Title
Targeted Movement Pattern Recognition for Infants with Perinatal Brachial Plexus Injury

Author
AbuZeid, Yasmeen

Publication Date
2019

Peer reviewed|Thesis/dissertation

UNIVERSITY OF CALIFORNIA, IRVINE

Targeted Movement Pattern Recognition for Infants with Perinatal Brachial Plexus Injury

THESIS

Submitted in partial satisfaction of the requirements for the degree of

MASTER OF SCIENCE

In Biomedical Engineering

by

Yasmeen AbuZeid

Thesis Committee:
Professor David Reinkensmeyer, Chair
Professor Susan V. Duff
Professor Dan M. Cooper

TABLE OF CONTENTS

LIST OF FIGURES **3**

LIST OF TABLES **4**

ACKNOWLEDGMENTS **5**

ABSTRACT OF THESIS **6**

1 INTRODUCTION **8**

1.1 Background 8

1.2 Literature Review 10

2 DESIGN OF NEUREWARDS **29**

2.1 Hardware 29

2.2 Software 30

3 METHODS **32**

3.1 Participants and data acquisition 32

3.2 Data visualization 37

3.3 Movement Classification 40

3.3.1 Hand-drawn Ellipsoids 40

3.3.2 Similarity measure 41

4 RESULTS **43**

4.1 Alignment detection 43

4.2 Choice of threshold 43

4.3 Efficiency of Similarity Measure 45

5 DISCUSSION **49**

5.1 Limitations 49

5. 2 Future Work 50

LIST OF FIGURES

Figure 1: Perinatal Brachial Plexus Injury (PBPI) 8
Figure 2: Mean response rate (Rovee et al) 12
Figure 3: Experimental Setup (Watanabe et al) 13
Figure 4: Trajectory and velocity (Watanabe et al) 14
Figure 5: In-home setup of mobile paradigm (Gekoski et al) 15
Figure 6: Learning, day 1 (Gekoski et al) 16
Figure 7: The Kicking Exercise (Campbell et al) 17
Figure 8: The humanoid experimental setup (Funke et al) 19
Figure 9: Alert and average leg movements (Funke et al). 20
Figure 10: Nao Robot interaction (Pulido et al) 21
Figure 11: Crawler setup and results (Chen et al) 23
Figure 12: SIPPC3 Crawling Assistant System in Use. 24
Figure 13: Experimental setup and results (Agrawal et al) 26
Figure 14: Experimental setup to assess learning (Duff) 27
Figure 15: Mean integrals of biceps activation (Duff) 28
Figure 16: EcoMini senor (Chou) 30
Figure 17: SolidWorks model for NeuRewards overhead mobile 30
Figure 18: Collection of four template movements lying down 33
Figure 19: Collection of 4 template movements while seated 34
Figure 20: Infant's Active movements 35
Figure 21: Sensor placement on adult's wrist with tape 35
Figure 22: 2D Acceleration plot against time for infant's four "template" movements 39
Figure 23: 2D Acceleration plot against time for adult's 4 "template" movements 39
Figure 24: Hand-drawn ellipsoids enclosing the four template movements. 41
Figure 25: 3D plot of acceleration vectors for (1) EF template & (2) EF from "desirable" .. 41
Figure 26: Chunks of EF template added into the "undesirable" sample 42
Figure 27: Alignment Detection Algorithm 43
Figure 28: Threshold Choice 44

Figure 29: Similarity measure between 4 template movements & “desirable” sample........ 46
Figure 30: Similarity measure between 4 template movements & “undesirable” sample .. 47

LIST OF TABLES

TABLE 1: Overhead Mobiles Literature Review... 18
TABLE 2: Map for Infant Template Movements.. 33
TABLE 3: Acceleration, Magnitude and Gyroscope data for Template movements. 38
TABLE 4: KS test for similarity between the four movements. 40
TABLE 5: EF, SA, SF, TF, Non-marked in Similarity Measure 48
TABLE 6: Desirable, Undesirable, Non-marked in Similarity Measure 48

ACKNOWLEDGMENTS

To begin, I would like to thank my thesis committee members, Dr. David Reinkensmeyer, Dr. Susan Duff and Dr. Dan Cooper for taking the time to review my thesis. It has been a pleasure working with my advisors, Dave and Sue and learning from their expertise. Their guidance and belief in me have given me hope in my contributions and always assured me that my work is a steppingstone towards the improvement of many lives. I am beyond grateful for their patience as I learn and grow throughout this study. This opportunity has taught me more than I had ever expected from data analysis, coding and persistence. My heart is full.

In addition, the Bio-robotics lab has been extremely supportive of my education and growth experience at UCI, especially, Dr. Joan Lobo Prat for encouraging me to pursue a MS degree, and Merav Senesh for guiding me through my project and being patient as I continue to expand my technical and analytical skills.

Throughout this project, I worked with graduate students who contributed towards the electronics and programming of NeuRewards, including Ali Hashemi, Crystal Han, and Michael Pollind and I am grateful for their time and effort. I would like to give a special thank you to Rahul Soangra at Chapman University who guided me through the data processing. Additionally, I would like to acknowledge professor Pai Chou, Ali Heydari and Gene who allowed me to use their EcoMini sensor for my project.

Last but not least, I sincerely thank my mom, dad, brother, grandmother and grandfather for their unconditional support in pursuing this degree and allowing me to explore my passions and follow my dreams.

ABSTRACT OF THESIS

Targeted Movement Pattern Recognition for Infants with Perinatal Brachial Plexus Injury

By

Yasmeen AbuZeid

Master of Science in Biomedical Engineering

University of California, Irvine, 2019

Professor David Reinkensmeyer, Chair

This thesis presents work toward a novel rehabilitation tool for infants with limited arm movement such as those who sustain a perinatal brachial plexus injury (PBPI). PBPI is a traction injury to peripheral nerves that occurs during the birth process. An injury to the upper trunk of the plexus (C5-6 spinal nerves) partially or fully denervates the skin of the upper arm and muscles of the elbow (i.e., biceps, brachialis) and shoulder (i.e., Deltoid, Sternal Pectoralis Major, Rotator Cuff). Initially, PBPI is typically treated with Passive Range of Motion (PROM) and positioning led by a physical therapist or occupational therapist. If recovery is limited, nerve microsurgery is indicated by 6 months of age. Recovery in infants with PBPI varies from 38 to 80% of infants depending on the initial condition and severity, as well as the rate of reinnervation. Yet, through technology, there may be methods available to increase the rate of recovery, leading to greater use of the affected arm. Infants as young as 3 months of age have been found to increase arm and leg movements through a paradigm of contingent reinforcement (i.e. rewarding desired movement patterns with audiovisual stimulation such as an overhead mobile). Before a

device can be fully constructed to provide contingent reinforcement for desired arm movements, those movements must be consistently detectable. Thus, for this thesis project, I studied automatic detection of the arm movements desired for young infants with PBPI using arm acceleration data.

Acceleration data was acquired from a wrist-worn sensor as an adult volunteer moved her arm in the desired motion. I implemented a template-matching algorithm based on taking the dot-product of a moving window of 3D acceleration vectors with template acceleration patterns, where the templates were movement samples deemed targeted and rehabilitative by an experienced physical therapist. I found that the algorithm detected rehabilitative movements with an accuracy of ~90%. The algorithm never identified a movement that was deemed as undesirable for this population of infants, by the physical therapist. These results reveal the potential for the template matching algorithm to be used in a contingent reinforcement paradigm capable of activating a toy to encourage infants with PBPI to make targeted rehabilitative arm movements.

1 INTRODUCTION

1.1 Background

Perinatal Brachial Plexus Injury (PBPI) is a type of peripheral nerve injury that occurs in approximately 560,000 live births worldwide (Chauhan et al, 2014). It occurs when the infant's shoulder is caught on the mother's pubic bone as shown Figure 1. This Erb's palsy form of the PBPI results in reduced motion into elbow flexion/external rotation. Infants often compensate for this partial to full paralysis by using other muscles, such as their triceps, to move the elbow and internal rotators, to move their shoulder. The use of habitual compensatory patterns often leads to secondary musculoskeletal conditions such as posterior shoulder subluxation (Duff et al, 2015).

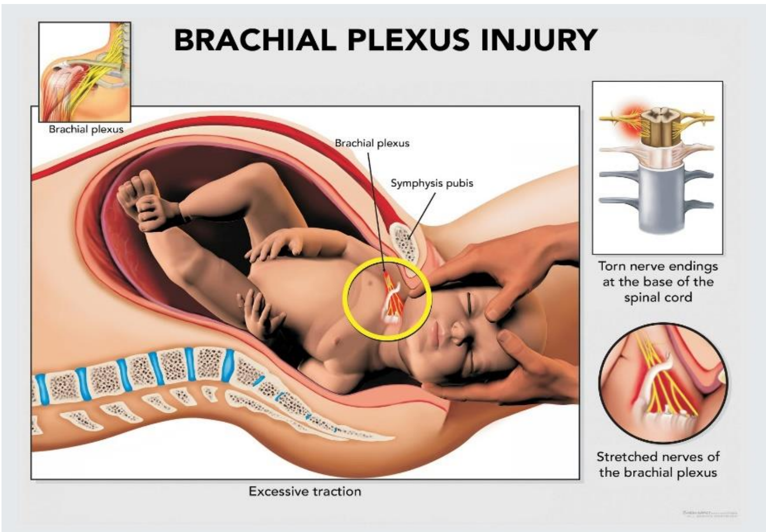


Figure 1: Perinatal Brachial Plexus Injury (PBPI). Taken from BBP Presentation OTAC.

Currently, therapeutic options for PBPI include rehabilitation and if needed, microsurgery. If infants are showing evidence of some neural recovery, they are not in need of microsurgery. Thus, they typically receive physical or occupational therapy.

Therapy often employs passive range-of-motion (PROM), positioning, methods to increase motor skills including reach-to-grasp behaviors and parent education. With PROM, the therapist manually moves the joints of the infant's arm to minimize secondary impairments and prevent joint and muscle contracture. Age appropriate motor behaviors are encouraged to increase strength and prehensile function. A current strategy being explored is the use of contingent reinforcement to foster self-generated motion and activation thus control of intact neuromuscular pathways. Microsurgery is needed when the nerves fail to recover sufficiently to restore necessary arm function (OrthoInfo). The options for microsurgery include neurolysis, nerve grafting or nerve transfer. Following microsurgery, the infant must learn to use the new connections, relying on use-dependent neuroplasticity and motor learning strategies. Post-operatively, the infant ofen requires a period of physical or occupational therapy, in which the therapist attempts to foster age appropriate motor skills and movement patterns involving the affected arm.

The goal of this project is to develop a sensor-based rehabilitation system that could be used to encourage self-generated, yet targeted movement using a contingent reinforcement paradigm in infants at risk for dysfunction. It is not possible to instruct an infant to perform certain movements, so, instead, therapists typically take the approach of rewarding desired targeted arm movements, using sound, expression, and movement of toys. It would be advantageous to therapists, patients, and infants if this approach could be automated, giving infants the incentive to practice desired movements at a high intensity. Thus, the work undertaken in this thesis contributes toward the design of an interactive toy that responds when the infant makes desired arm movements.

1.2 Literature Review

This literature review compares and analyzes publications in the field of rehabilitation technology designed to encourage targeted movement or muscle activation in children who are typically developing, as well as those with atypical conditions, and/or at risk for developmental delay. This review will reference 11 main papers to compare the goals, technologies used, experimental methods, data collection methods, outcome measures, and results. The long-term goal of each of these papers was to contribute to the field by designing a device that could be used to foster specific types of movement in children with movement-related impairments.

Children move in a variety of ways to modulate task-specific actions such as reaching, crawling, and walking (Pulido et al. 2018). The dynamic process of exploration and discovery allows them to control their bodies and interact with their environments. In contrast to typically developing (TD) infants, infants at risk (AR) for developmental delays often have neuromotor impairments which reduce their available strength, sensibility (i.e., proprioception), and coordination. These challenges may lead to greater difficulty with movement and potentially decrease motivation to move and explore.

According to the review by Pulido et al, (2018) contingency studies have demonstrated that, when movements are reinforced by the motion of an overhead mobile, infants with typical development as young as 3 months respond in several ways, including increasing the rate of arm movement (Watanabe et al. 2006) and the rate of leg kicking (Heathcock et al. 2004, Lobo et al. 2013), or moving a foot vertically across a height threshold (Sargent et al, 2014).

Overhead mobiles

Four of the papers I am reviewing use overhead mobiles to study the use of contingent reinforcement to increase movements of infants about 2-5 months old. One paper studied the effect on arm movements (Watanabe et al. 2006), and three papers studied the effect on leg movements (Heathcock et al. 2004, Campbell et al. 2015, Rovee et al. 1969).

A study by Carolyn Rovee was the first to experiment with conjugate reinforcement on 18 healthy infants ranging from 9-12 weeks of age. A conjugate reinforcement schedule is a variant of a continuous reinforcement (CRF) schedule where the rate, amplitude, or intensity of the reinforcer is proportional to the target response (Rapp, 2008). In the original study, a cord was tethered to the ankle, such that foot or leg movement directly triggered sway and movement of mobile figures attached to a suspension bar (Rovee et al. 1969). In that study, the experimental group received an initial session, consisting of 3 periods: a 3-minute baseline to record the infant's natural movements, a 15-minute acquisition period where the cord was attached to the leg, and finally, a 5-minute extinction period where the cord was unattached. The control group received the same initial and extinction periods and only the acquisition period changed. The control group was divided into two types of feedback: visual-somesthetic feedback which included visual and touch feedback, and visual feedback only. Specifically, during the acquisition period, the experimenter presented the control group with moving figures that were continuously activated similar to the moving figures seen in the experimental subjects' acquisition period. Touch feedback was provided to the control group from the attached ankle cord.

Thus, in the experimental group the figures were triggered to move by leg movement and in the control group, the figures moved continuously.

Although there were no sensors used to detect the movements, two observers independently recorded the responses as a reliability check. Figure 2 shows the mean responses per minute represented as a solid line for the experimental group, a dotted line with circles for the visual-somesthetic control group, and a dotted line with squares for the visual only control group. There was an increase in the mean number of responses in the experimental group in comparison to the control groups. This paper was referenced as a foundation for the further studies using the mobile paradigm.

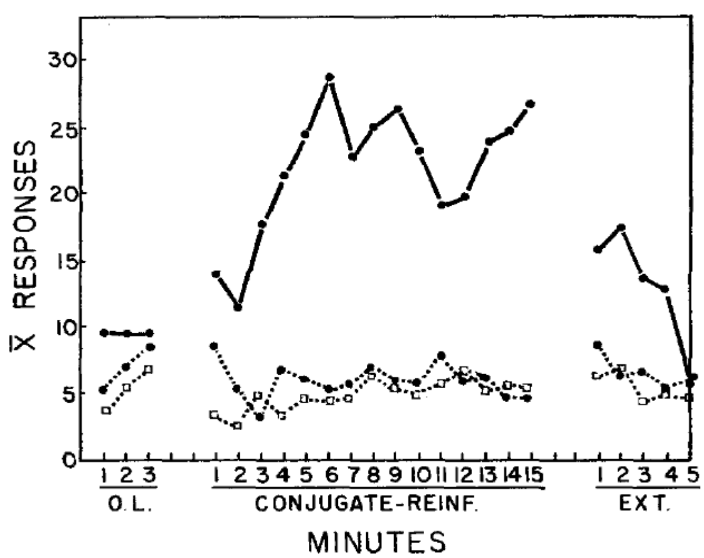


Figure 2: Mean response rate as a function of reinforcement condition over 46 minutes of continuous testing.

Watanabe and colleagues examined interlimb movement patterns in 48 healthy infants aged 2–4 months while the infants attempted moving a mobile with string attached to each wrist as shown in Figure 3a (Watanabe et al. 2006). The purpose of this study was to encourage infants to learn to produce more arm movement by rewarding every movement with a shaking mobile. During the final testing period (period 6), **extinction**, the arm was not attached to the overhead mobile, thus, the infants were not rewarded. If the infant exhibited arm movement without the reinforcement it would provide evidence of learning (Watanabe et al. 2006). The experimental design is portrayed in the flowchart in Figure 3b.

(a) (b)

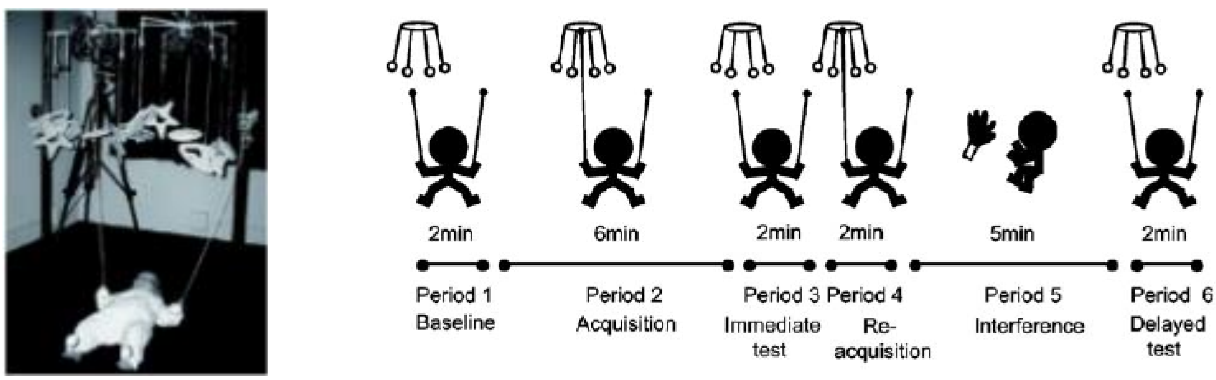


Figure 3: (a) The setup of experiment in the connected periods. (b) The flowchart of the procedure.

The group used a 3D motion capture system to measure the trajectories of the arm movements. From that, movement velocities and frequencies of movement were analyzed ($\dot{x}$, $\dot{y}$, $\dot{z}$). The results shown in Figure 4 reveal an increase in frequency of movement and velocities in period 3 (immediate test) compared to period 1 (**baseline**). Additionally, from testing on different ages, the results suggested that 2-month-olds can acquire and retain general body movements that induce contingent motion in an overhead mobile.

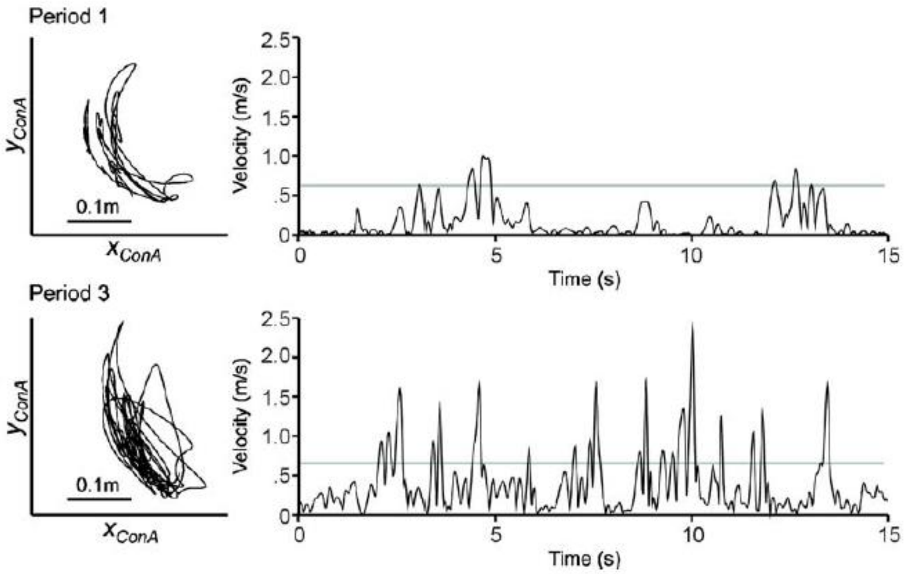


Figure 4: Typical examples of 15 seconds trajectory and velocity data of the connected arm (right arm in this case) for a 3-month-old infant in Period 1 (baseline) and Period 3 (immediate retention test).

Similarly, Heathcock and colleagues examined the learning and memory abilities of a group of infants with respect to their leg movements, using an overhead mobile, as shown in Figure 5a (Heathcock et al, 2004). They compared the movements of 10 full-term infants who had control over the mobile against a comparison group of 10 infants who did not have control over the mobile. In addition, they compared the movements of a group of 10 preterm infants who had control over the mobile to the same comparison group of 10 infants without control. Figure 5a shows the duration of the study for the full-term infants. Based on the literature (i.e., Gekoski et al, 1984) the preterm infant group was not expected to display learning during the first session, or either short-term or long-term memory periods during the first week. Therefore, the duration of the study for the *preterm infant group* was extended to 6 consecutive weeks, where days 1 and 2 from the schedule in Figure 5b were repeated each week. Every 15-minute session was divided into 3 periods.

During the **baseline period**, the mobile was attached to the left stand so that kicking did not produce any movement of the mobile. In the next **acquisition period,** the mobile was switched to the right stand for the full-term and preterm groups so that kicking resulted in a rewarding movement of the mobile. In the final **extinction period**, the mobile was placed so that kicking did not produce any movement of the mobile. In the comparison group, the mobile was placed so that the infant's movement did result in mobile movement.

(a) (b)

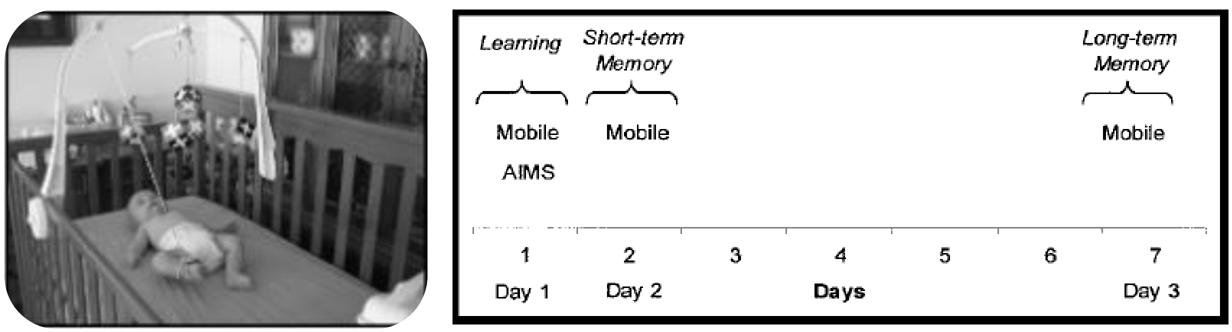


Figure 5: (a) In-home setup of mobile paradigm. (b) Schedule of sessions for full-term and comparison groups.

Hip and knee range of motion were **not measured** during kicking. However, the group visually estimated a kick to include > 15 degrees of simultaneous hip and knee extension. The acquisition period was broken down into 3 periods, as shown in Figure 6. The kicking rates for all periods were normalized to baseline kicking rates and used to compare amongst groups. Learning was considered to occur when the following 2 criteria were met:

(1) the kicking rate was higher in the extinction period, after exposure to the mobile contingency than in the baseline period, before exposure,

(2) the kicking rate was greater than that observed in the comparison group during a single session.

The results show that the full-term group learned during the session on day 1 (Figure 6). Although the preterm group did kick greater than their own baseline level during some test sessions, yet, they did not meet both criteria for learning during any testing session across the 6-week period.

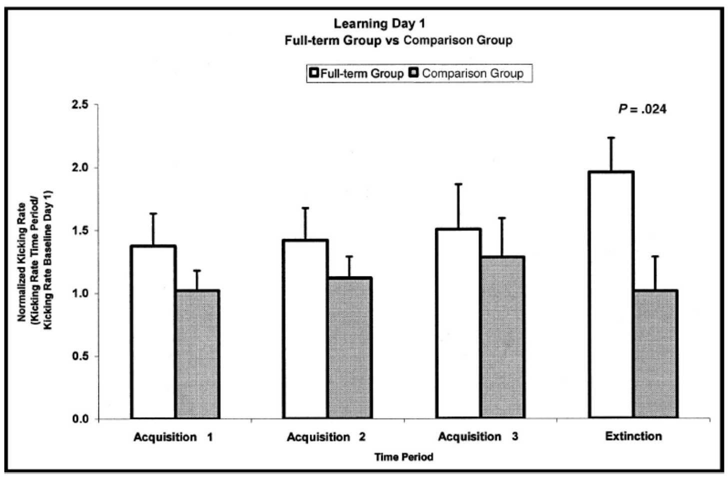


Figure 6: Learning, day 1: Group means and standard deviations of normalized kicking rate between the full-term and comparison groups.

Campbell and colleagues have studied infants with Periventricular Brain Injury (PBI) at risk for poor developmental outcomes using an overhead mobile as reinforcement, in comparison to infants with TD and Cerebral Palsy (CP). 9 infants were in the exercise group and 7 infants in a control group with no mobile reinforcement (Campbell et al, 2015). In contrast to the previous 3 papers in which the experiments were run by researchers, this experiment was performed by the infant's parents in their home and recorded for assessment by researchers at the end of the study. For the exercise group, parents were asked to perform kicking exercises for 8 minutes per day, 5 days per week for

2 months, by encouraging the infant to kick using toys that produce light and sound when the toy moved (Figure 7a). Unlike the previous papers, the number of sessions for this study was higher, as this was geared towards rehabilitation for infants with PBI. Infants from the control group with no exercise were assessed at the beginning and the end of the study. Similar to Heathcock and colleagues (2004), the criterion for a leg movement was visually evaluated at more than 15 degrees in either direction from the resting position. No sensors were used to measure the movements, and the movements/minute were evaluated for each session, as shown in Figure 7b. Overall, the movement rate for TD infants and infants at-risk increased throughout the study. However, it decreased for delayed infants.

(a)

(b)

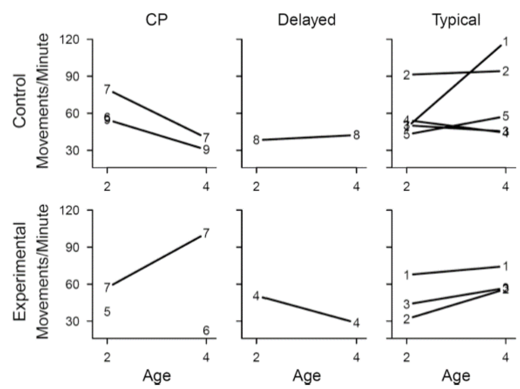


Figure 7: (a) The Exercise: The mobile (sound and movement deactivated) is attached to a wooden stand that slides under the infant bath seat in which the child is seated. A noise-making toy hangs from the mobile to provide both visual and auditory feedback when the infant kicks. (b) Longitudinal Change in Total Leg Movement Frequency of Individual Children by Age, Outcome, and Group Assignment. CP, cerebral palsy. Numbers in the graph correspond with subject numbers.

In a review of this study, Sargent and Huang comment on the treatment duration and suggest that parents will likely need more than just monthly visits to adhere to a treatment frequency (Sargent & Huang, 2015). The results show that a majority of the children in the study increased the frequency of leg movements between 2 and 4 months in response to being tethered to the mobile while supported in an infant bath seat. However, there is no support that the tethered kicking intervention increased the frequency of kicking beyond the effects of maturation (Sargent & Huang, 2015).

Authors	**Infant Group**	**Measurement Evaluated**	**Evaluation Tool**	**Results**
Rovee et al, (1969)	Typical	Mean response/ minute	Visually evaluated	Increase in mean responses/minute
Watanabe et al, (2006)	Typical	Movement trajectory and velocity	Motion Capture System	2-month-olds can acquire and retain general body movements that induce **contingent** motion in an overhead mobile
Heathcock et al, (2004)	Full term/ pre-term	Kicks/minute	Visually evaluated (>15 deg)	Full-term group learned during the session on day 1. Preterm group did not show learning during any session across 6-weeks
Campbell et al, (2015)	Periventricular Brain Injury (PBI)	Movements/ minute	Visually evaluated (>15 deg)	8/13 infants with longitudinal data increased frequency of leg movement

TABLE 1: Summary of the four papers according to the targeted group, measurement evaluated, tools used, and their results.

Humanoid - Imitation

Two papers in this review use a humanoid imitation and rewarding method to encourage infants to perform specific movements. Funke et al studied infant responses to non-contact interactions with a small humanoid robot as foundational work that will introduce appropriate strategies for future interventions with the more vulnerable population of AR infants (Funke et al, 2018). Nine healthy infants were seated in front of a humanoid robot that performed 4 interaction conditions; 1) raising arms and saying “yay”, 2) kicking legs and saying “kick”, 3) stationary and saying “yay”, 4) stationary and saying “kick”.

(a) (b)

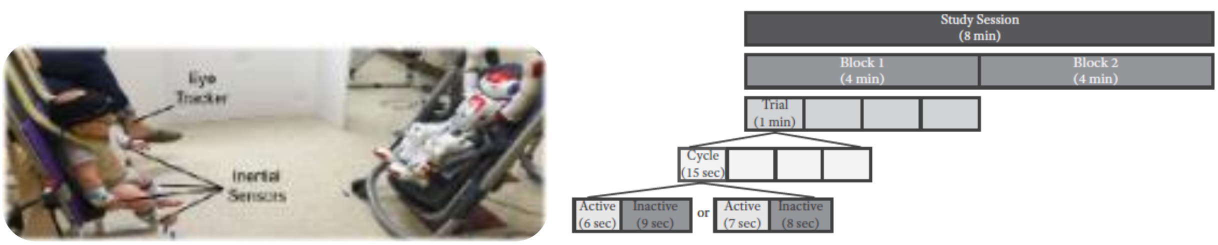


Figure 8: (a) The experimental setup in which an infant observes and reacts to a Nao robot. (b) Graphic explaining the flow of the experiment and the makeup of trials within each experiment session.

Throughout the sessions, **visual attention, gaze,** and **physical response** were measured using an eye tracker and APDM Opal inertial sensors (Portland, OR) secured to the wrist and ankles. Visual attention was used to calculate percent alert, which was shown to increase during the robot’s active phases, as shown in Figure 9a. As shown in Figure 9b, the infants tended to move more during periods of robot inactivity and seemed more visually attentive when the robot was moving. This suggests that pauses in robot activity promoted infant movement. Although the robot performed arm and leg movements separately, there was no correlation between which limb the robot moved and which limb the infant moved.

(a) (b)

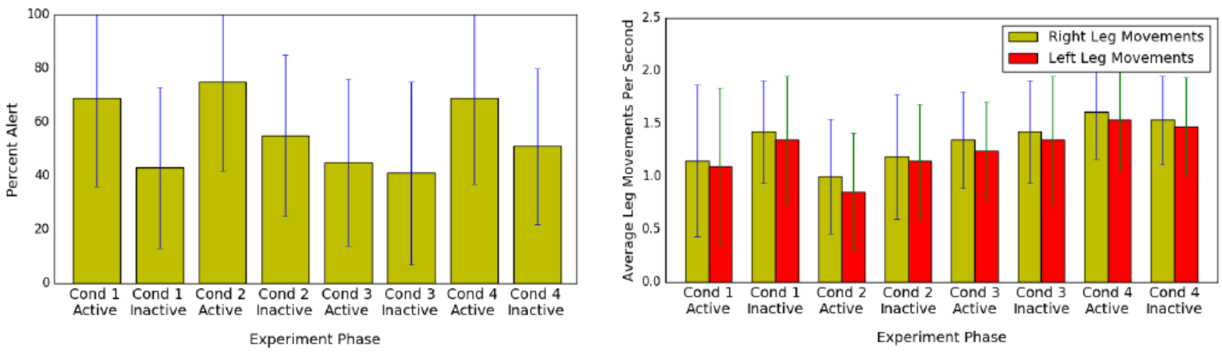
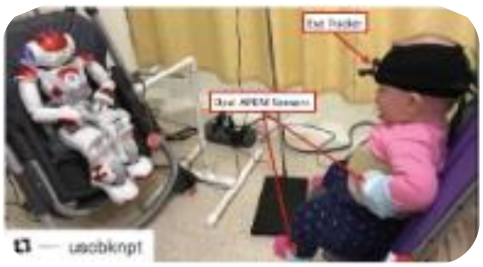


Figure 9: (a) Visualization of the percent of time infants spent being alert while the robot was active and inactive in each condition. (b) The average number of right- and left-legged movements per second during the active and inactive phase of each condition.

Since Funke and colleagues highlight the importance of the robot inactivity on increasing the frequency of movement, it is important to consider the amount of inactive time allotted between mobile rewards as well, to allow enough time to promote of arm movement.

Rather than focusing on reinforcing motion patterns, the same group performed another experiment to reinforce the peak acceleration of a movement to encourage infants to increase the peak acceleration of their leg movements over time (Pulido, 2018). This study used the same humanoid robot to introduce various difficulty levels to activate the robot's "rewarding movement". The infant's baseline movement was measured as the robot remained inactive. Then, the robot demonstrated the reward action three times, which was a basic knee flexion kick at a ball on a string in front of the infant as shown in Figure 10a. After a demonstration, the contingency phase of the study ran for 8 minutes. If the infant produced an acceleration from the right leg above a fixed threshold of 3.0 m/s^−2, measured by the OPAL inertial sensors, the robot would perform the reward action. Additionally, the eye tracker was used to measure the infant's engagement in the task. The average acceleration peak of the infant's leg was used to set a higher threshold for the reward activation in every segment, as shown in Figure 10b.

(a) (b)



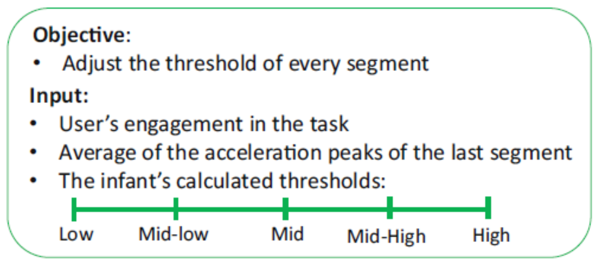


Figure 10: (a) An infant study participant interacting with the NAO robot in the previous study. (b) Representation of the contingency problem.

This experiment met the goal of determining whether the robot could encourage the infant to reach higher accelerations from their movements to receive better rewards from the robot. Although it was not graphically represented in the paper, the reinforcement learning based model was able to determine the best threshold configuration in terms of peak acceleration and indicate the thresholds that would reach higher rewards values. Additionally, the model is sensitive to the degree of variance amongst participants. Maintaining these thresholds in a session would help to maximize the average of the acceleration peaks and the number of peaks detected.

As suggested in Pulido and colleagues' study, an algorithm specific to each infant for movement classification is optimal for this contingent reinforcement paradigm to be effective. Infants not only exhibit different movement features (speed, smoothness), but also different learning levels. Thresholds for "desirable" movements should be set individually or based on the infants' ability in perform those movements.

Crawlers – (early mobility)

Pediatric crawlers promote crawling for children who have difficulty tolerating movement, while supporting body weight. The crawlers on the market have a platform or suspended support sling on caster wheels, which reduce required effort on arm and leg muscles (Proctor,1989, Williams, 2007). These devices may not be suitable for mobility-impaired infants (Chen et al, 2010). Therefore, Chen and colleagues have built a crawler to provide typically developing infants an opportunity for exercise while exploring the environment. As shown in Figure 11a, Chen and colleagues designed a device such that infants could use two mice, one in each hand, to control a robot using the natural limb movements. A stereo camera was used to track an infant's face to correlate head direction with robot heading, as well as hands or leg movement to set forward velocity, in addition to accelerometers on the arms and legs. Lastly, they used electromyography (EMG) to detect biceps or leg muscle contraction while the infant crawled to direct the speed and direction of the robot as a reward for limb movement.

An experiment with this prone crawler, was conducted on 2 infants, 2 days a week, for a total of 4 days, in which driving time, path length, and path complexity were measured throughout the sessions. The findings indicate that driving time and path length increased linearly with the number of driving days as shown in Figures 11b and 11c, and the paths became richer with more complex maneuvers at the end of the 4 days. However, more experiments are needed to show if infants can learn to purposefully drive the robot.

(a) (b) (c)

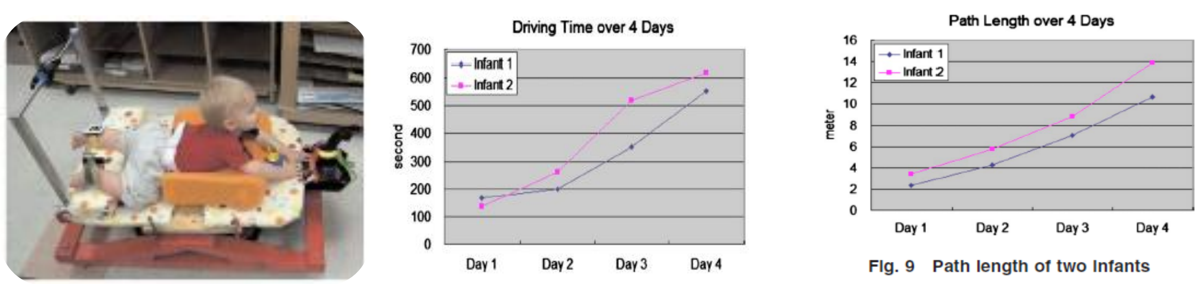


Figure 11: (a) Overview of the infant base with the foam wedge for supporting the infant, camera for capturing leg motion, and joystick for turning. (b) Driving time for two infants over the 4 training days. (c) Path length of two infants.

Additionally, infants at risk for cerebral palsy are at a severe disadvantage in learning to crawl as compared with typically developing infants. Miller and colleagues (2015) built a system out of a suit that allows kinematic reconstruction of infant movement. EEG sensors monitor their neural responses; and an assistive robot named the SIPPC3, amplifies the effectiveness of their crawling actions to reduce the required weight bearing for successful prone locomotion (Miller et al, 2015). The kinematic suit shown worn on an infant is displayed in Figure 12. This suit enables the infant to trigger robot movements through crawling-like actions, even when their limbs are not in contact with the ground. The sensors on the suit detect the configuration of the infant's limbs and trunk in real time. The SIPPC3 is also advantageous for mounting cameras to record head, arm and foot movements. Actions are recognized by the system using the following set of heuristically-derived rules by the group, including:

(1) allowable position and velocity of a subset of the limbs,

(2) priority,

(3) robot response (forward, backwards, turn left or right),

When these rules are met, the crawling actions are amplified. The group has tested this method of assisting motion on 3 infants so far and are continuing the study of this device for 30 infants. The EEG has shown suppression of the mu rhythm in the motor cortex which is indicative of goal-directed activity, suggesting that infants can use the robot to engage in goal-directed activity.

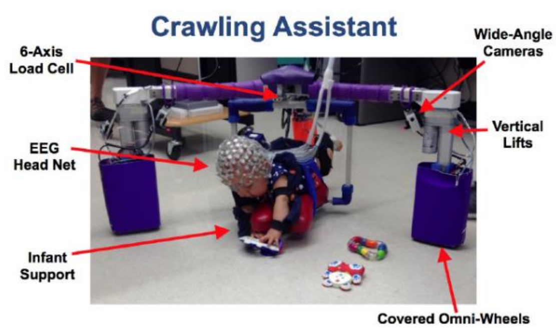


Figure 12: SIPPC3 Crawling Assistant System in Use.

Robot Enhanced Mobility – (later mobility)

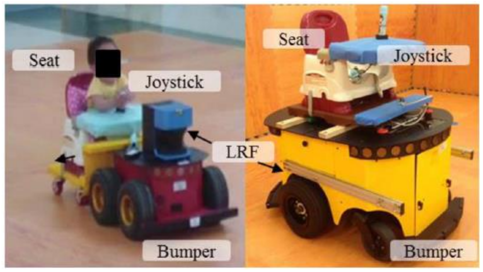
Agrawal and colleagues believe that infants with Cerebral palsy (CP) may benefit from robot-enhanced mobility, in which the mobility comes from a robot driven by the child using a joystick (Agrawal et al, 2014). The authors report the results from two pilot studies conducted in children with CP, who performed two tasks across multiple training sessions. Five infants were recruited for a short-term study (10 training sessions, 20 mins each), five were recruited for a long-term study (30 training sessions, 20 minutes each, 3 times a week for approximately 10–12 weeks) and five served as a control group. As shown in Figure 21, 2 tasks were asked per session:

Task 1: move from areas 6 to 2 then 5 to 4;

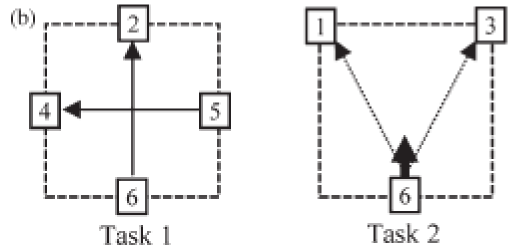
Task 2: move from areas 6 to 1 then 6 to 3.

Hand gestures, sounds, and toys were used as rewards to encourage the infants to drive the robot. After training with the robot, the children who performed 30 training sessions in the "long-term study," showed that they could learn to drive a robot using a joystick, as they advanced in their driving skills. They showed significant improvements in their $success\ ratio = \frac{\#\ of\ successes}{\#\ of\ trials}$, and clinical scores on the Gross Motor Function Measure, Quality of Upper Extremity Skills Test, and Pediatric Evaluation of Disability Inventory, as displayed in Figures 13a and 13b. The increase in the success ratio and clinical scores are promising results for the paradigm of contingent reinforcement in infants with developmental delays as it shows the potential for learning among infants participating in my study. Clinical scores were measured before, middle and after robotic training for 30 sessions, as shown in Figure 13d. The x-axis labels are clinical measures including hip/knee flexion, manual ability to handle objects, shoulder/elbow/wrist flexion, self-care, mobility, social function, self-care with caregiver assistance, mobility with caregiver assistance, and social function with caregiver assistance, respectively.

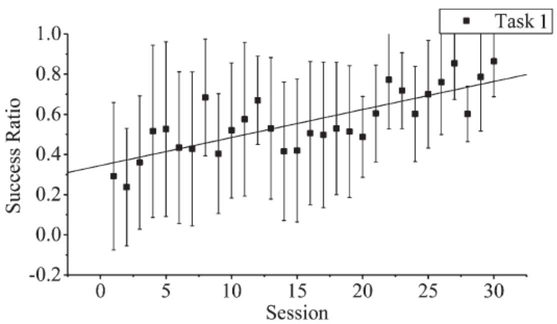
(a)



(b)



(c)



(d)

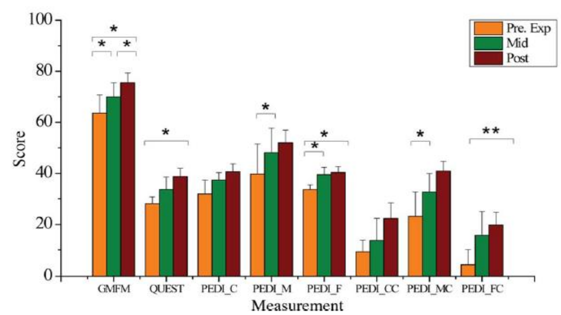


Figure 13: (a) (Left) Pioneer-AT (short-term) and (right) PowerBot (long-term). Both experimental setups consist of a mobile robot as a platform, a conventional joystick, an LRF, and a booster seat. (b) Schematic description of tasks 1 and 2: A bold arrow indicates the initial starting direction. (c) Average value and standard deviation of success ratio for 30 sessions of the robot-trained experimental group. (d) Clinical measurements of five experimental children before, middle, and after robotic training for 30 sessions (∗$p < 0.05$, ∗∗$p < 0.01$).

EMG-triggered musical video

Contingent reinforcement is also a feasible paradigm useful to increase muscle activation in infants at-risk. Duff and colleagues (2017) developed a surface EMG-triggered program using a musical-video as the reinforcement for muscle activation. The set-up for this study is shown in Figure 14 and was used to assess learning in typically developing infants and infants who sustained perinatal brachial plexus injury (PBPI). Thirteen typically developing infants and six infants with PBPI were recruited for two 1-hour sessions. The infants sat in a corner seat with a tray and surface EMG sensors were placed on the mid-biceps muscle of each arm. Initially, the average biceps muscle activation (Volts) was determined for each arm (100s) and set as the threshold or baseline. Then, the training session was conducted. During training, when the infant activated the biceps above the pre-set threshold the musical video would play. Learning was measured by the amount and duration of muscle activation during 5-minute sessions (300s) with each arm as Volts*seconds (Vs).

Figure 14: Experimental setup to assess learning.

As shown in Figure 15, both groups displayed a mean increase in the integral of muscle activation from baseline during the reinforcement period. Yet, the activation significantly increased from **baseline** in the affected arm of the group with PBPI by the 2nd and 3rd 100 s intervals of reinforcement as shown in Figure 15. This method of contingent reinforcement is novel in comparison to the previous papers in this review because it allows the infant to explore operation of a toy or video through reinforcing **movements** for a specific muscle group based on clinical condition.

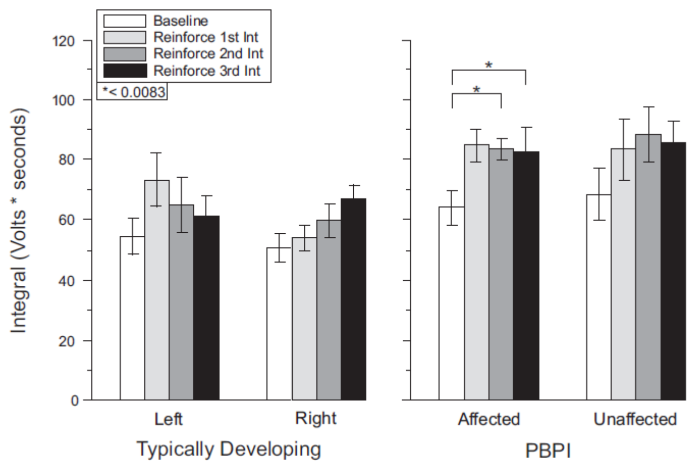


Figure 15: Mean integrals of biceps activation at baseline and during reinforcement (reinforce) for typically developing (TD) children (left) and children who sustained perinatal brachial plexus injury (PBPI, right).

Summary

Given this research, it has been shown repeatedly that typical developing infants, as well as infants at-risk, are able to increase specific movements using the paradigm of contingent reinforcement. Contingent reinforcement has been implemented using strings attached to the infant limbs, computer vision, and EMG-based muscle activity sensing. A range of reward types have been shown to be effective in increasing movement, including shaking toys, humanoid robot movement, robotic overground mobility, video, and music. The at-risk populations that have been studied are infants with developmental delay, cerebral palsy, pre-term conditions, brain injury and PBPI.

2 DESIGN OF NEUREWARDS

In the context of PBPI, an important goal is to distinguish “rehabilitative” from “non-rehabilitative” **movement** or **muscle activation**. This requires algorithms that can detect “desired” movements amongst the large set of random movements that infants typically make. As described above, detection of rehabilitative movement has previously been shown using surface EMG-based sensing of biceps activity. However, EMG-based approaches have the disadvantage of requiring that sensors be affixed in accurate positions above the target muscle, and are only able to detect activity of specific muscles rather than desirable, whole-arm movement patterns. Here, we studied detection of rehabilitative arm movements using acceleration data from a wrist sensor. Specifically, the goal of this project was to wirelessly reward “desired” arm movements by activating an overhead mobile with visual and auditory feedback. The target age was 3-6 months as this is thought to be a developmental period when infants have significant neuroplasticity for learning to use residual pathways, and is an age prior to the frequent 6-month cut-off for microsurgery.

2.1 Hardware

NeuRewards consists of two major components: a wrist sensor and an overhead mobile. The wrist sensor, EcoMini, was developed in Professor Pai Chou’s Electrical Engineering lab at the University of California, Irvine. EcoMini collects raw data for acceleration (with gravity), gyroscope and magnetometer via Bluetooth Low Energy (BTLE), with a sampling rate of 100Hz and powered by a 3.7V Lithium ion battery.

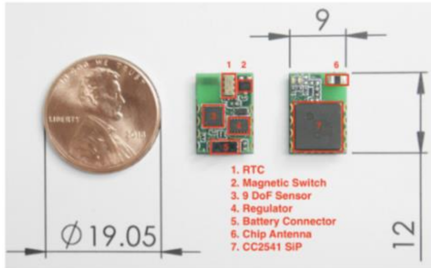


Figure 16: EcoMini senor hardware (Chou).

The overhead mobile consists of an Arduino board and Bluetooth Low Energy module connected to an overhead mobile by TinyLove, to deliver reward to the infant. The components include a battery, PMOS, motor for spinning, and a mini MP3 player for Arduino (DFPlayer) for auditory feedback.

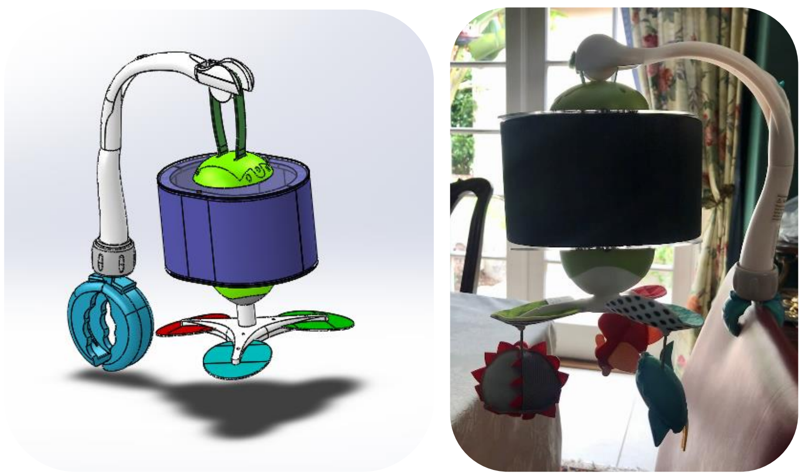


Figure 17: SolidWorks model for NeuRewards overhead mobile enclosing electronics for reward activation.

2.2 Software

Dr. Pai Chou's group developed the data collection software for the Ecomini on Python, which saves acceleration, gyroscope, and magnetometer readings, as well as a timestamp. Upon powering on, the sensor is calibrated during the first 3 seconds, where it must remain stationary. The average value of the first 3000 samples in each axis is taken.

These averages are considered biases that are later subtracted from the readings of the corresponding axes. After calibration, data collection may begin. This code was modified to add "marks" using a keyboard to annotate the data when a desired movement occurred with the assistance of Michael Pollind, graduate student at Chapman University. After data collection, all the measurements were analyzed and visualized offline, on MATLAB R2018a.

3 METHODS

3.1 Participants and data acquisition

Arm movement data was collected from a 4-month-old typically developing infant while she was lying in supine and seated, to develop and test an algorithm used to classify rehabilitative from non-rehabilitative movements. To acquire a target set of movements from the infant, a physical therapist, Dr. Susan Duff held the infant's arm and moved it to mimic "desirable" rehabilitative movements and "undesirable" compensatory movements. To foster active movements, a toy was used to attract the infant's attention and encourage desirable movements. Additionally, I performed the same movements myself while lying in supine.

For the two subjects, we gathered three desirable movements: (1) elbow flexion (EF), (2) shoulder abduction (SA) (3) shoulder flexion (SF) and one undesriable movement (4) triceps flexion (TF), which involved elbow flexion into gravity using the triceps muscle. For TF, the subject abducted and internally rotated the shoulder then brought the hand toward the face (mouth) by eccentrically contracting the triceps into elbow flexion. EF, SA, SF are rehabilitative movements which are important to detect, in order to be rewarded. TF is a compensatory movement that infants at-risk perform to bring their hand toward the face (mouth) and must not be rewarded. Figure 13 shows all 4 movements.

Infant

During the infant's data collection, EcoMini was secured to a soft strap with paper tape to avoid sliding of the sensor on the skin (Figure 18a). The soft strap was attached to the right wrist. Acceleration, gyroscope and magnetometer data for the four movement types (Table 2) were acquired using the sensor as the therapist passively moved the limb into each of the four positions. Each movement started at a specific location and palm orientation (Table 2). For each movement type, two repetitions were performed.

Movement type	Rehabilitative	Starting position	Posture	Palm orientation
Elbow flexion (EF)	Yes	Beside hip	Lying down	Palm down
			Seated	Palm neutral
Shoulder abduction (SA)	Yes	Beside hip	Lying down	Palm neutral
			Seated	Palm down
Shoulder flexion (SF)	Yes	Beside hip	Lying down	Palm down
			Seated	Palm neutral
Tricep flexion (TF)	No	Vertically above shoulder	Lying down	Palm down
			Seated	Palm down

TABLE 2: Map for Infant Template Movements

(a) (b) (c)

(d) (e)

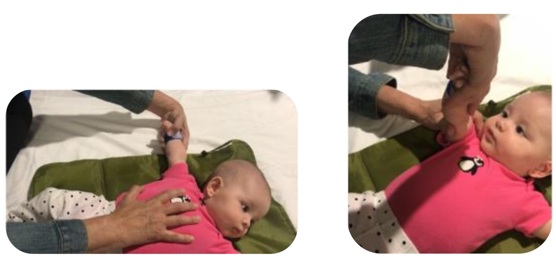


Figure 18: Collection of four template movements lying in supine. (a) Sensor secured to the wrist with a soft wristband at desired orientation and position. (b) Elbow flexion, (c) Tricep flexion, (d) Shoulder abduction, and (e) Shoulder flexion.

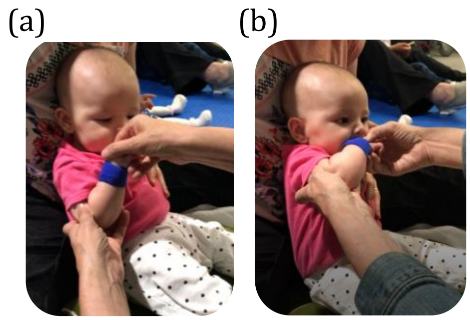


Figure 19: Collection of template movements while seated: (a) desirable Elbow flexion with shoulder adducted, (b) undesirable elbow flexion in shoulder abduction and internal rotation. Shoulder abduction & flexion images were not taken.

Then, two minutes were allocated for the infant to freely perform self-initiated movements while seated and while lying down. During this time, Dr. Susan Duff shook a toy to encourage rehabilitative movements. After one of each of the three "desirable" movements were performed, the data was marked by pressing a key on the computer keyboard. Specifically, when Dr. Duff saw a "desirable" movement, she told the operator to mark the dataset.

Upon powering on the sensor for data collection, the sensor was secured on the infant's wrist, and not stationary on a surface. Therefore, it did not calibrate properly, leading to incorrect acceleration values.

Another limitation with the infant data collection was that, although I entered a mark when Dr. Duff identified a desirable movement in the free movement collection period, there was a delay between the key button press and the actual movement, making it difficult to specify when the movement occurred.

(a) (b)

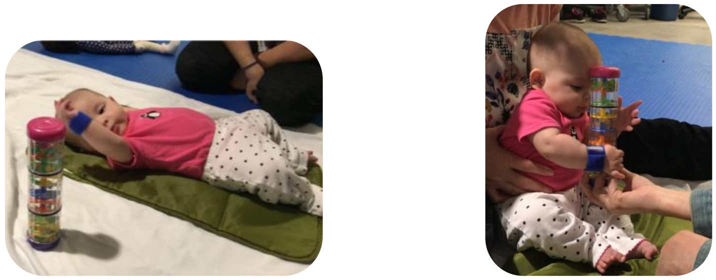


Figure 20: Active movements were performed, including "desirable" movements. (a) in supine, and (b) seated.

Adult

To obtain a better data set, I performed the same movements collected for the infant, but this time I took care to properly calibrate the sensor and to more accurately mark the data. Since the supine position is age appropriate for infants' rehabilitation strategies in young infants, I performed the movements in supine to mimic their movements. Upon powering the sensor, I calibrated the sensor by keeping it stationary for the first 4 seconds, unlike during the infant's data collection. Once calibrated, I performed the four template movements, with five repetitions each. The sensor was placed at the same location and orientation as for the infant (Figure 21).

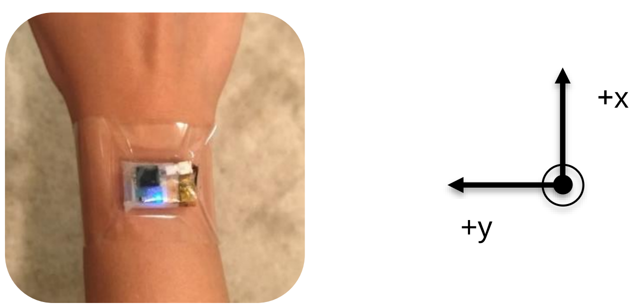


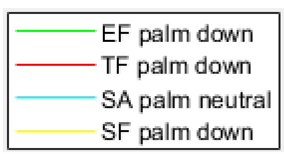
Figure 21: Left) Sensor placement on adult's wrist with tape. Right) Sensor's axis orientation

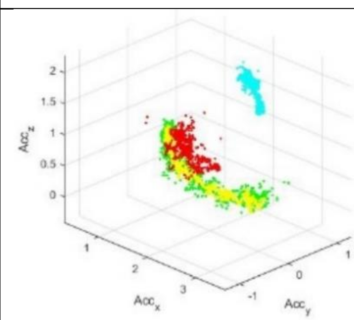
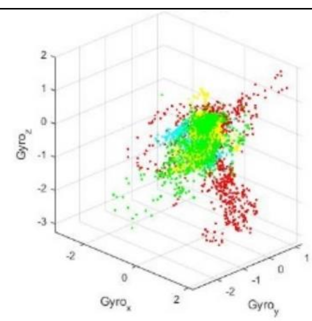
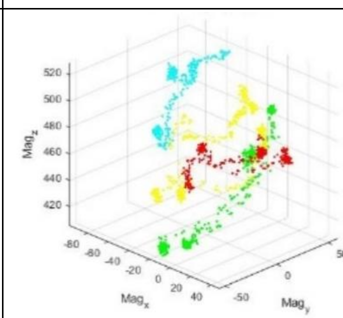
To mimic the infant's active movements and achieve a large "desirable" data sample of movements, I performed **random movements** + "**desirable**" movements (EF, SA, SF) for 10 minutes, also in supine. During this time, a colleague ran the data collecting program on Python as I performed the movements. My colleague marked the data with the keyboard, simultaneously verbally informing me which movement to make (i.e., "EF"). I immediately performed the corresponding movement upon command. This method accurately marked the beginning of each movement. I also collected a "undesirable" data sample for approximately five minutes where I **performed random movements** + "**undesirable**" movement (TF) and excluded the "desirable" movements (EF, SA, SF). My colleague again carefully marked the timing onset of the undesirable movements.

3.2 Data visualization

Infant

To visualize the data acquired, it was plotted in 3D space and their differences were examined. Accelerometer, gyroscope and magnetometer data for template movements, **lying in supine** are displayed in a 3D space in different colors to visualize their unique properties. Magnetometer data was disregarded as it was affected by interference with metal objects surrounding the sensor. Comparing gyroscope and acceleration data, acceleration showed the most visual differences across movement types, which is why it was chosen to be analyzed alone. The movements, starting positions and palm orientations were the same for the infant and the adult subject. However, the differences in values are due to the sensor calibration issue in the infant data set. Therefore, all the later data analysis was performed on the adult data set which was correctly calibrated. Table 3 shows the acceleration, gyroscope and magnetometer data in 3D space.



Subject	Acceleration	Gyroscope	Magnetometer
Infant			

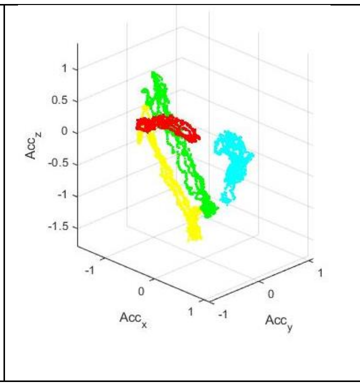
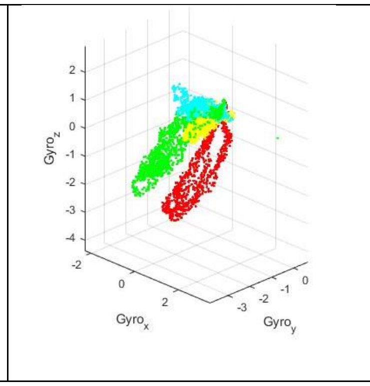
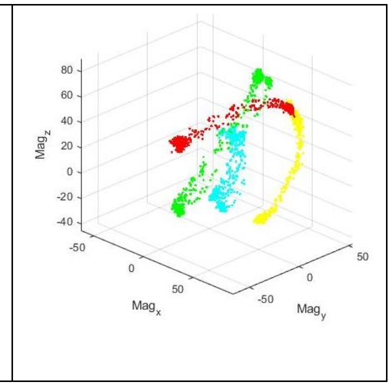
Adult			

TABLE 3: Acceleration, Gyroscope, and Magnetometer data for "template" movements for the infant and adult subjects, in 3D space.

Then, time history of the raw acceleration values in x, y, z, as well as their 3D vector magnitude were analyzed to ensure the values were logical for each movement. As mentioned, the acceleration values from the infant were incorrect due to the calibration error, which is shown in Figure 22. Elbow flexion (EF) and shoulder flexion (SF) revealed similar patterns, due to their movement similarity.

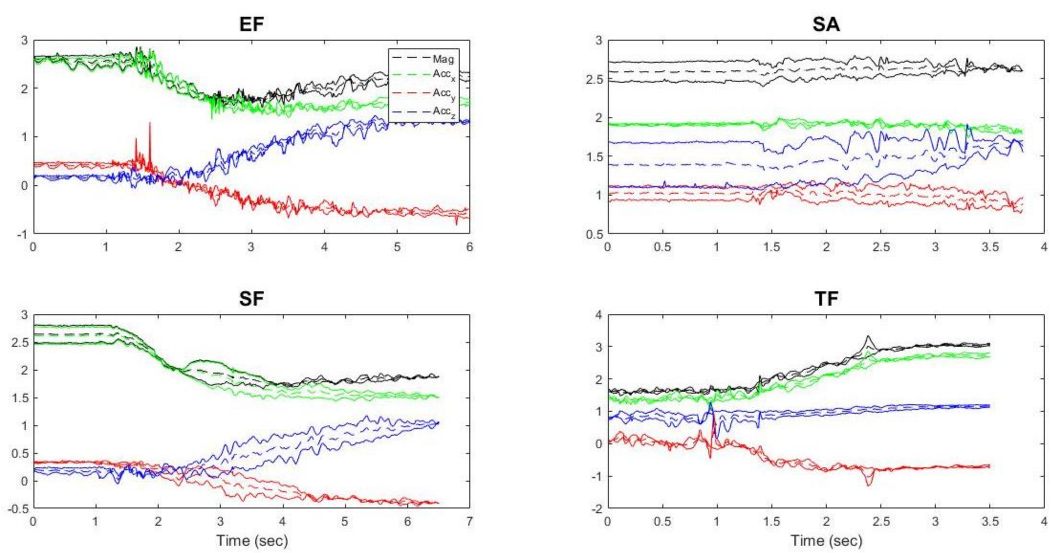


Figure 22: 2D Acceleration plot against time for infant's four "template" movements. Acceleration in x-direction (green), acceleration in y-direction (red), acceleration in z-direction (blue) and magnitude of acceleration vector (black).

In the adult data set, the time history of the acceleration in x, y, z directions, and the 3D vector magnitude were also plotted and analyzed. Each movement has its unique acceleration pattern. It is noticeable that elbow flexion (EF) and shoulder flexion (SF) are very similar in their movement patterns. Most importantly, it is crucial that elbow flexion initiated with eccentric triceps activation (TF) is **not** rewarded, amongst EF, SA, and SF.

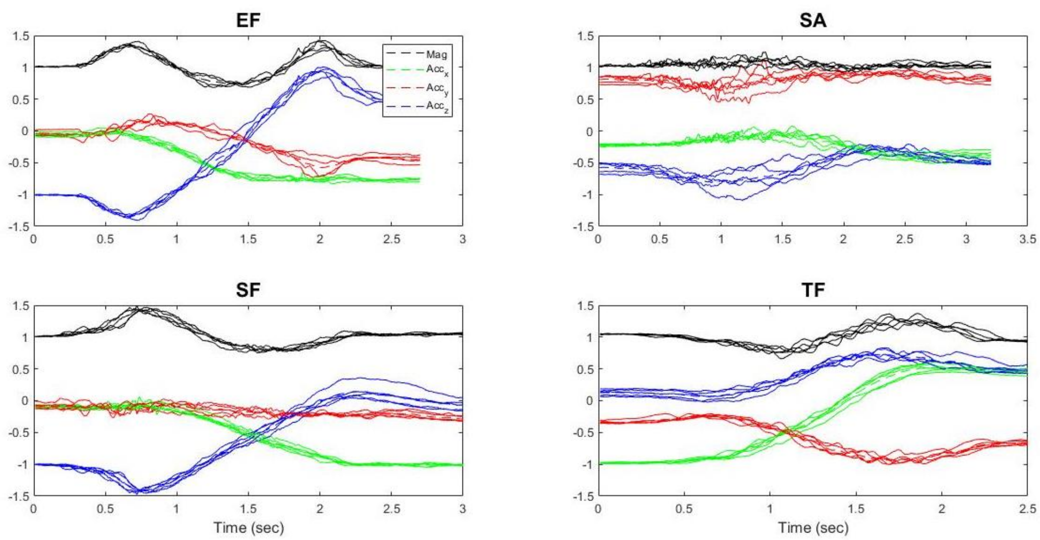


Figure 23: 2D Acceleration plot against time for adult's four "template" movements. Acceleration in x-direction (green), acceleration in y-direction (red), acceleration in z-direction (blue) and magnitude of acceleration vector (black).

A Kolmogorov-Smirnov (KS) test was performed on the acceleration magnitude of the four template movements to evaluate the similarity between distributions. The null hypothesis is that the distributions are the same. The null hypothesis is rejected between all movements ($p<0.05$). However, EF and SF have the most similar distributions (KS test, p-value=0.0035).

KS Test p-values	EF	TF	SA	SF
EF	1	1.1216e-04	3.1944e-16	0.0035
TF	1.1216e-04	1	1.4928e-20	1.9385e-04
SA	3.1944e-16	1.4928e-20	1	2.0028e-11
SF	0.0035	1.9385e-04	2.0028e-11	1

TABLE 4: KS test for similarity between the four movements' magnitude distributions.

3.3 Movement Classification

3.3.1 Hand-drawn Ellipsoids

Our first attempt was to classify these acceleration patterns based on volumes or ellipsoids that they reside in, in 3D space. Although the shapes elegantly wrapped the different patterns, as shown in Figure 24, there were a few limitations:

(1) There was an overlap in the patterns across the 4 movements and the shapes did not fully enclose just one pattern.

(2) The shapes were hand drawn over the data set.

(3) After running a set of random active movements including "desirable" movements over their templates, they did not fit in their expected shapes.

Therefore, this classification method was disregarded after this step.

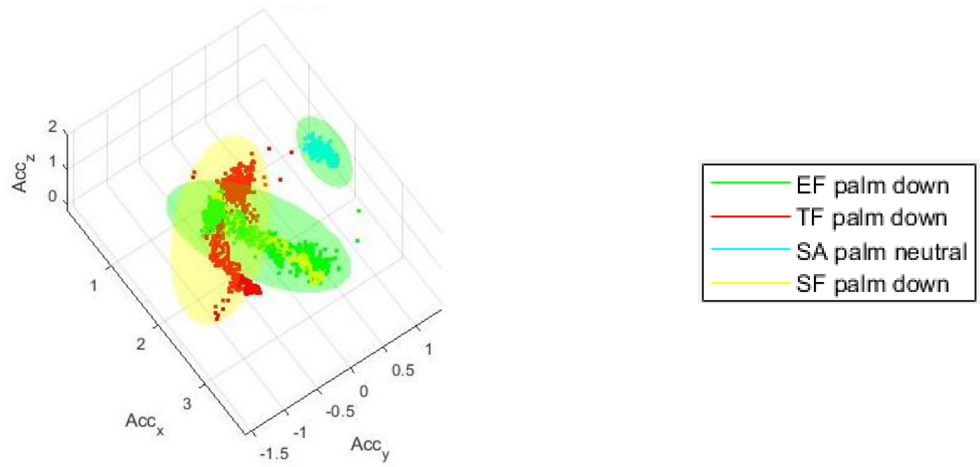


Figure 24: Acceleration of Infant's template movements, lying down. Hand-drawn ellipsoids enclosing the four template movements. The green ellipsoids enclose "desirable" movements, and the red ellipsoid encloses "undeisrable" movements.

3.3.2 Similarity measure

To overcome these limitations, we shifted towards looking at the acceleration vector. Here, we took the average of 5 repetitions, for each of the 4 movements. Figure 25 shows a quiver plot of the EF template and the first EF performed in "desirable" sample of active movements, against time on the x axis.

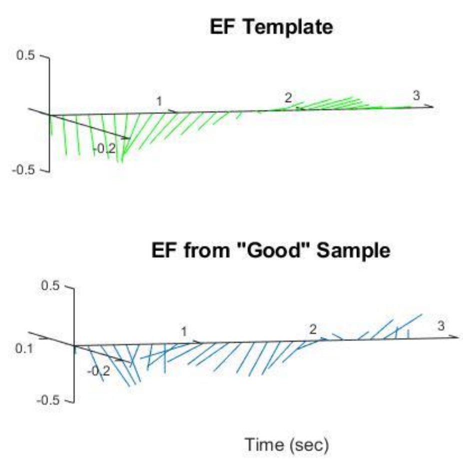


Figure 25: 3D plot of acceleration vectors for (1) EF template and (2) EF from "desirable" sample against time in seconds

This template acts as a window that passes over a large set of random movements, to find a “match”. The similarity measure is obtained from a hand velocity study (Shadmehr et al, 1994), where the dot product of the template and the data set is calculated for each data sample, until the end of the data set. Then the average of the dot products is taken to quantify the similarity between the template and the data set. This calculation produces a set of numbers between -1 and 1. The larger the number, the more similar that window of data is to the template.

$$< U, Y > = \sum_{i=1}^{n} \mathrm{u_i} \bullet y_i \qquad (1)$$

$$\varepsilon(< U, Y >) = \frac{1}{n} < U, Y > \qquad (2)$$

$$avg(signal \bullet template) \qquad (3)$$

For proof of concept, four equally spaced chunks of the EF template were added into the “undesirable” sample with no EF movements. The similarity measure was applied, and the signal was plotted. As can be seen, the similarity measure produced peaks of magnitude 1 at the time instants when the EF template was artificially inserted into the random movement data.

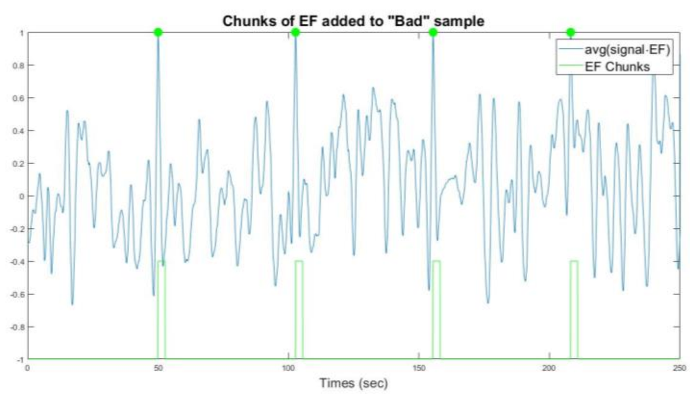


Figure 26: Chunks of EF template added into the “undesirable” sample (green bars). Peaks in the similarity measure are shown at the location of the EF template (green dots).

4 RESULTS

4.1 Alignment detection

For each movement, I found the peaks detected from the similarity measure. Then, I created an algorithm that locates the number of peaks "aligned" with the data marks. For each mark, I looked 3 seconds before and 3 seconds after the mark in the similarity measure. If the peak fell in this period, then the peak was detected as identifying a template movement. If not, it counted as a "spuriously identified" (SI) movement, as shown in Figure 27.

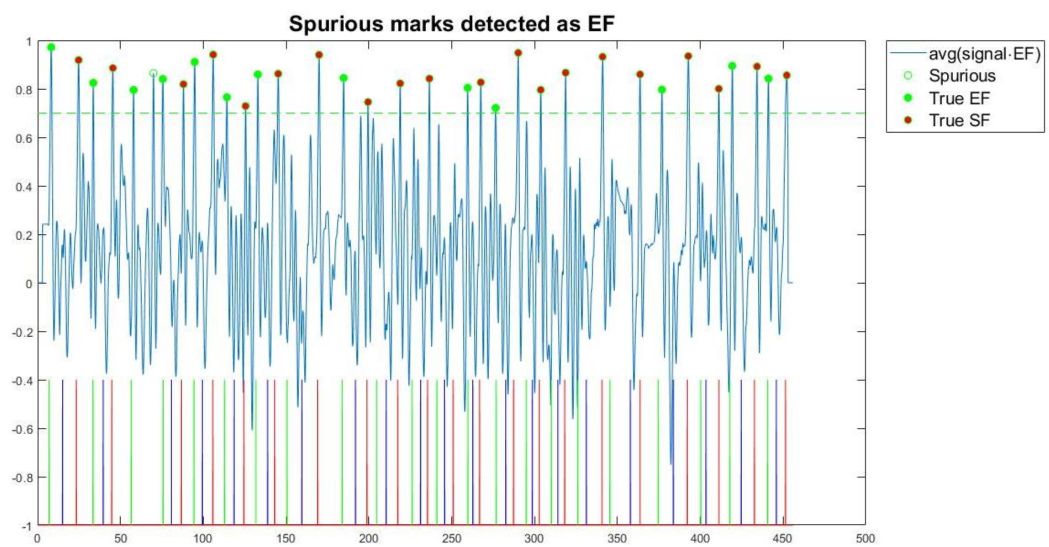


Figure 27: Example of similarity measure of "desirable" sample with EF template. All circles were detected as EF. However, they aligned with EF marks, SF marks, and also no marks at all.

4.2 Choice of threshold

To choose the optimal threshold for peak detection, a set of thresholds from 0.5 to 0.95 in increments of 0.05 were analyzed for their True Positive (TP) ratio and Frequency of Spuriously Identified (FSI) Movements. As stated above, SI movements are considered any peaks that are not aligned with EF, SA, SF, TF marks.

$$True\ Positive\ (TP)\ =\ \frac{\#\ of\ detected\ EF\ movements}{total\ \#\ of\ inputted\ EF\ marks}$$

$$Freuency\ of\ Spuriously\ Identified\ (FSI)\ movements$$

$$=\ \frac{\#\ of\ SI\ movements}{total\ \#\ of\ detected\ movements}$$

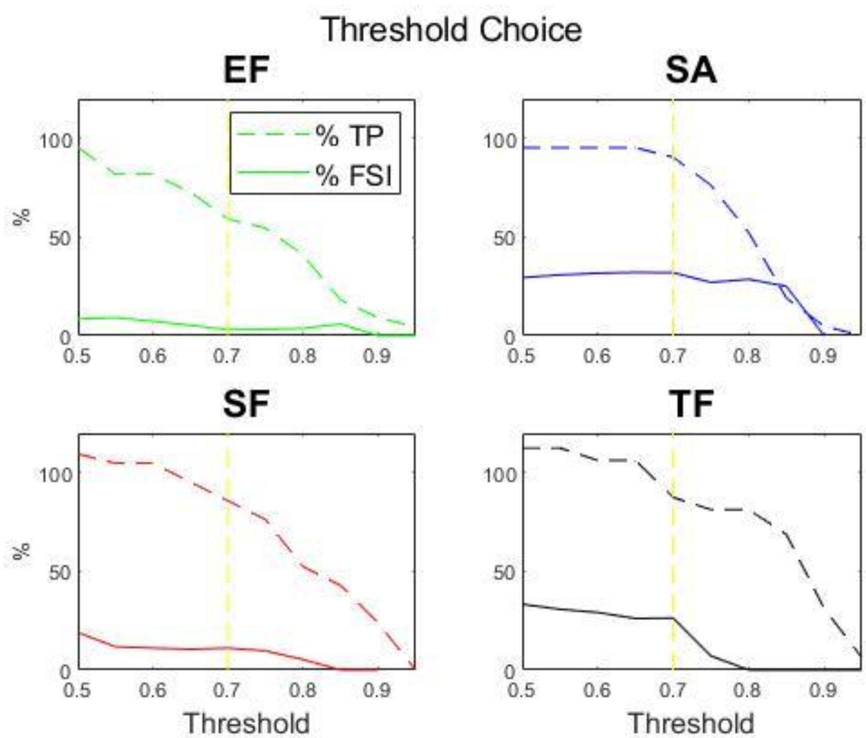


Figure 28: True Positive (TP) rate and Frequency of Spuriously Identified (FSI) movements are plotted for similarity measure thresholds ranging from 0.5 to 0.95, for the four template movements.

The True Positive value decreased as the threshold increased since less peaks were being detected. After a threshold of 0.75, the FSI rate increases because the number of detected marks decreased. A threshold of 0.7 was chosen as it had a relatively low FSI rate and relatively high TP ratio.

4.3 Efficiency of Similarity Measure

The similarity measure for the EF template was applied to the "desirable" sample in the first plot of Figure 29. The closer the result is to 1, the more similar the movement is to the template. The chosen threshold of 0.7 was taken to detect the peaks, with a minimum peak distance of 3 seconds between peaks. The second plot shows the SA template applied onto the "desirable" sample. The third shows the SF template with the "desirable" sample. Lastly, the fourth plot shows the similarity measure for TF on the "desirable" sample. Note that TF was not performed in the "desirable" sample, and therefore is important that it is not detected.

Due to the similarity the accelerations associated with the EF and SF "desirable" movements, as identified above, the peaks in the first plot for EF align with the red SF marks as well. Figure 23 and table 4 show the similarity between distributions of EF and SF, consecutively, and therefore they have the most overlap in peaks and marks.

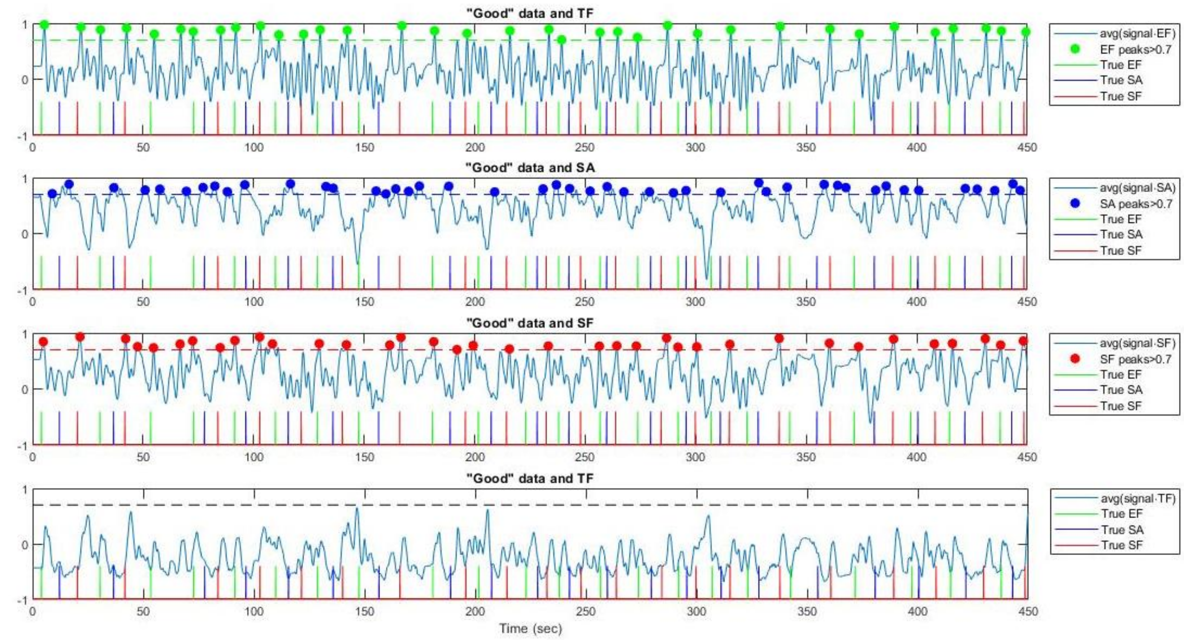


Figure 29: Similarity measure when the four template movements were applied to the "desirable" sample of data that included both random movement and EF, SA, and SF movements. The sticks at the bottom of each plot represents the inputted marks EF (green), SA (blue) and SF (red). Each plot shows the similarity measure between the sample's acceleration vectors and the movement template' acceleration vectors. The dots above 0.7 threshold are the similarity peaks.

Figure 30 shows the similarity measure calculated for all four movements templates applied to the "undesirable" sample of data that included random movement and TF movements. SF was detected twice in the "undesirable" sample because I accidentally performed SF to get my arm vertically above my shoulder for the initial position of TF.

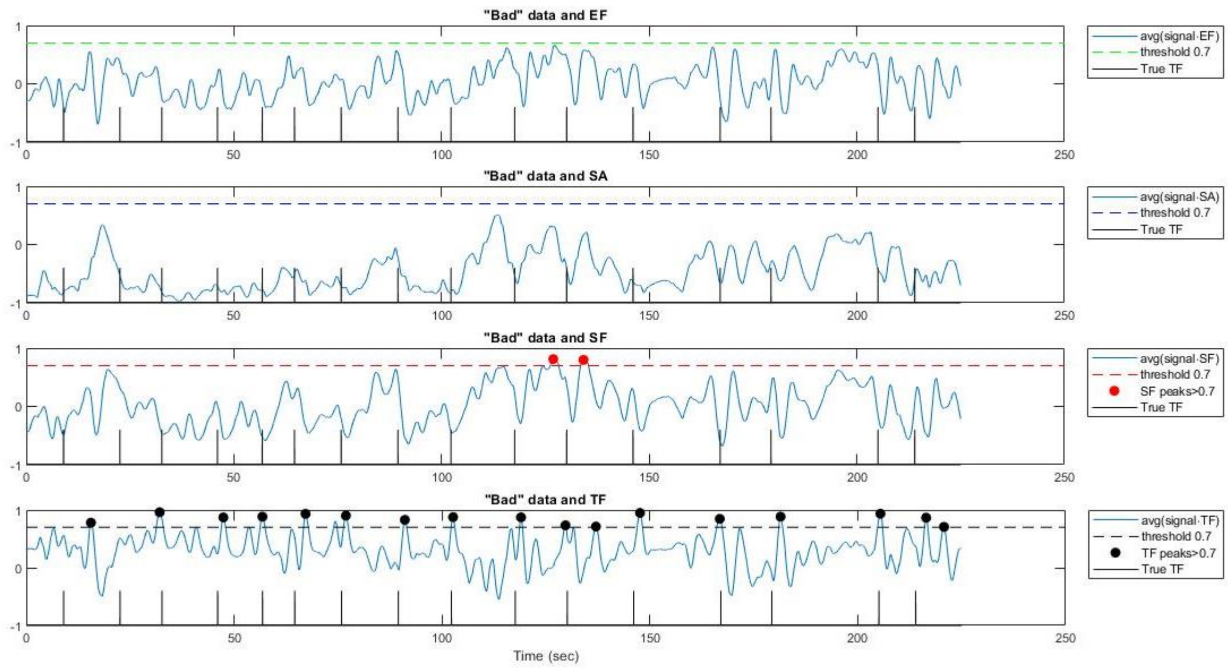


Figure 30: Similarity measure when the four template movements were applied to the "undesirable" data sample, which contained random arm movement plus TF. The black sticks at the bottom of each plot represent the marks inputted for TF.

For the chosen threshold of 0.7, the table below shows the percentage of detected peaks for each mark. The green boxes represent the algorithm performance for the "desirable" sample of arm movement, and the red boxes represent the algorithm performance for the "undesirable" sample of arm movement. The right column presents the rate of spurious movements that were detected and that did not align with marks, for each movement. The bottom row represents the number of marks that were not detected.

			TRUE				
			DESIRABLE			UNDESIRABLE	Spurious
			EF	SA	SF	TF	
DETECTED	DESIRABLE	EF	$\frac{13}{22} = 59.1\%$	—	$\frac{20}{21} = 95.2\%$	—	$0.13\ peak/min$
		SA	$\frac{7}{22} = 31.8\%$	$\frac{19}{21} = 90.5\%$	$\frac{7}{21} = 33.3\%$	—	$1.87\ peak/min$
		SF	$\frac{14}{22} = 63.0\%$	—	$\frac{18}{21} = 85.7\%$	$\frac{2}{16} = 12.5\%$	$0.533\ peak/min$
	UN-DESRIABLE	TF	—	—	—	$\frac{14}{16} = 87.5\%$	$1.33\ peak/min$
	Non-marked	random	$\frac{3}{22} = 13.6\%$	$\frac{2}{21} = 9.52\%$	$\frac{1}{21} = 4.76\%$	$\frac{2}{16} = 12.5\%$	N/A

TABLE 5: Green boxes represent the movements detected as desirable. Red boxes represent the undesirable movements detected as desirable or undesirable. The rest show the number of extra peaks detected, or marks that were missed.

		TRUE		
		Desirable	Undesirable	Spurious
Detected	Desirable	(TP) $\frac{57}{64} = 89.1\%$	(TP) $\frac{2}{16} = 12.5\%$	(FP) $2.53\ peaks/min$
	Un-desirable	(FP) $\frac{0}{64} = 0\%$	(TP) $\frac{14}{16} = 87.5\%$	(FP) $1.33\ peaks/min$
	Non-marked	(FN) $\frac{7}{64} = 10.9\%$	(FN) $\frac{2}{16} = 12.5\%$	N/A

TABLE 6: A broader view of table 5 that groups the "desirable" movements together. The "true" movements represent the inputted marks, and the detected movements are the peaks from the similarity measure. The "desirable" values are with respect to the "desirable" sample. The "undesirable" values are with respect to the "undesirable" sample.

5 DISCUSSION

In working toward an automated arm therapy system for infants with PBPI, I studied detection of rehabilitative (or "desirable") arm movements using acceleration data from a wrist sensor. I implemented a template-matching algorithm based on the dot-product of a moving window of 3D acceleration vectors with the template acceleration pattern. I found that the algorithm detected desirable movements (i.e. EF, SA, or SF) with an accuracy of ~90%. The algorithm erroneously identifying spurious movements as desirable at a rate of about 1-3 movements per minute. In addition, I found that the algorithm detected when an undesirable arm movement (i.e. TF) occurred with about 88% accuracy. Importantly, the algorithm never identified an undesirable arm movement as a desirable arm movement. These results show the potential for the template algorithm to be used in a contingent reinforcement paradigm to encourage infants with PBPI to make arm rehabilitative movements.

5.1 Limitations

The main limitation of this work is that I applied the identification algorithm only to one adult subject. Future work should apply the algorithm to a series of infants with and without PBPI. Future work should also compare other algorithms for identifying target movements.

Another limitation is that I assumed that the "desirable" sample of arm movement did not contain any "undesirable" (i.e. TF) movements, and that the "undesirable" sample of arm movement did not contain any "desirable" movements (i.e. EF). Since two SF movements were detected in the "undesirable" sample, there could have been unintentional SF movements in that sample. I also assumed that any marks in the desirable and undesirable sample were inputted within a 6 second window of telling the subject to move. This alignment detection window might have taken into consideration extra movements, or also missed some movements that were performed at a delay.

5. 2 Future Work

The next steps should include acquiring the four template movements from an infant, with sensor calibration, while also acquiring a sample of arm movement that contains desirable and undesirable movements, to determine how well the template-matching algorithm works for infants.

I calculated the template movement as the average of five movements performed at about the same speed. As currently implemented, the template algorithm will not accurately identify movements with the same spatial movement pattern as the template movement, but that are preformed more quickly or more slowly. Future research should study how to automatically modify the template to identify spatially-similar movements performed at different speeds.

We have built the overhead mobile to play music and spin upon receiving a signal from the sensor. Future work should apply the algorithm in real time and activate the toy to provide a reward (i.e. to spin the mobile and play music or parent's voice).

Another option to explore is the use of a mechanically built contingent reinforcement system that rewards desirable movements based on a pattern or trajectory that the arm follows, reducing the complexity of pattern recognition through an algorithm.

REFERENCES

Chauhan, Suneet P, et al. "Neonatal Brachial Plexus Palsy: Incidence, Prevalence, and Temporal Trends." *Seminars in Perinatology*, U.S. National Library of Medicine, June 2014, www.ncbi.nlm.nih.gov/pubmed/24863027.

Duff, S. V., & DeMatteo, C. (2015). Clinical assessment of the infant and child following perinatal brachial plexus injury. *Journal of hand therapy : official journal of the American Society of Hand Therapists*, *28*(2), 126–134. doi:10.1016/j.jht.2015.01.001

Vu, Vicky, and Bojorquez, Lauren. "Multidisciplinary Team Approach and Therapeutic Intervention of Infants and Toddlers with Brachial Plexus Injury." *BPP presentation OTAC 10.28.18.*

"Brachial Plexus Injuries - OrthoInfo - AAOS." *OrthoInfo*, orthoinfo.aaos.org/en/diseases--conditions/brachial-plexus-injuries/.

Duff, S. V., et al. "Using Contingent Reinforcement to Augment Muscle Activation After Perinatal Brachial Plexus Injury: A Pilot Study." *Physical & Occupational Therapy In Pediatrics*, vol. 37, no. 5, 2017, pp. 555–565., doi:10.1080/01942638.2017.1290733.

Pulido, José Carlos, et al. "Adaptation of the Difficulty Level in an Infant-Robot Movement Contingency Study." *Advances in Intelligent Systems and Computing Advances in Physical Agents*, 2018, pp. 70–83., doi:10.1007/978-3-319-99885-5_6.

Watanabe, Hama, and Gentaro Taga. "General to Specific Development of Movement Patterns and Memory for Contingency between Actions and Events in Young Infants." *Infant Behavior and Development*, vol. 29, no. 3, 2006, pp. 402–422., doi:10.1016/j.infbeh.2006.02.001.

Heathcock, J.C., Bhat, A.N., Lobo, M.A., Galloway. "The Performance of Infants Born Preterm and Full-Term in the Mobile Paradigm: Learning and Memory." *Physical Therapy*, 2004, doi:10.1093/ptj/84.9.808.

Lobo, M.A., Galloway, J.C.: Assessment and stability of early learning abilities in preterm and full-term infants across the first two years of life. Res. Dev. Disabil. 34(5), 1721–1730 (2013)

Sargent, Barbara, et al. “Infant Exploratory Learning: Influence on Leg Joint Coordination.” *PLoS ONE,* vol. 9, no. 3, 2014, doi:10.1371/journal.pone.0091500.

Rovee, Carolyn Kent, and David T. Rovee. "Conjugate reinforcement of infant exploratory behavior." *Journal of Experimental Child Psychology* 8.1 (1969): 33-39.

Rapp, John T. “Conjugate Reinforcement: a Brief Review and Suggestions for Applications to the Assessment of Automatically Reinforced Behavior*.” Behavioral Interventions*, vol. 23, no. 2, 2008, pp. 113–136., doi:10.1002/bin.259.

Gekoski, Marcy J., et al. “Early Learning and Memory in the Preterm Infant.” *Infant Behavior and Development*, vol. 7, no. 3, 1984, pp. 267–276., doi:10.1016/s0163-6383(84)80042-9.

Campbell, Suzann K., et al. “Behavior During Tethered Kicking in Infants With Periventricular Brain Injury.” *Pediatric Physical Therapy*, vol. 27, no. 4, 2015, pp. 403–412., doi:10.1097/pep.0000000000000173.

Sargent, Barbara, and Carolyn Huang. “Commentary on ‘Behavior During Tethered Kicking in Infants With Periventricular Brain Injury.’” *Pediatric Physical Therapy*, vol. 27, no. 4, 2015, p. 413., doi:10.1097/pep.0000000000000184.

Funke, Rebecca, et al. “A Data Collection of Infants’ Visual, Physical, and Behavioral Reactions to a Small Humanoid Robot.” *2018 IEEE Workshop on Advanced Robotics and Its Social Impacts (ARSO)*, 2018, doi:10.1109/arso.2018.8625800.

Proctor, D. C., and Proctor, J. M., 1989, “Creeper for Handicapped Children,” U.S. Patent No. 4,796,903.

Williams, M. E., 2007, “Crawling Aid for Handicapped Infants,” U.S. Patent No. 7,182,351.

Chen, Xi, et al. “Design of a Novel Mobility Interface for Infants on a Mobile Robot by Kicking.” *Journal of Medical Devices*, vol. 4, no. 3, 2010, p. 031006., doi:10.1115/1.4002322.

Miller, David P., et al. “Robotic Crawling Assistance for Infants with Cerebral Palsy.” *Artificial Intelligence Applied to Assistive Technologies and Smart Environments:* Papers from the 2015 AAAI Workshop.

Agrawal, Sunil K., et al. “Robot-Enhanced Mobility Training of Children With Cerebral Palsy: Short-Term and Long-Term Pilot Studies.” *IEEE Systems Journal*, vol. 10, no. 3, 2016, pp. 1098 1106., doi:10.1109/jsyst.2014.2368455.

Shadmehr, R, and Fa Mussa-Ivaldi. “Adaptive Representation of Dynamics during Learning of a Motor Task.” *The Journal of Neuroscience*, vol. 14, no. 5, 1994, pp. 3208–3224., doi:10.1523/jneurosci.14-05-03208.1994.