Development and Evaluation of a Multimodal Sensor Motor Learning Assessment

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***Abstract*— Motor learning is the ability to acquire a new motor skill, which plays an important role in rehabilitation as patients learn exercise programs or modify movements to regain pain free function. In this paper, we design an easy-to-use multimodal sensor system to assess motor learning. We developed a motor learning assessment device with a touch screen and Leap Motion to record the subject hand movement during a Serial Reaction Time Task(SRTT). The SRTT consists of upper limb reaching to targets in multi-dimensions. The device records metrics of time and movement efficiency and examines motor learning based on data analysis. This device can provide clinicians with data that can inform their approach to training. We recruited a total of 11 participants, with and without chronic pain to evaluate the device using a classifier model to assess participants' performance. The model shows our system works well to identify motor learning differences in individuals with and without chronic pain.**

I. INTRODUCTION

Motor learning, or the ability to acquire a new motor skill, is essential to everyone's life. Whether it is learning to play an instrument or a new sport, or to successfully arrange icons on a new smart phone, the ability to acquire a new motor skill affords individuals the opportunity to function more efficiently in their respective environments. Learning a new skill can be difficult and sometimes requires considerable time and effort, in the form of practice, to master the skill. The study of motor learning focuses on understanding both the mechanisms (e.g., memory) required and the type of practice related factors that impact learning and eventually performance [1]. Rehabilitation specialists, like Physical and Occupational Therapists, rely heavily on the concepts of motor learning to help restore a person's ability to function in their environment following injury [5], [6]. It is therefore important to have assessments that examine the clients ability to motor learning under conditions that exemplify functional movement.

Over the last few decades, researchers have used a variety of behavioral tasks and practice related factors to better understand the mechanisms involved in learning a motor skill. A classic behavioral task that is widely used is the serial reaction time task (SRTT) [2]. During this task, individuals are instructed to react to a continuously repeating series of stimuli presented in a fixed order. Participants respond to the stimuli by pressing a button on a button box or keyboard with each key corresponding to a stimulus on the screen as shown in Figure 1(a). During the task, participants do not have explicit knowledge of the repeating sequence of stimuli. As participants repeat the task, the time to complete the sequence decreases as the participants learn the embedded sequence. To probe learning of the pattern, random stimuli are presented. If the participant has learned the sequence, the anticipation of the sequenced stimuli results in increased errors and time during initial presentation of random stimuli. While the SRTT is an elegantly simple paradigm to assess motor learning, there are drawbacks to using the commonly used button box or keyboard for the assessment. Pressing buttons or keys requires minimal physical movement compared to many of the functional activities trained in therapy. While the SRTT has been expanded to use a computer and mouse [3], [4] to respond to stimuli on the screen providing opportunities to examine movement error in combination with time, the range of motion required to complete the task is still very limited and one dimensional. Engineering a computerized motor learning assessment that is easy to use and includes extensive metrics of time and movement quality to examine the process of motor learning while allowing for a wider range of motion (as shown in Figure 1(b)) to complete

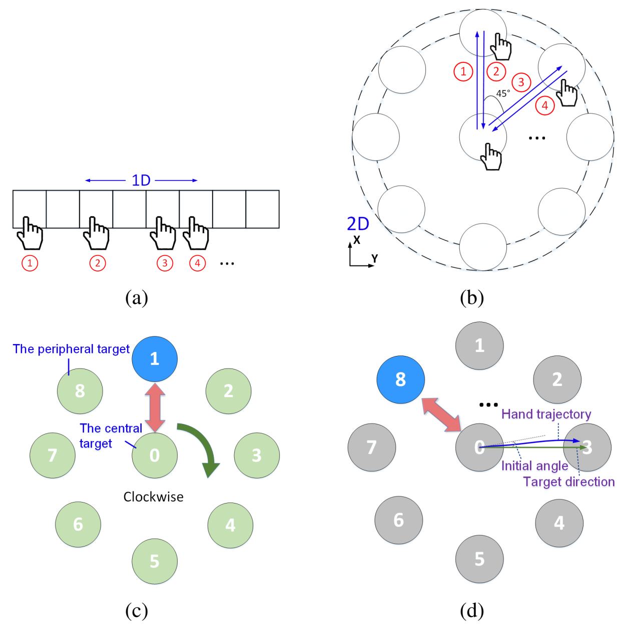

Fig. 1. Comparison of (a) 1D motion button box paradigm, to motor learning system (b) multidimentional range of motion (c) known clockwise movement of the simple motor condition (d) other conditions are not explicitly known.

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the learning task would provide clinicians with an important instrument not currently found in rehabilitation.

Motor learning assessments to identify changes in motor learning with aging or changes associated with pathology (e.g. stroke or chronic musculoskeletal pain) is important to rehabilitation specialists needing to develop efficacious treatments to restore function [7], [8]. We propose a method to improve rehabilitation specialists ability to examine motor learning using a variation of the SRTT. Our multimodal sensor motor learning system consisting of a touch screen and a hand movement sensor automatically recording time and movement path data. A paradigm previously described in the literature [3], [4] has been adapted to go beyond a one dimensional movement. Targets are arranged in a circular pattern with use of a central target to keep all movements to and from peripheral targets a fixed distance. This adapted paradigm with a multimodal system allows a detailed analyses of the motor learning process. In addition, we have added a condition to assess motor performance to be used as a control, if necessary, for potential movement differences between groups. The purpose of this paper is to describe the development of this new approach to analyze motor learning of a multi dimensional upper extremity task, as well as, demonstrate the effectiveness of the system to distinguish between a group of healthy individuals and a small group of individuals with chronic neck pain.

II. Motor Learning Program Design

A. Rationale

Upper extremity use during daily activity is ubiquitous, such as preparing food or opening doors. These activities require reaching movements. In rehabilitation, programs managing chronic neck or upper back pain include upper extremity movement exercises designed to meet the patient's needs [6], [8]. Patients need to effectively learn these exercises to restore movement and reduce pain. It is our quest to better understand the motor learning process to help clinicians develop more efficacious approaches to training patients with impaired movement secondary to pain.

B. Motor Learning Task

An SRTT motor learning paradigm, previously described, is adapted and used to tease apart differences between persons with and without chronic pain. As shown in Figure 1, during the motor learning task, participants reach outward from the central starting location to a highlighted peripheral target; then return to the central target. The distance between the center of the central target and the center of the peripheral target (11cm) is constant for all movements in the paradigm. The motor learning paradigm consists of three conditions, a simple motor condition, a random order condition, and a sequence condition. The potential to anticipate target position is different in each condition. The combination of conditions allows us to tease apart motor performance ability from the ability to motor learning.

C. Metrics

In this study, we investigate the ability of individuals with chronic neck pain to acquire an upper extremity motor sequence compared to healthy age matched peers. The evaluation metrics examine time and movement efficiency in terms of initial angle of movement and movement path. These areas of interest are examined with multi-level refinement.

- Time: The following are recorded 1. total time to complete the block, 2. time to complete a cycle (completion of 8 peripheral targets and corresponding movements to the center target) and 3) an outward/inward target index is calculated. The outward (center to peripheral target) and inward movement (peripheral to center target) times are used to calculate an index, $index = \frac{outward - inward}{outward + inward}$. When the time interval is the same for both movements, the index is 0. A positive score shows that outward movements required more time than inward movements.
- The path distance: The length of the hand trajectory between the center target and the peripheral target in each movement is calculated and examined for the block, a cycle and at a target level.
- The initial angle: The difference between a straight line to the target and initial movement direction at the beginning of the movement (shown in figure 1). We examine this metric at a target level.

III. Sensor System Design

A. System Overview

Our motor learning system aims to precisely and efficiently sense the touch time of targets and hand movement to targets in the motor learning paradigm. In this study, we examine participants with chronic pain. We provide the system overview in Figure 2 in an upper limb motor learning task. Development of the motor learning assessment comprises two key components, hardware integration and software development.

B. Hardware Integration

As shown in Figure 4(a), hardware integration is necessary to sync hand motion data from Leap Motion with touch screen data. Leap Motion mainly contains two monochromatic IR cameras and three infrared LEDs. It captures the hand movement and then synthesizes 3D position data (x, y, and z coordinates) of the palm, thumb, index, middle, ring and pinky fingers. In addition, a Dell S2240T 21.5" Touch Screen is used to collect touch data. It detects the time for each touch, the position of where the user is touching and the position of the center of the current button that is lit. Its sampling time is 0.0165s. The computer collects and records these data.

C. Software Development

The software contains four parts: login, calibrate, select the condition (simple, random or sequence) and analyses. In each session, we calibrate with the right index finger and select the condition. The interfaces of calibration and selection are

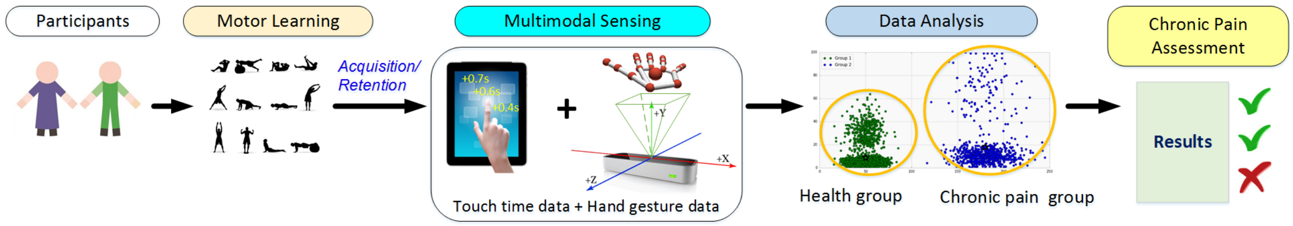


Fig. 2. The system consists of five parts: participants, motor learning, multimodal sensors, data analysis and motor learning assessment.

shown in Figure 3(a). The software is developed in Unity. It is an all-purpose game engine that supports graphics. The software is run on a Dell laptop with Windows 7.

(a) The interface for calibration. (b) The interface for selecting task.

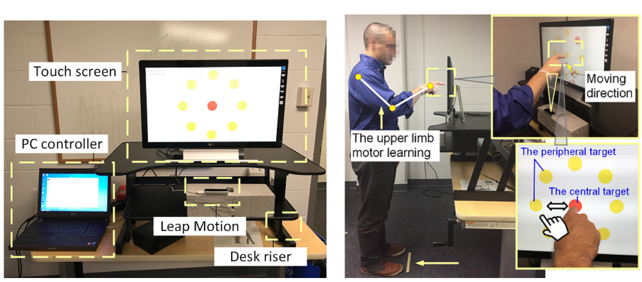
Fig. 3. The software interfaces for (a) calibration with right index finger and (b) choosing the condition.

IV. Evaluation

A. Participant Status

The protocol was approved by the University at Buffalo Institutional Review Board, and all participants provided informed consent prior to participation. Inclusion criteria included: 1) Participants with chronic mechanical neck and upper back pain present for greater than 3 months, 2) Healthy age-matched individuals. Exclusion criteria included: 1) Significant orthopedic involvement such as severe arthritis 2) Recent injury to the neck or upper extremity 3) Neurological pathology 4) Uncorrected vision. A total of 5 adults without and 6 adults with chronic neck pain were recruited.

B. Methodology



(a) Hardware integration. (b) Methodology.

Fig. 4. The hardware integration of multimodal sensors in the motor learning system. The participant stands in front of the touch screen with their hand over the Leap Motion. When the target illuminates, the participant touches the target. The next target is then illuminated. The touch screen detects the touch time. The Leap Motion senses hand movement.

The upper limb motor learning assessment consists of three conditions, simple, random and sequence [9]. In all conditions, the participant will start on the center target and an audio cue will be given at the start of the block. Movements will always alternate between the center target and one of the peripheral targets.

- Simple Motor condition: serves as a measure of the participants maximal rate of movement to assess motor abilities. The pattern of movement is explained to participants. The movement will alternate between the center target and peripheral targets, and the peripheral target will follow a clockwise pattern.
- Random condition: peripheral targets are presented in an unpredictable manner. Participants must attend to the entire screen to find the next illuminated target. This assesses participants attention and reaction time.
- Sequence condition: continuously repeating sequence of targets to assess implicit learning of motor task. As participants are able to anticipate the next target, time to touch the target diminishes and movement efficiency increases.

Participants stand in front of the touch screen with their chest aligned with the central target. An adjustable table and sit-to-stand desk riser are used to avoid differences in height interfering with proper alignment. Participants are instructed to reach as quickly and accurately as they can to each target. Once the appropriate condition is selected, targets change color from yellow to red signifying the participant should touch that target, see Figure 4(b). Participants are given the option to take rest breaks to avoid fatigue.

There are 12 blocks: 2 simple motor (M), 4 random (R) and 6 sequence (S) in the following order: M-M-R-R-S-S-S-S-R-R-S-S. Participants are informed of the pattern in the simple motor task (M), participants do not have explicit information about the stimuli in the other blocks. show in Figure 5. Each block consists of 64 movements.

C. Data Analysis

In this section, we analyze the data to provide empirical results to quantify motor learning performance. Figure 5 shows the details of time analyses for the two groups. The first two blocks are the simple condition, which cost minimal time in both groups. The following order of blocks R-R-S-S-S-S-R-R-S-S, allows us to compare movement time and efficiency when the target sequence cannot be anticipated (random) and when the target sequence may be implicitly learned allowing anticipation of the next target (sequence). The total time to complete the sequence blocks (B5-8)

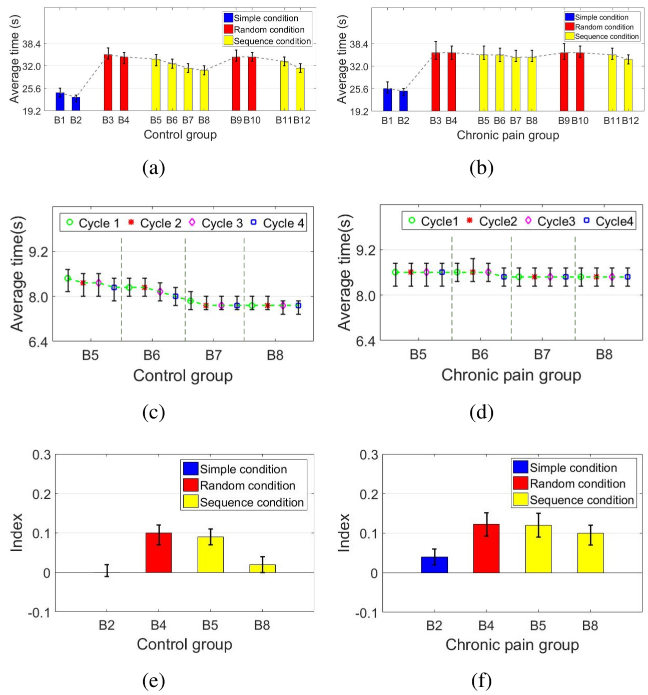


Fig. 5. Total time to complete block for control group (a) and group with chronic pain (b). Total time to complete cycle of sequence for (c) control group and (d) group with chronic pain. Outward/Inward target index, with 0 representing equal movement time in each direction, for (e) control group and (f) group with chronic pain.

TABLE I

INITIAL ANGLE OF MOVEMENT FOR THE SEQUENCE CONDITION

Block	Target	Initial angle(°)	
		Control	Chronic
Last cycle in B8	1	4.9	18.1
	2	3.4	16.8
	3	6.7	18.9
	4	5.9	24.1
	5	7.6	8.3
	6	13.2	39.1
	7	9.9	20.3
	8	10.1	12.1

notably decreases for the control group. Examining each cycle of the repeated pattern in the sequence blocks, we see a steeper rate of learning for the control group compared to the group with chronic pain. Examining performance at a target level, the index comparing movement to the center target (explicit knowledge) to movement to the peripheral target, the index approaches 0 for the control group near the end of B8. Again suggesting equivalent anticipation of the center and peripheral targets for the control group.

In Table I, we concentrate on the initial angle of movement for the last cycle of the repeated sequence in B8. We note that the control group anticipates the learned pattern in B8 with a more direct angle to the target. Demonstrating convincingly that the control group has learned the pattern. In Table II, the movement path distance data is expressed as a percentage of the average path distance in the simple motor condition. The simple motor condition, treated as base distance, is used to normalize data. This feature is especially important if there

TABLE II

PATH DISTANCE AS A PERCENTAGE OF MOTOR ABILITY

Base distance (cm)	More distance compared to base distance (%)					
B1& B2	B4	B5	B8	B9	B11	B12
Control (380)	10.3	10.1	5.6	11.2	10.6	5.9
Chronic (420)	12.1	11.7	10.3	12.7	12.1	10.8

is a large discrepancy in simple motor movement times, i.e. motor abilities, between groups. We could observe that the percentage of path distance for the control group diminishes after practicing the sequence condition and the value in B8 is almost half of B4 or B5 (B12 is half of B9 or B11), while for the chronic group B8 and B12 are much similar to previous blocks respectively. These further suggest that the control group has learned the sequence.

Moreover, after acquiring the touch time and hand movement data, an SVM classifier model with a Gaussian kernel was deployed to assess chronic pain status. Training the model using data from the 11 adults and running tests on the same data, we achieved 90.91% accuracy, demonstrating our system works well.

V. CONCLUSIONS

In this work, we developed and evaluated a multimodal sensor motor learning assessment. We designed an SRTT with a multi-dimensional paradigm. We demonstrated the ability to distinguish between a control group and a group with chronic pain using the motor learning assessments metrics of time and movement efficiency. Further, we deployed a classifier model to assess the chronic pain status of the participants, which demonstrates our system works efficiently.

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