Design of a Robotic Mobility System with a Modular Haptic Feedback Approach to Promote Socialization in Children

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Abstract—Self-initiated mobility is a causal factor in children’s development. Previous studies have demonstrated the effectiveness of our training methods in learning directional driving and navigation. The ultimate goal of mobility training is to enable children to be social, that is, to interact with their peers. A powered mobility device was developed that can localize itself, map the environment, plan an obstacle-free path to a goal, and ensure safety of a human driver. Combined with a positioning system, this system is able to apply a force field using a modular haptic feedback approach to train subjects to drive towards an object, a caregiver, a peer, or a group of peers. System feasibility was tested by designing a ‘ball chasing’ game. Results show that the system is promising in promoting socialization in children.

Index Terms—Force-feedback joystick, Socialization in children, Human tracking, Mobile robot path planning and control

1 INTRODUCTION

In typically developing infants, the emergence of independent mobility is associated with advances in perception, cognition, motor, and social skills [1], [2]. Our previous studies have demonstrated success in providing power mobility devices to children with special needs [3]–[6] and expediting motor learning of driving skills using a force-feedback joystick [7], [8]. Our results suggest that the use of a force-feedback joystick may yield faster learning than the use of a conventional joystick.

The ultimate goal of our research is to train children with special needs to be social, i.e., to interact with peers and caregivers. Previous studies [4], [5] have shown that although special needs children become more mobile and interactive when driving a powered mobility device, they still may not demonstrate peer-typical socialization. Therefore, we would like to design a robotic mobility system that can promote interaction between peers by combining our mobile robot and haptic technology.

In [8], we have trained children with and without mobility impairments to purposefully and safely navigate indoors while avoiding obstacles using the ‘assist-as-needed’ force field. However, in that experiment, we only targeted individual driving skills. No peers were present in the training area. The robot was not able to track other children in the play area. Moreover, the experiment was done in a fixed maze with fixed goals. The training robot was programmed to navigate only inside this particular maze and does not work if the environment is changed or the goal is moving.

Several smart wheelchairs are available that are capable of obstacle avoidance, path planning, and can be controlled using different shared control methods [9]–[12]. Users can control the device indirectly such as providing only driving direction or the user input is modified based on the underlying algorithm. Another important class of human-machine interaction is through haptic feedback. Users experience certain feedback force from the joystick and the joystick output is directly mapped to the wheelchair speed command. This type of control may be more suitable for motor learning since the driver has direct control of the wheelchair. Moreover, different haptic algorithms can be implemented to either reduce error [7], [8], [13] or enhance error [14]. However, all these studies have focused on enhancing individual driving experiences. To the best knowledge of the authors, this is the first study that attempts to promote socialization in children using a powered mobility device and a tracking system, and demonstrates the feasibility with a ball chasing game.

Our system is designed to work in both static and dynamic environments with obstacles and other children. In order to facilitate this game, the robot has to accurately build a map of the environment, know the position of the peers, and then plan paths...
to follow peers or achieve targeted goal points via a controller. This motion is then mapped to a force-feedback joystick to set up force tunnels to train children to learn this behavior. The robot must also be able to slow down or stop in front of an unexpected obstacle since the motion commands are given by the child using a joystick.

2 MODULAR HAPTIC FEEDBACK APPROACH

We have formed a systematic modular approach for motor learning of adults and children with or without special needs during the past few years (Fig. 1). Specifically, first, crucial motor tasks are identified for a human to learn. Then a mobility device with a controller is designed to accomplish this task autonomously so that it can be used to teach humans to learn this task. Training is through a force-feedback joystick. The desired controller output is mapped to the haptic device to set a specific force field to train the subjects. The force field can be either assisting to reduce error or repelling to enhance error. This approach has been successfully applied to learning of a number of motor tasks, such as directional driving [7], navigation [8], line following [14], etc.

The rest of the paper is organized as follows: Section 3 describes the experiment setup of the robot hardware and a tracking system. Detailed capabilities of localization, path planning and control, force feedback and safety issues are presented in Sections 4, 5, and 6 respectively. Section 7 presents the experiment protocol of a group study with 10 toddlers. Training results and discussions are presented in Section 8 followed by conclusions.

3 EXPERIMENT SETUP

Our robotic mobility device was designed to ensure comfort, performance, and safety (Fig. 2). The base robot is a Pioneer 3-DX, which is equipped with encoders to record the trajectory of the vehicle. A lidar was mounted at the front of the robot to map the environment. The seat was mounted on an aluminum extruded frame with low inertia, while still providing a stable base for a child to sit on the robot.

There are many approaches available to track humans, using lidar [15], vision [16], or a combination of these [17]. However, most of these sensors must face the target in order to be effective. Since the robot is controlled by a child, it is likely that the robot faces away from the target during motion. Moreover, we did not find a vision or laser based tracking algorithm that can reliably distinguish targets especially when the targets are far away from the sensor. Therefore, an Indoor Positioning System (IPS) from Ubisense was used for locating points during the experiment.

The experiments were conducted in the gymnasium of the Early Learning Center (ELC) of the University of Delaware (Fig. 3). Five Ubisense receivers were mounted on the walls around the gymnasium and were connected to a computer server. The target to be tracked carries a tag which emits Ultra Wide Band signals that are picked up by these receivers. The server runs our software using the Ubisense API that can calculate the 3D position of the tag and sends this information, together with the unique tag ID, to the mobile robot through wireless network. In addition, tags can be placed on children moving in
the environment. The position of each child and object can be identified using the tag ID. The system has the advantage of tracking multiple tags, making it possible to track multiple moving objects and children.

4 Localization
Under the assumption of no-slip in the wheels, the states of a mobile robot satisfy Eq. (1):

$$\begin{align*}
\dot{x}_c &= v \cos \theta \\
\dot{y}_c &= v \sin \theta \\
\dot{\theta} &= \omega.
\end{align*}$$

where \((x_c, y_c)\) are the coordinates of the robot center and \(\theta\) is its orientation. However, this no-slip condition is not always satisfied. As the robot moves, the odometry accumulates error. In this study, the IPS readings of the robot are fused with odometry data recorded from the wheel encoders to compensate for slip errors in position of the vehicle.

A Ubisense tag was placed at \(l_t\) ahead of the robot. The IPS observes the tag position:

$$y(t) = \left( x_c(t) + l_t \cos \theta(t) \right) \left( y_c(t) + l_t \sin \theta(t) \right)$$

Clearly, the tag is mounted at \(l_t\) ahead of the robot to make the system fully observable so that all three states of the robot can be updated.

The odometry data was then fused with IPS readings by following the procedure of an Extended Kalman Filter. This algorithm achieved a position accuracy of 0.1m and orientation accuracy of 5 degrees in the experiment. This was calculated by repeated measurements of the estimated robot position at several known fixed locations.

5 Integrated Path Planning and Control
Since the environment is dynamic, the robot uses a certainty grid map to record static and slow moving obstacles [18]. Several map-based path planning algorithms are available [19] that include potential fields, roadmaps, sampling based algorithms, etc. Planning algorithms on grid maps are typically based on A* or D*. The path planning problem in this study faces the following challenges: i) The environment has slowly moving obstacles, fast moving human subjects, and changing goals. ii) Fast planning is needed, as children become quickly impatient, usually within seconds. iii) The robot follows the joystick command given by the child; it is likely that it will deviate from the desired path. Although many of the algorithms above are capable of dealing with dynamic environments, none of them is designed to cope with the uncertainty due to the driver inputs. A quick recovery technique is needed to avoid unnecessary replanning.

5.1 Path Planning
In this experiment, inspired by Pathak et al. [20], an integrated path planning and control approach was developed to plan an obstacle-free path to the moving goal and control the robot autonomously. Unlike [20], the planning algorithm is an online algorithm and does not make assumptions about the shape of the obstacles. In a certainty grid map, it is very convenient to generate an obstacle-free square centered on cell \((x, y)\) instead of a bubble (Fig. 4).

We found that if the path planning is guided by A*, the computation time is too long to be used for training (Fig. 5 (a)), although the resulted path is optimal. Therefore, while still using the heuristic function which is the Euclidean distance from a cell to the goal, we relax the algorithm by not expanding the cells inside any square which is already on the closed list. Since if a square is generated and placed in the closed list, a good enough path from the start point to this square is already found. By relaxing the algorithm, the computation time is fast and can be used to train children (Fig. 5 (b))

Algorithm 1 generates an obstacle free square centered on cell \((x, y)\), which is an essential step in the path planning algorithm. It starts from the center and checks each of the 4 sides of the square with increasing size. A heuristic method is used here: if a cell has
clearance \( r \), the adjacent cell has clearance at least \( r - 1 \) but at most \( r + 1 \). This reduces the time complexity of computing the clearance of the adjacent cells from \( O(N^2) \) to \( O(N) \). If the square size is not large enough for the robot to drive through, this cell will not be expanded, making it convenient to adjust to different sizes of vehicles.

This path planning algorithm returns a series of intermediate goals from the start to the final goal. The robot simply needs to follow these goals one by one. The eventual path length traveled along this non-optimal plan can be reduced by carefully designing a controller and switching strategy.

### 5.2 Controller

Initially, the current square is the square centered on the first immediate goal, which is the Start. Therefore, the robot is always inside the current square initially. The switching strategy is outlined in Algorithm 2. Note that as long as the moving goal is still inside the square, no replanning is needed. As long as the robot is inside some square, the center of the next square is always its next intermediate goal, thus avoiding any ambiguities in path following if the robot deviates from the desired path. Since the center of the next square is always on the edge of the current square, the robot always has a line of sight with the next goal before switching. This eliminates the possibility that the robot will be trapped in local minima.

Once the current goal is determined, the robot can track this goal using the potential field based controller developed in [8]:

\[
\begin{bmatrix}
    v \\
    \omega
\end{bmatrix} = -(K_1 B^T + K_2 F) \nabla U
\] (3)
where \( K_1 = \begin{pmatrix} k_1 & 0 \\ 0 & k_1 \end{pmatrix} \), \( K_2 = \begin{pmatrix} k_2 & 0 \\ 0 & k_2 \end{pmatrix} \), 
\( k_1, \ k_2 > 0, \ B^T = \begin{pmatrix} \cos \theta & \sin \theta & 0 \\ 0 & 0 & 1 \end{pmatrix} \), 
\( F = \begin{pmatrix} 0 & 0 & 0 \\ -\sin \theta & \cos \theta & 0 \end{pmatrix} \), 
\( \nabla U = \begin{pmatrix} \frac{\partial U}{\partial x} & \frac{\partial U}{\partial y} & 0 \end{pmatrix}^T \), 
and 
\( U = U_a + U_r \) (4)
is the sum of the attractive potential function and the repulsive potential function.

The attractive potential \( U_a \) is set on the current goal and, if any moving obstacle is inside the current square, the repulsive potential \( U_r \) is set according to [8]. Then, the robot can globally track the goals while locally avoiding obstacles.

Figure 6 shows the simulation using this potential field based controller. Note that the zigzag path (in green) is short cut to a much smoother path (in blue) due to the controller and the switching strategy. The ratio of \( k_1 \) to \( k_2 \) determines the shape of the simulated trajectory. However, since we do not have a metric to determine the quality of the path, we cannot find an optimal value as we did in [14]. In this experiment, we set \( k_1 = 1, \ k_2 = 2. \)

6 Human-Robot Interaction and Safety

6.1 Haptic Algorithm

The control commands for \( v \) and \( \omega \), computed in Eq. (3), can be viewed as ideal commands which an autonomous driving algorithm would have imparted to the robot. However, in the experiments, the movement commands are given by the human driver through the joystick. Based on the idea of Sec. 2, all we need to do is send the desired control commands to the force field algorithm.

The ‘assist-as-needed’ force field was the same as [7], [8], [14]. A cone angle of \( 2\alpha \) was defined around the desired direction of joystick motion \( \beta \) (Fig. 7). In the ‘assist-as-needed’ paradigm for training, no correction force was applied on the hand, if the driver initiated a joystick motion within the cone. The only input to this algorithm is the tunnel direction \( \beta \). In our experiment, the pure forward/backward motion of the joystick was associated with the translation of the vehicle while left/right motion of the joystick was associated with the rotation of the vehicle. The forward/backward joystick position was scaled using the maximum translational velocity \( v_{\text{max}} = 0.5 \text{m/s} \) while the left/right position was scaled using maximum rotational velocity \( \omega_{\text{max}} = 30 \text{deg/s} \). Hence, given the desired control inputs \( v \) and \( \omega \), the ideal joystick movement direction was mapped to:

\[
\beta = \arctan \left( \frac{v}{v_{\text{max}}} / \frac{\omega}{\omega_{\text{max}}} \right) \quad (5)
\]

![Fig. 7. (Top) Force tunnel shown by virtual walls around nominal joystick motion direction. (Bottom) Force direction when desired direction \( \beta = 45^\circ \) and half tunnel width \( \alpha = 15^\circ \). The contour lines show the gradient of the force strength. The damping effect is not shown.]

6.2 Driving Safety

Since the robot follows commands from the joystick and it is possible that a subject can override the force field, precautions must be taken to prevent the robot from crashing into obstacles.

In this experiment, the maximum velocity of the robot can be as high as 0.5m/s. Due to the dynamic constraint, the robot cannot immediately reach any set velocity. Therefore, system dynamics must be considered. Inspired by the dynamic window approach [21], the robot pose after executing a velocity command \((v, \omega)\) is predicted and checked for collision (Fig. 8). We set the maximum translational acceleration to be \( a_v = 0.3 \text{m/s}^2 \) and the maximum rotational acceleration to be \( a_\omega = 100\text{deg/s}^2 \). After considering the specifications of the Pioneer3-DX robot and the total weight of the robot assembly and the weight of the driver. A velocity command \((v, \omega)\) is considered to be safe if, after executing \((v, \omega)\) for 1 control cycle and \((0, 0)\) for all the following cycles, the robot does not collide into obstacles. Therefore, the robot pose is estimated in 2 steps.
Fig. 8. Pose prediction after executing velocity command \((v, \omega)\). A bounding box is also shown around the predicted pose.

1) Predict the robot velocity in 1 cycle after executing \((v, \omega)\) given the velocity \((v_0, \omega_0)\) at time \(t\):

\[
v_1 = \begin{cases} v_0 + a_v \Delta t & \text{if } \frac{v-v_0}{a_v \Delta t} > 1 \\ v & \text{otherwise} \end{cases}
\]

\[
\omega_1 = \begin{cases} \omega_0 + a_\omega \Delta t & \text{if } \frac{\omega-\omega_0}{a_\omega \Delta t} > 1 \\ \omega & \text{otherwise} \end{cases}
\]

where \(\Delta t = 0.1s\) is the control cycle for Pioneer3-DX robot. Then, the robot pose in 1 cycle after executing \((v, \omega)\) is predicted by:

\[
\begin{align*}
x_c(t+\Delta t) &= x_c(t) + \frac{v_0+v_1}{2} \Delta t \cos \frac{\theta(t)+\theta(t+\Delta t)}{2} \\
y_c(t+\Delta t) &= y_c(t) + \frac{v_0+v_1}{2} \Delta t \sin \frac{\theta(t)+\theta(t+\Delta t)}{2} \\
\theta(t+\Delta t) &= \theta(t) + \frac{\omega_0+\omega_1}{2} \Delta t
\end{align*}
\]

(7)

2) Predict the robot velocity after a full stop by executing \((v = 0, \omega = 0)\), using the equations above with:

\[
\Delta t = \max \left\{ \frac{v_1}{a_v}, \frac{\omega_1}{a_\omega} \right\}
\]

(8)

Then if none of the cells inside the bounding box (Fig. 8) is occupied, the current velocity command is considered safe and is sent to the motor controller. Otherwise, a stop command \((0, 0)\) is given.

7 EXPERIMENT PROTOCOL

A ball chasing game was designed to test the system feasibility. In this game, a caregiver and some children pass a ball to each other at one side of the gymnasium and attract a child driver at the other side to the ball (Fig. 9 and 10). If the driver successfully reaches the group, the ball will be passed to him/her. The driver and the ball were separated by at least 5m at the beginning of each trial. Note that the driver and the caregiver can start anywhere behind the start lines so that the driver does not simply learn a trajectory. A Ubisense tag was installed inside the ball so that the robot always knows the ball position and can plan an obstacle-free path to the ball.

The experiment was conducted on 10 typically-developing children, 2-3 years old, assigned randomly into two groups. The training group included 5 toddlers with an average age of 2.56 ± 0.26 years and were trained to drive with the force field. The control group also included 5 toddlers with an average age of 2.66 ± 0.28 years, who drove without the force field. The parents of all children signed a consent form approved by the University of Delaware Institutional Review Board. The experiment consisted of three sets of movements on a single day.

1) Baseline: 2 trials without the force field were collected for both groups.
2) Training: Children in the training group were trained with the force field for 4 trials while children in the control group operated without the force field for 4 trials.
3) Post-training: 2 trials without the force field were collected for both groups.

Each trial ended in a minute, or if the child successfully got the ball, whichever occurred first. During each trial, the robot pose and the ball position were
Fig. 11. Mean and standard error of the minimum distance of the two groups over 8 trials. Trial 1-2 are the baseline. Trial 3-6 are the training trials. Trial 7-8 are the post-training trials. Error bar shows 1 standard error. For clarity, only half of the error bars are shown.

Fig. 12. A typical training trial of the control group. The child driver started at (5.28, 11.64) and was supposed to get the ball at (7.50, 6.00). The ball moved around with the caregiver and some peers to attract the driver. Recorded for data analysis. The minimum distance from the robot to the ball during each trial was calculated as the outcome measure to compare the performance of the two groups.

8 Results and Discussion

Figure 11 shows the minimum distance over 8 trials for both groups. During the baseline, the performances of the two groups were almost the same. With the force field turned on, the minimum distance of the training group to the ball was significantly lower than the baseline (paired t-test on the minimum distance during Trial 3 and Trial 2, \( p = 0.011 \)). This did not happen with the control group.

Figure 12 shows a typical training trial from the control group. The driver failed to join the group to play with the ball within 1 minute. Figure 13 shows a typical training trial from the training group. The child driver started at (6.52, 10.32) and was supposed to get the ball at (6.90, 3.80). (Top) A desired path was planned at the beginning of the trial to pass two moving obstacles towards the ball. (Bottom) As the robot moved forward, the right obstacle moved in the way. A new desired path was planned to the ball.
replanning was needed since the goal was always inside its square.

Toddlers in the training group also showed short-term learning due to the force field. After the training, the minimum distance was significantly lower than the baseline (paired t-test on the minimum distance during Trial 8 and Trial 2, \(p = 0.019\)) for the training group. There was no significant difference between the baseline and post-training trials for the control group (\(p = 0.804\)). In fact, all of the children in the training group got the ball in most of the training and post-training trials. Only some of the children in the control group got the ball and this was only for a couple of trials out of 8.

In this experiment, the haptic force was the same for all the subjects in the training group. The learning rate maybe better if the force is well-matched to their own neuromuscular dynamics [22].

The focus of this study is on the design and testing of a robotic mobility device to promote socialization in children. In the future, more experiments should be conducted to test for long-term learning and learning in children with special needs such as mobility impairments. In this experiment, the goal was to go to the ball. However, in real life, the same tracking system can be creatively implemented to encourage or train children with special needs to drive to his/her peers, teachers, etc. It is possible that keeping close to and playing with peers is more important than simply learning to drive towards peers. One way of doing this is to track all the peers in the play area using the tracking system and calculate each social group. Then the planning algorithm can be used for the robot to visit each group or to be attracted to the closest group when the driver wanders around and the haptic feedback can be used to train the driver to learn this behavior. Interaction with peers is the most desirable outcome measure, as well as developmental scores and psychological assessment. These will be explored in the future using this system.

9 Conclusion
This is the first study that attempts to promote socialization in children by designing a robotic mobility device and an interface using a tracking system. The powered mobility device is able to accurately localize itself in the training environment, map obstacles, plan a path to a goal, set a force field according to the executed path to train subjects to drive towards the goal, and prevent the driver from running into obstacles. The tracking system is capable of tracking multiple targets. By combining our ‘assist-as-needed’ haptic algorithm, the system can be used to train children to interact with caregivers and peers. A ball chasing game was developed as a simple, standardizable activity that would model a likely social scenario for children. System functions and feasibility were tested by a group study involving 10 toddlers. Results showed that all system modules functioned well. Children in the training group drove closer to the ball possessed by a group of peers with the help of the force field and also demonstrated short-term learning.

In the future, this device will be used to conduct more experiments on children with special needs to test for long-term effects, as well as developmental scores and psychological assessment.

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References


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