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Haptic Recreation of Elbow Spasticity

Hyung-Soon Park,PhD*, Jonghyun Kim, PhD, and Diane L. Damiano, PhD
Functional & Applied Biomechanics Section, Rehabilitation Medicine Department
Clinical Center, National Institutes of Health
Bethesda, MD, USA
E-mail: parkhs@cc.nih.gov

***Abstract*—The aim of this paper is to develop a haptic device capable of presenting standardized recreation of elbow spasticity. Using the haptic device, clinicians will be able to repeatedly practice the assessment of spasticity without requiring patient involvement, and these practice opportunities will help improve accuracy and reliability of the assessment itself. Haptic elbow spasticity simulator (HESS) was designed and prototyped according to mechanical requirements to recreate the feel of elbow spasticity. Based on the data collected from subjects with elbow spasticity, a mathematical model representing elbow spasticity is proposed. As an attempt to differentiate the feel of each score in Modified Ashworth Scale (MAS), parameters of the model were obtained respectively for three different MAS scores 1, 1+, and 2. The implemented haptic recreation was evaluated by experienced clinicians who were asked to give MAS scores by manipulating the haptic device. The clinicians who participated in the study were blinded to each other's scores and to the given models. They distinguished the three models and the MAS scores given to the recreated models matched 100% with the original MAS scores from the patients.**

Keywords – Elbow spasticity, Haptic device, Modified Ashworth Scale

I. INTRODUCTION

Spasticity is a well-known symptom of altered skeletal muscle performance occurring in disorders of the central nervous system. It is a common feature of the patients who suffer from brain and spinal cord injuries, such as stroke, cerebral palsy (CP), and traumatic brain injury [1]. Clinical assessment of spasticity is important to prescribe treatment options for the patients, and to monitor progression of rehabilitation. The assessment is manually performed by the clinician. For example, in the elbow spasticity test, a clinician holds patient's upper arm and forearm while the patient is relaxing. The clinician moves the forearm quickly, and feels the resistance. The diagnosis of severity is determined by resistance that the clinician feels during the manual assessment. Clinical instruments such as Ashworth scale [2], Modified Ashworth Scale (MAS) [3], and Tardieu scale [2] have been widely used, and several studies have tested reliability of the clinical instruments, demonstrating the need for improving the reliability by providing clinicians with structured training [4-5].

The accuracy and reliability of physical assessment can be enhanced by increasing quality and amount of training that clinicians receive. Clinical training (with real patients), however, is challenging because of the following reasons; many patients with diverse severity of spasticity need to be recruited; safety of the patients should be carefully considered; and the amount of assessment trial is limited due to fatigue of the patients. In contrast, training by haptic devices is free from those limiting factors, and therefore it can provide easily feasible training opportunities to the clinicians. The haptic device used for the training should be able to present accurate and realistic recreation of the spasticity.

The first and the second authors contributed equally to the work.

There have been a few studies on training with haptic devices. For elbow spasticity, the upper limb patient simulator [6] and haptic simulator [7] were developed. The leg-robot was developed for displaying ankle clonus, a symptom of ankle spasticity [8]. There was a device which simulates contracture in hand for training of hand stretching [9]. These existing studies, however, have the following common limitations; there was no correspondence between the haptic recreation and the clinical instruments, and the haptic recreation implemented on the device was not accurately evaluated by clinicians.

This paper proposes a mathematical model of elbow spasticity based on clinical data classified by MAS score, the most frequently used instrument in clinical practice [2]. There have been several attempts to build a model of spasticity, but the models reported are too simple [7-9, 10], purely descriptive [11-12] or focused only on recreating catch [13], which is defined as a sudden appearance of increased muscle tone during the fast passive movement [14]. From our clinical data and the descriptions in the MAS, we found that other characteristics of spasticity in addition to catch are also important in determining the severity of spasticity. For an accurate and realistic model of spasticity, we propose a model consisting of three phases of the movement: pre-catch, catch, and post-catch.

By using the proposed model and the clinical data, three different MAS scores were implemented in the HESS (Haptic Elbow Spasticity Simulator). In order to evaluate the accuracy of the standardized haptic feel, well-experienced clinicians participated in the blinded experiment.

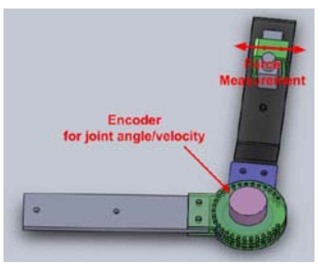
II. METHODS

A. Clinical assessment of spasticity based on MAS

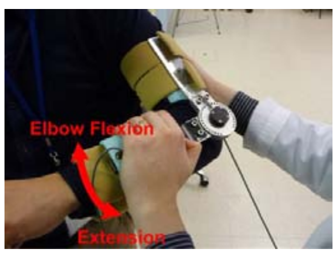
First, we accumulated database of quantitative data (position, velocity, and force) with respect to MAS scores. In order to obtain quantitative data with corresponding MAS scores, we developed a manual spasticity evaluator (MSE) (Fig. 1a) which can measure elbow joint angles (position), angular velocities, and the force (or torque) exerted (or felt) by clinicians while they manipulate subject's elbow joint. Surface EMG sensors were attached over the biceps and triceps to record muscle activation during the test. Three clinicians examined four children with cerebral palsy (CP). All guardians of the children (mean age: 12.5±4.1) gave written informed consent approved by the National Institutes of Health IRB. After aligning the MSE device with the patient's elbow joint (Fig. 1b), the clinicians were asked to perform a clinical assessment of spasticity in elbow extension. They performed both slow and fast extension of the elbow, and determined the MAS score based on the written criteria in the Appendix. The MAS scores rated by each clinician from each subject are summarized in Table I. There was difference in MAS scores made by each examiner. To build a mathematical model, we used the most common scores.

TABLE I. MODIFIED ASHWORTH SCALES OF SUBJECTS

Subject		#1	#2	#3	#4
MAS score of each examiner	#1	1	3	1+	2
	#2	1	2	1+	2
	#3	1+	2	1+	1+
Scores used for the modeling		1	2	1+	2



(a) Design of MSE



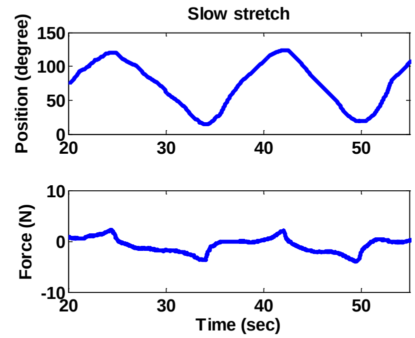
(b) MSE attatched at elbow

Figure 1. Prototyped manual spasticity evaluator (MSE)

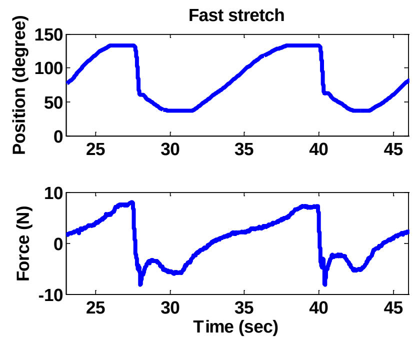
B. Mathematical model of spasticity

To build the mathematical model of spasticity, we analyzed the experimental data obtained. In a representative data collected from the clinical assessment of a patient with spasticity, there is a sudden increase in muscle tone during the fast passive limb movement, which appears as the negative peak in the force plot (Fig. 2b); however in slow stretch (Fig. 2a) this does not occur. Moreover, after the sudden increase, one can see that the degree of muscle tone (resistance torque) is remarkably greater than that of muscle tone at slow stretch (Fig. 2). These two differences in muscle tone between slow and fast stretch has been explained by the following typical characteristics of spasticity: catch, the sudden appearance of increased muscle tone [14], and its velocity-dependence [2]. The catch has been essentially used to determine severity of spasticity.

In order to model the characteristics of muscle tone effectively, we divided the motion into three phases: pre-catch, catch, and post-catch (Fig. 3). Since each phase has different characteristics, we propose the model of a spastic joint as a set of several mathematical equations that represent three phases, respectively.



(a) slow stretch



(b) fast stretch

Figure 2. Typical data collected from clinical assessment

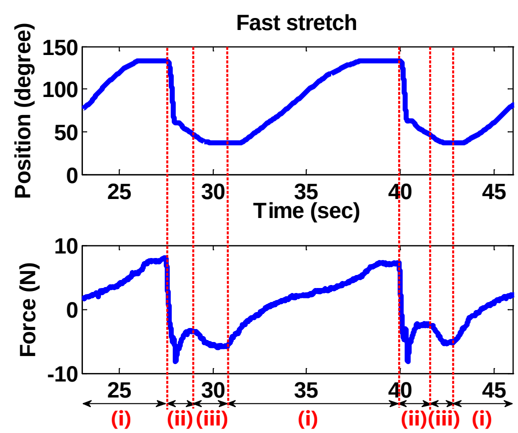


Figure 3. Three phases in elbow spasticity: (i) pre-catch, (ii) catch, and (iii) post-catch

In the pre-catch phase, we assumed that passive elbow resistance can be regarded as a linear mass-spring-damper system:

$$\tau_{pre} = m\ddot{\theta} + b\dot{\theta} + k\theta \,. \tag{1}$$

where m denotes mass (inertia) of the forearm and hand; b damper; and k spring (stiffness).

There have been studies which applied the equation (1) for representing non-spastic [15] or spastic elbows [10]. Moreover, the clinical data collected under slow stretch also agrees with this assumption. Since there was no catch under slow stretch, the whole data set collected under slow stretch can be treated as a pre-catch phase. For instance, the force (or torque) measured during the assessment (Subject 3, slow stretch) and the estimated force (or torque) obtained based on (1) had 11.4% of average error (Fig. 4), which validates the assumption.

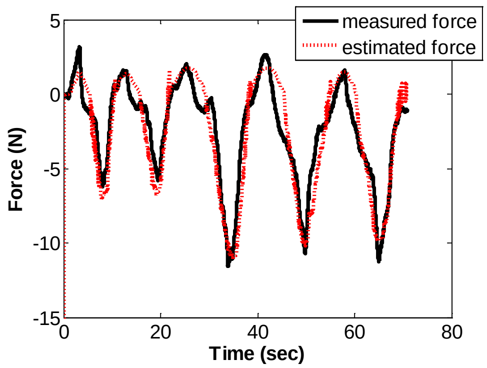


Figure 4. Comparison between measured force in clinical assessment and estimated force based on (1)

The pre-catch phase ends with the occurrence of the catch at a specific joint angle, also termed stretch reflex threshold [16]. Hence, determining catch angle is also essential in modeling accurate pre-catch phase. From the literature, higher velocity stretches evoke the catch sooner in the motion, and thus the catch angle is inversely proportional to the stretch velocity [16]. Moreover, the catch angles depend on the initial posture (or length of the muscle) [17]. Based on this information, the catch angle is determined as follows:

$$\theta_{catch} = \theta_i + \frac{L}{\dot{\theta}_{pre}}, \tag{2}$$

where L denotes the catch angle constant; θ_i the stretching angle at the beginning of pre-catch phase; and $\dot{\theta}_{pre}$ the average speed of stretch in pre-catch phase.

In the catch phase, it was reported that impulse-like function was a suitable form for modeling the sudden increase of force due to the catch [13]. Regarding the magnitude of this increase, we found individual differences as well as velocity-dependency of the magnitude from the clinical data collected. Moreover, the residual torque after the peak muscle tone is significant and the amount of the residual torque is closely related to MAS score. Therefore, the following equation represents the behavior during the catch phase:

$$\tau_{catch} = h\dot{\theta}_{c\_st}\delta(t) + \tau_{pre\_en} \tag{3}$$

$$\text{with} \quad \delta(t) = \begin{cases} 1 & \text{if} \quad t - t_{c\_st} < \Delta t_c \\ q \quad (q<1) & \text{if} \quad t - t_{c\_st} \geq \Delta t_c \end{cases}$$

where h is a constant that relates the stretching speed to the peak torque at catch (named as catch torque constant); $\dot{\theta}_{c\_st}$ the stretching speed at the beginning of catch phase; τ_{pre_en} the torque at the end of pre-catch phase; q (<1) a constant representing the amount of the residual torque after the peak torque (named as residual torque constant); t_{c_st} the time when the catch phase begins; and Δt_c the time duration that the peak torque maintains.

Along with the peak torque at the catch and its residual torque, the time duration of catch phase needs to be determined which automatically defines the end of catch phase and the beginning of post-catch phase. From the clinical data collected, we observed that the time duration of catch phase is inversely proportional to the stretch velocity which is modeled as follows:

$$t_{c\_du} = \frac{D}{\dot{\theta}_c}, \tag{4}$$

where D is a constant that relates the stretching speed to the time duration of the catch phase (named as catch duration constant), and $\dot{\theta}_c$ the average stretching speed within the catch phase. For instance, t_{c_du} and $\dot{\theta}_c$ in (4), and their multiplication ($t_{c\_du}\dot{\theta}_c$) are shown in Fig. 5 from clinical data (Subject #3, fast stretch). It verifies the model (4) because $t_{c\_du}\dot{\theta}_c$ maintains within a constant level over multiple trials.

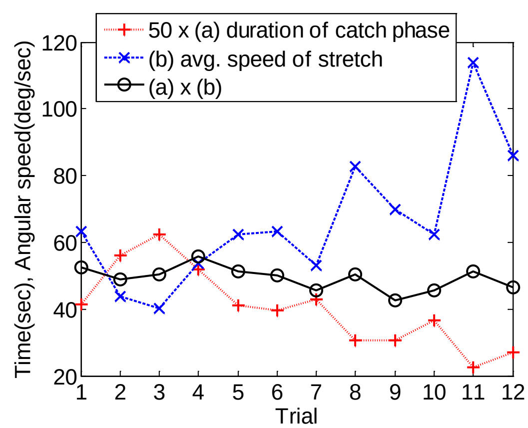


Figure 5. Clinical data supporting equation (4)

After the catch phase, there is a secondary increase in resistance torque which continues from the residual torque determined by q in Eq. (3). The rate of increase in the post-catch phase is slower than that in the catch phase. To our knowledge, no research has modeled this phenomenon. We, however, found that the secondary increase also is significantly related to the MAS score. The instruction written in MAS also implies the importance of modeling it; the clinician is instructed to focus on resistance after catch to distinguish MAS 1 and 1+ (see Appendix).

From the clinical data, we found that this resistance torque is position dependent. Hence, the torque in the post-catch phase is proposed as follows:

$$\tau_{post} = k_{post}(\theta - \theta_{post\_i}) + m\ddot{\theta} + b\dot{\theta}\,, \qquad (5)$$

where k_{post} denotes the stiffness in post-catch phase; θ_{post_i} the initial degree of elbow joint in post-catch phase. Note that we do not need to determine the duration of post-catch phase because post-catch phase ends if the speed of stretch is smaller than the speed threshold ($\dot{\theta}_{th} \approx 0$), which occurs when the clinician stops the movement.

C. Haptic device and control scheme

A haptic device, HESS (Haptic Elbow Spasticity Simulator), has been developed (Fig. 6) to recreate the resistance that the clinicians felt during the patient assessment. The device consists of a mannequin forearm, BLDC motor and controller (Barrett Technology Inc., Cambridge, MA, USA), and a cable-driven speed-reducing mechanism. The mannequin forearm was designed based on anthropometric data [18]. Since the BLDC motor has about ten times greater bandwidth as compared to the MR (magnetorheological) brake in [8], the haptic simulation which requires fast response (e.g. catch) can be implemented more accurately. Moreover, thanks to the cable-driven mechanism [19], the device could be designed back-drivable (low friction) and accurate (zero-backlash).

Based on the mathematical models in equations (1)~(5), we propose a control scheme, illustrated in Fig. 7, to implement spastic elbow through HESS. At first, the haptic device is controlled by (1) at the pre-catch phase. If the clinician manipulates the device slowly, the catch phase does not occur throughout ROM. If the joint angle is greater than the catch angle (2) under the fast stretch, the device is controlled by (3) in the catch phase, and thus the clinician can feel the sudden increase of torque. After the catch phase defined by (4), the clinician feels the secondary increase in torque determined by (5) throughout the remainder of ROM.

This control scheme was implemented under a real-time operating system, Xenomai, with 1 kHz sampling rate. Since the mannequin forearm has the average inertia and size of the subject's forearm, we do not need to include inertial effect in the torque command ($m\ddot{\theta}$ in (1) and (5)), which generally contains high-level noise due to numerical differentiation involved in calculating in $\ddot{\theta}$.

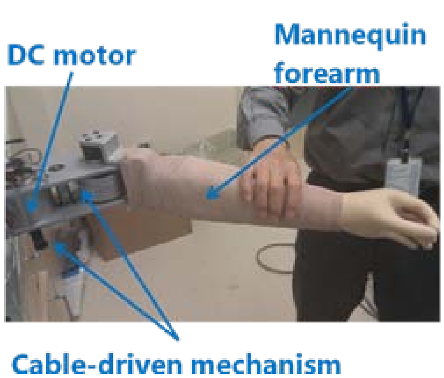


Figure 6. Haptic Elbow Spasticity Simulator (HESS)

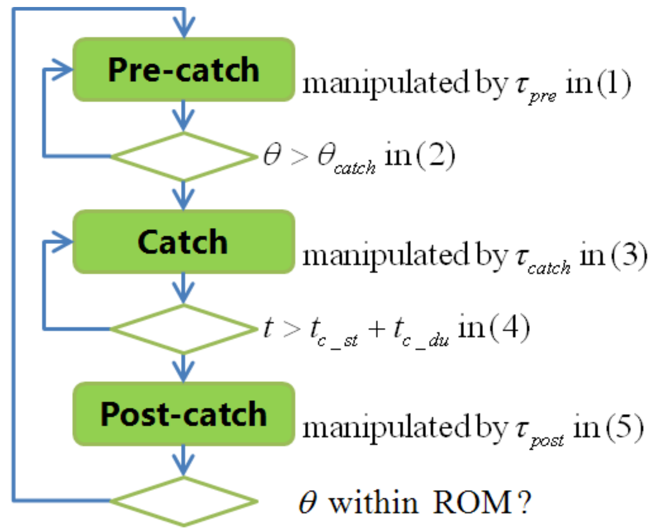


Figure 7. Flowchart of proposed control scheme

III. RESULTS

A. Estimating parameters of the spasticity model

In order to quantify the haptic feel, the parameters in the mathematical model were estimated for each MAS score. We focused only on three scores (1, 1+, and 2) in the MAS, because scores 0 and 4 are trivial to test, and there was no subject with MAS 3. However, we anticipate that it will be easier to distinguish MAS 3 from others based on the MAS instruction (see Appendix).

By analyzing the clinical data and the mathematical models in (1)~(5), three standardized parameter sets were obtained as Table II. Table II shows that different MAS scores have differences in all four parameters: smaller catch angle constant (L) and catch duration constant (D), and larger catch torque constant (h) and residual torque constant (q) for the higher MAS scores.

TABLE II. ESTIMATED PARAMETER SETS OF ELBOW SPASTICITY MODEL AT EACH MAS SCORE

	L	h	q	D
MAS 1	2000	1.5	0.15	60
1+	1500	2.0	0.5	50
2	1000	2.5	0.55	40
common	Δt_c =0.1; k_{post} = 15; $\dot{\theta}_{th}$ = 20; b and k depend on dynamic of subject's arm			

B. Evaluating accuracy of haptic model

The estimated parameter sets of the mathematical models were implemented on HESS, and the two clinicians were asked to manipulate HESS programmed for three different parameter sets of the model (MAS 1, 1+, 2). Fig. 8 shows the typical position and force profiles measured during the in-person assessment and the haptic assessment.

The clinicians successfully distinguished all the three parameters sets and gave the intended MAS scores to all trials (100% correct) while they were blinded to the parameter sets. In addition, the feedback obtained from the clinicians was fairly positive during the experiment; they said that the feel recreated by the haptic device was realistic and similar to the feel from the patient.

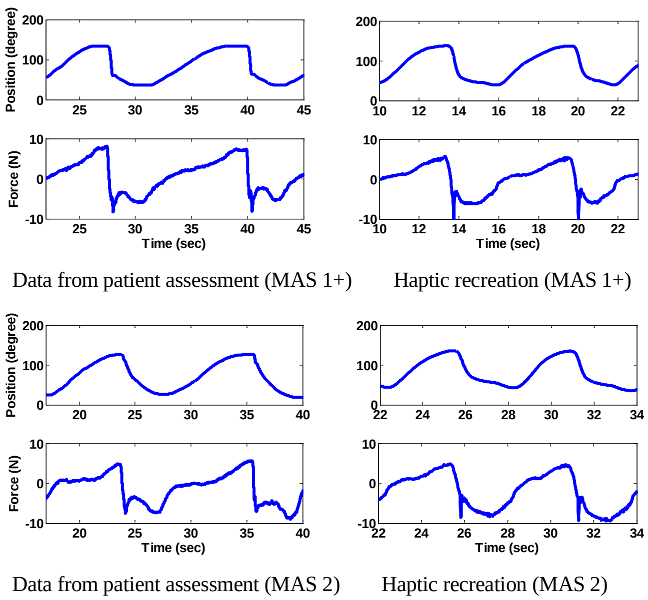


Figure 8. Position and force profiles measured from in-person assessment (left) and haptic assessment (right) at MAS 1+ (upper) and MAS 2 (lower)

IV. Discussion and Conclusion

There have been previous studies on building mathematical models of elbow spasticity [7-13]. There also have been studies which correlated quantitative parameters to the clinical instruments. In a study which used isokinetic stretching device to test spasticity, it was reported that rate of change in resistance and the onset angle of stretch are closely related to the Ashworth Scale [20].

The key difference of our approach from the previous studies is that we kept the clinical assessment the same as it has been and tried to recreate it by modeling it. It would be easier to model the spastic joint under isokinetic stretching because the responses will be more consistent and regular across the trials. However, when the examiners control the stretching speed, stretching speeds are not constant over the range of motion. For example, they slow stretching speed when they feel sudden increase in resistance. This reaction to the catch influences the rate of increase in resistance torque making the model more complicated. Since our purpose was to recreate the real clinical assessment, we employed different modeling methods rather than simplifying the assessment itself. We classified movement of the spastic joint into three phases: pre-catch, catch, and post-catch. Thanks to the classification, we were able to recreate realistic haptic feel of spasticity in spite of the complexity involved in modeling elbow spasticity.

Among the many parameters used in our mathematical model, it is interesting that four parameters (L in (2), h and q in (3), and D in (4)) are closely correlated to the severity of spasticity by MAS. Since these parameters are closely related to the presence of a catch, this study shows the importance of the catch in spasticity. Studies on the correlation between these parameters and MAS score (or other instruments, such as Tardieu scale [2]) will help to quantify the severity of spasticity.

The current study involved four children with CP and more data will need to be collected and modeled to cover a broader range of patient populations, more MAS scores (e.g. MAS 3), and other clinical instruments. Regardless, this study showed feasibility of providing an accurate mathematical model of the spastic joint.

The haptic device (HESS) with the accurate models can implement a standardized haptic recreation of spasticity. It also provides a more feasible training opportunity to clinicians where they can experience various types of clinical responses from real patients. The more accurate and easily feasible training will contribute improving the accuracy and reliability of clinical assessments.

Appendix

Modified Ashworth Scale (MAS) [3]

0 No increase in tone

1 Slight increase in muscle tone, manifested by a catch and release or minimal resistance at the end of the ROM when the affected part 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 easily moved

3 Considerable increase in muscle tone, passive movement difficult

4 Affected part rigid in flexion or extension

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