A Computational Approach to Earlier Detection and Intervention for Infants with Developmental Disabilities

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Introduction

One in six (almost 17%) children in the US are diagnosed with developmental disabilities [1], resulting in reduced education, career, and wellness outcomes. In infancy and early childhood, developmental disabilities can cause difficulties with motor functions, such as crawling and walking, cognitive functioning, such as language skills and problem solving, and social skills, such as turn-taking and social referencing. These impairments can persist throughout life, negatively impacting independence, employability, and health. Addressing these impairments is often unaffordable for families; direct medical expenses and larger nonmedical or indirect expenses associated with special education, home and automobile modifications, transportation, and limited employment due to loss of independence, can reach over $1 million over the lifetime of an individual with developmental disabilities. This issue is exacerbated by the lack of sufficiently early detection. While developmental disabilities typically begin before birth, some, including Autism Spectrum Disorder (ASD), Attention Deficit Hyperactivity Disorder (ADHD), and learning disabilities, are often not accurately diagnosed until years later. Additionally, although research recommends frequent, high-intensity early interventions, the current standard of care involves less intense and later therapy [2]. This delays interventions that could lead to improved quality of life and greater independence, and therefore reduced societal and healthcare costs. The high costs of developmental disabilities, paired with insufficient early diagnosis and intervention methods and services, highlight the great need for increased resources for accessible early detection and interventions.

The proposed work synthesizes and builds on a large body of research toward operationalizing data-driven early interventions that has demonstrated the following building blocks: 1) early interventions hold promise for addressing developmental disabilities; 2) play is a key pathway to discovery and learning; 3) machine learning algorithms can be applied to human behavior data to personalize interventions; and 4) intelligent human-machine interaction can lead to behavior change. Building on that foundation, *we propose to develop, deploy, and evaluate a computational approach to safe, affordable, and robust in-home interactive behavioral data collection that can evaluate outcomes, and provide a platform for early detection and intervention*.

Leveraging the power of human-machine interaction, big data, machine learning, and machine vision, we envision an affordable tangible play system for infants that provides opportunities for early detection of likely developmental delays through natural play in the home, and provides a platform for interventions. An integral part of this approach will be an interactive robotic toy. The toy will serve as a programmable, real-world stimulus that produces novelty to attract infant attention and can encourage and test specific infant behaviors; physically embodied robots have been widely demonstrated to enable meaningful interventions that improve social, learning, and motor functions in children and infants, and are more engaging than screens [3]. Integrating a robotic toy will allow us to test standardized, interactive play activities and to implement personalized play activities to assess developmental milestones.

We will collect a body of data on infant play behaviors with the interactive robotic toy, as well as interactions between the infant and a caregiver with the toy. Using machine learning with data from each infant, we will search for infant behaviors which may be signs of developmental disability. After creating a model from an infant's behavior patterns, we will compute personalized interaction policies based on each infant's unique needs. Data from our research will be made available to parents, physicians, and the AI community to advance the early detection of motor and social developmental disabilities. Therefore, our approach has the potential both to advance early detection of potential symptoms of developmental disability and to create interventions that are personalized to address each infant's specific needs. If our research is successful, it will help inform the diagnosis process for physicians and enable long term, computationally-enabled interventions to reduce disability and improve motor, cognitive, and social abilities for numerous infants with or at risk for developmental disabilities (AR). This would facilitate more independent living and decreased dependency and spending on assistive resources later in life.

Background

Developmental Disabilities: Detection, Intervention, and Cost

Today, diagnoses and interventions for many developmental disabilities may not occur until years after birth and are affected by the socioeconomic status of infants' families. For example, children from near-poor families are typically diagnosed with ASD almost a year later than their counterparts from families over 100% over the poverty line [4]. These differences could be mediated by the ability to collect and analyze data describing infant behavior over an extended period of time for computational evaluation to inform pediatricians and assess the infant relative to national health standards. Additionally, AR infants receive early intervention less frequently than recommended; 2% to 78% of infants across the US states are likely to be eligible for intervention, yet 1.5% to 6.9% are served. Socioeconomic status is a key factor; parents with inadequate resources are less likely to view intervention as immediately needed [5].

The high costs associated with developmental disabilities impose further burdens on affected families and on the US economy. For example, Cerebral Palsy (CP), one of the many motor disabilities, which affects 0.1% of the US population, has the estimated lifetime cost of over $900,000 [6], with the corresponding cost of over $12 billion for individuals with CP born in 2000 alone. Estimates for disabilities affecting cognitive function are higher, with a lifetime cost per person of $1.04 million. In fact, lifetime costs for individuals born with cognitive impairment have risen exponentially; in 2003 they were over $51 billion [6] and a more recent estimate places *the annual US cost of ASD alone* at $126 billion per year [7]. Additionally, due to the demands of caring for children with disabilities, mothers of individuals with delays and disabilities are less likely to be employed, and work fewer hours than parents of children without health issues [8], placing additional financial strain on families and the economy.

Our work aims to address these healthcare and financial challenges by creating a computational method for in-home play-based diagnostic interactions that generate personalized infant data, increasing the accessibility and quality of early diagnoses and interventions. This will facilitate greater independence for those with developmental disabilities and decreased cost to families and the US economy.

Related Computing Research Toward Detection and Intervention

Our computational approach to increasing resources that address developmental disabilities is informed by past work demonstrating machine learning as a tool for detecting abnormal infant behaviors and driving behavioral change. Shivakumar et al. [9] introduced a low-cost vision system to track infant movement with respect to toys; this work identified metrics to evaluate infant movement and identify certain risk factors for cerebral palsy. Goodfellow et al. [10] used machine learning algorithms with movement data from wearable sensors worn by infants for one day to predict group membership: whether the infants were typically developing (TD) or AR. Howard et al. [11] introduced an intelligent mobile to provide contingent feedback and encourage infant kicking; the system used wearable sensors to analyze infant kicking patterns toward detecting risk for cerebral palsy. These projects indicate the great potential for computing and machine learning to aid in the early detection of developmental disabilities.

Our team has begun to explore the use of machine learning combined with assistive and socially assistive robots to encourage infant motor movements. Our past work [12] introduced Socially Assistive

Robotics (SAR) as a potential tool to guide and stimulate the learning of motor skills for infants; we used the Nao humanoid robot to reinforce leg movement in infants, and saw an increase in leg movement rate and imitation of robot movements in 9 of 12 infants. We demonstrated the potential for and importance of machine learning towards personalized SAR interventions for infants by introducing a model for adapting the difficulty level of an interaction based on infant motor performance [13]. Scassellati et al. [14] explored the use of SAR to involve infants in social interactions as well, using a robot and virtual agent to engage in sign language interactions for deaf infants. These technologies show promise in guiding the increase of developmentally appropriate infant motor and social skills; however, they have involved physical constraints on the infant rather than free movement and play, and were implemented only in laboratory environments, and on research systems that were not self-contained and affordable for the consumer market. We propose an approach and system that is self-contained, affordable, and robust, so that it can facilitate large-scale studies and the adoption of intervention for long term use.

Proposed Work

Our team proposes to leverage current machine learning methods to detect potential indicators of developmental disability in infants and to compute optimal, personalized intervention policies to reduce disability. We will build an interactive, accessible, and robust play system for infants that can be deployed in the home to collect data on infant motor and social behaviors and then to conduct and evaluate interventions. We will use an interactive robotic toy as a platform to guide infants and toddlers in therapeutic play activities in an unconstrained environment to encourage and reinforce developmentally appropriate behaviors. Data collected from interactions with the robot and caregivers involved in play will be analyzed with machine learning techniques as well as made available to the research community to identify potential signs of developmental disability. We will use these data to develop computational models enabling the robotic interactions to adapt over time toward personalized intervention protocols unique to each infant's needs. Unlike past work, which has typically focused solely on data collection or on one type of non-personalized interaction, the proposed approach addresses both. Additionally, unlike the majority of robot interventions, which involve short term single-use interactions, the system will be small, safe, and robust enough to be left in the home for a long term intervention.

System Development

Our system will consist of a commercially available, affordable (~$150) platform such as Sphero that enables system development, combined with an inexpensive overhead camera, microphone, and a mobile application that can be updated with new interventions and can provide feedback to parents, caregivers, researchers, and physicians. We will employ computer vision techniques to track the activity of the robot and child during interactive play. Leveraging existing technologies allows us to implement a platform for our computational research within half a year.

Pilot Testing

We will pilot test our platform through initial, single-session uses in the homes of families with infants, including both TD and AR infants. Using our established methods, we will continue current recruiting practices with the Los Angeles metropolitan area health care providers, day care clinics, libraries, and the university community by word-of-mouth and fliers. During pilot testing, we will evaluate single session, contingency-based interactions between the infant and robot to encourage motor movement, as in [11] and [10]. This testing will validate our system performance to be at or above the level of past interactions that can increase the frequency of specific infant motor movements through contingent rewards in the form of robot behaviors. We will collect video data of the infants as well as feedback from caregivers to inform iterative system design while also collecting a body of data that can inform the design of future interventions. Creating a system and simple interaction to encourage specific motor activities while collecting initial data will serve as an intermediate metric of success.

Additionally, we will use pilot testing as an opportunity to record video data from interactions between the parent and child during the play interaction with the robotic toy. Free play with toys has been used as a method to study common interactions between parent and child [15]. Such interactions are essential to the social development of infants, and parent-mediated intervention addressing communication between parents and infants at risk for ASD has been introduced as a potential method for reducing the severity of symptoms associated with ASD [16]. By collecting data for such interactions, we will extend the use of our approach to evaluate and encourage both motor and social behaviors in infants. We will leverage our past study designs and expertise in data collection with vulnerable populations in order to complete this step within half a year. Data from pilot testing will enable the development of long term, personalized, and adaptive computational models for detection and intervention for AR infants.

There is an inherent risk associated with collecting identifiable data from infants and their families. We will mitigate this risk through privacy training, including HIPAA, for all researchers or developers involved in handling participant data. All user study protocols will be approved by the Institutional Review Board (IRB) at the University of Southern California; the proposing team has decades of experience with IRB processes.

Building Computational Models for Detection and Long Term Intervention

We plan to use machine learning methods to determine each infant's: 1) risk of developmental disabilities and 2) personalized, adaptive intervention behaviors best suited to the infant's unique needs. Data from the pilot study, domain knowledge, and past research will inform the prior for a computational model of robot behavior during the intervention to guide the infant in play activities, including both solo-play and play with parents. We will identify potential signs of developmental delay or anomaly based on infant play and movement patterns. Continued evaluation of the infant's abilities and subsequent adaptation of the system will enable long term, personalized interventions that grow with the infant; based on the data collected during each play session, the model will learn which actions are optimal for encouraging desired infant behaviors. As a larger body of data is collected from many infants, both AR and TD, they will inform developmental expectations.

We will evaluate our computational approach through a long term, in-home user study with 50 infants. This will include AR infants as well as a control group of TD infants. We will also compare the results of the experimental group to a control group of AR infants that have not yet received this intervention. Each infant will engage in multiple interactions with the robot each week for 1 month. Regular updates on the status of the interactions and certain motor or social skills will be provided to parents and caregivers through the mobile application throughout the study. Children will be assessed by a physician prior to the intervention, after the intervention, and at an extended period of time later to assess the efficacy of the intervention. We will also collect data throughout the study regarding parent and caregiver reactions to the system. Deidentified data generated throughout the study will be made available to the research community. This will provide a baseline for tracking infant progress and development during interventions and can be used in the identification of abnormal behaviors. Contributing a dataset that can be used to track measurements of infant milestones over time, observing developmental gains of an experimental group, and achieving caregiver satisfaction with our system will serve as long term metrics of success. Given the long term nature of this step, we anticipate that model development and testing will take a year to complete. Participation in our study may reduce the amount of time that infants spend in other interventions or research; we will disclose alternative resources to caregivers through a consent form prior to the study. Additionally, caregivers may withdraw their infant from the study at any time.

If our work is successful, we will have created an affordable, standardized in-home approach for deploying robotic diagnoses and interventions for infant developmental disabilities. Additionally, our research will have introduced a type of intervention that can adapt and personalize to individual infants' needs over time. These contributions will increase the feasibility of early intervention, the amount of data on infant motor and social development, and the ease of collecting data for caregivers, pediatricians, and the research community. This can facilitate earlier diagnosis as well as access to early intervention. Providing families of at-risk infants with improved early intervention resources could promote typical child development and independence and decrease disability, reducing healthcare costs throughout life.

Resources

To evaluate interventions on a large scale, it is essential to have a robust platform that can easily be deployed in multiple homes without extended supervision and maintenance by the researchers. To begin development for a consumer-grade integrated system for home use, we will need to work with professional software developers. We seek funding to begin the process of creating the computational system that will allow both interaction development and data analysis by researchers or physicians as well as easy use by caregivers. We anticipate that this work will require 1-2 software developers working over 6 months to allow iterative design of the platform. Assuming a yearly salary of $100,000 for each developer, we anticipate an expense of $100,000 in direct costs. We apply for the award through the Computing Community Consortium to begin funding this platform, which is essential for validation of our research approach, as well as exposure to Schmidt Futures and opportunities for additional funding.

Costs beyond system development will include faculty time ($30,000 direct cost for three senior faculty members), student researcher compensation, and expenses related to study coordination, equipment, and participant compensation. Funding for 1 PhD student and two undergraduate students over 2 years will require $120,000 in direct costs. By alternating the timing of participation in the long term user study to involve only 10 participants at a time, we can keep the cost of equipment to roughly $5,000 in direct costs. Participant compensation will total about $25,000 in direct costs. Therefore, the overall project cost estimate is approximately $280,000 in direct costs. However, being able to scale to more deployed systems will result in more data and significantly higher project outcomes.

Team

We propose a teaming of the key contributors to the advancement of this project:
Human-machine interaction expertise: Prof. Maja Matarić, Lauren Klein; Machine learning expertise: Prof. Fei Sha; Child development expertise: Prof. Beth A. Smith

The team's success will be propelled by the synergy of expertise in child development, human-machine interaction, and machine learning. This project will benefit from an ongoing research collaboration between the Interaction Lab (PI: Matarić), Infant Neuromotor Control (INC) Lab (PI: Smith) and Theoretical and Empirical Data Science Lab (PI: Sha) at the University of Southern California.

Prof. Maja Matarić, founder and director of the Interaction Lab, pioneered the field of Socially Assistive Robotics and has two decades of experience leading research projects involving both short term and long term robotic interventions for individuals with motor and social disabilities. Prof. Beth A. Smith leads the INC Lab, and focuses on interventions that address neural and functional development for AR infants. Prof. Fei Sha is an international expert in Machine Learning with application to health and medical data. Sha has a 7-year collaboration with Matarić on real-world deployments of ML-based socially assistive robots used for behavioral interventions with children. Lauren Klein, a second year PhD student in the Interaction Lab, is the student lead of this collaboration. The team's ongoing collaboration will be leveraged to accelerate project progress.

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