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Measuring Movement Quality of the Stroke-Impaired Upper Extremity with a Wearable Sensor: Toward a Smoothness Metric for Home Rehabilitation Exercise Programs

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Abstract— **Remote patient monitoring systems show promise for assisting stroke patients in home exercise programs. While these systems typically measure exercise repetitions in order to monitor compliance, a key goal of therapists is to also monitor movement quality. Here we develop a measure of movement quality – Peak Intensity – that is a measure of movement smoothness that is implementable with a wrist-worn inertial measurement unit (IMU) in the context of performing repetitions of an upper extremity exercise. To calculate Peak Intensity, we assume we have an accurate count of the number of exercise repetitions in an exercise set, then calculate Peak Intensity as the total number of movement peaks from the continuous stream of IMU data generated across the set, divided by the number of repetitions. Using wrist-worn IMU measurements from 19 participants with chronic stroke performing a sample exercise in which they picked up and moved blocks across a divider (i.e. the Box and Blocks Test) we show that Peak Intensity is moderately correlated with a widely used measure of movement quality, the Quality of Movement score of the Motor Activity Log. Peak Intensity is also strongly correlated with a measure of hand function (the BBT score itself), but is more sensitive at greater levels of impairment. Finally, we show Peak Intensity can be validly derived from either wrist acceleration or angular velocity. These results suggest Peak Intensity could serve as an indicator of movement exercise quality for therapists monitoring home rehabilitation, and, potentially, as a means to provide augmented feedback to patients about their exercise quality.**

I. Introduction

The pandemic has amplified the growing interest in improving home exercise programs for individuals who have experienced a stroke. In the US, new billing codes have been introduced that can be applied to reimburse for home exercise programs that are being remotely monitored. To improve home exercise program technology, we have been working to develop a system that combines an app-based activity management system with sensor-based measurement of limb movement. The idea is that the therapy app can be used to prescribe exercises, with the therapist specifying desired number of exercise sets and number of repetitions per set, and then the sensor can be used to count repetitions actually achieved. However, in discussions with therapists, they noted that they desire to not only have information about the amount of movement completed at home, but also movement quality.

Development of sensor-based, home exercise technology is also justified by the finding that incorporation of augmented feedback can foster upper extremity recovery after stroke [1]–[3]. Moreover, in augmented feedback research, it has been shown that providing information about movement quality (a form of Knowledge of Performance), can be more effective than providing information about movement completion (a form of Knowledge of Results) [4]. This finding is consistent with therapists' desires to provide augmented feedback about movement quality.

A key question, then, is: what aspects of movement quality should be quantified and presented to patients and remotely monitored by therapists during home exercise programs? Based on interviews with therapists, we suggest there are four main items of interest: range of motion, speed of motion, smoothness of motion, and the degree of compensatory or incorrect movement patterns. The focus of this work is to develop a measure of movement smoothness that is implementable with a wrist-worn inertial measurement unit (IMU) in the context of performing repetitions of an upper extremity exercise.

Movement smoothness characterizes skilled human motor ability. Human movements typically become saccadic in neurological injuries and diseases, including after stroke, appearing to be comprised of many sub-movements [5], [6]. One of the hypotheses for such discontinuities is the loss of coordinated muscle co-contraction [7], [8]. The amelioration of patients' movement smoothness after neurological injuries has been proposed as a major target in movement rehabilitation [9].

To assess how fluently subjects can move their limbs and evaluate the progression of recovery, a wide variety of smoothness metrics have been developed and used for assessment, with much of the work coming in the context of upper extremity recovery after stroke [10]. Smoothness

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metrics analyze mathematical characteristics of the movement profile, such as the number of peaks in the velocity profile of movement, the magnitude of jerk, or the broadness of the frequency profile [11], [12]. In stroke rehabilitation, such smoothness metrics have been shown to be strongly correlated with standardized clinical assessments of upper extremity movement impairment, such as the Fugl-Meyer Upper Extremity Assessment [13]. Smoothness metrics thus are a potential marker for analyzing how one recovers motor dexterity after neurological diseases [11], [12], [14]. Smoothness metrics derived from wearable sensors worn throughout the day by stroke patients have also been proposed to reflect movement quality, independently of functional status of the limb, based on principle components analysis of combined clinical and smoothness metrics [9].

Although smoothness metrics have been used to evaluate how fluently one moves [11] or to see how one develops motor control [8], to our knowledge, no study has attempted to provide feedback from a wearable sensor to people using smoothness as the indicator of movement quality. Here, we present first work toward developing a method for measuring smoothness during performance of home exercises while wearing an IMU on the wrist. Our ultimate goal is to provide smoothness feedback as both a reinforcer of recovery and a guide to therapists monitoring home rehabilitation exercises.

II. Methods

A. Peak Intensity Metric

Melendez et al. proposed a series of guidelines for deriving smoothness metrics from the sensor readings obtained from an IMU [16]. However, in the context of continuous measurement of unsupervised, repetitive movement, it is difficult to directly apply existing metrics. This is because these metrics have been developed for well-defined, discretely-attempted movements, such as targeted reaches, with data typically acquired in a controlled laboratory setting. Thus, the problem of developing smoothness metrics for home-based wearables can be seen as having two subproblems: identifying discretely attempted movements and then calculating smoothness for each movement.

Generalized movement segmentation remains an outstanding challenge. There have been many algorithms proposed for segmenting movements from continuous streams of data [17], but the robustness of these algorithms to a wide variety of movement types and levels of impairment remains questionable [18]. Here, we propose a potential solution applicable in the context of performing home rehabilitation exercises in prescribed “sets” and “reps”: measure smoothness across the entire exercise set, then divide the aggregate smoothness by the number of reps, producing a “smoothness per rep”. In this scenario, we assume an accurate rep count, whether it is from a sensor system designed to count specific exercises or a patient report (i.e. when an exercise prescription system asks a patient to do “10 reps”, we assume they do 10 reps). Further, such an approach requires that the smoothness metric be linear, in the sense that the sum of smoothness for individual exercise repetitions equals the total smoothness across the entire set of repetitions.

In considering potential smoothness measures, we observed that prominent measures, such as SPARC and Log Dimensionless Jerk [12], do not satisfy this linearity property. However, another popular measure does: the number of peaks. This is because the sum of the number of peaks for individual repetitions is, indeed, equal to the number of peaks across an entire set of repetitions.

To find the peaks, we used the peak detection algorithm proposed by Brakel [19]. In this algorithm, peaks are defined as points further than a threshold from the moving mean calculated over a window of the data, and this threshold is defined as a multiple of the standard deviation of the data for the same window. Using a combination of the moving mean and the raw data, we can calculate the z-score for each data point, and define that point as a potential peak, as described here:

$$\bar{\mu}_i = \frac{1}{N}\sum_{i}^{i+N} \mu_i \tag{1}$$

$$\sigma_{\mu_i} = \sqrt{\frac{\Sigma_i^{i+N}(\mu_i - \bar{\mu}_i)^2}{N-1}} \tag{2}$$

$$\mu_i = I_n x_i + (1 - I_n)\mu_{i-1} \tag{3}$$

$$z_i = \frac{x_i - \bar{\mu}_{i-1}}{\sigma_{\mu_i}} \tag{4}$$

$$\hat{y}_i = \begin{cases} 1 & if \quad |z_i| \geq z_{th} \\ 0 & if \quad |z_i| < z_{th} \end{cases} \tag{5}$$

where $\bar{\mu}$ represents the average of the data window N (set to 100 for incorporating a single motion in a rep), σ represents the standard deviation of the window, I (set to 0.1 for the remaining of the calculations) represents the influence of the new data to the previous μ, z represents the z-score, and $\hat{y}$ corresponds to potential peaks where the calculated z-score is larger than the threshold z_{th}. We then select a single peak for regions where there are multiple potential peaks in sequence. Finally, we enforce that all peaks are at least 0.5 seconds apart from another peak, removing those at smaller intervals. With the peaks defined, we can calculate the Peak Metric PM_z by counting the number of peaks in one exercise set. Then, we normalize this metric by the number of movement repetitions, based on the premise we evaluate movement smoothness at the end of movement execution. We call this metric the Peak Intensity:

$$Peak\ Intensity = \frac{PM_z}{N_m} \tag{6}$$

where N_m represents the number of movement repetitions in one set of an exercise. Using this metric, we evaluate movement smoothness for targeted exercises in which one performs the same movement repeatedly.

B. Human Subjects and Experimental Set-Up

As an example of an upper limb exercise that mimics an exercise that might be included as part of a home exercise program, we asked 19 individuals with upper extremity impairment after a stroke to perform the Box and Blocks Test (BBT). All subjects provided informed consent and the experiment was approved by the UCI Institutional Review Board. For this test, they attempted to pick up as many small blocks as they could in one minute, moving them across a divider and dropping them. They performed the BBT three times, with the first two measurements separated by 3 weeks, and the next two by three months. At each session they performed the test with both arms, which we will call the "impaired" and "unimpaired" arms. They wore an inertial measurement unit (the "Manumeter") on each wrist, which recorded three axes of linear acceleration and three axes of rotational velocity at 52.6 Hz. Due to data loss in some BBT sessions, we obtained data for 34 impaired arm tests, and 37 unimpaired arm tests. Further descriptions can be found in [20]. An experienced physical therapist supervised the BBT, and also administered the Motor Activity Log, a subjective self-ranking of how well (HW) and how much (the Amount of Use Scale – AS) the participants felt they used their upper extremity for various activities of daily living. An MAL HW score can vary from 0 to 5, with a score of 1 corresponding to "The weaker arm was moved during that activity but was not helpful"; a score of 3 to "The weaker arm was used for the purpose indicated but movements were slow or were made with only some effort" and a score of 5 to "The ability to use the weaker arm for that activity was as good as before the stroke".

C. Data Pre-processing

We preprocessed acceleration data using the Madgwick filter [21] to remove the gravity from sensor measurements:

$$ {}^{S}\mathbf{a}(t) = \; {}^{S}\mathbf{a}_{\mathbf{raw}}(t) - \; {}^{S}\mathbf{g} \tag{7}$$

where $\boldsymbol{a}_{raw}$ is the raw acceleration in the sensor frame *S*, and $\boldsymbol{a}$ is acceleration used for analysis. $\boldsymbol{g}$ is the gravity subtracted from the raw acceleration using the filter. Then we low pass filtered both acceleration and angular velocity signals using a second-order Butterworth filter with a 5 Hz cutoff frequency. We computed the smoothness metric by applying it to the magnitude (i.e. L2-norm) of the three-axis acceleration or angular velocity signals, following the approach by Melendez [16].

III. Results

We calculated the Peak Intensity metric for 19 individuals with a stroke using data acquired from an IMU worn on the wrist at they performed a repetitive grasp-transport-release exercise – the BBT. Figure 1 shows the relationship between Peak Intensity and the BBT score, with Peak Intensity calculated using either linear acceleration and angular velocity readings obtained from the IMU. Peak Intensity obtained from either acceleration or velocity was strongly correlated to the BBT score, but was more sensitive to BBT Score at higher levels of impairment. Increasing the z-score used in the peak detection algorithm shifted the best-fit curves to Peak Intensity-BBT relationship, but maintained their shape.

Figure 2 shows the correlation between Peak Intensity and a measure of movement quality – the Motor Activity Log How Well Score (MAL-HW). Peak Intensity was significantly and moderately correlated with movement quality when Peak Intensity was derived using acceleration readings ($r = 0.631$, $p < 0.01$) or angular velocity readings ($r = 0.584$, $p < 0.01$). Peak Intensity was also correlated with MAL-AS score for both acceleration readings ($r = 0.583$, $p < 0.01$) and angular velocity readings ($r = 0.517$, $p < 0.05$).

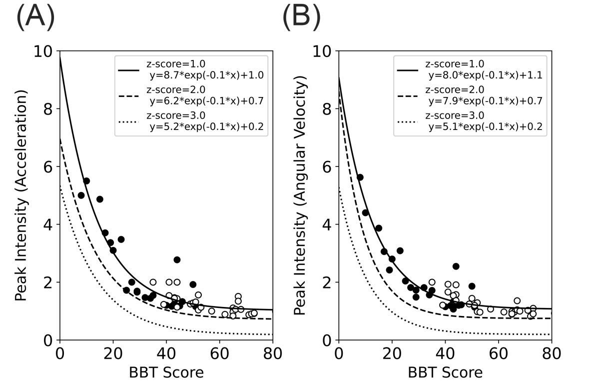

Figure 1. The relationship between Peak Intensity and the BBT score. (A) Peak Intensity based on the acceleration measurements. (B) Peak Intensity based on the angular velocity measurements. The black dots and white dots represent data from impaired and unimpaired arm movement, respectively when the threshold for z-score used in the peak detection algorithm was equal to 2.0. The three lines in (A) and (B) show exponential curve fits to Peak Intensity vs BBT score, combining the impaired and unimpaired arm movement data. The solid lines represent Peak Intensity with z=1.0 threshold. The dashed lines represent Peak Intensity with z=2.0 threshold. The dotted lines Peak Intensity with z=3.0.

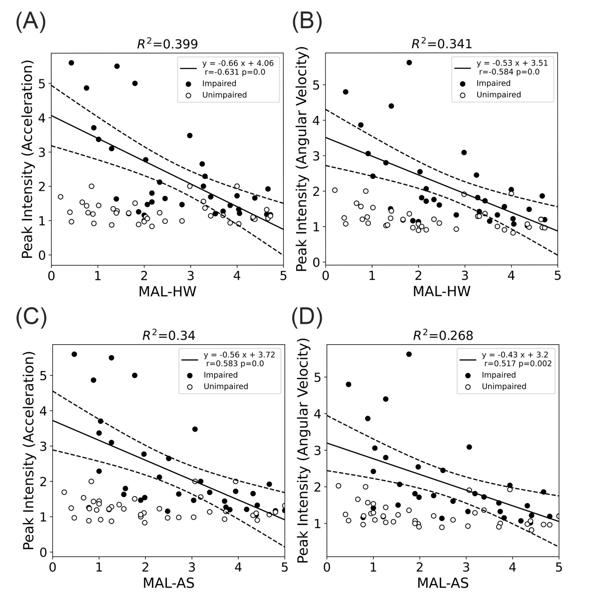

Figure 2. The correlation between Peak Intensity and MAL. The threshold for z-score was 1.0, and the cutoff frequency for the Butterworth filter was 5.0 Hz. The solid lines represent a linear fit of Peak Intensity taken from impaired subject data using the least squared method. The dashed line represents the confidence interval. The black dots represent peak metrics obtained from the impaired arms of subjects. The white dots represent Peak Intensity obtained from the unimpaired arms of subjects, plotted at the value of their MAL score for their impaired arm. (A) and (B): The correlation between Peak Intensity and MAL-HW obtained from acceleration and angular velocity, respectively. (C) and (D): The correlation between Peak Intensity and MAL-AS, obtained from acceleration and angular velocity, respectively.

IV. Discussion

A key, unsolved goal in remote patient monitoring for home exercise programs after stroke is to quantify movement quality and not just movement quality. Here, we found that a marker of movement smoothness – Peak Intensity –

correlated with stroke participant's own assessment of their movement quality using an established clinical scale – the MAL-HW. This suggests that Peak Intensity may be useful for providing movement quality feedback as both a reinforcer of recovery and a guide to therapists monitoring home rehabilitation.

We proposed a method for calculating Peak Intensity that separates the problem of segmentation from that of smoothness quantification. Specifically, we calculated the number of peaks across the continuous stream of IMU data generated across the exercise, then divided by the number of repetitions. In this scenario, we assume an accurate rep count, whether it is from a sensor system designed specifically to count certain exercises or a patient report. Clearly, the metric would become less accurate if the rep count is inaccurate. However, our working hypothesis is that rep counts that come from patient self-reports or sensor-based training systems designed to count specific exercises will be more accurate than generalized segmentation algorithms at present.

Peak Intensity has several potential advantages compared to other smoothness metrics. It is insensitive to the amplitude and velocity of a movement trajectory. It is also intuitive to relate to. Having a higher Peak Intensity corresponds to making a greater number of submovements while attempting to do an exercise, and thus this number can be linked to physical events – i.e. the submovements. Finally, Peak Intensity can be derived from either wrist acceleration or angular velocity using a single wrist-worn sensor, as we showed.

The peak detection algorithm we used has the advantage of having an explicit way to adjust its sensitivity by changing the z-score threshold, which may be useful in tuning the algorithm to sensors with different noise levels.

Previous work conducted in our lab examined the effect of providing wearable feedback to persons with stroke on the amount of finger and wrist movement they produced throughout the day [20]. We found that this form of feedback did not significantly increase the hand movements the participants made at home. There were also no significant differences in clinical outcomes between the experimental group and a control group that wore the sensor but did not receive feedback. One interpretation of these results is that it is not enough to simple provide feedback on movement counts to promote recovery. Rather, it is necessary to provide a plan for exercise (i.e. a home exercise program) as well as feedback on movement quality. Indeed, this is the established paradigm in home rehabilitation that therapists currently promote, although they have no way to provide feedback on movement quality between visits. In our future work, we plan to test whether providing a dedicated home exercise program, with feedback about movement quality provided by a wearable sensor, can improve upper extremity stroke recovery.

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