a small group of radio experts, who in turn make up only a small fraction of the planetary science community—e.g., as expressed by Withers et al. (2014).

Because planetary radio science observations are performed using the spacecraft’s communications antenna(s), which are a primary component of the bus of every space mission, and given that radio science teams are required to deliver curated data archives to the respective space agency, there is an increasing wealth of radio science data products (e.g., on the PDS Geosciences and Small Bodies Nodes’ Radio Science archives: NASA Planetary Data System 2021a; 2021b)—elaborated in Section 4—awaiting software tools to make their processing, analysis, and interpretation accessible to the larger science community, beyond telecommunications experts. Unfortunately, no publicly available tools are yet tailored to these data sets, limiting their science return and contribution to the planetary science community.

In a first step toward addressing this deficiency, we develop herein a public, intuitive software tool with a graphical user interface that automates the processing and analysis of BSR surface occultation data acquired by NASA’s Deep Space Network (DSN) ground stations. The development of this tool, PARSE (“Processing and Analysis for Radio Science Experiments”), was spurred on by the challenges encountered during the opportunistic BSR experiment performed by NASA’s Dawn mission at Asteroid Vesta (Palmer et al. 2017). In this grazing-angle surface-scatter experiment, the telecommunications high-gain antenna (HGA) aboard the spacecraft was used to transmit a continuous, direct signal with right-hand circular polarization (RCP) to be received by DSN stations on Earth (Figure 1). As the spacecraft occasionally passed behind the asteroid into an occultation from the receiver’s perspective—becoming obscured from view—part of the HGA beam forward-scattered from the surface of the asteroid (i.e., at grazing incidence). The PARSE tool allows for the signal data collected by the downlink stations during these occultations to be processed and analyzed by a wider community of planetary scientists, outside of experts and telemetry engineers.

The observable of an orbital BSR experiment, i.e., the raw data, is the amplitude versus time data that are subsequently recorded at the DSN station. By converting the amplitude time series into the frequency domain using the Fourier transform, we bin the incoming signal by its frequency distribution in search of the surface-scattered signal. This echo signal is identifiable as being weaker than the direct signal—as it has scattered from the surface of the target body, reducing its strength due to topography, the surface’s roughness at the wavelength scale (centimeters to decimeters), and the dielectric properties of the surface material—and Doppler-shifted relative to the direct signal (by an amount $\delta f$), due mainly to the orbital velocity of the spacecraft with respect to the target surface (Palmer et al. 2017; Palmer & Heggy 2020). By assessing the power difference between the secondary peak and the carrier signal, we can infer the radar scattering properties of the target’s surface (e.g., centimeter-to-decimeter-scale surface roughness) through various scattering models (e.g., Palmer et al. 2017; Palmer & Heggy 2020).

Specifically, to retrieve relative surface roughness, the radar cross section $\sigma$ (in areal units) of each footprint illuminated by the radar lobe of the HGA (i.e., the echo site) must be constrained. The central latitude and longitude of the echo site are determined using SPICE kernel geometry to calculate the point of interception on the surface of the target body given the pointing direction of the HGA aboard the spacecraft (Acton et al. 2018). The radar cross section $\sigma$ quantifies the cross-sectional surface area of a perfectly isotropic scatterer (e.g., a smooth metal sphere) that would reflect the same echo power. For a given acquisition geometry, $\sigma$ depends on the surface’s dielectric and roughness properties at the radar wavelength and is quantified by the ratio of received echo power to transmitted power (Willis & Griffiths 2007). Hence, larger values of $\sigma$ are associated with stronger echoes.

In turn, echo strength depends on the roughness of the surface at wavelength scales, the angle of incidence, and the dielectric properties of the target’s surface material at the observing radar frequency (e.g., X band). In the case of forward-scatter BSR observations like those by the Dawn mission at Asteroid Vesta, we can assume that each surface echo is measured at the same angle of incidence (almost 90°) and that each scatters from equal surface area since the spacecraft is pointed in a fixed orientation toward Earth during each entry into or exit from an occultation. Hence, instead of normalizing $\sigma$ by area, one can normalize the observed $\sigma$ of each echo site to that of the site of strongest reflection and then combine this with estimated surface dielectric properties to infer relative centimeter-to-decimeter-scale surface roughness across the target body (relative to the selected reference site) (Palmer et al. 2017). Retrieving surface echoes using PARSE is detailed in the online User’s Guide (https://github.com/PARSE-team/PARSE).

This software tool is intended for use on future orbital space missions to planetary bodies whose surface properties still have limited characterization, whether this is the first space mission...
to this body or because the only data collected are from fly-by missions and are therefore of low resolution. The Dawn mission’s BSR observations of Asteroid Vesta present a particularly useful case study for the validation of PARSE as well as insight for its use at other unexplored small bodies. Asteroid Vesta has been extensively characterized by Dawn, meaning that its shape, surface texture, and gravitational field can be used to validate BSR observations, which are of primary importance for future exploration of small bodies. Additionally, this is an effective case study for comparing with future small-body BSR observations, because the differential Doppler shift ($\delta f$) between the direct signal and surface echo is small, owing to the size of the body (radius approximately 285 km) and the subsequently low orbital velocity of the spacecraft around the target body (approximately 200 m s$^{-1}$).

Interpreting Vesta’s surface textural properties from the raw data—a time series of complex amplitudes ($I$ and $Q$ data) that are recorded simultaneously by two separate channels: right and left circular polarization (RCP and LCP; Asmar & Renzetti 1993; DSN No. 820-013, 0159-Science, Rev. B 2008)—took several years, however, owing to complex acquisition geometries around such a small body with an unknown and weak gravitational field prior to mission encounter. Opportunistic forward-scatter BSR experiments performed at small bodies like Vesta occur at grazing incidence angles and a slow spacecraft orbit that result in surface echoes with unexpectedly small Doppler shifts from the direct signal ($\delta f$), making these surface-scattered echoes difficult to identify in the raw data without using proper processing parameters tailored to the mission (Palmer et al. 2017; Palmer & Heggy 2020). Furthermore, unlike backscatter BSR experiments that are performed at smaller bistatic angles (i.e., $\theta_{bs} < 180^\circ$), forward-scattered echoes are not distinguishable from the direct signal by any differences in polarization, as they maintain the same sense of circular polarization as the transmitted (direct) signal (in this case, right-hand circularly polarized or RCP; Palmer et al. 2017). Since the method of measuring the ratio of RCP to LCP signal (the circular polarization ratio; Campbell 2002) to retrieve absolute surface roughness is not applicable to forward-scatter observations, to derive the relative surface roughness, Palmer et al. (2017) instead measure the relative strength of reflected power from each echo site.

The complexity and time-consuming nature of radio science data analysis, particularly for surface-scatter experiments, are also exemplified by the European Space Agency’s Rosetta mission to Comet 67P. Rosetta’s Radio Science Investigation (RSI) experiments included BSR observations of the comet’s surface, which were successfully performed in late 2014 but remain unpublished owing to complex acquisition geometries around such an irregularly shaped small body, yielding nonintuitive results (Peytavi et al. 2018, 2020 conference abstracts).

By automating the steps to process and analyze such observations, PARSE can be used to supplement the investigations of other instruments aboard a spacecraft, such as providing constraints on surface roughness at wavelength (centimeter to decimeter) scales—which in turn is an important input parameter for thermophysical models of planetary regoliths (e.g., Rognini et al. 2020), for detailed geomorphological mapping of planetary surfaces (e.g., El-Maarry et al. 2015), and for surface trafficability assessments of potential sites for landing and sampling missions (e.g., Gunnarsdottir et al. 2008; Rozitis et al. 2020). The initial release of PARSE specifically addresses forward-scatter BSR experiments, while future releases will support backscatter BSR experiments as well. With this increased support, depending on the observation geometry, BSR surface-scatter experiments can also be used to characterize the electrical properties of the target’s surface, which in turn can aid in identifying locations of potential icy volatile occurrence in the shallow subsurface (e.g., Campbell 2002; Simpson et al. 2011; Thompson et al. 2011; Mitchell et al. 2018).

As international space agencies continue to prioritize sample return missions and exploration of small bodies (National Academies of Sciences, Engineering, and Medicine 2019), the development of this tool is timely given its ability to support the above mission objectives while in flight—by enabling the expedient assessment of the target’s surface texture and sites with potential icy volatile occurrence. This is accomplished using raw radio science data acquired by the onboard communications antenna that is included on all spacecraft, meaning that opportunistic forward-scatter orbital BSR observations are feasible despite constraints by mission requirements or limited opportunities. The ability to quickly analyze radio science data with PARSE on active missions therefore presents an opportunity to reduce risks associated with landing, anchoring, trafficability, and drilling on planetary surfaces (e.g., Gunnarsdottir et al. 2008; ElShafei & Heggy 2013; Rozitis et al. 2020).

In the following sections, we introduce PARSE, describe the interface’s functionality and implementation, and provide a tutorial case of how to use PARSE to extract key features from the Dawn at Vesta dataset—which is bundled with this distribution of the software for the user’s convenience. For more details, please refer to the PARSE User’s Guide (https://github.com/PARSE-team/PARSE/blob/main/UsersGuide_v1.pdf).

2. Software Description

In this first release, PARSE allows users to process and analyze BSR data sets through an intuitive cross-platform desktop interface, available on GitHub (https://github.com/PARSE-team/PARSE), which maximizes the accessibility and usability of this software for new users, as well as experienced ones.

PARSE is entirely written in Python 3 to maximize the public accessibility of its source code, as Python is free, open-source, and widely used across a range of disciplines. The back end for PARSE handles data ingestion and processing using NumPy (for efficient compatibility with Matplotlib), SciPy, and Astropy, which provide support for efficiently managing data. Astropy is utilized to ensure compatibility with another one of our dependencies, an open-source GitHub repository that uses Python 3 to read header files that are formatted according to NASA’s PDS3 standards (Kelley 2014). For details on all back-end architecture, refer to the PARSE User’s Guide (https://github.com/PARSE-team/PARSE).

The front end is a cross-platform, local, desktop interface implemented using PyQt5, which is a Python binding for the C++ GUI development framework known as Qt. Components of the front end that visualize data use Matplotlib, leveraging its back-end API to display a dynamically updating plot as a widget inside of the interface.

PARSE is compatible with (1) published BSR data from the Dawn mission (Palmer et al. 2017), a subset of which is included in this software distribution; (2) raw DSN radio science data formatted according to NASA’s PDS3 standards specifically for binary tables with 32-bit sample packing (see the prebundled
sample of Rosetta data as an example); and (3) user-defined data sets, all of which are described in the above-mentioned PARSE User’s Guide. There are slight variations in the data ingestion pipeline for each of these three use cases (further discussed in Section 2.2). Below, we present the interface design and underlying algorithms used to process and analyze forward-scatter radio communications data. The PARSE workflow is summarized by Figure 2, and a brief illustrative example is provided in Section 3. The detailed User’s Guide is available on the project’s GitHub repository.

2.1. Start Window

After launching the PARSE desktop application, the initial window includes options for the user to select the source of the data set for processing (Figure 3, top). Additionally, this window includes a menu panel that provides access to convenient resources, such as the PARSE User’s Guide, a link to a short video tutorial that guides the user through a basic example for the PARSE interface, and contact information for bug reporting.

2.2. File Selection Window

Each data set is formatted according to a particular NASA PDS data standard (as described within the accompanying PDS3 header/metadata files). As such, once the user has specified the source of the data set in the initial window, the PARSE interface then uses one of three pipelines to read the data, preparing it for subsequent processing.

If the user selects one of the built-in mission cases, such as Dawn or Rosetta, each of these corresponding pipelines then opens a file selection window (Figure 3, bottom) that displays a list of the included data files, conveniently sorted according to key metadata, such as the start and end times of the recording, the antenna frequency band (e.g., X or S), and the signal polarization. The user then chooses a pair of these files (one RCP, one LCP)—i.e., simultaneously acquired data in right- and left-hand circular polarization—in order to read its contents and proceed to the signal processing window. The process of reading the data file is multithreaded to improve the interface responsiveness.

Alternatively, selecting a user-defined data set triggers a separate data ingestion pipeline that prompts the user to upload a local data file from disk. The selected file must be correctly formatted as an ASCII text file (.txt), as detailed in the PARSE User’s Guide. PARSE accepts ASCII data files to ensure cross-platform compatibility and an intuitive data format for the user. After loading the data, PARSE proceeds to the signal processing window.

2.3. Signal Processing

After choosing the data file and supplying basic target body information and spacecraft orbital parameters, users are then shown recommended processing parameters in the left panel of

Figure 2. Flowchart summarizing the functionality of the PARSE tool for processing opportunistic forward-scattered radar signals from orbital planetary occultations.
the signal processing window (Figure 4) and given the ability to conveniently adjust them. All input parameters are individually described by hovering the cursor over the “tool-tip” info icon next to each parameter and fully detailed in the PARSE User’s Guide (https://github.com/PARSE-team/PARSE/blob/main/UsersGuide_v1.pdf). When the user applies the changes, PARSE uses the specified parameters to process the data, generating a sequence
of power spectral density plots across the time series. A toolbar located at the bottom of the window affords the user some basic controls for navigating the time series. Signal processing can be computationally intensive, so it has been multithreaded, thereby decreasing processing time and improving interface responsiveness.

### 2.3.1. Calculating the Theoretical Differential Doppler Shift

The underlying algorithm for calculating the differential Doppler shift ($\delta f_{\text{calc}}$)—which is computed after entering the input parameters that are grouped under “Acquisition Geometry” in the left panel of Figure 4—is adapted from Palmer & Heggy (2020). The differential Doppler shift is the theoretical frequency separation between the received direct signal and the received surface-scattered echo. This parameter is needed to assess the optimal frequency resolution of the output power spectra. The smaller the $\delta f$ (i.e., the closer the direct and echo peaks on the power spectrum), the higher the frequency resolution $f_{\text{res}}$ necessary to distinguish the direct signal from the echo.

The theoretical differential Doppler shift is calculated from acquisition geometry parameters as follows for BSR occultation observations (see Palmer & Heggy 2020 for the full derivation, including calculated values for several active and proposed planetary missions):

$$|\delta f_{\text{calc}}| \approx \left( v_{\text{SC|orbit}} / \lambda_0 \right) \cdot \sin(\theta_{\text{SC|orbit|phase}}) \\
\cdot \sin(\theta_{\text{ult}}) \cdot \left( \theta_{\text{ult}} + \frac{1}{2} \theta_{\text{bw}} \right)$$  \hspace{1cm} (1)

where:

$$\theta_{\text{SC|orbit|phase}} = \frac{v_{\text{SC|orbit}} \cdot t_{\text{occ}}}{2(\text{R}_{\text{body}} + h_{\text{SC}})}$$  \hspace{1cm} (2)

where $v_{\text{SC|orbit}}$ (m s$^{-1}$) is the spacecraft orbital velocity, $h_{\text{SC}}$ (m) is the spacecraft’s altitude above the target body’s surface, $\lambda_0$ (m) is the wavelength, $\text{R}_{\text{body}}$ (m) is the target body’s radius, $t_{\text{occ}}$ (s) is the occultation duration (on the order of 1–30 minutes), and $\theta_{\text{bw}}$ (rad) is the spacecraft antenna beamwidth (assumed to be $\sim$1.6° (0.028 radians) for high-gain X-band antennas; Palmer & Heggy 2020).

The above computation is specifically applicable to downlink BSR surface occultations of atmosphereless bodies larger than a few kilometers in diameter. For a complete list of boundary conditions, see Table 1 of Palmer & Heggy (2020).

### 2.3.2. Computing Power Spectra

Output power spectra are generated using the input parameters that are grouped under “Signal Processing...
Parameters” in the left panel of Figure 4, where a moving average of discrete fast Fourier transforms (FFTs) is applied to segments of the amplitude time-series data $A_Q(t)$ and repeated to generate a time series of power spectra. We specifically use Welch’s average periodogram method (e.g., Solomon 1991), which is succinctly expressed as

$$\overline{P}_{spec}(f) = \frac{1}{KLU} \sum_{m=0}^{K-1} \sum_{n=0}^{L-1} w(n) A_Q(n + mD_{hop}) e^{-i2\pi fn}$$,

where $\overline{P}_{spec}(f)$ is a single output power spectrum displayed on the Signal Processing window of PARSE; $K$ is the number of power spectra that have been averaged together; $A_Q(t)$ is the raw input data, a time series of complex-valued signal amplitudes; $L$ is the length of the sliding window (i.e., the number of samples from $A_Q(t)$ over which to apply an FFT and a windowing function $w(t)$); $D_{hop}$ is the step size of the sliding window (in units of samples); and $U$ is the normalization factor corresponding to the windowing function $w(t)$. To implement the above formula in PARSE, we use the Matplotlib function “psd” (documentation at https://matplotlib.org/stable/api/mlab_api.html#matplotlib.mlab.psd) and its default windowing function, a Hann smoothing filter.

User-adjustable input parameters include the desired frequency resolution $f_{res}$ (Hz), the number of spectra $K$ to average (or, alternatively, the time span of the output power spectrum, which PARSE uses to compute the corresponding $K$ number of spectra to average), and the sliding window step size as a percent overlap between sequential windows. A suggested value for $f_{res}$ to resolve surface-scattered surface echoes from the direct signal peak is first computed from their expected frequency separation $\delta f_{calc}$ (per Section 2.3.1 above). Accounting for the sampling rate $f_s$ (Hz) of the raw amplitude data (i.e., the inverse of the amplitude data’s temporal resolution), PARSE then automatically calculates the number of samples $L$ upon which to apply an FFT ($L = f_s/f_{res}$), as well as the equivalent FFT integration time in seconds ($\tau_{int} = 1/f_{res}$). The sliding window step size is then converted from the user-defined “percent overlap” to $D_{hop}$ samples (where $D_{hop} = D_{hop}(\% \cdot \tau_{int} \cdot f_s / f_{res}$).

All the above parameters and their output per Equation (3) are illustrated in Figure 5.

2.4. Signal Analysis

When the user pauses the animation on a plot and then selects the “Power Spectral Analysis” tab, PARSE will calculate and display key features of the current plot. To benefit new users, some of these key values are overlaid on the current plot and marked with annotations. This affords users a more visual and intuitive approach to analyzing the power spectral density plot (Figure 6). For more experienced users, these key output values are also listed in the left panel under the “Results” section.

From this screen, the user can choose to export the plot as a standard image file, with or without its key features labeled. Alternatively, the current plot can be exported as an ASCII file containing the coordinate pairs of each point.

![Figure 5. Welch’s average periodogram method for digital signal processing used to generate output power spectra in PARSE. A sliding window is applied to segments of length $L$ samples from the time series of complex amplitudes ($I$ and $Q$ data) at intervals of $D_{hop}$ samples to generate $K$ individual power spectra, which are then averaged together to produce the final output power spectrum.](image)

3. Illustrative Example: Identifying Surface Echoes in Dawn Bistatic Radar Data

We now provide an illustrative example with a typical pipeline to extract key features from the Dawn at Vesta data set, which is bundled with PARSE. After launching the desktop application, the user chooses “Mission: Dawn at Vesta” on the start screen (e.g., Figure 3, top window) and proceeds to the file selection window (Figure 3, bottom window). Here the user can conveniently compare each file’s date, time of acquisition, polarization, and transmission frequency (e.g., S or X band). The user then highlights a file set of interest—an RCP file with its matching simultaneously acquired LCP file, each of which contains a time series of signal amplitudes—and then loads the file pair by selecting “Process” to proceed to the signal processing window.

PARSE automates the conversion of the amplitude time series into plots of power versus frequency. The user only needs to input basic parameters for the spacecraft’s orbital geometry and target body (predefined for the Dawn and Rosetta missions; top left panel of Figure 4). Clicking “Apply Changes” calculates the theoretical value of $\delta f$ (i.e., the differential Doppler shift between the direct signal and any surface echoes, Figure 7) following the algorithm of Palmer & Heggy (2020), which is then used to automatically suggest processing parameters. The algorithms used to compute the differential Doppler shift and to generate the power spectra are discussed in Section 2.3.

A time series of power versus frequency plots are generated on the right as a playable video (Figure 4). Below this main plot is a smaller overview plot of signal strength versus time so that the user can quickly identify where the peak is strongest (i.e., not blocked/occluded by Vesta; the direct signal) and where it is weakest (when the spacecraft HGA is completely blocked from view by Vesta, hence showing only receiver noise). The transition between these two plateaus (label b) in Figure 4 is the period of interest when surface echoes occur. Clicking “Play” will cycle through these plots of power versus frequency over time; a vertical blue bar on the overview plot will move along with the video time stamp. When the user encounters a plot of interest (e.g., possible sighting of the echo signal—e.g., at time stamp 03:47:08 in the preloaded Dawn file), clicking “Pause” and selecting the “Power Spectral Analysis” tab at the top left will navigate to the next window (Figure 6).

Here, the signal analysis window lists several output parameters to be used in analyzing the echo signal characteristics: relative power of the two peaks; the observed frequency difference ($\delta f_{obs}$) to validate against $\delta f_{calc}$; the standard deviation of noise power from the mean (in units of dB), i.e.,...
measured over frequencies where no signal is present; and the bandwidth of each peak. These parameters are provided for both the RCP and LCP signals. In the case of radio occultation experiments with high grazing incidence angles (producing forward scatter), the polarization of surface-scattered echoes will not change from that of the transmitted signal (in this case, RCP), such that LCP power should be weak.

From here, it is the work of the user to further interpret the results in the context of the target’s surface properties. The reader is encouraged to refer to the procedures detailed by Simpson (1993), Simpson et al. (2011), and Palmer et al. (2017) to interpret the observed polarization and power characteristics of potential echo signals in terms of surface properties, as these relationships cannot be generalized across different planetary surfaces or for different missions. In the case of Dawn at Vesta, Palmer et al. (2017) measured differences in echo strength between different occultation events and mapped the sites of these surface echoes onto Vesta to assess spatial variations in surface reflectivity, and in turn to assess the distribution of surface roughness at the centimeter-to-decimeter scale.

**4. Impact and Implications**

The first major benefit of using PARSE is the user’s quick ability to calculate the Doppler shift that results from surface scattering ($\delta f_{\text{calc}}$) during the moments preceding and following occultations, simply by inputting the spacecraft’s orbital geometry and basic physical properties of the target body, enabling quick assessment of where the surface echo would fall on the received spectrum and whether it is detectable within the frequency resolution, where the latter is constrained by the spacecraft’s onboard communications system (e.g., Chen et al. 2000; Asmar et al. 2005). The ability to quickly perform this calculation is particularly important for missions to small bodies, for which the spacecraft’s slow orbital velocity yields a small frequency separation $\delta f$ between the direct signal and echo (e.g., Figure 7; Pätzold et al. 2007; Palmer et al. 2017). Hence, by calculating $\delta f$ prior to performing BSR observations, the user can assess the conditions under which the experiment will be feasible (e.g., if an onboard ultra-stable oscillator (USO) is needed for very high frequency resolution, or a particular spacecraft altitude). For example, the $\delta f$ calculated for Dawn at Vesta, given an orbital velocity of 200 m s$^{-1}$ at its lowest altitude of 200 km, is approximately 5 Hz (when the occultation duration is set to 10 minutes), such that an echo is detectable without an onboard USO. However, if the experiment had been performed at a higher altitude, e.g., 460 km, and hence a slower orbital velocity of 160 m s$^{-1}$, the $\delta f_{\text{calc}}$ decreases to $\sim$1 Hz, which would have required an onboard USO (not equipped on the Dawn spacecraft) to perform a successful BSR experiment.

During an active mission, the PARSE tool can also enable users to quickly verify whether telemetry data acquired around occultations can be used to characterize surface textural and electrical properties through an opportunistic BSR experiment without having to go through unnecessary intensive post-processing of the data. Specifically, the user can assess whether the surface-scattered echo is visible in the received signal in

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**Figure 6.** PARSE signal analysis window: outputs key observables for analysis of the signal power–frequency plot selected from the previous signal processing window, including the relative strength of the global maximum (nominally the direct signal) compared to a local maximum computed within a user-selected frequency range (nominally the echo signal).
terms of its signal-to-noise ratio and its $\delta f_{\text{obsv}}$. This capability is particularly useful for bodies with irregular shapes, unknown composition, and unknown gravitational fields (e.g., Peytavi et al. 2020).

In addition to assessing the feasibility of performing opportunistic BSR observations, PARSE accelerates the processing and analysis pipelines of acquired data, enabling the user during mission operations to perform real-time assessments of the textural and electrical properties of planetary bodies to support landing, anchoring, and sampling experiments, particularly for small bodies of unknown surface physical properties. Examples of such challenges include the landing of Philae during the Rosetta mission at Comet 67P in 2014, which underwent several unplanned bounces off the rocky consolidated surface before settling beneath the shadow of an overhang (Ulamec et al. 2015, 2017), and the OSIRIS-REx touchdown on Asteroid Bennu, which required intensive reconnaissance to identify a viable sampling site unobstructed by boulders (Lauretta et al. 2019).

Real-time assessment of textural and electrical surface properties is enabled by PARSE’s ability to characterize various radiometric properties (e.g., signal power, Doppler shift, bandwidth) of the BSR-observed surface echo and its evolution under different geometries and from different locations on the surface of the body. In turn, these radiometric properties are the input parameters for the signal analysis pipeline. In particular, one of the key data products that can be derived from PARSE is the difference in radiometric power between the peak of the direct signal and the surface-scattered echo, which can be used to characterize relative surface roughness variability, in addition to potentially constraining ambiguities on the explored body’s electrical properties (in circumstances when roughness can be assumed constant). These surface properties can especially enhance the mission’s science return when compared with observational data products from other onboard instruments—such as maps of shallow subsurface hydrogen concentrations, thermal inertia, surface mineralogy, and surface age—together providing insight into the major geologic processes that have acted to shape these planetary surfaces. Furthermore, in the absence of optical imagery, such as in shadowed regions of planetary bodies, such BSR observations can be used to characterize surface properties in areas that otherwise would remain unexplored, as radar observations do not require an external light source (e.g., Patterson et al. 2017).

Planetary radio science will be increasingly used with onboard spacecraft telecommunications systems, as it can be used to reduce the ambiguities on the surface physical properties as observed by other instruments at low cost and low risk to the baseline mission. Hence, the telemetry from these missions will be widely used in the future with PARSE as described above to enhance the science return and minimize the operation risk of such missions by making BSR data analysis accessible to a larger group of experts. This software tool allows the users to assess the surface electrical and textural properties of planetary bodies through both planned and opportunistic BSR occultation observations (e.g., Asmar et al. 2019). Furthermore, as space agencies move toward the use of distributed spacecraft missions, such as the two-spacecraft BepiColombo mission to Mercury, each with an antenna on board (e.g., Milillo et al. 2020), this will result in more

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**Figure 7.** Example of the differential Doppler shift ($\delta f$) or frequency separation between the direct signal and BSR surface echoes for two different missions (Simpson & Tyler 2001; Palmer et al. 2017). The $\delta f$ for the Mars Global Surveyor’s BSR observations on the left is several orders of magnitude larger than the $\delta f$ for Dawn BSR at Vesta owing to the much slower spacecraft orbital velocity around a small body, which is accounted for by PARSE when suggesting reasonable processing parameters for a given mission. (Plots are adapted from Simpson & Tyler 2001 and Palmer et al. 2017.)
opportunities for high-quality BSR observations of planetary surfaces.

Finally, as the volume of planetary radio science data continues to grow with the increasing number of space missions, publicly available tools such as PARSE will be of primary importance to introduce new users to mine these complex data sets. Additionally, our software will enable the reprocessing and analysis of even decades-old archived radio science data sets, such as radio occultations of the Moon’s tenuous ionosphere (Choudhary et al. 2016). Overall, aggregating a large volume of high incidence angle BSR observations of different planetary bodies will enable us to characterize the primary geophysical processes that act to shape different types of planetary objects in the solar system, such as small bodies, moons, and the terrestrial planets. It also enables us to understand whether centimeter-to-decimeter-scale surface roughness variability correlates with optically observed surface features and to assess safe surface trafficability, thereby enabling identification of nominally smooth sites for future landing, roving, or sample return missions. As this volume of data expands with each space mission, a statistical understanding can be formed, hence helping members of the planetary science community to better understand how physical processes play a role in the formation of planetary surfaces.

5. Conclusions and Future Work

PARSE (Processing and Analysis for Radio Science Experiments) is an open-source downloadable GUI (Windows and MacOS X compatible) written in Python that automates the processing and analysis of raw BSR radio science data sets collected by NASA’s DSN—tailored specifically to planetary surface occultations in this first release. PARSE enables the rapid, in-flight analysis of opportunistic BSR occultation experiments that are performed using a spacecraft’s onboard communications antenna. In addition, the tool allows the processing of historical BSR data in a more standardized way and to be benchmarked against newly acquired data in terms of the accuracy of retrieving surface physical properties and radiometric accuracy of the signal processing. BSR surface-scatter observations can be used to quantify surface roughness at the centimeter-to-decimeter scale, for example, which can be used to constrain thermophysical models of planetary regoliths, support detailed geomorphological mapping, and reduce risk associated with site selection for landing and sampling missions. The development of PARSE significantly broadens the user base of such radio science data sets beyond current experts and out into the planetary science community at large.

The current version of PARSE analyzes data that result from forward scatter during opportunistic occultations, but future releases will include support for backscatter BSR surface observations (e.g., Simpson et al. 2009) that can be made with controlled observation geometry. The ability to analyze, in a single tool, forward scatter and backscatter will also allow rapid analysis of planetary atmospheric radio occultation experiments, which are of particular interest in light of recent selection of two NASA missions to Venus (Ando et al. 2020; NASA Press Release 2021) and characterization of Earth’s ionospheric and tropospheric scintillations from signal noise analysis (e.g., Armstrong 1998; Morabito 2007). Additional capabilities will include the ability to ingest NASA SPICE navigation files to precisely constrain observation geometry input parameters (Acton et al. 2018), compatibility with PDS4 formatting, and support for existing Arecibo data sets and other Earth-based radio observatories, including other variations of DSN binary tables of raw radio science data, e.g., for previous missions.

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