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Motivating Spontaneous Infant Kicking Motions through Long Term Learning Utilizing a Robotic Mobile System

Victor Emeli[1] and Ayanna Howard[2]

***Abstract*— Our research investigates methods and systems to allow for early detection of motor impairment in infants and innovative interventions with the goal of improving long-term outcomes. A robotic baby mobile is utilized to motivate spontaneous kicking motions, which is used as a marker for predicting the potential of motor development delays. Our previous work investigated how the different stimuli modalities of a baby mobile can encourage infant kicking. We utilized a 3D camera system to detect the kicking motions, as well as recorded specific metrics of each kicking episode. In this work, we investigate the possibility of an infant having a preference of baby mobile stimuli that results in increased and sustained kicking motions. This preference is learned over multiple sessions with one infant and utilizes a Markov Decision Process to develop a policy.**

I. INTRODUCTION

Our work investigates the potential benefits of deploying a robotic baby mobile system (Figure 1) in the home for early detection and intervention for infants at risk for motor impairments like cerebral palsy (CP). CP is a neuromuscular development disorder that is caused by a non-progressive impairment to the fetal brain. The result is a permanent motor impairment which affects movement and posture development [1], [2]. One main indicator of impaired motor development is the progressive development of spasticity in muscle groups. The legs contain the largest muscle groups in the body and are vital to most human activity. For at-risk infants, physical therapy that encourages prolonged kicking motions while lying in the supine position can help reduce the onset of spasticity, especially if initiated at an early age [20]. Traditionally, this physical therapy is conducted by health professionals in a clinical setting, which can be labor intensive and costly. A method that increases physical therapy opportunities by providing an in-home system that motivates frequent kicking motions and operates without immediate clinical supervision would be beneficial. Previously we conducted a pilot study to explore the effectiveness of utilizing a robotic baby mobile [15] and developed measurable metrics to quantitatively analyze each kicking episode [19]. These works were motivated by past research into the positive effects of robotic therapy in this area [16].

[1]V. Emeli is with the Institute for Robotics and Intelligent Machines, Georgia Institute of Technology, Atlanta, GA USA (corresponding author e-mail: ve7@gatech.edu).

[2]A.M. Howard is with the Electrical and Computer Engineering Department, Georgia Institute of Technology, Atlanta, GA USA (e-mail: ayanna.howard@ece.gatech.edu).

Fig. 1: Robotic Mobile System.

The complete robotic system also consists of a 3D sensor that utilizes skeleton-based joint tracking and the Eigen-Joint [4] algorithm to classify the kicking motions of an infant. The results activate the robotic baby mobile stimuli in an attempt to motivate the infant to continue kicking. This work specifically conducts a long term study over multiple session with one infant to determine if a learned combination of baby mobile stimuli can increase infant kicking. The states of the infant, actions of the robotic baby mobile, and state-action transition pairs are tracked over multiple sessions. This data is employed to design a Markov Decision Process (MDP) to provide a policy for motivating continued kicking instances. A MDP is a discrete time stochastic control process. It provides a framework for modeling decision making where outcomes are partly random and partly under the control of a decision maker. The MDP assumes the Markov property, which is defined as the effects of an action taken in a state depends only on that state and not on the prior history. The policy is calculated by executing a form of dynamic programming called value iteration [17] which outputs the policy after convergence.

II. RELATED WORKS

Recently, new innovative methods for early detection of CP have been investigated to rectify the limitations of conventional methods that require a trained professional like The Prechtl General Movement Assessment (GMA) Test [2]. The use of an infant mobile to study learning and memory has been investigated in previous research [7], [8], [9], [10]. The mobile was used to determine if mobile movement had an effect on the actions of an infant through learning and if the infant retained the learned behavior once the mobile was removed. Rabeya et al. [11] designed a robotic infant mobile that is used as a stimuli in a goal and reward based method to study infant psychology and behavior changes based on the stimuli presented to them. The pilot study gave good insight into the potential success of using an infant mobile as a reinforcement learning reward for certain kicking actions. We improve on this work by replacing the manual activation of the infant mobile stimuli with a computer vision based machine learning approach. An optimal policy trained by a MDP is then employed to select different stimuli to encourage the continued kicking of an infant based on the activity detected by the vision sensor.

Other recent approaches have used machine learning based vision techniques to track and classify specific kicking motions [13]. The algorithm leverages KAZE points to track infant kicking and collect kinematic data. Although this method uses a simple 2D camera, it depends on specific feature detection on the shoes and pants of the infant. Additionally, the functionality of the method may suffer from degradation if prominent features are not available. Serrano et al. [12] used the Kinect V2 depth camera to analyze infant leg motion. This study was conducted in the infant's home using point cloud segmentation, which allowed parents to be close in proximity and engage in parent-infant play. Although, this method was conducive to an in-home environment, additional research is necessary to correctly identify and classify actual kicking motions, since this work analyzed all leg motions.

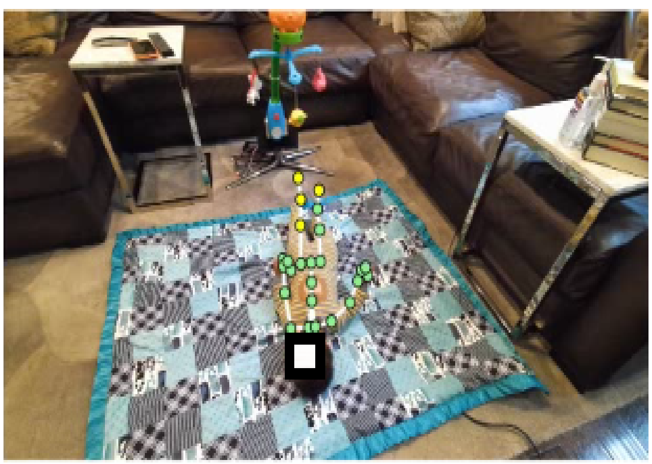

Fig. 2: Robotic Mobile System deployed in a home environment (view from 3D sensor).

We leverage the existing infant mobile research and add the use of a robust machine learning based computer vision system. The system investigates achieving long term learning in order to maximize the number of kicking actions of infants by calculating a policy using a MDP. If this approach is successful, it could result in earlier detection of possible motor impairments and improve physical therapy sessions. Figure 2 illustrates the in-home deployment of the system.

III. METHODS

The methodology for learning the mobile stimuli preferences of an infant includes observing their actions over multiple sessions. The robotic baby mobile stimuli are randomly activated during the initial sessions, while the infant's response is recorded by the 3D sensor. The resulting state-action pairs and transition are used to develop a MDP, which is trained to output a policy for choosing the best actions of the robotic baby mobile, given the state of the infant. The experimental procedures were approved by the Institutional Review Board (IRB) and the infant's parent signed the IRB approved consent form permitting their involvement in the sessions. The infant was healthy with no known risk factors for CP.

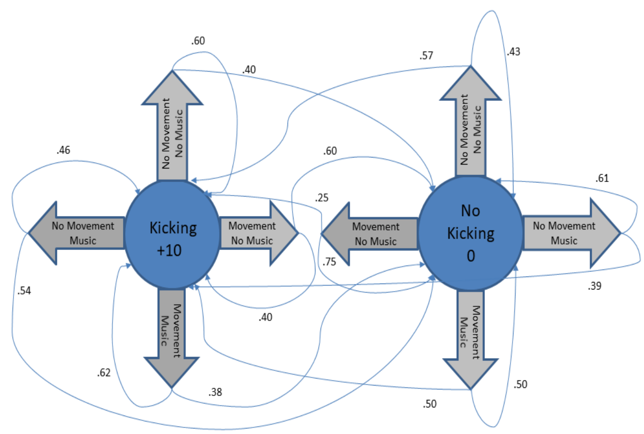

Fig. 3: Markov Decision Process showing the 2 infant states (Kicking, Not Kicking), 4 robotic mobile actions (No Movement/No Music, Movement/No Music, No Movement/Music, and Movement/Music), rewards for each state, and the transition probabilities after each action.

A. Markov Decision Process

The MDP attempts to calculate an optimal policy to encourage maximal kicking episodes. It is characterized by a tuple (S, A, R, T, λ), where: S = set of states, A = set of actions, R = reward function, T = transition function, and $lambda$ = discount factor.

The S consists of (1) Not Kicking and (2) Kicking states and the A consists of (1) Mobile Movement/Mobile Music, (2) Mobile Movement/No Music, and (3) No Mobile Movement/No Mobile Music, and (4) No Mobile Movement/Mobile Music actions. The reward function is +10 for the Kick state and 0 for the No Kick state. The discount factor is set to 0.9.

Based on our previous work, the mobile movement has the greatest effect of motivating an infant to kick [15]. To improve on our previous work, we investigate the possibility of each infant having a preferred baby mobile stimuli policy that results in maximized kicking instances. We observe the infant's state (Kicking/No Kicking), while randomly cycling through the baby mobile actions (1) Mobile Movement/Mobile Music, (2) Mobile Movement/No Music, (3) No Mobile Movement/No Mobile Music, and (4) No Mobile Movement/Mobile Music). We conducted seven sessions over a 4 week period with a five month old male infant for a total of 76 minutes of interaction, while recording the state-action pair and transitions for each session. The resulting MDP is illustrated in Figure 3 showing the infant states, baby mobile actions, transition probabilities, and reward functions. The infant Kicking state is given a reward of +10 and the No Kicking state is assigned a reward of 0. The observation of the change in the state-action pairs during a session provides the transition probabilities. This completes the MDP which allows us to calculate a policy. We use value iteration [17] to solve our MDPs because the environment is deterministic and all parameters are fully observable. Given a MDP $< S, A, T, R >$, the goal is to find the optimal value function V_{π}, which indicates the value of the reward that is received in each state. The series of states that results in the highest cumulative rewards is the optimal policy. Value iteration is a form of dynamic programming that is based on the Bellman equation, which attempts to maximize the optimality of a solution by looking ahead and factoring in discounted future states.

B. Kicking Metrics

In our previous work, we investigated quantitative metrics to measure kick characteristics during infant sessions [19]. The metrics include kick activity and kick amplitude. We will calculate kick activity and kick amplitude to quantify the change in kicking instances between the random mobile stimuli baseline and the MDP-based mobile stimuli.

Kick amplitude is determined by calculating the standard deviation of each knee using:

$$k = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - \bar{x})^2}$$

where k is the data set standard deviation, N is the data set size, x_i is each value from the data set, and $\bar{x}$ is the data set mean.

We define kick activity as the sum of the change in displacement in reference to the z-axis over the change in time of the knee from one sample to the next, where one measurement is represented as:

$$|\frac{\Delta z}{\Delta t}| = |\frac{z_t - z_{t-1}}{t_t - t_{t-1}}|$$

The resulting sum of all measurement within a kicking instance is described as $k_{activity}$, where :

$$k_{activity}{=}\sum_{i=1}^{N} |\frac{\Delta z_i}{\Delta t_i}|$$

The higher the sum, the greater the kick activity and the infant is perceived to be engaged in more active kicking during this time frame.

IV. Results

The results of comparing the MDP-based robotic baby mobile stimuli actions vs. the random baseline and its verification through kick metric quantification are summarized in this section.

TABLE I: Value Iteration table after convergence.

	No Kicking	Kicking
No Movement/No Music	53.7173	X
Movement/Music	X	64.1885

A. MDP Policy

The transition tables are constructed based on the transition of the infant kicking state after a baby mobile action is executed (Figure 3). Value iteration is used to calculate the expected value of each state-action pair and the highest values for each state are used to create the resulting policy. The highest expected value after convergence, which illustrates the best action for the robotic baby mobile to execute for each infant state is shown in Table I. If the infant is in the No Kicking state, the mobile will execute the No Mobile Movement/No Mobile Music action and the Mobile Movement/Mobile Music action will be executed if the infant is in the Kicking state.

TABLE II: Random Robotic Mobile Actions Baseline (170 Kicking Instances)

	Avg. Kick Amplitude	Avg. Kick Activity	Total Kick Activity
Left Leg	43.77 mm	984.54 mm	168240.76 mm
Right Leg	52.57 mm	1258.71 mm	203557.95 mm

TABLE III: MDP-based Robotic Mobile Actions (170 Kicking Instances)

	Avg. Kick Amplitude	Avg. Kick Activity	Total Kick Activity
Left Leg	56.60 mm	1698.42 mm	288731.45 mm
Right Leg	66.11 mm	1789.22 mm	304166.72 mm

B. Kick Metric Measurements

Once the MDP policy (Table I) was calculated based on seven sessions using the random mobile actions, it was utilized to test against the baseline. Subsequently, we conducted two test sessions, one using the random mobile action baseline and the other using the MDP-based policy. Each test session was completed on different days. Based on visual observation, the MDP-based policy seemed to encourage the most kicking activity when compared to all of the previous random baselines. The average kick amplitude, average kick activity, and the total kick activity were calculated between the test random baseline and the MDP-based policy. Table II and Table III illustrate the results. For the MDP policy, average kick amplitude increased by 29.3% for the left leg and 25.8% for the right leg. Average kick activity increased by 72.5% for the left leg and 42.1% for the right leg. Total

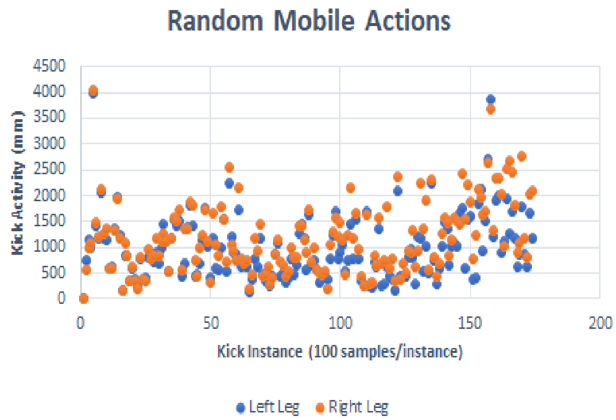

Fig. 4: Random Robotic Baby Mobile Actions. Kick Activity measures the distance travelled by each knee per kicking instance. Each kicking instance contains 100 samples of kicking activity.

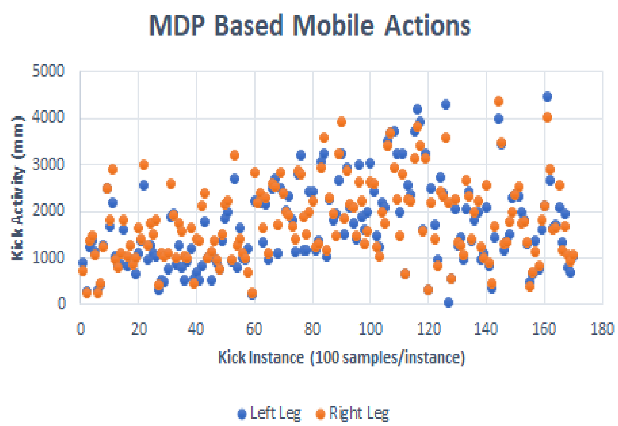

Fig. 5: MDP Based Robotic Baby Mobile Actions. Kick Activity measures the distance travelled by each knee per kicking instance. Each kicking instance contains 100 samples of kicking activity.

kick activity increased by 71.6% for the left leg and 49.4% for the right leg, when compared to the random baseline.

Figure 4 and 5 plot the kick activity of the random baseline and the MDP-based policy for each leg. It shows that the MDP-based policy results in more instances of sustained higher kick activity, which correlates with the results in Table II and III.

V. Conclusion

We investigate the possibility of determining if a robotic mobile can motivate continued infant kicking by customizing the mobile stimuli based on the preference. This was accomplished by using a MDP to conduct long term learning over numerous sessions and calculating an optimal policy. Our results show that a calculated policy may perform better than activating random stimuli to motivate infant kicking. The results were verified visually and by quantifying kick characteristic metrics. Our next steps will be to conduct more sessions with additional infants to determine if the trend is sustained.

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