Fluidity as a Measure of Movement Quality

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Abstract— **In this paper, we present 'fluidity' as a metric for quantifying movement quality, and validate the measurement of fluidity in an unobtrusive, wireless, low-power manner in an operational setting. Full-body movement quality is difficult to unobtrusively quantify due to the high operational complexity and precision often required, but doing so is critical for the effective study of human-system interactions. In the human spaceflight domain, the operational impacts of adaptation to microgravity are not adequately characterized. Spaceflight studies have been focused on single-limb or single-joint kinematics; a gap remains in functional whole-body movement assessment, which is important for risk characterization of spaceflight-degraded physiology, contingency, and planetary exploration scenarios. As a proxy for whole-body movement quality, we propose an adapted definition of biomechanical 'fluidity' from prior literature, improving it to be mathematically meaningful. Coupled with the development of a wearable on-body sensor system, we validated a novel, low-power, wireless kinematic monitoring technique in laboratory and operational (i.e., parabolic flight) environments. Pilot test results demonstrate discriminatory validity of fluidity across gravity levels, as well as between nominal and degraded movements. Beyond spaceflight, assessment of movement quality in an unobtrusive manner can provide real-time, precise knowledge about human performance across applications in exercise physiology, rehabilitation, and human-robotic interaction.**

I. INTRODUCTION

Microgravity poses a significant challenge to human physiology. The proprioceptive system, responsible for the control and awareness of our motions, is highly gravity dependent [5]. Control of space systems (e.g., vehicles, rovers, control panels) is a high-level integrative function of the central nervous system (CNS), which relies on neural pathways that have developed and evolved under Earth gravity [5][6]. CNS maladaptation in microgravity can lead to decrements in coordination and movement control, creating risks in impaired control of spacecraft, vehicles, and other systems. [7]. Inappropriate movements, which could cause damage to the crew and equipment, have been observed in some capacity during the first days of spaceflight [8][9][10][11].

Functional impacts of performance degradation due to proprioceptive adaptation are not yet fully understood, pointing to a research gap in the characterization of operationally-relevant movements in the context of spaceflight [12][13][6]. Whole-body movements are of particular interest since crewmembers and spaceflight participants engage in them during flight. The shortened flight time condenses high-risk critical events (such as launch and landing), where the passengers may not be ready to perform the needed movements during contingency scenarios. For example, the NASA Crew Escape Systems manual highlights several emergency egress modes out of the crew capsule, where tasks such as egressing seats and hatches may be applicable to commercial spaceflight systems [14]. When first encountering an altered gravity environment, arm movements are often inappropriate and inaccurate, suggesting similar maladaptation for whole-body movements [9][10][11]. Past spaceflight research has shown that motor control strategies adapt after approximately four weeks in the microgravity environment [15]. Furthermore, for many commercial spaceflight passengers, this is their first time experiencing microgravity, since a parabolic flight experience is not a part of the required training protocol [16]. Therefore, initial proprioceptive response at a whole-body level is important to characterize for two main reasons: 1) to contribute to the body of knowledge of physiological adaptations to microgravity and 2) to inform the design of spaceflight participant peripherals (spacesuits, capsules, seats, displays, controls).

In prior work, we introduced the concept of "proprioceptive competence," a term describing a specific ability that falls within the broader collection of all physical and physiological adaptations [26]. As a means to assess and quantify proprioceptive competence, we employ the metric of fluidity by incorporating elements from the multi-level framework of movement quality proposed by Camurri et al. [18], and modifying the fluidity definition provided by Piana et al. [17][1] to meaningfully compare analogous movements between gravity levels. Motivated by the aforementioned proprioceptive challenges in microgravity, we collected joint kinematic data with a wearable sensory system in laboratory (normal gravity, 1g) conditions and in parabolic (microgravity, 0g) flight, between which we would anticipate significant differences in movement quality. With the initial results, we demonstrate the usability of this metric to assess movement quality and discuss the application of the metric toward non-spaceflight paradigms.

II. METHODS

A. Fluidity Index Derivation

A prior mathematical definition for joint jerk-based fluidity was proposed by Piana et al. [1], and we present updates

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that expand the use cases of this definition. This process takes accelerometer data, either magnitude-only or in axial components, and yields a Fluidity Vector of length equal to the movement duration, as well as a Fluidity Index that summarizes the movement. Note that a *movement* can be defined arbitrarily – a pointing gesture, sit-to-walk task, or a dance.

The magnitude of acceleration from the components of acceleration is

$$a = \sqrt{a_x^2 + a_y^2 + a_z^2}$$

where a_x, a_y, and a_z are the x, y, and z components of acceleration. Here, a is a time-varying vector.

Jerk is defined as

$$j = \frac{da}{dt} \tag{1}$$

where a is acceleration in g's (Earth's gravitational constant) and t is time in seconds.

Piana et al. provided an existing mathematical definition of fluidity [1]:

$$\text{FI} = \frac{1}{\int (j_i + 1)dt}$$

where j_i is the ith time index of the previously defined jerk and FI is a numerical index that describes the fluidity of a movement over the entirety of the movement. Although details were not provided by Piana et al., we speculate the jerk (j_i) is the magnitude of the jerk and the 1 is added to the integrand to keep the denominator of the fraction positive and non-zero.

Two limitations exist with the definition. The index is not bounded, and possible values for FI exist between $(0, \infty)$, depending on the duration of the movement. The index also penalizes movements with longer time duration, as the integral is over time. For a movement with a longer time duration, FI will be smaller than that with a smaller duration even if the average jerk, smoothness, and movement quality of the movements are the same. Or, short jerky movements can have the same FI as longer smooth movements.

To meaningfully cross-compare movements of unequal duration, we considered two approaches which are conceptually equivalent but mathematically distinct. For both, we start with a non-negative (as we are only concerned with the magnitude) time-varying vector of jerk,

$$|j_i| =< |j_1|, |j_2|, \cdots, |j_n| >$$

Approach 1 – Arithmetic Mean

Find the time-varying Fluidity Vector such that

$$FV =< \frac{1}{|j_1|+1}, \frac{1}{|j_2|+1}, \cdots, \frac{1}{|j_n|+1} > \tag{2}$$

The range of values is constrained from $(0, 1]$. We add 1 to the denominator to prevent dividing by zero.

The modified FI is then

$$FI_{AM} = \frac{\sum FV}{n} \tag{3}$$

which is the arithmetic mean of the Fluidity Vector. This value can be interpreted as the average of fluidity values over the whole movement, where fluidity is inversely proportional to jerk.

Approach 2 – Harmonic Mean

The second approach starts with the average of the modified jerk vector for the Jerk Index, where 1 is added to prevent dividing by 0 in the Fluidity Index definition later.

$$JI = \frac{\sum(|j_i|+1)}{n} \tag{4}$$

FI is then the reciprocal of JI

$$FI_{HM} = \frac{n}{\sum(|j_i|+1)} \tag{5}$$

and this definition is the harmonic mean of the Fluidity Vector (Equation 2). This value can be interpreted as the reciprocal of the average jerk values over the movement.

Both definitions utilize an averaging function, a summation, and an inversely proportional relationship between fluidity and jerk. However, the subtle difference in the order of operations make these two definitions numerically different, per the HM-AM inequality, where 0≤HM≤AM for all combinations of numbers. For a conservative estimate of fluidity, we opt to take the harmonic mean definition offered in Equation 5. This new definition is a normalized version of the metric proposed by Piana et al. and can now be used to compare meaningfully across movements that are unequal in duration.

$$FI_{\text{modified}} = \frac{n}{\sum(|j_i|+1)} \tag{6}$$

where n is the number of timesteps and j_i is the jerk at each time step from $i = 1, ..., n$.

B. Experimental Setup

As a pilot validation, we had one participant take part in 10 laboratory movement trials and 10 parabolic flight trials, for a total of $N = 20$. The human participant study protocols adhere to the guidelines set by MIT's Institutional Review Board (Committee on the Use of Humans as Experimental Subjects) under protocol number 2111000521.

The flight was hosted on a Zero Gravity Corporation (Virginia, USA) Boeing-727 aircraft. A wearable sensor garment was designed to collect acceleration data at the wrists, elbows, shoulders, hips, knees, and ankles, for a total of 12 joints [2]. The prototype was designed to be self-sufficient (e.g., powers itself, collects data without user management, and wireless) in the parabolic flight environment [2]. A data rate of 100 Hz was set as the baseline target frequency based on literature for measuring biomechanics in similar task-based settings [3][4].

To compare data across laboratory (1g) and parabolic (0g) environments, we developed a translation task that would capture similar intent across the different gravity levels. The task setup is visually represented in Figures 1 and 2. The ground experimental task comprised rising out of a seated position on a chair, translating 4 meters, and touching a target to signal traverse end. The flight experimental task comprised rising out of a supine position on the plane floor, translating 3.8 meters, and touching a target on the corner between the plane ceiling and the bulkhead wall to signal traverse end. Although the translation paths were different, they both equate to functional whole-body movements that a crewmember would be expected to accomplish early on in their microgravity exposures. The parabolic flight included 20 parabolas total, 10 of which provided suitable microgravity parabolas for the experimental protocol. These occurred during parabolas 6-9 and 12-17, which correspond to the trial numbers used for analysis. For consistency, the ground trials corresponding to the flight parabolas were used.

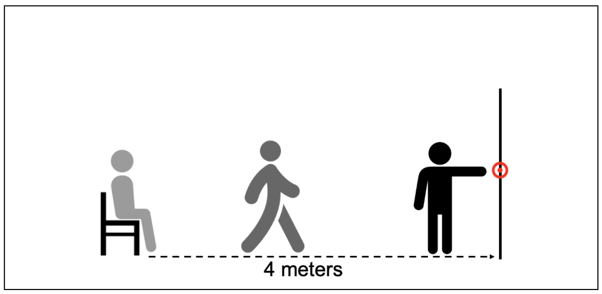

Fig. 1. Laboratory experimental task setup. Participants started in a seated position, then traversed a distance of 4 meters, and touched a target in front of them to conclude the traverse.

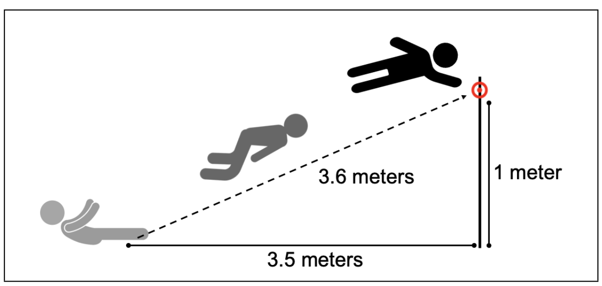

Fig. 2. Parabolic flight experimental task setup. Participants started in a supine position, then traversed a distance of 3.6 meters, and touched a target to conclude the traverse.

III. RESULTS

To limit the effect of noise in our data, we filtered out frequencies higher than 20 Hz, which is the upper end of the frequency of human motion [27][28]. From the original data sampled at 100 Hz, we performed low-pass filtering and downsampling to 40 Hz, which is the Nyquist frequency needed to reconstruct signals below 20 Hz. The data set was tested for normality with the Kolmogorov-Smirnov (KS) test. Homoscedasticity (equality of variances) was tested with Levene's Test, which is less sensitive to departures from normality, as an alternative to Bartlett's Test. We expected, and found, a non-normally distributed data set since the numerical values of the independent variable have a ceiling (human movement is limited) and we have a small sample size.

We compared laboratory (1g) and parabolic flight (0g) joint fluidity during a translation task to assess the ability for the FI metric to discriminate between different gravity environments. Mean joint FI values were plotted for each trial of ground and flight data with variances as error bars in Figure 3. We used the Wilcoxon two-tailed signed rank test to test the difference between the medians of two conditions. Comparing the medians of ground and flight whole-body FI values at $\alpha = 0.05$, we calculated the Wilcoxon test statistic W = 3 (df = 19, $p = 0.01$). We have evidence to reject the null hypothesis at an $\alpha = 5\%$ significance level. We saw a statistically significant increased median fluidity for the flight condition ($FI_D = 0.76$) compared to ground ($FI_D = 0.67$). One explanation for this significant result is that the fluidity of constrained and goal-oriented traverses is not adversely affected, or could be increased in microgravity. Goal-oriented traverses could provide the participant with a focus point and consequently prevent the flailing that first-time participants resort to during initial microgravity exposure. Further experimentation with an increased participant pool and a broader set of dynamic movements, both constrained and unconstrained, would contribute power to this explanation.

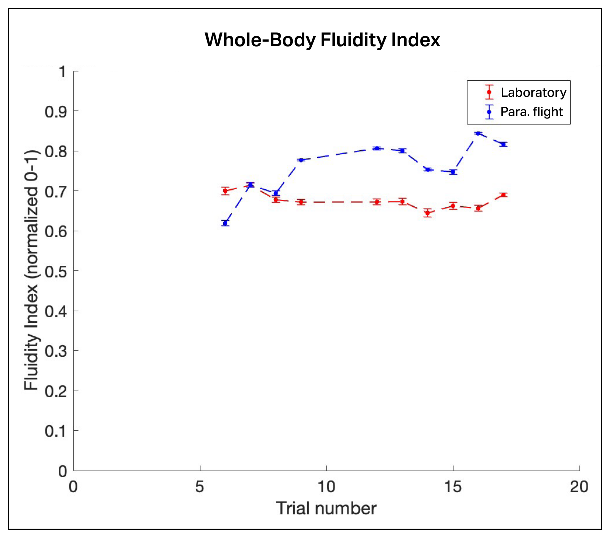

Fig. 3. Whole-body Fluidity Index values (averaged over all accelerometers) derived from joint acceleration for each trial are plotted for laboratory and parabolic flight conditions. Mean averaged joint FI values over each trial are plotted with variance error bars. Dashed lines are used for ground/flight grouping, but no data points exist between the trials.

Our updated fluidity metric was also able to capture decrements in movement quality during the ground trials. During one traverse, the participant kept their gaze on the floor. This traverse was distinct from all other ones, as assessed in the video playback. The value of whole-body FI in this trial was lower than all other ground trials (2.45 standard deviations lower than the mean) and the variance was greater as well. We observed a correlation between an alteration in movement quality and a decrease in the fluidity metric, validating the usage of fluidity as a metric to quantify movement quality. Whole-body and joint-specific FI values were generally consistent for the ground trials, which we expected given that repetitions of gait should provide consistent fluidity within the experimental protocol. When analyzing joint-specific FI values over time, we observed greater differences in the flight and ground trials in the lower body than in the upper body. The upper body, which performs similar functions and magnitude of movements in both gravitational environments, had similar FI values in ground and flight; the lower body, which has been shown to atrophy disproportionately due to experiencing lower force impacts in microgravity, had generally higher flight FI values compared to ground [19].

IV. DISCUSSION

As a demonstration of utilizing fluidity as a metric for movement quality, we compared an analogous translation task between laboratory (1g) and parabolic flight (0g) environments. We found a statistically significant difference between the 1g and 0g whole-body FI values, even when accounting for within-sample dependence. We demonstrated that FI has potential to discriminate between environmental conditions where fluidity or movement quality is expected to be impacted.

Fluidity is a novel, meaningful, and flexible metric for movement quality. Since this methodology does not target a specific biomechanical reflex or otherwise require a specific set of experimental procedures, fluidity can be utilized across many contexts. Significantly, fluidity can be measured unobtrusively in an operational environment. For example, fluidity can be continuously monitored during training for a personal baseline, then continuously in the new environment to observe and quantify environmental changes, injuries, and adaptation. As a potentially task-invariant metric, fluidity can be assessed across different tasks and longitudinally to provide individualized insight into movement quality.

Joint-based measurement systems are relatively invariant across individuals, as joints are well-defined locations and provide consistency in wearable placements across trials within each participant. Critical in operational environments, wearable systems such as the one introduced herein are unobtrusive and allow for a full range of motion, which allows more accurate data collection. This joint-based methodology also allows data analysis across the whole body by aggregating data across all joints, or the analysis of specific joints or parts of the body (e.g., upper/lower body, extremities).

The potential applications of this fluidity metric are broad and stand to augment the quantification of proprioception and whole-body motion in both the spaceflight paradigm and a myriad of Earth-based research. In spaceflight, the measurement of fluidity can be used to assess habitats during the design phase, allowing habitats to be designed in ways more conducive to natural motion upon entry into the microgravity environment, ultimately reducing injury risk – especially amongst relatively inexperienced commercial passengers. In addition to the characterization of whole-body motion and its relationship to the spacecraft system, the fluidity metric can be leveraged to gain insights into the operational state of the crew member. Postural changes have been suggested to relate to behavioral health [20], so we posit that tracking the fluidity metric over time could be used to support non-invasive behavioral health monitoring, triggering further investigation when unexpected changes in motion trends occur; this could add a valuable dimension to existing efforts investigating mental health monitoring through suites of non-invasive sensors [21]. This could be extended to assess social dynamics of the crew, building upon studies that have examined crew interactions [22] and adding a layer of postural and movement information that would allow the monitoring of not only the frequency of contact with other crewmembers, but also changes in the physical quality of those interactions.

A key application area in Earth-based study falls within the concept of entrainment in human-robot interaction (HRI) [23]. Physical entrainment – synchronization of movement to accomplish a task – of a human-robot team allows peak productivity, but there are not generally accepted methods of measuring when this point of entrainment is reached. The fluidity metric could be leveraged in this capacity for monitoring both the human and robot and tracking their whole-body movement during an action until they reach a steady state. More broadly within HRI, the fluidity metric can be applied to studies of trust and safety during interactions with embodied robots, providing a simple method of quantifying whole-body motion. More broadly still, the study of human movement through physical challenges (e.g., aging, amputation, neuromuscular disease) could leverage the fluidity metric as another dimension of monitoring. The assessment of prosthetic limbs generally focuses on comfort and mobility and often rely on survey-based metrics for these assessments [24]; it is possible that the fluidity metric could provide a more holistic assessment of movement that could be monitored over time. In the aging process, it is known that body movements change [25], but we do not have methods of daily movement monitoring to predict losses of balance and potential falls. Monitoring fluidity in the home could provide this assessment from the moment a study participant gets out of bed, comparing their fluidity to previous days and weeks to predict potential decrements.

The results of our experiment validated the usability of the revised Fluidity Index to meaningfully compare functional whole-body movements across gravitational environments. We created a normalized fluidity metric to evaluate movement quality across tasks of varying duration under different gravity levels. Significantly, this metric was able to capture time-dependent increases in movement quality and proprioceptive performance. FI was also able to capture qualitative differences in movement quality in the laboratory environment, as well as serve as a quantifiable, consistent baseline for a given task. Consistent fluidity values in a given environment-task combination provide evidence for a meaningful quantitative baseline for assessing movement and proprioceptive adaptation in altered environments. We performed a pilot study validation of the fluidity metric, which has future applications toward capturing intent, comfort, and familiarity with an environment in a myriad of spaceflight (e.g., habitat design, passive monitoring human-system/habitat interaction) and Earth-based (e.g., predictive monitoring of aging populations, injury and recovery assessment) contexts.

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