An Instrumented Glove for Augmenting Spasticity Assessment with Objective Metrics

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***Abstract*— In this contribution, we propose an instrumented glove worn by experts to augment subjective assessments of spasticity with an objective, repeatable metric with reduced inter- and intra- rater variability and improved resolution over current best practices. We present the system design and validation using commercial, off the shelf (COTS) components. The glove includes spatially-resolved, force-dependent resistive sensor elements and an inertial measurement unit (IMU). We describe development of a mock patient equipped with a mechanism to adjust the arm stiffness, a load-cell and an IMU 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 0.9 with untrained users. With experts trained in spasticity assessment, the correlation was 0.7 and 0.8 with and without outliers, respectively. (N = ?) We identify the sources of errors during expert assessment trails and the limitations of the COTS realization of the glove and the mock patient. We conclude with recommendations for improving the glove electronics, mock patient realization and guidelines for experts to incorporate limitations of electronics in the proposed system to improve spasticity assessment and patient care.**

***Index Terms*— Cerebral Palsy, Modified Ashworth Scale, Neuromuscular disorders, Objective metrics, Spasticity assessment.**

I. Introduction

Spasticity is a condition with increased muscle-tone or stiffness of the limbs and manifests in multiple neuromuscular disorders including Cerebral Palsy (CP), Multiple Sclerosis (MS), Traumatic Brain Injury (TBI), Stroke, Spinal Cord Injury (SCI), Paralysis, etc. It is typically caused by damage in the part of brain and/or spinal cord which is responsible for motor control. It is estimated that spasticity affects more than 12 million people around the world. About 80 percent of people with cerebral palsy and multiple sclerosis have spasticity of varying degree. About 400,000 people in the United States have MS and hence with some degree of MS-related spasticity [1]. 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 [2-4]; 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.

Multiple methods have been proposed to assess spasticity, the most commonly used being a subjective scale called the Modified Ashworth Scale (MAS) [5-6]. The methods and scales for spasticity assessment lacks repeatability, consistency, or objectiveness [7-8]. This results in inaccurate prescription of treatment which is either inadequate or copious to the patients resulting in either no relief or seizures. Some of the methods proposed for spasticity management are described in the next section.

The current best practice of spasticity assessment requires a high level of medical training and yet result in inconsistent numbers with high inter- and intra- rater variability. Typically, spasticity assessments are done weeks and months apart. Given the subjective nature and poor resolution of the MAS scale, it becomes difficult to incorporate long-term assessments in patient care. Consequently, accounts from patients and their family members are also factored in treatment options.

Due to the above reasons, this research focused on a repeatable, objective and consistent metric that can be employed easily across clinicians or raters of varied medical expertise. We developed an instrumented glove with an array of sensors to sense force and arm motion and compute an objective rating reflecting the amount of work done to move the limb. We also built a "mock patient" to serve as the "ground truth" and aid the development of this instrumented glove.

The paper is organized as follows: Section II describes current spasticity assessment and prior research to address the lack of repeatable assessment scales. Section III describes the development of the instrumented glove and the mock patient. Section IV details the experimental protocol for data collection, description of clinical trials and algorithms that go into calculating the metric. Section V presents the results from the experimental data and the algorithms from Section IV. Section VI is the conclusion and the future scope.

II. Prior Work

There are many methods to diagnose spasticity. There are clinical scales, which basically are based on a doctor's "feel" of the patients' stiffness. Therefore, these methods are very subjective. Clinical methods of assessment include:

1. Ashworth and Modified Ashworth Scale: MAS is the most widely used metric on account of its simplicity. MAS is a highly subjective rating [7, 9-10]. It has high inter- and intra-rater variability [11-12]. It has also been claimed that MAS does not consider the velocity aspect and only captures resistance to passive movement [13-14]. It does

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not distinguish between neural and non-neural causes of resistance [13]. Considerable research has been put into understanding spastic models, yet none address developing an objective metric.
2. Tardieu and Modified Tardieu Scales: In MTS, the angle for catch (using goniometers) at high velocity stretch and the angle for full passive range at slow velocity stretch responses are measured [15]. Thus, it considers the velocity aspect of spasticity. It is suggested as the more appropriate metric over MAS because of this [15]. The MTS performs better in case of intra and inter-rater reliability than MAS [16]. It's inter-rater reliability is still not very good [16] [17]. Even though it is closer to actual description of spasticity given by Lance [18], the MTS is still subjective in nature. This is proven by change in variability (both) before and after training of raters. It is less popular than MAS because MAS is simpler.
3. Hypertonia Assessment Tool [19]
4. Composite Spasticity Scale [20]
5. Gross Motor Function Classification System - Expanded & Revised (GMFCS - E&R) [21]
6. King's Hypertonicity Scale

Secondly, there are neuro-physiological assessment tools which are inclusive of the neurological aspect of spasticity. There methods don't always correlate to the actual level of spasticity even though the measurement correlation is usually high. These methods also often rely on voluntary motion by patients which is an undesirable property in assessment as the patients may or may not move to their full extent and this might cause them inconvenience. Some neurophysiological assessment tools are as follows:

1. Electromyography
2. Tonic stretch reflex testing
3. H-reflex

- ✓ The neuro-physiological tests use some sensors to get measurements. There is some consistent disadvantage that all these tools display. They instrument the patient and they do not have a defined translation to extent of spasticity. All the neurophysiological tools and their variants are not commonly used since literature does not back these methods up with a direct correlation to level of spasticity [22-23]. None of these methods correlate to spasticity levels and merely give measurements of passive reflex threshold, velocities and stretch angles

The third type of assessment tools are biomechanical tools. These are machines or use some mechanical tools to assess spasticity. Some of these methods are:

1. Myotonometer
2. Wartenberg Pendulum Test
3. Three-dimensional pendulum test
4. Dynamometry
5. Measures using goniometry
6. Inertial sensors
7. Stiffness tool with robotic-assisted gait orthosis

These methods either get too bulky for the patient or reply on the voluntary motion of the patients which is not reliable [24]. Some studies also mention a not so significant correlation with clinical scales [25-27].

Many researchers have taken different approaches to address the lack of quantitative assessment of spasticity. Wearable devices [28-30] and EMG sensors [31] 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 [31, 32] were carried out on patients with spasticity to characterize the patients' muscle tones under flexion and extension. Wu et al. [33] measured the catch angle reliably by determining the instantaneous velocity and the time derivative of torque. Research by Park et al. [34] also targeted measurement of catch angle and elbow range of motion. Both 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 [35] or haptic simulations [36] to determine key physical parameters that contribute to spasticity. One of the most common models is the Haptic Elbow Spasticity Simulator (HESS) [37-39], 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. [40] 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. Experimental Setup

The experimental setup consists of two parts: a) the instrumented glove and the b) mock patient. The instrumented glove is intended to be worn by the raters/clinicians who assess the patients. The sensors on the glove would then give an estimate of the extent of spasticity. We have decided to instrument the raters instead of the patients for the following reasons:

1. It is more convenient for the patients to not wear instruments or sensors as seen from previous studies in section II
2. Considering the doctor-patient ratio, it makes more financial sense to instrument the doctors

The mock patient is a validating ground truth for the glove. This is used to simulate consistent conditions for the glove to test.

A. 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, [41]) and an inertial measurement unit (IMU) consisting an accelerometer, gyroscope and a magnetometer [42]. 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. 1 (right). 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 1 (left). 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 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.

Figure 1: Instrumented glove and IMU

B. Mock Patient

The mock patient has an arm structure as shown in Fig. 2. 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 embedded load cell (model HX711 [43]) 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/s2. 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 gyroscope [44] 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.

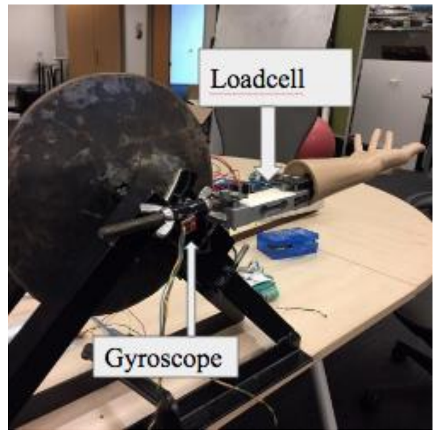

Figure 2: Mock patient with loadcell and gyroscope

IV. Experiments and Algorithms

Two sets of data collection were done. One has 15 datasets from 8 non-clinician raters from a MAS range of 1+ to 3 (the MAS range settings we suggested by an expert - AS). The second data collection was done among 6 clinicians from various affiliations [47].

A. Experimental protocol

The raters should hold the mock patient arm parallel to the wrist with thumb on the top side of them arm. In that position, they should do multiple flexion and extension maneuvers for a 20 second duration. This counts as on trial. The raters do this for multiple weight settings. In this experiment, there are 6 weight settings at 3 pound increments from 5 to 20 pounds. All 6 trials count as one set. All the clinician and non-clinician raters did these sets for the purpose of this experiment.

For each of the trials, there are four data streams collected from 4 sensors: glove pressure sensors, loadcell, gyroscope on the glove and gyroscope on the mock patient.

B. Algorithm

We get 4 sets of data from the entire setup. Force data and gyroscope data from both the mock patient and the glove. The consistent metric, as mentioned above, is power. However, certain pre-processing steps need to be followed to obtain meaningful data information. The block diagram in Fig 3 explains the algorithm in use.

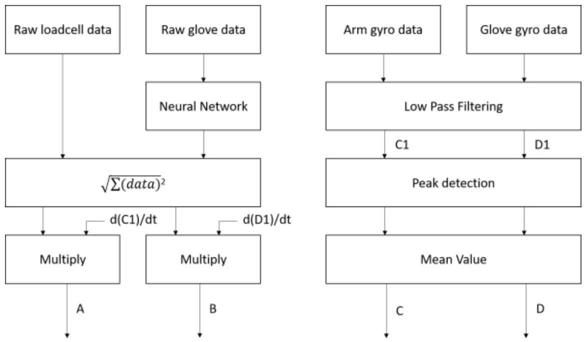

Figure 3: Block diagram of algorithm

The force data from glove pressure sensors has the highest amount of error among the four sensors. A neural network has been employed to remodel this force data without the error terms using data from loadcell. The description of neural network is mentioned in the next section. The square root of sum of squared of the data is found for both force data. This assess the frequency content of the signal. Alternate intuition is to find the square root of sum of data FFT squared. This intuition is also due to assessment of energy content of the data. Both these yield the same result owing to the Parseval's theorem. For the gyroscope data from both the mock patient and glove, we do FFT based low pass filtering and find the peak values. The median of these peaks is considered as the value of speed in computing power. Thus, finally, the product A*C for glove and B*D for mock patient give the power expended in the maneuvers (since F=m*a and a=dv/dt). The analysis in [46] mentioned drift in signals as a major source of error. This algorithm aggregates the effect of drift and thus gives better result.

Figure 4 shows the glove force vs loadcell force measure data. Similarly, figure 5 shows the glove and mock patient gyroscope data waveforms. The actual force in Newtons is found by multiplying the glove (or loadcell) data with its corresponding acceleration found using gyroscope data.

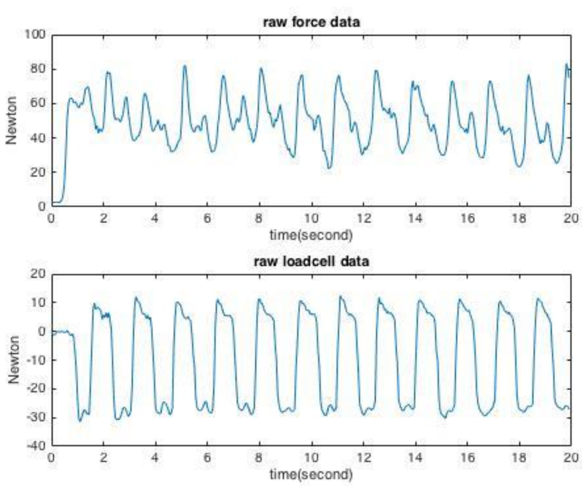

Figure 4: Glove and loadcell force data

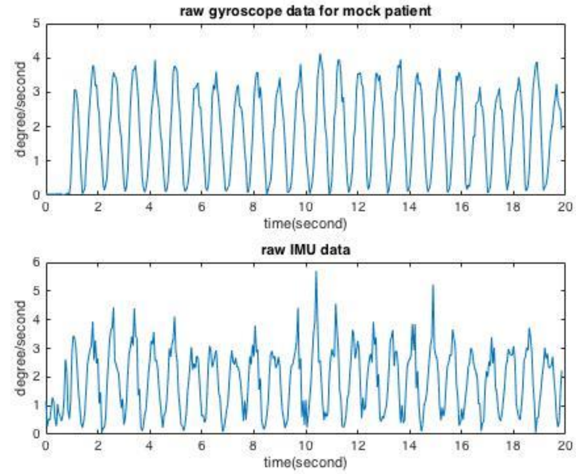

Figure 5: Mock patient gyroscope data (top) and glove gyroscope data (bottom)

C. The Neural Network

The instrumented glove contains a total of 349 sensing elements and records data at 20Hz. Thus, there are 349 dimensions for each sample. However, since each rater has different gripping and hand size, simply take the sum of the output of all the sensing elements will not match the loadcell reading in the mock patient. Even with same rate, there are disturbance can come from changing of gripping during the trial. Thus, it requires a robust approach to map the glove data to the loadcell reading. Since the dimension of the glove data is much larger than the dimension of the loadcell reading, the mapping can be solved using a neural network.

The neural network contains an input layer, one hidden layer, and one output layer, and there are 100 neurons in the hidden layer, and 1 neuron in the output layer. The activation function between each layer is the tanh function. Moreover, the network is trained using stochastic gradient descent with regularization factor. Since the neural network needs to perform regression, the loss function is 2-norm loss.

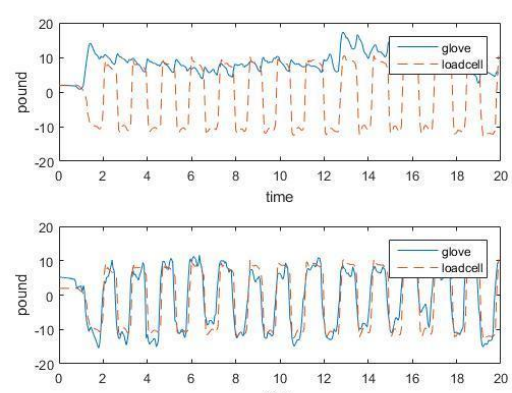

Figure 6: Glove vs loadcell before and after NN

During the training process for every rater in non-clinician and clinician datasets, one rater's data was put into the testing set and all of the other rater's data was put into training set. This training process can make sure that this approach can be generalized across different rater.

In the first plot of Figure 6, the glove data is simply generated by taking the sum of the output of the sensing elements. The glove data in the second plot is processed using the neural network. It is obvious that the glove data in the second plot is more correlated with the loadcell reading.

V. RESULTS

For the data collected from clinicians and non-clinicians, power expended is calculated as explained in section IV.B. This section shows the results thus obtained.

For the non-clinician data, the correlation between glove and loadcell force is shown in Figure 7. The Pearson correlation coefficient obtained is 88%.

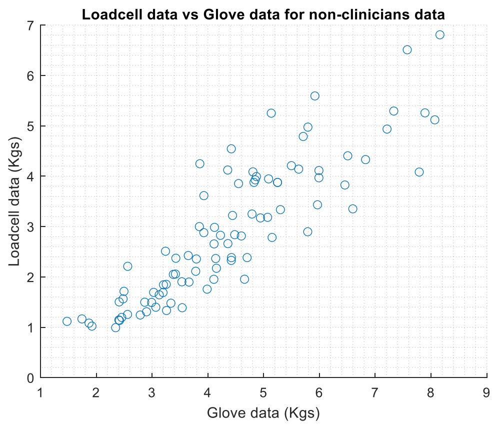

Figure 7: Loadcell data vs final glove data for non-clinicians' data. The correlation obtained is 88%

The correlation between mock patient and glove gyroscope data (C vs D on Figure 3) is give in Figure 8. The Pearson correlation coefficient obtained is 83%.

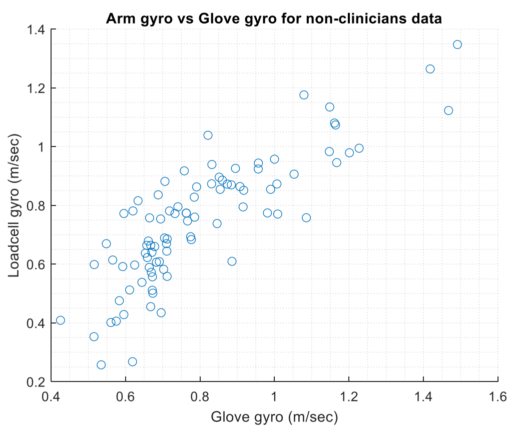

Figure 8: Arm gyro data vs glove gyro data for non-clinicians' data. The correlation obtained is 83%

The final result (A*C vs B*D in Figure 3) for the non-clinicians' data is given below in Figure 9. The final result and Pearson correlation coefficient obtained is 90%

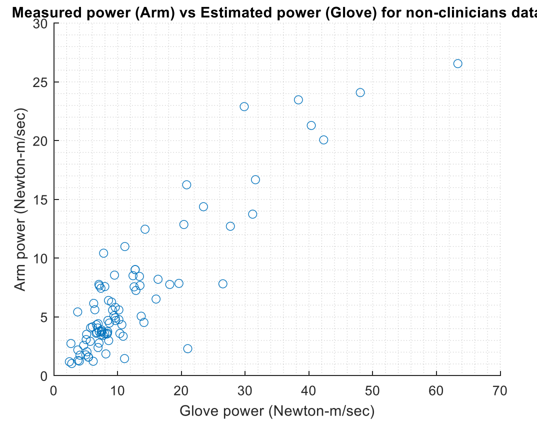

Figure 9: Final measure power (Arm) vs estimated power (Glove) in non-clinicians' data. The correlation coefficient obtained is 90%

To further evaluate how the algorithm performs across different raters, the variation of final correlation between mock patient (measured) power and glove (estimated) power across raters is shown in Figure 10.

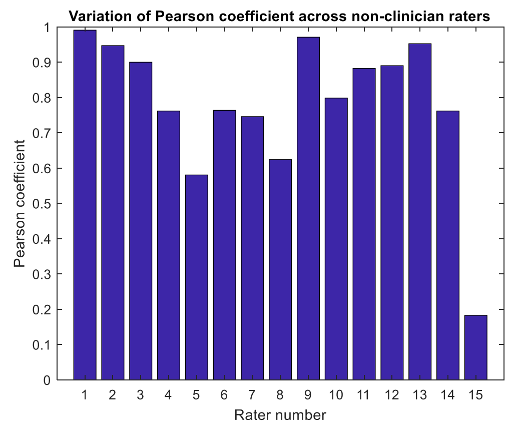

Figure 60: Variation of Pearson correlation coefficient (between final measured arm and estimated glove power) across non-clinicians

Similarly, to investigate how the algorithm performs with varying weight settings across all raters, the said correlation is plotted for different weights across all raters in Figure 11.

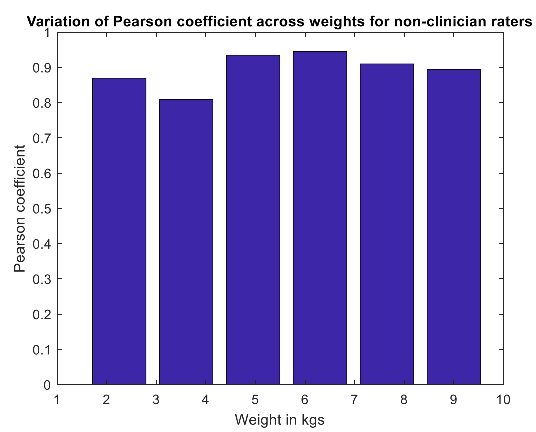

Figure 11: Variation of Pearson correlation coefficient (between final measured arm and estimated glove power) among all non-clinicians across different weight settings

The similar results are show in the following figures for the clinician datasets. It is noteworthy that with the non-clinician data, the experiment protocol was followed as instructed to the non-clinician raters. Thus, the results for non-clinician raters is under more controlled environment as compared to the clinicians' data where some bias was introduced due to highly varying grip (as compared to what was mentioned in section IV.A) and left handed doctors using a right handed-glove.
The correlation between loadcell data and glove data is shown in Figure 12. The correlation coefficient is found to be 89%.

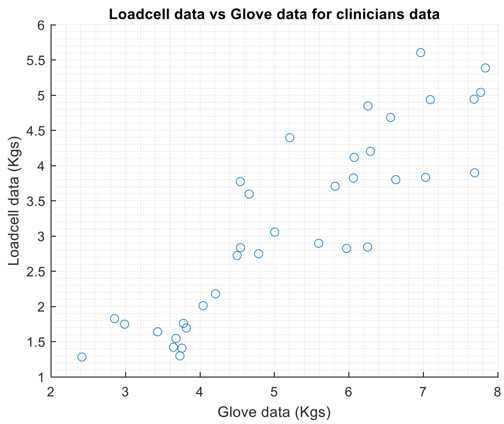

Figure 72: Loadcell data vs final glove data for clinicians' data. The correlation obtained is 89%

The correlation between mock patient gyro data and glove gyro data is shown in Figure 13. The correlation coefficient is found to be 71%.

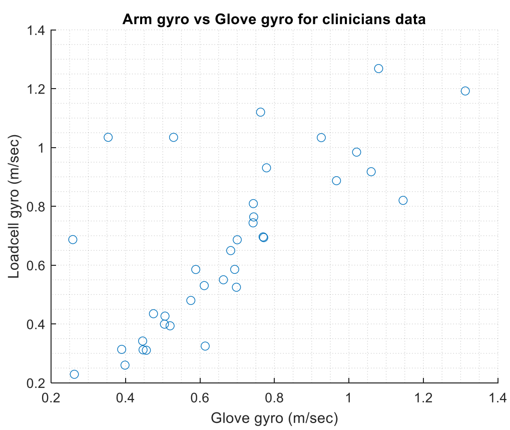

Figure 13: Arm gyro data vs glove gyro data for clinicians' data. The correlation obtained is 71%

The correlation between final measured power and estimated power is shown in Figure 14. The correlation coefficient is found to be 74%.

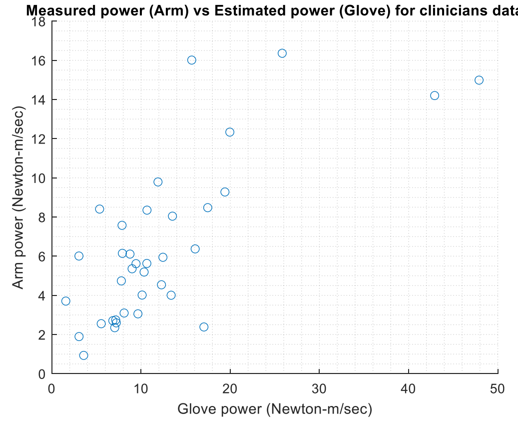

Figure 14: Final measure power (Arm) vs estimated power (Glove) in clinicians' data. The correlation coefficient obtained is 74%

The variations of correlation between measured and estimated power across different raters and different weights are shown in Figure 15 and Figure 16 respectively.

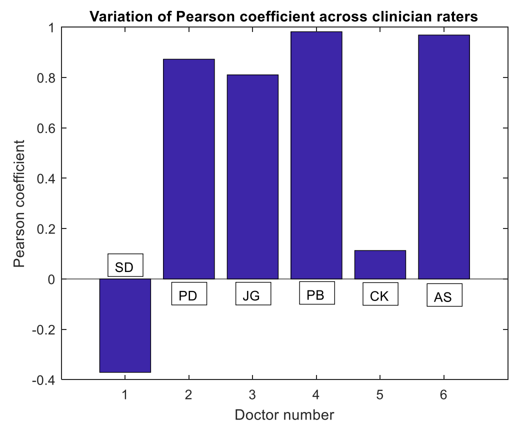

Figure 15: Variation of Pearson correlation coefficient (between final measured arm and estimated glove power) across clinicians in descending order

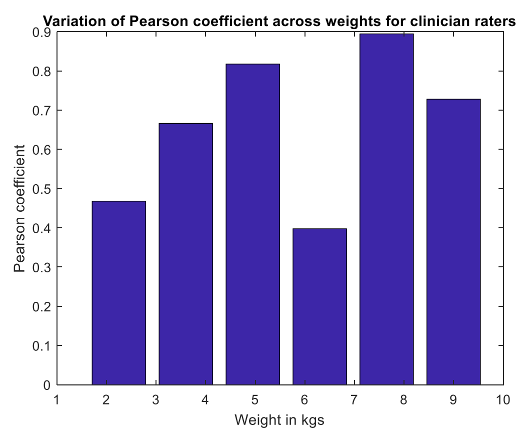

Figure 16: Variation of Pearson correlation coefficient (between final measured arm and estimated glove power) among all clinicians across different weight settings

For various weight settings, the MAS value as assigned by the clinicians for various weight settings is shown below.

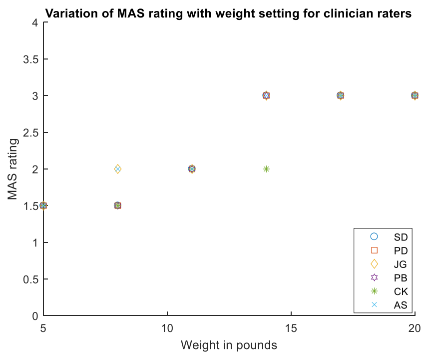

Figure 17: Variation of MAS rating by clinicians for varying weight settings

VI. Conclusion and Future Scope

In conclusion, we see that the glove gives very reliable variation and correlates to the ground truth. In cases where the correlation falls, the raters are either left handed (PD, JG and PB) or had high grip variations. As can be seen in Figure 10, the correlation is very stable across various raters, thus showing very positive signs for mitigation of inter-rater variability which is a huge concern in the other subjective metrics. By comparing Figures 9, 14 and 17; we see that there is a definite correlation between the estimated power and the MAS rating. Thus, we conclude that this estimate shows positive signs of being consistent unlike clinical tools in Section II. It also shows that it can correlate to MAS unlike the neurophysiological tools. By the consistency across weights in Figure 11, we can also conclude that it has the potential to be a repeatable metric. Thus, with some more improvement, this can be a repeatable, consistent and objective metric with a definitive mapping to standard spasticity measures. This glove needs to be only worn for assessment and thus does not require any clinical expertise on the rater's part.

For the future developments in this research, we aim to make the glove robust against grip variations. We also aim to improve the current mock patient to include high variety of spasticity profiles based on real patient data. As can be seen in Figure 17, the mock patient is repeatable for weight settings and thus can be used to train inexperienced clinicians in spasticity assessment. We are experimenting with the resolution of the glove sensors in order to print our own flexible force sensors instead of the COTS sensors which have been established to have considerable variance [45] (up to 34%). Even though current algorithms mitigate drift effects, to allows for higher flexibility with sampling and processing, we would like to get all the sensors on a common clock. All these steps are essentially to improve sensor reliability and to mitigate grip issues.

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