

# Methodology for the Scientific Physical and Operations Characterization (SPOC) of Terrestrial Fieldwork

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Future human space exploration will include a variety of scientific investigations and pursuits that will require fieldwork. However, the current processes that scientists employ to complete their fieldwork in present-day terrestrial settings are not well documented and measures do not currently exist to quantify performance (e.g., work cadence/timing or assumed posture duration/frequency). Given how little is known about the biomechanical movements exhibited during scientific fieldwork conducted on Earth, this presents potentially significant limitations for future missions. A wearable sensor array of inertial measurement units (IMUs) attached to major body segments (e.g., thighs and sternum) enables unobtrusive monitoring of biomechanical movements during longitudinal, unstructured data collections. The specific focus of this paper is describing the methodology developed for classifying different movements, postures, and equipment interactions exhibited during a pilot study in which a participant completed operationally relevant tasks over a 90-minute period. The results provide support for the feasibility of this approach for additional (and longer duration) terrestrial events. Additionally, the classified data will be used for biomechanical metric development, tool usage tracking, and strategy differentiation within planetary relevant contexts. Overall, this work will have implications for successfully conducting planetary scientific fieldwork by informing the design and development of space suits, instruments and tools, human-suit-tool interfaces, training protocols, and mission planning/execution.

## Nomenclature

<i>DWT</i>	= discrete wavelet transform
<i>EVA</i>	= extravehicular activity
<i>FIS</i>	= fuzzy inference system
<i>IMU</i>	= inertial measurement unit
<i>sEMG</i>	= surface electromyography
<i>SPOC</i>	= Scientific Physical and Operations Characterization
<i>NASA</i>	= National Aeronautics and Space Administration

## I. Introduction

THE future of human space exploration will include scientific investigations and pursuits that will necessarily involve fieldwork to, for example, collect geological samples and survey new environments, first on our moon and then on Mars. In preparing for these missions, a considerable amount of work has been conducted to identify these scientific investigations and pursuits as well as the associated logistics and resources necessary to complete them. NASA's Lunar Exploration Analysis Group (LEAG) and Mars Exploration Program Analysis Group (MEPAG) created and maintain extensive dynamic documents that catalogue the different scientific investigations and pursuits

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to be conducted in the future.<sup>1,2</sup> For example, the LEAG document describes objectives and investigations relating to one of three themes: 1) Scientific, 2) Feed-Forward, and 3) Sustainability. In the Scientific Theme alone, more than 130 different planned investigations span a range of disciplinary fieldwork including geological, combustion, and astrophysics studies. As noted by the 2019 Annual LEAG Meeting findings, “Although a ‘Science Strategy of the Moon’ document has not yet been released by NASA, nor has a draft been widely circulated, development of such a strategy is critical, and will require close planning and cooperation across mission directorates if robust progress is to be made in achieving the consensus lunar science priorities that have been described and reaffirmed in community documents.”<sup>3</sup>(pg.2) Without clear prioritization, it will be exceedingly difficult to maximize mission efficiency and success given the range of possible scientific investigations being proposed. Many operational designs and decisions rely on this information including mission operations, training protocols, and tool development.

Currently, the vast majority of research associated with planetary scientific fieldwork focuses on detailing the steps necessary to achieve these scientific goals from both engineering and operations perspectives. For example, NASA’s Human Research Roadmap highlights many challenges associated with extravehicular activities (EVAs), particularly as they relate to developing field operations for crewmembers.<sup>4</sup> Future missions on our moon and Mars will involve performing more EVAs, which requires monitoring and assessing performance to maximize mission success.<sup>5</sup> However, as is highlighted by Paul,<sup>6</sup> the sensor-measured human performance data (e.g., heart rate and respiration rate) collected during the Apollo missions conducted nearly 50 years ago represent the limited extent of our knowledge of human performance conducting planetary scientific fieldwork. While the breadth of the science pursued during the Apollo missions mirror much of planned future Artemis missions,<sup>7</sup> many new experiments were not considered previously during Apollo (for example, the Feedforward experiments in the LEAG document<sup>1</sup> focus on utilizing our Moon as a proving ground for future missions to Mars and beyond). Furthermore, many experiments were conducted at pre-specified locations or as convenient for the astronaut, which may not be the case for future missions and particularly for those on Mars.

Past research has studied scientific fieldwork mainly from an analog operations perspective. In other words, spaceflight constraints are brought into terrestrial field sites with the intent to understand how fieldwork could be performed under simulated mission conditions. An array of investigations have been performed such as scientific fieldwork ethnographies conducted during the Haughton-Mars Project (HMP)<sup>8</sup> and operational tests of scientific fieldwork within NASA Extreme Environment Mission Operations (NEEMO)<sup>9</sup> and Biologic Analog Science Associated with Lava Terrains (BASALT)<sup>10</sup> analog tests. Using both the HMP and the Apollo EVA missions as a foundation, a framework was developed that organizes parameters and constraints defining planetary EVAs with special attention paid to the amount and importance of time spent on various activities during planned (and re-planned) scientific fieldwork.<sup>11</sup> Hodges and Schmitt<sup>12</sup> reflect on and emphasize the practicality and importance of refining advanced planetary geologic fieldwork on Earth, which would necessarily include incorporating advanced technologies and robotic assistants into the process. The Desert Research and Technology Studies (Desert RATS) are related to this purpose, with the 2010 round of testing focusing specifically on the geologic observation, sample collection strategies, and tools/technologies needed during planetary fieldwork and surface exploration.<sup>13,14</sup> However, it should be noted that these studies<sup>8-14</sup> do not directly address the need to characterize the biomechanical and motor control capabilities during terrestrial fieldwork. The previous studies focused largely on how scientific fieldwork was conducted from an operations perspective, but not for how the human physically accomplishes those tasks. In reference to the Apollo missions, Sullivan noted, “Many experiments flew on more than one mission, and improvements were made for the follow-on flights based on the difficulties experienced.”<sup>7</sup>(pg.12) Given how much science is currently being planned for the Artemis missions, there will likely be scant opportunities for multiple attempts for any single investigation if an experiment proves to be too difficult for the astronaut to complete.

While the aforementioned studies addressed various questions critical to the success of future missions, there remains a significant need to understand the physical, operational, and logistical underpinnings of the science astronauts will be expected to achieve. The Scientific Physical and Operations Characterization (SPOC) project<sup>15</sup> is focused on addressing these gaps in our knowledge by directly studying scientists on Earth performing professional terrestrial fieldwork to create a terrestrial baseline that will represent the best-case scenario (unencumbered experts in a 1g environment) across a broad spectrum of scientific disciplines. The project will also provide opportunities to study the variability within and across field expeditions. In doing so, demonstrated behaviors and strategies will be unobtrusively observable from scientific fieldwork that can be used to inform the design and development of EVA that hope to accomplish similar scientific goals. The focus of this paper will describe the first step to the data processing approach, which is activity classification for the automatic parsing of data from wearable sensor arrays of inertial measurement units (IMUs) attached to major body segments of scientists for unobtrusive, unstructured data collections.

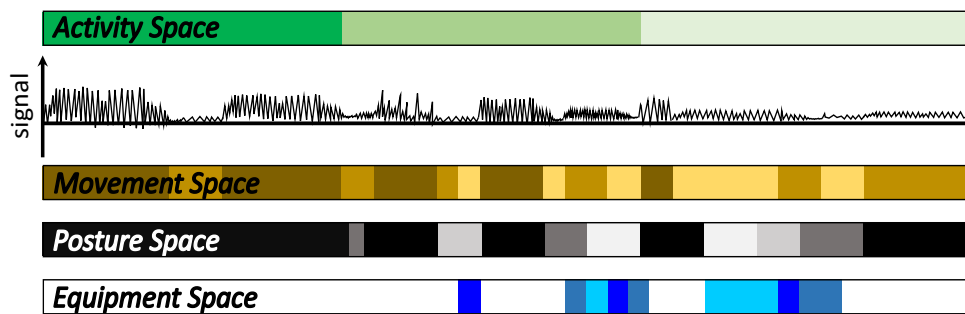
Activity classification approaches broadly fall into one of two categories: 1) supervised and 2) unsupervised. The supervised approach requires correctly labelled data to develop a classification algorithm whereas the unsupervised approach automatically determines the number of states or clusters in the data with each theoretically corresponding to a specific activity.<sup>16</sup> In this paper, a supervised activity classification approach is employed largely because there are specific activities that we are interested in identifying and analyzing. Historically, most activity classification approaches with body-worn sensors also fall into the category of a supervised approach.<sup>16</sup> Previous work relevant to this paper have employed fuzzy logic, wavelet transforms, and thresholds for identifying a variety of different activities. Salarian et al.<sup>17</sup> used fuzzy logic to identify lying down, sitting, standing, and walking as well as transitions from sit-to-stand and stand-to-sit using data collected by IMUs attached to the trunk and shanks. Similarly, Boissy et al.<sup>18</sup> used data from an IMU attached to the trunk to identify falls in a variety of testing conditions using postural and acceleration information. Further, several studies have used wavelet analysis to either identify gait events<sup>19,20</sup> (e.g., stance phase) or different types of gait<sup>21</sup> (e.g., level walking versus climbing stairs). This approach exploits that walking is a distinctly periodic movement when considering the kinematics of the lower extremities. Finally, threshold-based approaches have successfully been used in the past to differentiate between different kinds of activities like stationary postures and dynamic activity.<sup>22</sup> The work presented herein combines and builds upon these previous studies to detect specific activities of interest for planetary fieldwork tasks.

The remainder of this paper is structured as follows. Section II describes the methodology and methods for the activity classification approach to categorize human action according to motions, poses, and tools. Also included in this section is a description of the experimental protocol for a pilot data collection. Section III presents the activity classification results for each of the three aforementioned categories as well as brief discussions about implications for potential stakeholders. Finally, Section IV summarizes the significance of these efforts and describes next steps for the SPOC project.

## II. Methods

The first step to processing and analyzing the wearable sensor data is activity classification, which facilitates the automatic parsing of the data into relevant (pre-defined) classes (i.e., a supervised approach). Considering that a single data collection could be as long as 12 hours depending on the nature of the scientific fieldwork being conducted, automatic data parsing is important to circumventing manually parsing the data, which would otherwise limit how much data could reasonably be collected and processed. When utilizing a supervised approach to activity classification, classes are pre-defined such that they can then be identified in the data based on an understanding of the underlying activity. In this work, that classification was made in a physically inspired manner, meaning by capitalizing on distinct kinematic characteristics that reliably occur during an instance of the activity. For example, walking gait is usually discussed in terms of gait cycles that are bookmarked by successive footfalls that are detectable in the foot-mounted IMU data by identifying short duration, high acceleration impact events. Furthermore, it is potentially advantageous to categorize classes into different activity classification spaces based on how the classes are related to one another, especially when one considers that a participant could be occupying multiple classes at the same time. For example, a participant who is kneeling while inspecting a geological sample is simultaneously occupying a pose-related class and a movement-related class that are not strictly unique to one another (e.g., other movements occur in the kneeling pose and other poses are assumed when inspecting a sample).

The activity classification approach pursued in this work occurs in two different stages, which are illustrated in Fig. 1 alongside a hypothetical wearable sensor signal. The first stage, and the focus of this paper, detects classes in



**Figure 1. Activity classification stages.** *The Movement, Posture, and Equipment Spaces are detectable from the IMU and sEMG data whereas the Activity Space is inferable from those three spaces. Different shades of each space indicate a variety of subcategories that might exist within a given space.*

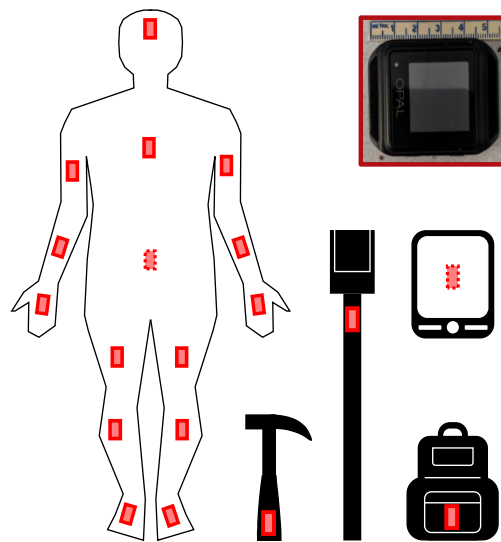
one of three spaces of interest using the wearable sensor data. These three spaces are the Movement, Posture, and Equipment Spaces, which are defined by motions, poses, and tools, respectively. The second stage consists of mapping the wearable sensor data to an Activity Space that is defined by operationally relevant tasks and will be inferable from the three aforementioned spaces. A description of the pilot data collection in the next section offers context for each of the activity spaces in the first stage (Movement, Posture, and Equipment) in the subsequent sections.

### A. Experimental Protocol and Pilot Data Collection

The pilot data collection took place at NASA Johnson Space Center (JSC) at an outdoor site known as the Rockyard, which is depicted in Fig. 2. Procedures were approved by the NASA JSC IRB and the University of Michigan IRB. Prior to the data collection, the participant was outfitted with a full IMU array as well as a few of the more commonly used tools as illustrated in Fig. 3. Additionally, an example of the type of IMUs used in this study is pictured (Opal, APDM, Portland OR; sensor characteristics available at <http://www.apdm.com/wearable-sensors/>). The data collection spanned four different regions within the Rockyard: 1) the rock field, 2) the Martian mound, 3) the sand dunes, and 4) the Lunar surface. The participant progressed through these four areas in this order, spending approximately 20 minutes in each region for a total testing session time of about 90 minutes. Within each region, the participant completed geologically relevant fieldwork activities including reconnaissance, sampling, and documentation. During reconnaissance, the participant traversed the region and inspected geological samples (either by eye or using a hand lens) to gather information to broadly characterize the region. During sampling, the participant collected samples using various tools including a rock hammer, an Apollo-era scoop with extension handle, and sample bags. During documentation, the participant used a tablet to take pictures of the samples and the site the sample came from (frequently with a known object for scale).



**Figure 2. Aerial view of the Rockyard.** Image from Google Maps. The participant progressed through regions of the Rockyard in the following order: 1) rock field, 2) Martian mound, 3) sand dunes, and 4) Lunar surface.



**Figure 3. IMU array for pilot testing.** IMUs are attached to all major body segments and important, commonly used tools. An image of the IMU is in the upper right corner.

### B. Posture Space

The Posture Space is defined by the different poses that scientists assume to conduct their scientific fieldwork. The poses scientists assume is important to study since there are restrictions on the types of movements and ranges of motion that are available to the human within a space suit. For example, earlier generation space suits made kneeling exceedingly difficult (though not impossible), especially when the space suit was pressurized.<sup>23</sup> Furthermore, from a range of different disciplines like occupational health, there are certain poses that are more likely to induce an injury.<sup>24</sup> Thus, it is becoming increasingly important to evaluate what kinds of poses are assumed by scientists when conducting fieldwork to better understand the posture frequency and duration, as well as the potential injury risk mechanisms for future EVAs. For near future plans to return to our Moon in 2024, it is unlikely this information will be used for significant redesigning aspects of the current space suit. However, this information will be useful in assessing what will be feasible in the space suit. For aspects of planetary fieldwork that will not be possible in the space suit, changing

tool designs could potentially make up for these mobility deficits. Additionally, certain poses that will increase the potential for risk of injury can be tracked, which could be used for training purposes.

To reliably and automatically identify different poses, a Mamdani fuzzy inference system (FIS) was used to map inputs (features) to outputs (classes).<sup>25</sup> In classical set theory, an element has exclusive membership for a single set (i.e., membership to all other sets is zero).<sup>25</sup> In fuzzy set theory, elements are allowed to have memberships for multiple sets; however, the degree,  $d$ , of that membership is dictated by user-defined characteristic membership functions ( $d \in [0, 1]$ ) and fuzzy rules.<sup>26</sup> In this case, the features input into the FIS are the inclination angles (orientation relative to vertical) of the IMUs mounted to the sternum, thighs, and shanks. The outputs of the FIS are numerical values that correspond to one of following four poses: 1) upright, 2) bent over, 3) kneel, or 4) crouch. These poses are pre-defined through observation of the data collection and examples of each are shown in Fig. 4. In addition to absolute and relative amount of time spent in each pose, transitions between poses are also examined. The importance of these transitions between poses can be observed from video collected during the Apollo EVAs. In particular, the videos highlight the difficulty astronauts had in transitioning to certain poses based on the reduced gravity and soft-structure of the space suit.



**Figure 4. Classes within the Posture Space.** *Examples of the different poses that occurred during the pilot data collection. From left to right, the poses includes upright, bent over, kneel, and crouch.*

### C. Movement Space

The Movement Space is defined by the different motions that scientists execute when conducting their fieldwork. However, given the unconstrained and unstructured nature of the data collections, it is unlikely and intractable to expect to be able to identify every single motion that could theoretically occur over a 12-hour day of scientific fieldwork. Therefore, this space is reasonably limited to identifying important motions of interest, which currently includes walking gait and stationary periods. Walking gait can vary dramatically based on the intention behind the locomotion. For example, locally reorienting shuffle steps are kinematically very different from global ambulation intended to relocate geospatially to another location. While a total step count could reasonably have important implications (e.g., thermal analyses for working within a permanently shadowed region), it may not be necessary to calculate gait parameters for every step in the future. In between bouts of walking, stationary periods are identified based on the data collected at the feet. Within these stationary periods, it is further determined if the person is completely still or is potentially interacting or inspecting a sample of interest. This further breakdown will offer some perspective on the work cadence of collecting samples. For example, several samples could be collected and inspected during reconnaissance of a potential sample site to gain a sense for the geological composition of the area. Depending on the size of the sample site, the length of this reconnaissance period could vary.

Walking gait is a repetitive (periodic) movement that can be visually easy to identify especially when considering data collected by the IMUs mounted to the feet. The ease of visual identification is primarily because a gait cycle is frequently bookmarked by successive footfalls, which are impact events that are distinguishable in IMU data collected at the feet. For this reason, a discrete wavelet transform (DWT) is applied to the product of the angular velocity magnitudes of the feet using the ‘sym2’ mother wavelet and 10 levels of approximation coefficients.<sup>27</sup> A DTW is similar to a short-time Fourier transform but does not suffer the same limitations associated with constant bandwidth.<sup>28</sup> Essentially, it provides frequency content information with temporal relevance. The middle eight level coefficients are summed which are then used to identify regions in the data where walking occurs. The most detailed coefficients identify too many singular instances of foot movement and the most approximate coefficients are too coarse to glean



meaningful information. Local Walking is defined as taking anywhere between 3-8 seconds, which approximately corresponds to 1-3 gait cycles (footfall to footfall for the same foot) for an average speed walker.<sup>29</sup> Greater than that amount of time is considered Global Walking. Less than that amount of time is considered repositioning steps that are not prioritized for this analysis. While a fixed value is selected here based on terrestrial walking, the transition between Local and Global Walking will differ with planetary gravity and can be modified for these applications. For example, the Apollo astronauts tended to lope (a kind of skipping behavior) rather than walk on the Moon.

In between these regions of Local and Global Walking, stationary periods are identified using both the accelerometer and angular rate gyro data for the IMUs attached to the feet. At the beginning of the data collection, the participant stood still in a neutral posture for roughly 10 seconds. The data from this region of data is used to define a joint distribution of angular velocity and acceleration magnitudes that are probabilistically likely to occur during a stationary period. Calculating a Mahalanobis distance<sup>30</sup> for each sample during the data collection with respect to this distribution and comparing with a  $\chi^2$  test<sup>31</sup> evaluated at a significance level of  $\alpha=0.05$  identifies static periods where the feet are not moving. For these static periods, this analysis is repeated for the data collected by the IMUs attached to the hands to determine if the participant was Completely Stationary or engaging in another type of activity (e.g., inspecting a potential sample or documenting a sample site with the tablet), which is hereafter referred to as Partially Stationary. This breakdown allows for the interpretation of the work cadence associated with the different phases of the data collection. Overall, the breakdown by these different motions will show when the participant is moving versus stationary, and what (if any) kinds of activity are happening during those stationary periods.

#### **D. Equipment Space**

The Equipment Space is defined by the interactions that scientists have with tools that were previously identified by the scientists as useful or critical to conducting their fieldwork. Typically, tools are designed with a specific purpose or set of purposes in mind. However, there is the potential for scientists to use tools in ways that were unintended by the designers. Multiple modalities exhibited and utilized for a single tool may provide valuable information for EVA tool designers in the future who are aiming to create a set of multimodal tools that ultimately reduces the total number of tools. Additionally, the Equipment Space will likely be critical in inferring what operationally relevant tasks the participants are conducting with respect to the Activity Space. For example, rock hammer usage is likely going to be associated with sampling tasks whereas the tablet is likely going to be associated with documentation tasks. Furthermore, the biomechanical and/or motor control capabilities exhibited while interacting with the tools could offer valuable insight for developing training protocols and/or future tool designs. For example, if it is revealed that there are certain biomechanical capabilities (e.g., joint ranges of motion) that are required to use certain tools that are impossible to achieve in the current suit, then it is likely that the tools will need to be redesigned to augment those mobility discrepancies.

Only a subset of tools were instrumented with IMUs during the initial pilot testing, and these tools were identified beforehand with input from the participant as being significant to a geological sampling session. The tools that were instrumented included the backpack, rock hammer, tablet, and an Apollo-era scoop with an extension handle.<sup>32</sup> However, only the backpack and the rock hammer are analyzed presently. For the former, the total number of times the backpack is donned and doffed throughout the data collection is tracked. Additionally, when the backpack has been doffed, the number of times the participant handles the backpack and the duration of those interactions are also tracked. For the rock hammer, an investigation into the tool's versatility was conducted. Specifically, there are two modalities that are intended by the design of the rock hammer. The flat edge of the hammer is typically used to split rocks, either to observe the geological characteristics inside the specimen or to procure a smaller portion of the original specimen. The pick head side of the rock hammer is typically used to focus the force of the swing to as small a surface area as possible to maximize the impulse, which is particularly useful for harder specimen. However, other modalities that were not originally intended by the design also appeared during the data collection as well.

### **III. Results and Discussion**

Preliminary results for the different poses, motions, and tools within the Posture, Movement, and Equipment Spaces, respectively, are presented. Within each space's subsection, a discussion of the results and their implications is included.

#### **A. Poses**

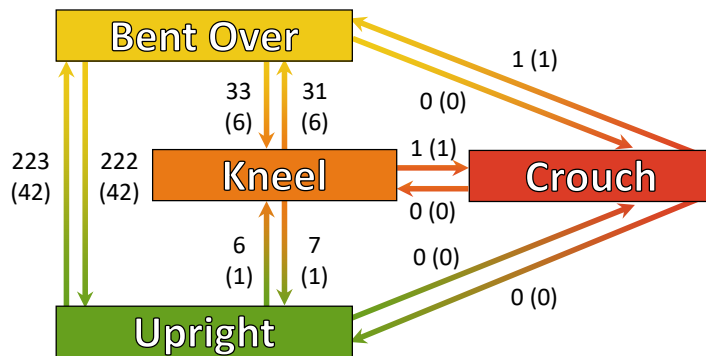
Table 1 describes the absolute and relative total amount of time spent in each of the pre-defined poses (upright, bent over, kneel, and crouch; see Fig. 4 for examples). Note the relative time does not add up to 100% because there

**Table 1. Time spent in each pose.** Absolute time is reported in minutes and seconds. Relative time is a percentage of the total time for the data collection. Mean time is the average over all instances of the pose. Standard deviation describes the variability in the time over all instances of the pose.

	Absolute Time (min:sec)	Relative Time (%)	Mean Time (sec)	Standard Deviation (sec)
Upright	59:11	62	13.7	26.9
Bent Over	20:32	22	4.3	5.3
Kneel	13:30	14	20.3	19.1
Crouch	00:05	<1	-	-

are transitions between poses that do not belong to any one of the poses as they have been described. The average and variability of the length of time spent in each posture is included with the exception of crouch for which there was only a single instance. These results provide context for how each of these poses are used. For example, while the absolute time spent in the kneel pose is less than that for the bent over pose, the mean time for the kneel pose is considerably higher (about 5x greater) than that for the bent over pose. This means the participant is assuming the kneel pose less frequently, but for longer durations as compared to the bent over pose. This finding is likely the result of the bent over pose being more versatile than the kneeling pose. For example, it is biomechanically more convenient to bend over to retrieve a tool from the ground than it would be to kneel to achieve the same task. However, it is important to note that the natural (unsuited) biomechanics exhibited while bending over is also not going to be achievable in the space suit. While the current version of the planetary space suit (xEMU) does allow the astronaut to bend over, the effects of their altered biomechanics is unknown, especially since astronauts will also need to manage their new center of gravity that is significantly affected by the suit's portable life support system (PLSS).

Figure 5 illustrates how the participant transitioned between each of the pre-defined poses throughout the data collection. Each arrow denotes a transition from one pose to another pose with the corresponding numbers denoting how many of that specific type of transition occurred during the data collection. By far, the most common transitions were between the upright and bent over poses. Interestingly, it is far more common to transition to the kneel pose by going through the bent over pose as opposed to the upright pose. This finding may partially account for the relatively short mean time spent in the bent over pose in Table 1. For example, transitions are by nature short duration events, and having many transitions through the bent over pose would bring down the overall average.

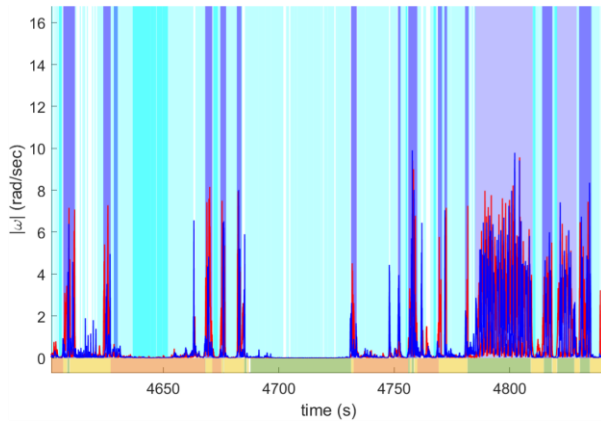


**Figure 5. Transitions between poses.** Arrows denote transitions and the number beside each denotes how many (and percentage of total number of transitions) of that transition occurred.

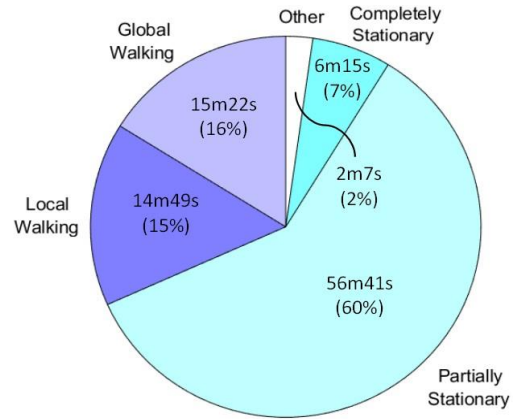
The results from the pilot data collection suggest that certain poses and transitions do not align well with what is currently possible or convenient for the current planetary space suit (xEMU). Future analyses will focus on understanding the tasks being performed for specific types of poses and transitions to enable the appropriate tool design and EVA planning to capitalize on the newly afforded mobility of the xEMU (with respect to the EMU or Apollo-era space suits) and support the required planetary fieldwork actions.

## B. Motions

Figure 6 illustrates a representative time series of the angular velocity magnitudes of the feet. The light purple, dark purple, light cyan, and dark cyan shaded areas denote periods of Global Walking, Local Walking, Partially Stationary, and Completely Stationary, respectively. Unshaded regions denote occasions when the participant is moving their feet in a way that is not consistent with sustained walking gait (e.g., shuffle steps or pivoting). For context, the green, yellow, and orange shaded regions at the bottom of the graph denote instances when the participant assumed the upright, bent over, and kneel poses, respectively. For example, Global Walking is generally completed



**Figure 6. Time series representation of motions.** Angular velocity magnitudes of right (red) and left (blue) feet. Light purple denotes Global Walking, darker purple denotes Local Walking, light cyan denotes Partially Stationary, and dark cyan denotes Completely Stationary. Shaded regions at the bottom correspond to the different postures.



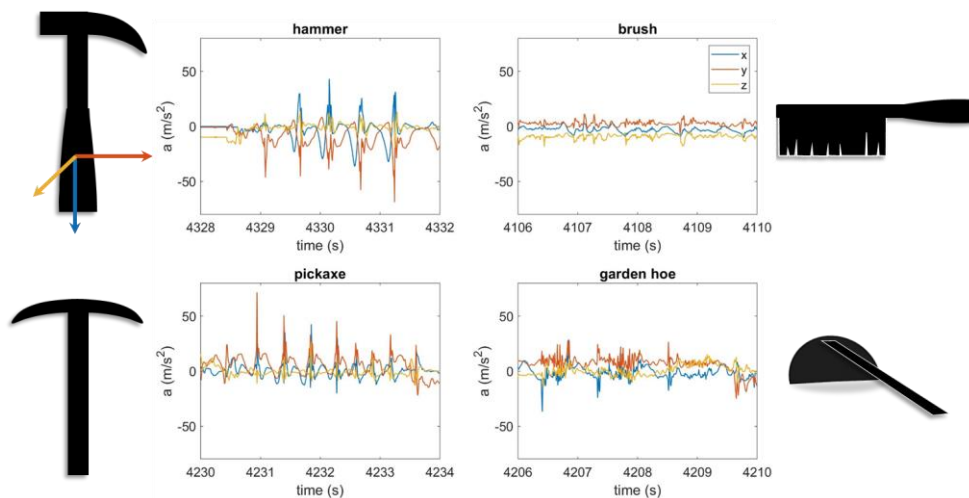
**Figure 7. Relative breakdown of different motions.** Each slice of the pie chart corresponds to one of the aforementioned motions as well as an “Other” category for undefined motions during the approximately 90 minute data collection. Absolute and relative amounts of time are also reported.

in the upright pose whereas Local Walking can be completed in either the upright or bent over poses. Local Walking while bent over would be aligned with inspecting a ground feature from different angles. Furthermore, while in the kneel pose, the participant is typically Partially Stationary or Completely Stationary, implying periods of inspection, cognitive processing, documentation, or sample collecting. Figure 7 illustrates the relative amount of time spent doing each of these different motions. About a third of the data collection (about 30 minutes) is spent walking either locally or globally whereas the participant is completely stationary for a little more than 6 minutes. Interestingly, about 127 seconds are spent doing “Other” motions that were undefined. It is likely that a significant portion of this time can be explained by some of the transitions between different postures, which is about 116 seconds of the data collection.

The participant spent the majority of the pilot data collection Partially Stationary. Future analyses will consider the amount of time spent within a specific region. When combined with information about tool usage, the timing for planning versus acting for a specific task could potentially yield information for defining future EVAs.

### C. Tools

Figure 8 illustrates the different ways in which the rock hammer was utilized by the participant during the data collection, two of which were intended by the design and two of which were not. As described previously, a geologist’s



**Figure 8. Time series representations of acceleration profiles for different modalities for the rock hammer.** The two graphs on the left are the intended uses for the rock hammer (hammer and pickaxe) whereas the two graphs on the right are unintended uses for the rock hammer (brush and garden hoe).



rock hammer has two different sides: 1) a flat side meant for breaking softer rocks and 2) a pickaxe side meant for forceful splitting of harder rocks. In both modalities, the data looks very similar in that there are obvious peaks in the acceleration predominantly along the y-axis (shown in red). Because the orientation of the hammer needs to rotate 180° about the x-axis (shown in blue) depending on which modality is being utilized, the peaks are in opposite directions (e.g., peaks are negative for hammer and positive for pickaxe). Note that the direction of travel of the hammer in the world frame (e.g., up versus down) does not change the direction of the impacts in the sensor-fixed frame. Two additional modalities were also exhibited during the data collection for which the participant used the rock hammer as a brush and a garden hoe. In the brush configuration, the hammer is rotated 90° about the x-axis such that the broad face is about flush with the ground. The curved pickaxe side was then used to effectively brush the top layer of soil into a sample bag. In the garden hoe configuration, the rock hammer is in the same orientation as the pickaxe but instead of inducing high force impact events, the curved edge was used to dig a trench to then acquire a sample roughly 5 cm below the surface. Between these two unintended uses (as well as the two intended uses), there will undoubtedly be differences in the biomechanical and motor control capabilities required to produce these acceleration profiles. If these capabilities are not currently possible within the space suit, then either training protocols or tools will need to be appropriately designed to support those underlying objectives.

Table 2 reports the results for the participant’s interactions with the backpack. Specifically, the number of times the backpack was donned and doffed as well as the amount of time spent in each of those conditions. The number of interactions the participant had with the backpack was tracked as well as how much time was spent handling it (e.g., retrieving or stowing tools and samples). It should be noted that interactions include the transitions of donning and doffing the backpack. Interestingly, more total time was spent with the backpack doffed than donned. Unsurprisingly, the number of times the backpack was doffed is the same as the number of times it was donned (given that the data collection started and stopped with the backpack donned). With respect to the number of times the backpack was handled, equipment designers are currently deciding on how best to transport equipment and samples to and from the lunar module during EVAs. Depending on the nature of the interactions with the backpack (e.g., retrieving a hand lens or stowing a geological sample), this information may assist in the decisions regarding which tools would be more conveniently attached to the suit itself versus stowed in a tool caddy or rover. Furthermore, these interactions may reveal the work cadence associated with different tasks that could have implications for planning versus acting during EVAs.

**Table 2. Backpack behavior.** Amount of time spent with the backpack donned, doffed, and handled with as well as the number of times the backpack was donned, doffed, and handled.

	Time (min:sec)	Count
Donned	37:14	19
Doffed	43:50	19
Handled	12:34	86

#### IV. Conclusion

The purpose of the SPOC project is to investigate what it means to successfully conduct planetary scientific fieldwork. To achieve these goals, it is prudent to unobtrusively investigate unconstrained terrestrial fieldwork with discipline-specific experts whose fieldwork is similar to what is planned for the Artemis program. The preliminary results presented in this paper demonstrate the promise of using wearable technologies like IMUs to study and better understand that planetary scientific fieldwork by first automatically parsing the data into operationally relevant segments in the Posture, Movement, and Equipment Spaces. Next steps include validation of the activity classification methodology using video captured during the data collection which is already underway to provide ground truth data for comparison. Furthermore, biomechanical metrics of performance like joint ranges of motion will be developed to better understand what capabilities are required to conduct scientific fieldwork. Future data collections in collaboration with the US Geological Survey are planned (tentatively for Fall 2020) to outfit scientists going out on day trips to conduct fieldwork. The insights resulting from this work could potentially inform the design and development of space suits, instruments and tools, human-suit-tool interfaces, training protocols, and mission planning/execution.

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