Assist-as-Needed in Lower Extremity Robotic Therapy for Children with Cerebral Palsy

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Abstract—Cerebral palsy (CP) is a group of disorders that can involve different brain and nervous system functions, the most prominent of which is movement. Recently, our lab developed the alpha-prototype of a novel pediatric ankle robot to aid recovery of ankle function in children with CP ages 5 to 8 years old. In this paper, we describe an amalgamation of new concepts and ones inherited from our 20-year experience on robot-assisted therapy for the upper extremities. Our scope is to present an algorithm that tracks the performance of children and adapts accordingly two gameplay parameters, namely the game speed and the target width. Our proposed algorithm uses concepts derived from the speed-accuracy tradeoff in an attempt to expedite optimal therapeutic results.

I. INTRODUCTION

Cerebral palsy (CP) is a universal problem. It is the most common developmental motor disability of children worldwide and affects more than 2 in 1,000 live births [1]. The most prevalent types of cerebral palsy are spastic, dyskinetic, ataxic, hypotonic, and mixed. The average lifetime cost of CP is estimated at $921,000 per capita [2] whereas the emotional cost of the affected families is intangible [3]. Prenatal and perinatal causes of CP are mainly related to prematurity [4]. As the survival rate of premature infants continues to increase, the overall cost of CP therapy is also expected to increase in the upcoming years.

Therapy for CP has a general goal: to help affected children to grow and develop to their maximum capabilities so that they may succeed as contributing members of society. The motivation behind physical and occupational therapy is best expressed by Hebbian ideas of nervous system plasticity, mainly that neurons that “fire” together, “wire” together. An assumed consequence for sensorimotor therapy (a term that encompasses physical and occupational therapy) is that it helps children “learn” motor control. Because their motor system never experience normal movement, children with CP receive sensorimotor therapy to promote habilitation and not rehabilitation (as in adults with stroke). Robotics are now facing a new challenge: to realize their promise to transform children-habilitation operations from labor-intensive to technology-rich augmenting the child’s potential for an independent and productive life.

A pioneer of its class, the MIT-MANUS is a robotic upper-limb manipulandum designed for clinical and neurological applications, aiming at shoulder and elbow training [5]. Clinical trials involving MIT-MANUS have shown that robot-aided neuro-rehabilitation has a positive impact in stroke rehabilitation, reducing impairment, improving function and quality of life in both stroke inpatients and outpatients without increasing total cost [6]-[8]. This has motivated the development of new modules designed for rehabilitation of anti-gravity arm movements, of the wrist, of the hand, and of the ankle [9]. Recently our lab introduced a pediatric version of the anklebot for children of ages 5 to 8 [10]. The pediatric anklebot is about to commence pilot testing with children with CP at Blythedale Children’s Hospital (Valhalla, NY), Bambino Gesù Children’s Hospital (Rome, Italy) and Riley Children’s Hospital (Indianapolis, IN).

Evidence suggests that appropriate forms of robotic therapy may reduce motor impairment and enhance functional motor outcomes [6]. For the upper extremities, active involvement of stroke patients is important [11]. The underlying activity-dependent neural plasticity is likely the key mechanism through which robotic therapy produces clinical benefits. Progressive training based on metrics of movement coordination yields substantially improved outcomes [12]. There is no reason to believe that an analogous “optimal” treatment, tailored to each patient’s needs and abilities, is not a reasonable starting point for also revolutionizing the care of youngsters with CP. As we continue to refine our understanding of what constitutes the most appropriate therapy, herein we expand the concept of performance-based progressive robot therapy, used in our upper extremities robotic devices, to the needs and the special characteristics of the lower extremities for children with CP.
II. DESCRIPTION OF THE PEDIATRIC ANKLEBOT

A. Hardware

The Pediatric Anklebot alpha-prototype was first presented in 2011 [10]. It is a low-friction, backdrivable device with intrinsically low mechanical impedance that allows normal range of motion (ROM) in all three degrees-of-freedom of the foot relative to the shank during walking overground or on a treadmill. The robot provides independent, active assistance in two of these three degrees-of-freedom, namely, dorsiflexion and inversion-eversion, and a passive degree-of-freedom for internal-external rotation. The kinematic design consists of two linear actuators mounted in parallel such that if both push or pull in the same direction, a dorsiflexion torque is produced at the ankle. Similarly, if the two links push or pull in opposite directions, inversion-eversion torque results (see Fig. 1). The device can deliver a maximum stall torque \( \sim 7.21 \text{Nm} \) in dorsiflexion and \( \sim 4.38 \text{Nm} \) in inversion-eversion. This torque capability does not afford lifting the weight of the child (approx 25%). At best, we can cue the child to use the voluntary plantarflexion function by providing supplemental support to the paretic ankle plantar flexors during this phase. The pediatric anklebot was designed to properly position the foot during the swing phase. The device possesses minimal friction and inertia to maximize the backdriveability.

The Pediatric Anklebot is actuated by two brushless DC motors (Maxon EC-powermax 22-327739) which are cogless and produce maximum continuous torque \( \sim 51.2 \text{Nm} \) that is augmented by a Rohlix linear traction drive. Motion and torque information is provided by two sensors: the first is a mini-rail linear encoder (MNS9-135 length, Schneeberger) mounted in parallel with the motors and possessing a resolution of 1\( \mu \)m. The linear dimensions measured by the encoders are used to estimate ankle angle in plantar-dorsiflexion and inversion-eversion. The second is a Gurley rotary encoder with 40960 lines. Load cells were added at each actuator output (LSB200:00105, 25 lb, 2mV/V Futek).

B. Software

1) Controller: At present, the controller implements an impedance controller with a programmable torsional stiffness and damping and a programmable reference. During therapy, the impedance controller guides the patient’s ankle with a minimum-jerk speed profile from a starting position to the end position. The command force is given by:

\[
F_x = \begin{cases} 
-k_{bw}(x - x_{m,j}) - bx & x < x_{m,j} \\
0 & x_{m,j} \leq x \leq t_m \\
-k(x - t_m) - bx & x > t_m 
\end{cases} \tag{1}
\]

\[
x_{m,j} = t_m \left[ 10 \left( \frac{t}{t_m} \right)^3 - 15 \left( \frac{t}{t_m} \right)^4 + 6 \left( \frac{t}{t_m} \right)^5 \right] \tag{2}
\]

where \( x_{m,j} \) is the controller’s minimum-jerk movement reference, \( k \) is the controller stiffness, \( k_{bw} \) is the “backwall” stiffness, \( b \) is the controller damping, \( t_m \) is the length of movement, and \( t_m \) is the duration of the movement in the x direction (dorsi-plantar, inversion-eversion, or any combination). The controller provides assist-as-needed and guides the ankle of the child only when there is a lack or insufficiency of motor ability [13].

To be consistent with the upper extremity therapy, the time allotted for the child to make the move, \( t_m \), and the primary stiffness of the impedance controller, \( k \), are varied based on the patient’s performance and variability, whereas \( k_{bw} \) is held constant.

2) Serious games: Goal-directed therapeutic “games” were designed to address motor impairments including poor coordination, impaired motor speed or accuracy, and diminished strength, as well as addressing cognitive or perceptual impairments. We developed initially a set of three games to be used specifically with the pediatric anklebot (see Fig. 2). The rationale for the development of those games is explained elsewhere [14]. Briefly, using the anklebot, a child can prevent a boat from crashing into the rocks, run through a race to collect animals to Noah’s Ark while attempting to avoid water splashes, and play a soccer game with the computer as his/her opponent (it can also

Fig. 1. Pediatric Alpha-Prototype Anklebot for Children with CP ages 5 to 8.

Fig. 2. A set of three serious games developed for the Pediatric Alpha-Prototype Anklebot to be played by children with CP ages 5 to 8. Top row shows the shipwreck (left), race for Noah’s Ark (right) and bottom row shows soccer 2014. Presentation of targets in each game is random.
allow a child to play against another child during tele-rehabilitation). For each of those games, the child moves a paddle (that corresponds to the runner, the ship barrier, or the goalkeeper/player, respectively) using his/her ankle. Dorsi-planter flexion and inversion-eversion control screen movements of the paddle in vertical and horizontal directions, respectively. Depending on the game, repetitions are counted (and displayed in the clock-style figure shown in the left of the game field) as the number of ship bounces, animals collected, or shots towards the opponent’s goalpost.

Game parameters were modified based on the performance of the child. Specifically, the speed of the moving target (defined as the speed of falling gates in the race game or the speed of the boat or the ball in the other game) and the size of the paddle were changed. The selection of adaptive parameters follows the analogy of the speed-accuracy trade-off (SAT) and are calibrated to get the child to score between 50 and 90 percent of the times.

III. PERFORMANCE-BASED ADAPTIVE ALGORITHM

A. Performance Metrics

The games track the child’s ability and encourage him/her to actively participate during therapy sessions. Four performance metrics are currently used, namely the ability to initiate movement (PM1), power to move from the starting position to the target (PM2), to reach the target in a timely manner (PM3), and to reach the target position (PM4). Excluding PM3, the other PMs have been used before for the upper extremities robotic therapy [13]. They were modified for lower extremities: PM1 records the number of times the child initiates the movement. This is found by comparing the ankle (dorsi-planter flexion or inversion-eversion) speed with a velocity threshold. The threshold is defined to be 10% of the maximum speed of the minimum-jerk reference profile, namely:

\[ V_t = 0.10 \left( 1.875 \frac{I_m}{t_m} \right), \]  

where \( l_m \) is the distance between targets in meter, \( t_m \) is the time allotted for the move and \( V_t \) is in m/s. PM2 is defined as the weighted sum of a kinetic measurement, PM2a, measured in Watts, and a kinematic measurement, PM2b measured in m, defined as:

\[ PM2a = \frac{1}{\tau} \int_0^\tau F_{\tau}(t) \dot{x}(t) \, dt, \text{ for } x(t) \leq x_{m.j}(t) \]  

\[ PM2b = \frac{1}{\tau} \int_0^\tau x(t) - x_{m.j}(t) \, dt, \text{ for } x(t) > x_{m.j}(t) \]

where \( F_{\tau} \) is the interaction force along the target axis, \( \dot{x} \) is the velocity along the target axis, \( x \) is the position along the target axis, \( x_{m.j} \) is the prescribed minimum jerk trajectory of the “back wall” of the impedance controller, and \( \tau \) is the total time of the movement. PM2 is used to adjust the speed of the moving target (and as a consequence, \( t_m \)) [13]. As \( t_m \) changes during the gameplay, \( V_t \) also changes making it

harder or easier for a child to initiate the movement. PM3 is a distinct metric introduced here, that quantifies the ability to point with the ankle on time with respect to speed and accuracy limitations. It measures the cognitive ability of a child to plan and execute the movement after pointing for the final position of the moving target. PM3 is separated into two distinct metrics, namely PM3a, that measures (in s) the speed of positioning the paddle in the final position and PM3b (unit-less) that grades the ability to minimize the movement displacement. PM3a is defined as:

\[ PM3a = \frac{1}{\tau} \left( \kappa_f \int_0^\tau f(t) \, dt + \kappa_g \int_0^\tau g(t) \, dt + \kappa_h \int_0^\tau h(t) \, dt \right), \]  

where \( f, g, h \) determine the time in which the center of the paddle, \( c \), is positioned exactly on target (\( |c| \leq w \)), near the target (\( w < |c| \leq 2w \)) and almost near the target (\( 2w < |c| \leq 3w \)), respectively, and \( \tau \) is the single-movement time. For the above inequalities, the target’s coordinate is considered as the origin. PM3a focuses on the patient’s ability to position the ankle properly on time. The quantized log scaling affords better resolution of a good and a bad pointing. PM3b detects excessive mechanical work due to involuntary movements or lack of motor control. Note that for the same movement, PM3a decreases with the width of the paddle. PM3b is defined as follows:

\[ PM3b = 1 - e^{-\left(\frac{r-a}{s}\right)^2}, \]

where \( r = \frac{l_u}{\ell_m} \in [0,1] \), the ratio of the displacement covered by the paddle, \( l_u \), to \( \ell_m \), \( d \) is the center of the logistic-type function and \( s \) the steepness factor. With a proper combination of \( d \) and \( s \), the patient might not be penalized until \( r \) is lowered to a certain value (e.g. for the red line in Fig. 3, \( r \) needs to drop below 0.6 for \( PM3b < 1 \)). The overall ability for a child to point with the ankle in a timely manner is calculated as follows:

\[ PM3 = PM3a \cdot PM3b - PMz, \]

where \( PMz \) is a constant to confine PM3 so that \( [PM3] < 1 \). For \( \{\kappa_f = 4, \kappa_g = 2, \kappa_h = 1\} \), PM3z = 2 (see Fig. 4). PM3 is used to adjust the width of the paddle. PM4 records the maximum distance the patient moved along the target axis.

Fig. 3. Performance index PM3b: Calibration curves from simulation.
B. Tracking Child’s Performance

The pediatric anklebot is able to track the child’s speed and accuracy capabilities every 11 repetitions (that constitutes a section) using a set of simple control laws:

\[ s[j + 1] = s[j] + \lambda_s \cdot PM2[j] \]  \hspace{1cm} (9)

\[ w[j + 1] = w[j] + \lambda_w \cdot PM3[j] \]  \hspace{1cm} (10)

where \( s[j] \), \( w[j] \) are the gameplay speed and paddle width during the \( j \) section, respectively, and \( \lambda_s, \lambda_w \) are the gains. During the initial \( m \) (out of \( M \)) repetitions of a session, the control system operates in a tracking mode to identify how well the child is able to complete the task.

C. Challenging Child’s Performance

The last \( M-m \) repetitions in a session are also grouped into sections of 11 repetitions. When the speed of the game or the width of the paddle are changed, the zero \( PM \) values occur at different levels of patient performance. At least one secondary performance measure is found to serve well as an indication of patient variability: The performance level (PL), is defined to be

\[
PL = \begin{cases} 
-1 & PM < -0.1 \\
0 & -0.1 \leq PM \leq +0.1 \\
+1 & PM > +0.1 
\end{cases}
\]  \hspace{1cm} (11)

The value of PL indicates whether patients perform worse (\( PL=-1 \)) or better (\( PL=1 \)) than their expected ability at \( PM=0 \). \( PL=0 \) denotes when patients perform approximately the same [13]. By considering average \( PM \) values and a weighted sum of the \( PL \) values in \( h \) consecutive sections, the controller adapts to children’s performance and variability, and challenges them to continue to improve. An integration of weighted \( PLs \) for both speed and accuracy is introduced. A window of size 3 is adjusted to each PL so that the current PL value is weighted by 4, and the previous two PL values are weighted by 2 and 1, respectively (see Fig. 5). The proposed performance-based adaptive algorithm is stated as follows:

\[ s[j + 1] = s[j] + \lambda_s \cdot a(PLsum) \cdot PM2[j] \]  \hspace{1cm} (12)

\[ w[j + 1] = w[j] + \lambda_w \cdot a(PLsum) \cdot PM3[j] \]  \hspace{1cm} (13)

where

\[
a(PLsum) = \begin{cases} 
1.00 & -14 \leq PLsum \leq -10 \\
0.75 & -10 < PLsum \leq -8 \\
0.50 & -8 < PLsum \leq -6 \\
0.25 & -6 < PLsum \leq -3 \\
0.25 & -3 < PLsum \leq 3 \\
0.50 & 3 < PLsum \leq 6 \\
0.75 & 6 < PLsum \leq 8 \\
1.00 & 8 < PLsum \leq 10 \\
1.50 & 10 < PLsum \leq 12 \\
2.00 & 12 < PLsum \leq 14 
\end{cases}
\]  \hspace{1cm} (14)

The desired effect of challenging patients to improve while keeping them motivated is accomplished, in part, by the asymmetry in the definition of \( a(PLsum) \). The asymmetry challenges improving patients to improve further, but makes the task easier, to a lesser extent, when patient performance is worsening. Note that although this approach uses a common criterion to challenge, a single gameplay parameter (speed or accuracy) is \textit{a priori} selected to change during the challenging part of the game. Figure 6 displays a hypothetical case of a 44-section challenging part of a therapy session (\( h=1 \)). The first row is the patient simulation \( PL \) values for speed, the second row is the patient simulation \( PL \) values for width and the third row displays the \( PLsum \) values that would result from the weighted integration of both \( PLs \).

We have recently initiated clinical testing to better calibrate our initial estimates for the parameters of the algorithm.
IV. DISCUSSION

The active assist-as-needed lower limb robotic therapy algorithm was motivated by the working hypothesis that the processes that underlie motor habilitation are similar to the processes that underlie motor learning. A difficulty associated with quantifying motor learning is that the underlying processes of learning in the central nervous system are not easily observed or measured. Several methods do exist that quantify electrical and biochemical activity in the brain as well as structural information about brain tissue, e.g., electroencephalography, magnetic resonance imaging, and positron emission tomography. Despite these technical achievements, the brain is exquisitely complex and the data is difficult to interpret. This requires one to infer that learning has occurred by measuring changes at the behavioral level [15].

By design the adaptive parameters, namely, the speed of the game (equivalent to the time allotted to move between targets) and the paddle-width, serve as indicators of patients' abilities to move and point: As PM2 decreases, children move faster and vice versa; as PM3 increases, children point better with their ankle and vice versa. We will test the validity of our design assumptions after our analysis of the parameters' evolution throughout the therapeutic protocol. Motor recovery follows an exponential progression similar to a motor learning "law of practice" or, especially in complex tasks, a two-time scale exponential function [16], [17]. The theory of multiple time scales is further supported by recent neurophysiological studies (e.g., [18]). According to that theory, the two superimposed exponential functions represent adaptation and learning processes. One characteristic time scale is relatively fast and captures the rapid adaptive change (warm-up) in performance at the beginning of a practice session. The other time scale is relatively slow and captures the persistent change that is more typically associated with learning [16]. But scooping the learning curves associated with the performance metrics is not the only aim of our research.

Adaptation of the gameplay parameters challenges the child with a perceptual task that is relatively simple but which retains the speed-accuracy dilemma present. For half a century, the SAT has been studied almost exclusively using abstract mathematical models. Only very recently have researchers begun to study the neural basis of SAT, using experimental methods and neurocomputational models [19]. Recent fMRI studies suggest that the modulation of SAT occurs in association areas (i.e., areas containing integrator neurons) and the pre-supplementary motor area rather than in early sensory and primary motor areas [20]-[22]. Furthermore, the data suggest that emphasis on speed is associated with an increase in baseline activity of cortical integrator neurons [20], [23]-[25]. Although behavioral data alone cannot be used to distinguish whether SAT is controlled by changing the firing baseline, threshold, or both (to address this question, one must analyze the spike activity), the selection of a challenging parameter (speed or accuracy) for a specific group of CP children might result in tangible knowledge about the SAT control mechanism inside the brain and ideally be used for optimizing therapy.

To address these concerns, our proposed algorithm incorporates some special characteristics. Let the range of the game speed be $R_s$ (pixels/s) and the range of the paddle width be $R_w$ (pixels). Then the control law gains are proposed to be as low as $\lambda_s = 0.1 \cdot R_s$ (pixels per unit PM2) and $\lambda_w = 0.1 \cdot R_w$ (pixels per unit PM3). Initial speed and paddle-width values are selected on the basis of severity of patient’s condition. The low gains secure that a balanced combination of the adapted parameters that best resembles the ability of each child will settle at the end of the tracking phase. In addition, $PM_{sum}$ is a single criterion (combines knowledge of PM2 and PM3) used for challenging the child either with speed or accuracy. That allows a comparative study on the effects that separate changes of the game speed and the paddle-width have on the motor learning and ideally on therapeutic procedures.

Furthermore, our proposed algorithm challenges the player at the end of each section. This allows fast adaptation to the constantly changing gameplay attitude of a child. Note that if the weights for the PL values are 1 and $h = 3$ (i.e., during three consecutive sections the speed of the gameplay and the paddle-width remain constant), then the pattern of challenge is similar to the one used for the upper extremities [13]. Lastly, there isn’t a “1-1” correspondence between the speed of the game and the time allotted for the move. Rather, in the start of each movement there is a time epoch that corresponds to the start/stop time of the device (intercept) superimposed on or intermixed with the time required for the brain to initiate a movement (reaction time). At present, these delays are introduced into the algorithm by allowing a temporal difference in the range of 200-500 ms between the time of movement for the moving target and the movement time for the controller.

V. CONCLUSION

The incorporation of behavior quantification techniques to CP habilitation using a robotic device seems very promising. The robot becomes a platform that combines behavioral psychology and physical therapy, among other disciplines. The proposed algorithm first identifies the ability of the youngster to move and point with the ankle, and then independently adjusts the speed of the gameplay and the size of the target. Knowledge of performance is used to challenge children to improve their performance or, at the very least, maintain it (reducing any slacking). We expect that our endeavor will provide the necessary tools to harness plasticity, to guide neurodevelopment during this forming period, and to prevent gruesome orthopedic problems.

REFERENCES


