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A tracking device for a wearable high-DOF passive hand exoskeleton

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***Abstract*— In previous work, we developed an exoskeleton (HandSOME II) that allows movement at 15 hand degrees of freedom (DOF) and is intended for take-home use. An activity tracking device was developed in order to track index finger movement with a pair of magnetometers and magnet. The goal was to detect grip attempts by the individual. Machine learning was utilized to estimate angles for metacarpophalangeal (MCP) and proximal interphalangeal (PIP) joints at the index finger. Testing was performed with healthy control and individuals with stroke.**

***Clinical Relevance*— This device and method of data collection during daily activities might be useful for stroke rehabilitation and compliance with home-based therapy programs.**

I. Introduction

Stroke motor rehabilitation of the upper extremity is motivated by mass task practice. Measuring someone's motor activity of the impaired limb while at home is essential information. The current standard to estimate spontaneous use of the extremity is the Motor Activity Log (MAL)[1]. However, the MAL is based on self-reported data that relies on memory and comprehension of the subject.

Exoskeletons can be effective for improving rehabilitation training during mass task practice. Take-home devices allow more practice time in natural environments that may promote spontaneous use of the impaired limb. There are several passive commercial hand exoskeletons available (SaeboFlex, SaeboGlove), however none provide monitoring of activity level of the impaired hand.

Our lab previously designed and tested the lightweight, passive, and portable HandSOME I device that was designed for pinch-pad grasp by bringing the pads of the thumb and fingers together [2]. Using similar principles, we subsequently designed HandSOME II (Fig. 1), a more complex exoskeleton with 10 elastic bands that assist 15 DOFs in the fingers and thumb. Full details on the HandSOME II mechanical design have been reported previously [3]. We present a method of measuring movement of the index finger while wearing the HandSOME II, thereby promoting compliance with home training programs.

II. Methods

A. Electrical design

In order to obtain activity data when the subjects use HandSOME II in their home training, we developed a data logging system to record index finger motion. Index finger movement is a part of almost all grasp types and it was not practical to instrument all of the digits because of space limitations. Additionally, there was not enough space to mount an encoder or potentiometer on the PIP joint. Instead, we used a pair of magnetometers (Adafruit, LSM303DLHC & Sparkfun, Mag3110) and a permanent disc-shaped magnet, to record the movement of the index finger with data logging performed by a microcontroller (Adafruit Feather M0 Adalogger) placed on the back of the hand (Fig 1).

The magnet was permanently bonded to the PIP and distal interphalangeal joint (DIP) finger linkage so that movement of either the PIP or MCP would rotate the magnet relative to the sensors (Fig. 2). The magnetic field strength from the magnet measured by the closer magnetometer is comparable to earth's magnetic field, so a second magnetometer was spaced further back on the hand to only measure the effect of earth's magnetic field. The two magnetometers are attached to the same rigid body and so should record the same magnetic field strength due to earth's field in all 3 axes. Theoretically, the difference between the two magnetometer signals, once calibrated, would be purely due to the position and orientation of the magnet relative to the closer magnetometer.

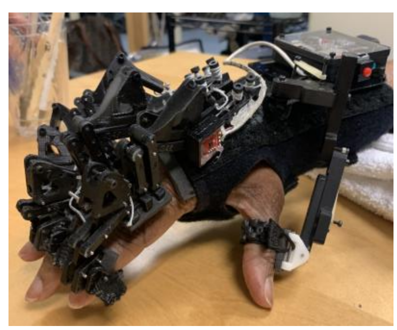

Figure 1. HandSOME II device with magnet activity tracker.

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For a take-home design, a lithium Battery, mini SD card, on-off switch, microprocessor, and second magnetometer are enclosed in a box bolted to the wrist splint on the back of hand. Data was recorded to a SD card and processed offline. Total device weight was 51.4 g plus the weight of the magnet. Primary data analysis focused on measuring flexion/extension activity and frequency of use. Wrist measurements were not recorded as the splint on the back of the hand was rigid and restricted wrist movement. The sampling frequency of the magnetometers was 160 Hz (LSM303DLHC) and 80 Hz (Mag3110).

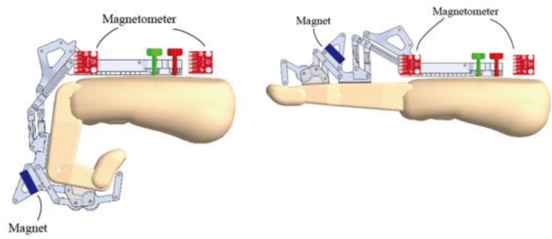

Figure 2. CAD drawing showing location of both magnetometers and the location of the magnet during finger flexion and extension.

B. *Data collection and Processing*

During subject testing (IRB 19-0058), the system was powered on and tethered to a computer through a USB cable. While the system is capable of running entirely on battery power and storing data to the SD card, we performed experiments in the lab using USB data transfer so that data could be viewed continuously during the experiment. A Matlab script collected triaxial readings from both magnetometer sensors for 45 seconds. Typical magnetometer readings are shown in Figure 3 as a subject performs reach and grasp tasks with blocks. During a time span of 45 seconds, the subject attempts to make multiple grasping efforts.

Data was processed and analyzed using Matlab. The script begins by calibrating the 2 sensors with trials where the arm is rotated but the finger was held extended, so that changes in the magnetometer readings were due to rotation of the device relative to earth's magnetic field. The goal of the calibration was to transform the data from the far sensor so that data from both sensors are identical values during these trials. The data from the far sensor was transformed via a multivariable regression, to remove differences in sensor sensitivity and any misalignment of the two sensors. The near sensor and transformed far sensor data then were subtracted to yield 3 differential x, y and z signals that were insensitive to arm movement. The model for the regression was:

$$M_f = A + B*M_n$$

Where M_f and M_n are 3x1 vectors of triaxial readings from the far and near magnetometers, respectively. A is a 3x1 vector of constants and B is a 3x3 matrix of unknown coefficients. A and B were estimated by multivariable regression. A 5 min trial was recorded of continuous arm movement in all planes, and the mean error after calibration for the three axes were 13.9(14.4), 11.6(12.2) and 9.8(9.9) ADU. The range of values for this data was 959, 749 and 975 ADUs for the 3 axes, respectively. Thus the error was 1.5, 1.6 and 1.0% of the full range for the three axes, respectively. Fig. 3 shows an overlay plot of a typical section of data for the 2 magnetometers after calibration.

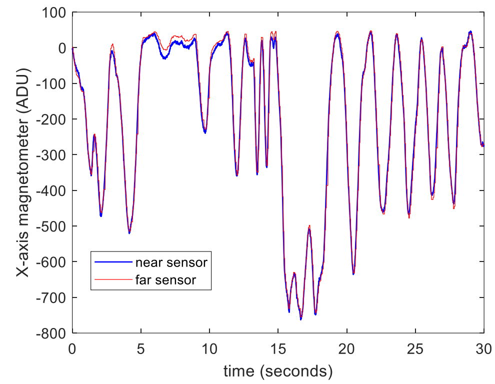

Figure 3. X-axis data from magnetometers during arm movements after transformation of the far sensor data. Sensitivity to arm movements are essentially eliminated by this calibration method.

A method was developed to detect the number of finger movements (Fig. 4). Differential x, y and z signals were smoothed with a Butterworth filter (.5 Hz cutoff). Peaks in the differential signals were clearly distinguishable when the finger rotates in the exoskeleton. We focused on changes in x and y axes and their combined magnitude (Euclidean norm) because these axes were most sensitive to finger movement. The "findpeaks" Matlab function was used, and the settings for peak width and peak prominence were empirically determined that best captured all of the movements, while rejecting noise in the data. A minimum peak width of 3 samples and a minimum peak prominence of 59 ADU units were used on the combined x & y data stream. X-axis data was processed with peak width of 3 samples and peak prominence of 38 ADU units. Y-axis data was processed with peak width of 6 samples and peak prominence of 49 ADU units.

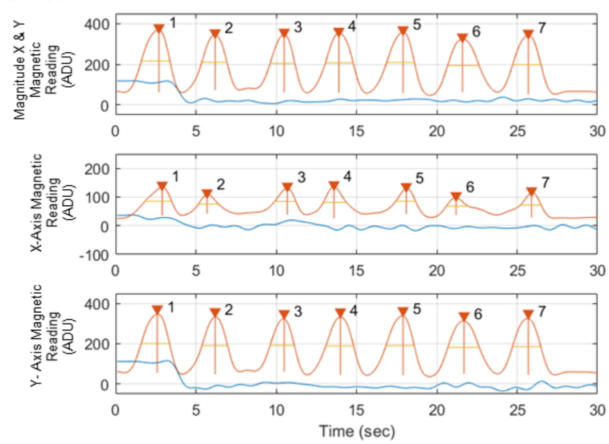

Figure 4. Differential magnetometer readings as a subject performs reach and grasp task with 2 in. block. *Red Line:* Subject is wearing exoskeleton. *Blue Line:* Subject is wearing the wrist splint, but human finger is not placed in the linkage, which is fixed into an extended position, guaranteeing there is no movement of the finger exoskeleton. The triangles mark the grasping movements as detected by the algorithm.

C. Testing and Validation Procedure

The unit was tested on 3 healthy and 3 stroke subjects (Table 1) to identify the accuracy of the activity tracker for subjects of various hand sizes while they perform various reach and grasp tasks while wearing HandSOME II. Objects were of various sizes and included: 1 inch wood block, 2-inch wood block, 3 inch wood block, marble, marker, and key. Two 45-sec trials of each object were performed while sitting down and standing. The goal was to determine if the algorithm could discriminate finger movements from several common arm movements, such as arm swing during walking, waving, etc. Trials were video recorded, and a human annotator marked the video when finger movement occurred to establish a ground truth for number of grip attempts. Small movements in the video that showed little change in magnetic readings were excluded.

Table 1: Stroke Subjects

Subject	Age	Gender	Time Since Stroke (Months)	FM (UL)	ARAT
1	53	F	62.5	28	4
2	71	F	10.6	52	39
3	66	M	72.1	43	38

D. Machine Learning Prediction

We also attempted to predict the MCP and PIP joint angles of the index finger using a machine learning approach similar to a previous study [4]. A test rig was built with 2 potentiometers that attached to the index finger exoskeleton and measured the MCP and PIP angles, while simultaneously recording data from the two magnetometers. The input to the models was the 3 differential magnetometer values, and the outputs were MCP and PIP angles. On 2 separate days, the experimenter performed 5 minutes of random movements of the index finger and hand rotations (30Hz data rate). The models were trained on 85% of Day 1 data and tested on the remaining 15% (randomly selected). The Day 1 model was also applied to Day 2 data. We used a two-layer feed-forward neural network with 25 hidden neurons and linear output neurons (Matlab Statistics and Machine Learning Toolbox).

III. Results

A. Grip Attempts Estimation

The number of grip attempts in the video were summed and compared to the summed number of grips identified by the activity logger (Table 2). The combined magnitude of x and y showed the highest accuracy overall. Percentage error of peak identification was calculated as the grip attempts from video annotation minus the grips from the magnetometer data, all normalized by the grips from video annotation. Trials were not analyzed when the object being gripped was dropped several times, as the finger movements were difficult to pick out in the video of these trials. Two 45-second trials were performed by healthy controls waving and rotating their arm continuously with their fingers held straight (2 trials while sitting and 2 trials while standing). Miscounts are provided in Table 1 for the amount of times the activity logger misidentified grips during these trials.

Table 2. Movement Tracking Summarized Results.

Subject	Grips (Magnetic Sensor)	Grips (video)	% Error	Arm Waving Miscounts (Sitting/Standing)
Control 1	140	140	0.00	(0/1)
Control 2	141	141	0.00	(1/1)
Control 3	140	134	-4.29	(1/2)
Stroke 1	122	116	-4.92	-
Stroke 2	76	84	10.53	-
Stroke 3	80	89	11.25	-

A. Machine Learning Angle Estimation

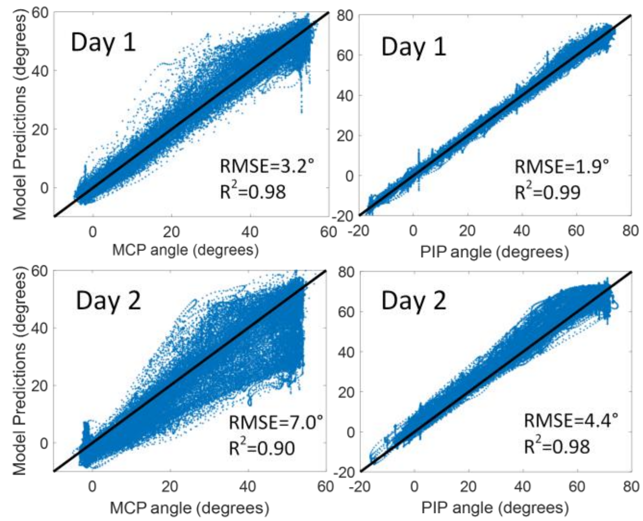

Figure 5. Neural network model predictions on Day 1 and Day 2 data.

The machine learning algorithm was able to predict joint angles on Day 1 with good accuracy. RMS error was 3.2 and 1.9 degrees for the MCP and PIP joints respectively, and r^2 values > .98. However, RMS error increased at both joints when the model based on Day 1 data was applied to Day 2, suggesting regular re-training of the models is needed (Fig. 5). While the plots in Fig. 4 report joint accuracy separately, it's important to note that the movement data for these experiments included some isolated joint rotations as well as simultaneous rotation of both finger joints, all synchronous with arm movements in different planes.

IV. Discussion

For activity tracking, similar designs have been explored. Ma in 2011 reported on a system consisting of a wrist band with multiple magnetic sensors and a magnet at the fingernail [5]. They showed that by incorporating a kinematic model, the finger posture could be calculated. Using a similar principle, Simmons in 2013 showed that by placing a magnetic sensor on each of the finger segments and a single magnet at the base of the finger, all three joint angles of the finger could be estimated [6]. Rowe fielded a system similar to our design consisting of 2 triaxial magnetometers on the wrist and a magnetic ring on the index finger [4]. The system could estimate wrist flexion/extension, radial/ulnar deviation, and finger flexion about the MCP. They reported 95% of estimated finger flexion/extension estimates were within 4.7 degrees of their actual values. Similar to their results, we also found errors in angle predictions increased over time and daily recalibration would be needed to accurately track joint angles over extended periods [7].

For the goal of tracking number of movements, our method seems promising. With control subjects, the algorithm was able to detect gripping movements for a range of objects (marble to 2 in block) with small errors. The algorithm also effectively rejects arm movements that have no finger movement. The tracking monitor was also tested with stroke patients. The challenges are that stroke subjects can have much slower and smaller gripping motions that are more difficult for the algorithm to identify. We showed a mean error of 8.9% in the 3 stroke patients tested. Further testing is needed to determine if this error level is acceptable for clinical testing. The device weight did not seem to hinder lifting the arm sitting or standing. However, for more severe patients the weight of the device may be an issue. All three stroke subjects had prior experience donning the device. They previously participated in a separate study that required donning independently.

Limitations of the device include the fact that the device is currently limited to one finger and cannot be easily extended more fingers. In lab testing, were able to estimate number of grip attempts and finger joint angles with good accuracy. During home use, it will be difficult to estimate the exact type of grip or activity being done with just grip attempts and angle estimations. Further sensors and improved classification algorithm will be needed. Additionally, daily retraining of the machine learning model may be needed for consistent estimate of joint angles. Alternatively, if the cause of the decrease in accuracy over time can be further studied, it might be possible to compensate for changes without the need for collection of new data using the test rig we used in the lab. However, we do expect grip counts will be accurate over time, as the same algorithm was used across multiple subjects over several days in the testing results reported in Table 1. Recalibration of sensors for the grip counts method would only require a trial of moving the arm about in different directions without finger movement. Additionally, it is well known that proximity to sources of magnetic fields, such as large metallic objects or surfaces, interfere with the device and cause large inaccuracy.

V. Conclusion

We have developed an activity tracker for a hand exoskeleton. Use of the device would allow tracking of finger activity when the user is at home. The design of the system allows use in tight spaces and constrained areas and does not significantly increase the size or weight of the exoskeleton. Data can be useful for clinicians to correlate improvements in motor ability with adherence to home training programs that emphasize highly repetitive movement practice. Future work will consist of extended home training with the activity tracker.

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