An Instrumented Glove for Improving Spasticity Assessment

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***Abstract*— An instrumented glove worn by caregivers that can augment subjective assessments of spasticity with an objective, repeatable metric with reduced inter- and intra- rater variability and improved resolution over existing standards is highly desirable. We present the design and preliminary results of such a system using commercial, off the shelf (COTS) components. The glove includes spatially-resolved, force-dependent resistive sensor elements and an inertial measurement unit. We developed a mock patient that is equipped with a mechanism to adjust the arm stiffness, a load-cell and a potentiometer to measure the work done to move the arm. The mock patient provides ground truth to validate the proposed concept. We report the power measured by the sensors in the mock patient to move the arm and the power estimated by the glove in moving the arm and show Pearson correlation coefficient of 0.64. We observe that raw sensor data and instrumentation errors contributed to significant outliers in these experiments. Initial assessments by clinician show promise of the proposed approach to improve spasticity assessment. Future work includes improvements to instrumentation and further clinical evaluations.**

I. Introduction

Spasticity is a debilitating condition and the most common physical symptom of acquired brain injury, stroke, or other neuro-muscular disorders such as cerebral palsy, which affects 764,000 people and is diagnosed in two to three live births out of every 1,000 in the United States. Patients with spasticity are unable to produce smooth and fluid limb movements due to the imbalance of signals from the brain and spinal cord to the muscles. The pharmaceutical industry spends billions of dollars developing drugs to relieve spasticity, but these efforts are stymied by the lack of repeatable, objective metrics to quantify the outcomes [1-3]; excessive dosage of drugs to treat spasticity can cause severe side effects such as such as seizures, blurred vision, and severe rashes, while inadequate dosage is ineffective at treating spasticity.

Score	Modified Ashworth Scale [28]
0	No increase in muscle tone
1	Slight increase in muscle tone, manifested by a catch and release or by minimal resistance at the end of the range of motion (ROM) when the affected part(s) is moved in flexion or extension
1+	Slight increase in muscle tone, manifested by a catch, followed by minimal resistance throughout the remainder (less than half) of the ROM
2	More marked increase in muscle tone through most of the ROM, but affected part(s) easily moved
3	Considerable increase in muscle tone, passive movement difficult
4	Affected part(s) rigid in flexion or extension

The current benchmark for assessing spasticity is the 6-point modified Ashworth score (MAS) shown in Table 1 [4,5]. There are several limitations to this MAS, including poor inter-rater reliability and poor sensitivity to changes in spasticity [6-8]. An approach that allows reproducible assessment with improved resolution is urgently needed to monitor patient progress under medication and eliminate negative reactions.

This research is aimed at improving spasticity assessment by augmenting MAS with an objective, repeatable measure that shows finer level of details than MAS and has reduced variability in intra-rater and inter-rater scores. In Section II, we present prior efforts to improve spasticity assessment. In Section III, we present the development of an instrumented glove that senses pressure and hand motion during spasticity assessment. Since MAS is a highly subjective rating, we initially lacked a reliable criterion measure for verifying the glove measurements. To overcome repeatability issues, we present in Section IV the development of a mock-patient that was used to generate a "ground truth" criterion metric for validating objective scores from the glove. We present experimental results in Section V. In Section VI, we discuss sources of errors in the instrumentation, present future work and conclusions.

II. Prior Work

Many researchers have taken different approaches to address the lack of quantitative assessment of spasticity. Wearable devices [17, 18, 20] and EMG sensors [19] have been deployed on patients to detect spasticity symptoms, but the drawback is that such devices can be inconvenient and uncomfortable for the patient.

Studies using electromyography (EMG) sensors [9, 19, 21] were carried out on patients with spasticity to characterize the patients' muscle tones under flexion and extension. Wu et al. [9] measured the catch angle reliably by determining the instantaneous velocity and the time derivative of torque. Research by Park et al. [10] also targeted measurement of catch angle and elbow range of motion. Both of the above studies were focused on identifying the presence/absence of a catch phase for correlation to a MAS score between 1 and 2, but these studies did not provide a continuous scale to quantify the different levels of severity.

The lack of a quantitative scale for spasticity was addressed by development of musculoskeletal models [11] or haptic simulations [12] to determine key physical parameters that contribute to spasticity. One of the most common models

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is the Haptic Elbow Spasticity Simulator (HESS) [5], [6], [7], in which the properties of spasticity are simulated with the muscle resistance as torque and the catch phase as an impulse. Development of the HESS simulator mainly benefits the doctors as they can practice MAS assessments without requiring actual patients. Their research focused on modeling of spasticity and emphasized on the factors that characterized each MAS level. Alternatively, a mathematical model by Zakaria et al. [16] formulated the resistance as torque and accounted for additional parameters such as the angular velocity, modulus of elasticity etc. The above models have yet to be translated into physical tests that can be implemented on patients to track the spectrum of spasticity conditions.

III. Instrumented Glove

Our approach to improve spasticity assessment is an instrumented glove worn by the doctor during patient evaluation. We integrated a spatially-resolved, force-dependent resistive sensor array (by Tekscan, [22]) and an inertial measurement unit (IMU) consisting an accelerometer, gyroscope and a magnetometer [23].

The force sensor on the glove measures the contact force being applied to move a patient's limb. The level of muscular resistance to motion indicates severity of spasticity. Figure 1 shows the force sensor integrated on to a golf glove. It has 18 sensing regions, with a total of 349 sensing elements that output a voltage proportional to the applied force. The raw output is a spatial map of 8-bit values for each sensing element. The data was collected at 20Hz. For our analysis, we used the sum of the output of all the sensing elements.

During the experiment, the researchers wore the glove and performed cycles of movement with the patient, such as elbow flexion and extension, and the sensor recorded the force F (Newtons) versus time as shown in Fig. 2.A.

The IMU is attached to the back of the glove as shown in Figure 1 (right). It is used to characterize the hand maneuvers during clinical assessment of spasticity. In this work, we use only the gyroscope data to estimate the power needed to manipulate a limb. The IMU data is collected at 20 Hz. The angular velocity v from gyroscope is converted to linear velocity at the location of the grip in the mock patient. The gyroscope data in a typical maneuver is shown in Figure 2B. We estimate the power to move the patient's limb as $F*v$.

In our initial study, five individuals with cerebral palsy volunteered to participate in this study. Participants and/or

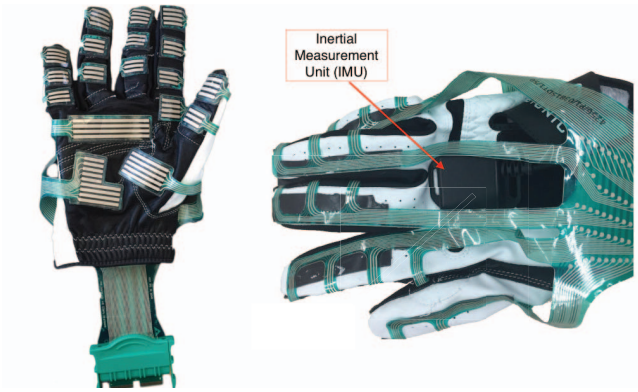

Figure 1: Instrumented Glove. The IMU is installed on the back of the glove.

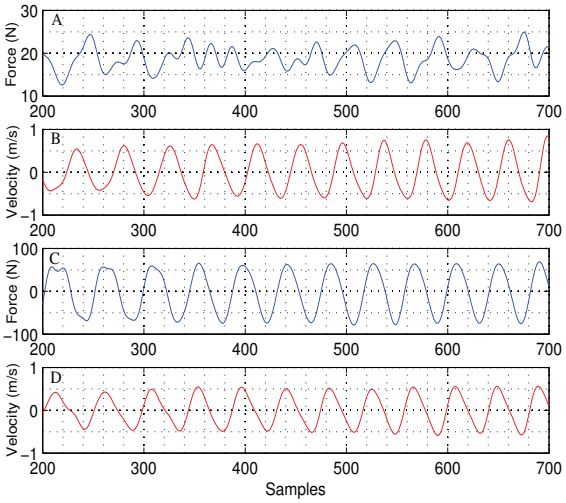

Figure 2: Low pass filtered raw sensor data. A. Total pressure from glove sensors over time. B. Linear velocity from gyroscope data. C. Force from load cell data. D. Linear velocity from differentiated potentiometer data. The positive half cycle corresponds to flexion and the negative half cycle corresponds to extension.

their parents provided informed consent as per the UCSD Human Subjects Internal Review Board regulations. Participants engaged in a modified Ashworth scale assessment with two physicians well-trained in this methodology (AS and his colleague) and then again by the same two physicians while wearing the spasticity measurement device. These data were collected in UCSD's Research on Autism and Development Laboratory.

In this experiment, there was substantial inter-rater variability resulting in only 27% agreement in MAS values. Consequently, we were not able to use these data to validate the estimates from the glove sensors. To mitigate this, we created a mock patient capable of generating criterion metric (ground truth) that can be used to validate the objective numbers estimated from the glove sensors.

IV. Mock Patient's Arm Structure

The mock patient has an arm structure as shown in Fig. 3. The arm has a lever connected to a disc clamped by a 5" C-clamp with stationary-bike brake pads, such that the resistance can be changed manually. The arm has an

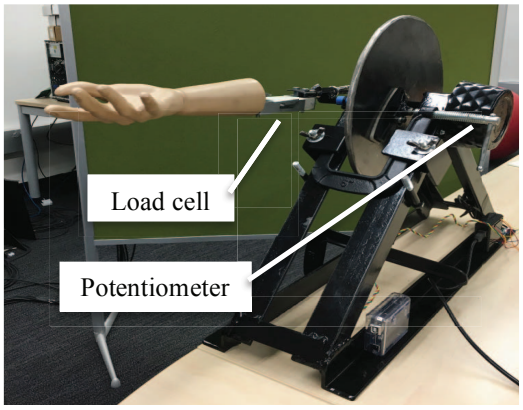

Figure 3: Model of the mock patient.

embedded load cell (model HX711 [24]) that senses the dead weight *m* due to the resistance set by the clamp. We compute the force to overcome this resistance as $F = m * a$, where a is standard gravity, 9.8 m/s^2. We use the term "preset resistance on the mock patient" to denote the force required to move the arm. The units are Newtons. The mock patient also has a potentiometer [25] to sense the angular velocity v during flexion and extension. We use this to measure the power as $F*v$, in N-m/s. In our experiments, we measure the power from the mock patient sensors and use it compare with the power estimated from the sensors in the glove worn by the rater.

V. Results

We investigated the agreement between measured power from the mock patient and estimated power from the glove. We focused on MAS values of 1+, 2 and 3 in this study. The values of 0 and 4 are easy to assess since they correspond to normal tone and rigid limbs, respectively. Similarly, a value of 1 is also easy to assess since it is characterized by catch and release. A well-trained physician in spasticity assessment (AS) tested the mock patient and identified the range of to be 20—90 Newtons for MAS values of 1+, 2 and 3. Spasticity is a highly velocity driven response [1], [2], [8], [14]. For both glove and mock patient, we converted the angular velocity to

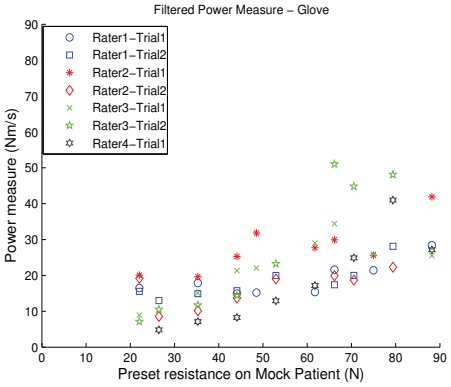

Figure 4: Power measurement for the instrumented glove

linear velocity (see Figure 1) and estimate the power to move the patient's limb as $F*v$. Here, we present experimental results for two trials by 4 researchers.

Figures 4 and 5 show the power measured from the glove sensors and mock patient sensors, respectively, for different preset resistances on the mock patient. Note that while there

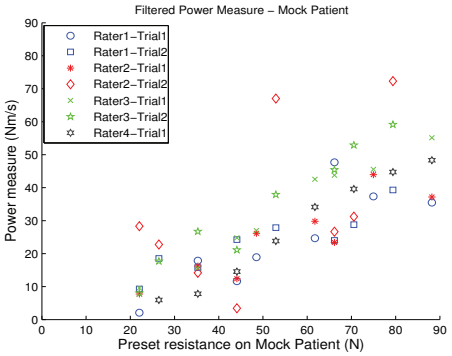

Figure 5: Power measurement for the mock patient

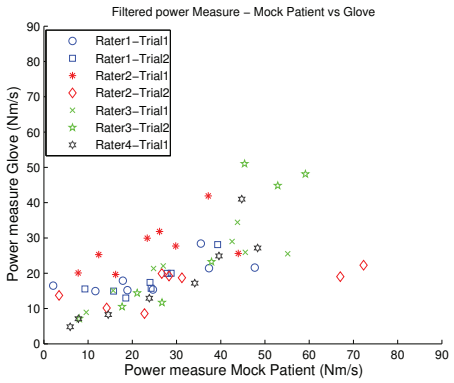

Figure 6: Instrumented glove versus mock patient

are outliers in both cases, the mock patient data shows better agreement with the preset resistances, compared to that of the glove. From Figure 1, it can be seen that the force data from glove does not follow the cyclical nature of other sensors. Figure 6 shows the power measured from the mock patient sensors versus power measured from the glove sensors. We note that there are bias and variability issues in all these experiments. The Pearson correlation coefficient between the mock patient and the glove was 0.64. When we compute the

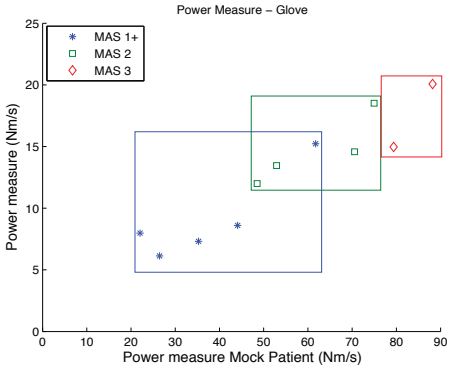

Figure 7: Power estimates for MAS values

agreement between the mock patient and glove for flexion and extension independently, the Pearson coefficients were 0.64 and 0.57 respectively. The experimenters gripped the mock patient at the wrist – flexion involved in pushing the mock patient arm, while extension involved pulling it.

We performed another experiment with a physician (AS) performing MAS assessment for various resistance settings of the mock patient, as shown in Figure 7. The physician did not know the resistance setting so that he could provide an unbiased assessment. This shows the promise of improving MAS ratings resolution with the instrumented glove.

VI. Discussion and Future Work

There are some sources of error such as grip variation, posture, etc. that could introduce certain bias and also result in outliers in the measurements. In addition, we observed certain errors in the pressure sensor, similar to other researchers ([29] reported up to 34% errors). Further, our COTS instrumentation used different clock domains for the potentiomenter, load cell, pressure sensor and the gyroscope. This resulted in significant drift in the alignment between

pressure and gyroscope data; load cell and potentiomenter data during each experiment. Future work must address (i) improvements in sensor reliability (ii) custom hardware to acquire glove sensor data with a common clock and mock patient sensor data with a common clock (iii) further testing by doctors to understand the statistical validity of results shown in Figure 7.

VII. Conclusions

Spasticity is a debilitating neurological, musculo-skeletal condition, affecting people with CP, TBI, stroke, etc. This research addresses development of an instrumented glove to be worn by doctors while performing MAS assessment, a gold standard in current standard of care for diagnosis and treatment of spasticity. We presented a design of the glove based on COTS components. In order to develop an objective metric from the glove measurements, we presented the development of a mock-patient arm with adjustable resistance to motion and sensors to report the load and angular displacement. We presented power (N-m/s) measured at the mock patient and estimated by the glove for various stiffness values that correspond to MAS values of 1+, 2 and 3. Our results demonstrate that the instrumented glove has a correlation of 0.64 with the mock patient. Preliminary assessment by a physician demonstrates that an objective metric based on measured power has improved resolution over MAS. Future work will include improvements to sensors, custom hardware to mitigate clock issues and additional characterization in clinical settings.

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