A Novel 3D Wheelchair Simulation System for Training Young Children with Severe Motor Impairments

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Abstract. Young children with severe motor impairments face a higher risk of secondary impairments in the development of social, cognitive, and motor skills, owing to the lack of independent mobility. Although power wheelchairs are typical tools for providing independent mobility, the steep learning curve, safety concerns, and high cost may prevent children aged 2 to 5 years from using them. We have developed a 3D wheelchair simulation system using gaming technologies for these young children to learn fundamental wheelchair driving skills in a safe, affordable, and entertaining environment. Depending on the skill level, the simulation system offers different options ranging from automatic control (i.e., the artificial intelligent (AI) module fully controls the wheelchair) to manual control (i.e., human users are fully responsible for controlling the wheelchair). Optimized AI algorithms were developed to make the simulation system easy and efficient to use. We have conducted experiments to evaluate the simulation system. The results demonstrate that the simulation system is promising to overcome the limitations associated with real wheelchairs meanwhile providing a safe, affordable, and exciting environment to train young children.

Keywords: Artificial intelligence, A*, gaming technology, power wheelchair, secondary impairment, severe motor impairment, simulation

1 Introduction

Independent mobility has been found to be closely related to a child's social, cognitive, perceptual, and motor development [1]. Hence, children with severe motor impairments are exposed to a higher risk for the secondary impairment in the aforementioned areas [2]. Although power wheelchairs are commonly used to provide independent mobility, children aged 2 to 5 years may find it difficult to use the wheelchairs on a daily basis. In addition, the high price of power wheelchairs may prevent the children from having access to a wheelchair at an early age.

In contrast, wheelchair simulation systems can provide a safe and affordable environment, in which children can practice fundamental wheelchair maneuvering skills at an early age. Sveistrup [3] pointed out that the wheelchair simulators can provide training in a functional, purposeful, and motivating context, which is a significant advantage over traditional training for wheelchair maneuverability. Rose *et al.* [4] demonstrated that the skills learned in virtual environments could be positively transferred to real environments. Holden [5] analyzed existing research results, which demonstrated experimental evidence that motor learning in a virtual environment may be superior to that of real-world practice.

In this study, we have employed the Unity 3D game engine [6] to develop a wheelchair simulation system. Users can control the wheelchair in three modes, namely, manual, automatic, and hybrid modes. The manual control mode gives a child full control over the wheelchair via a joystick. The automatic control mode, by contrast, utilizes our optimized A* algorithm to automatically maneuver the wheelchair through the environment. On average, the optimized algorithm takes half as much time to navigate than the un-optimized version due to the removal of redundant movements. The hybrid control mode allows for the control of the wheelchair to be shared by the human user and intelligence module. The optimized A* algorithm is also utilized, but in conjunction with an intent recognition algorithm so that the user and intelligence module can work together to control the wheelchair. When the user attempts to steer toward a goal, his/her intent is recognized by the intelligence module and a path is generated toward the intended goal. The intelligence module measures variances in the user's input to determine the probability of the user's intent to change goals. Once this probability reaches the intent threshold, the user's position, wheelchair orientation, and intent are used to determine the new goal. This novel strategy helps reduce frustration in young children by having the intelligence module handle fine motion control, while letting the child practice higher-level navigations.

2 Method

Fig. 1 shows two screenshots of our simulation system. **Fig. 1** (a) illustrates that the simulation system offers three control modes, namely, manual, automatic, and hybrid control. **Fig. 1** (b) shows a training scenario in our simulation system.

(a) Three control modes (b) A training scenario

Fig. 1. Screenshots of the Simulation System

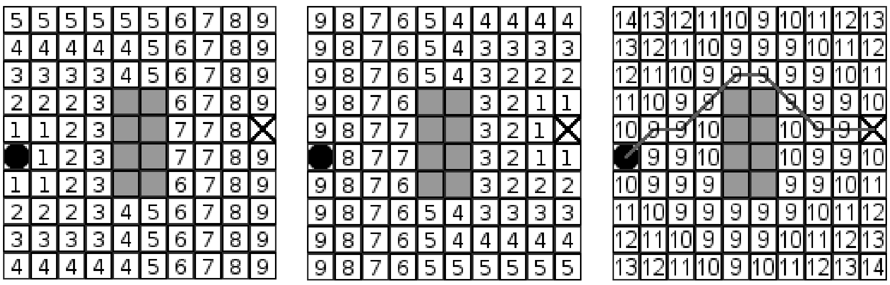
2.1 The Optimized Path Finding

Under the automatic and hybrid control modes, the simulation system needs to find a path from the wheelchair’s current position to the goal in order to assist in the smooth navigation of the wheelchair. To enable path finding, we first model the environment into a graph-like structure. Specifically, the graph structure is a grid of cells, where each cell has a position that relates to coordinates within the simulation system as shown in Fig. 2. The path considers obstacles along the way to avoid collisions. We employed the well-known A* algorithm, which is a heuristic search algorithm that is used to quickly and efficiently search through a graph structure and return the optimal path from a starting node to a goal node [7]. The heuristic function $f(n)$ used by A* is commonly defined as follows:

$$f(n) = g(n) + h(n) \tag{1}$$

where $g(n)$ defines the distance from the node n to the starting node; and $h(n)$ is the heuristic function that defines the estimated distance from the node n to the goal node.

In reality, we have found that the path generated by A* contained many unnecessary zigzag turns. We can explain this issue by using a simple example as shown in Fig. 2. The solid circle in Fig. 2 represents the starting node; the node marked with an "X" is the goal node; and the grayed out nodes are barriers, which cannot be processed. Particularly, Fig. 2 (a) to (c) show the values of $g(n)$, $h(n)$, and $f(n)$, respectively. Based on the heuristic values, a path is generated in Fig. 2 (c), which consists of 6 turning points. In fact, our simulation system contains a significantly larger number of cells than this simple example. As a result, the wheelchair turns very frequently and yields an unsmooth and uncomfortable driving experience.



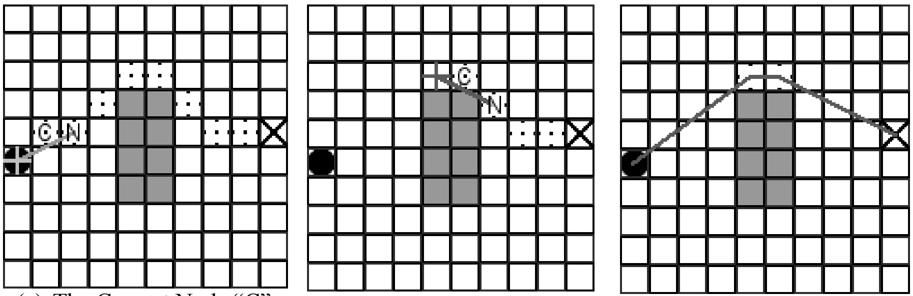
(a) Values of $g(n)$ (b) Values of $h(n)$ (c) Values of $f(n)$

Fig. 2. An Example that Illustrates the Issues of A*

To improve the quality of the generated paths, we have optimized the A* path finding algorithm such that it has been tailored to work more effectively and efficiently in our system. The optimized algorithm uses three markers during the optimization process, namely, the checkpoint marker, the current marker, and the next marker. The checkpoint marker is used to mark the last node found that will be included in the finalized path. The current marker is used to mark the current node that the algorithm is examining as it traverses the path. The next marker is used to mark the node that comes after the current node in the un-optimized path. This marker is important for determining whether the current node needs to be removed or not.

Initially, the algorithm starts by marking the beginning of the path with the checkpoint marker, marking the second node with the current marker, and marking the third node with the next marker (as shown in Fig. 3 (a)). Note that the node marked with

"+" represents the checkpoint marker, the node marked with "C" denotes that current marker, and the one marked with "N" is the next marker. After the nodes are marked, the algorithm checks to see if there are obstacles between the node marked with the next marker and the node marked with the checkpoint marker. If so, this means that the current node should be kept in the path and it is marked with the checkpoint marker. If there are no obstacles between the next node and checkpoint node, then the current node can be removed. Once the current node has been processed, the next node is marked as the current node and its child is marked as the next node. This process repeats until the goal is reached and the resulting path will have all redundant movements removed. Fig. 3 (a) shows an example of when the node marked with the current marker ("C") would be removed from the path. Fig. 3 (b) shows an example of when the node marked with the current marker ("C") would become marked with the checkpoint marker ("+"). Fig. 3 (c) shows the resulting path that has been run through the optimization algorithm. This optimization process is important not only because it generates a simpler path, but also because the optimized path can take less time to navigate compared to an un-optimized path.



(a) The Current Node "C" can be removed

(b) The Current Node "C" will become the checkpoint

(c) The Resulting Optimized Path

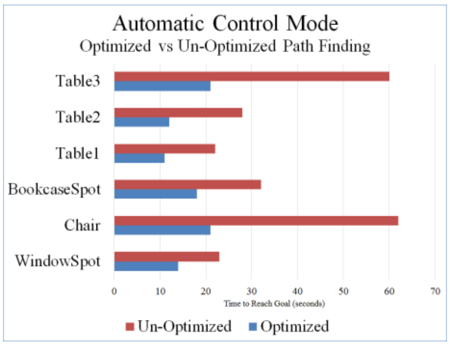
Fig. 3. The Optimized Path

2.2 Hybrid Control

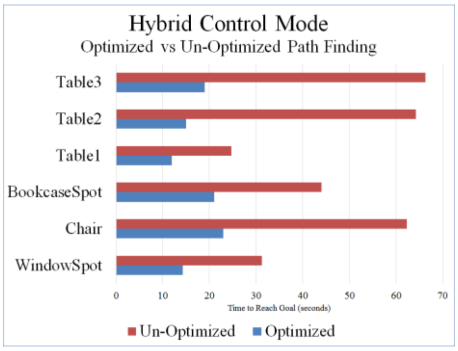
Different from the automatic control mode, where the user specifies a goal to reach, the hybrid control mode requires our simulation system to identify the user's driving intention, i.e., where the user desires to go. This is achieved by considering inputs from the user as well as the artificial intelligence module. While the hybrid control mode still utilizes the optimized A* algorithm, we have also developed an intent recognition algorithm to identify the intended goal. As the user's input from the joystick begins to oppose that of the AI module that is guiding the wheelchair, the player's input is gathered and stored for analysis. When new input is added to the dataset, the variance of the set is calculated and stored for later use. The variance of the dataset signifies the variability or spread of the data and is used for calculating the standard deviation of the set. This statistic is important because it will allow the artificial intelligence module to filter out negligible, involuntary movements of the joystick, such as slight hand tremors. After the variance is calculated, the current input from the user is compared to the dataset to see whether the input falls within the standard deviation of the data. If the input falls within the norm, it is considered negligible. Otherwise, it means that the user may want to move to a different goal and an intent counter is incremented to reflect this. As the intent counter increases, it will eventually surpass the intent threshold. When this happens, the artificial intelligence module utilizes the input from the user to determine where the user is intending to go. To do so, the user's input is first converted into an angle that is relative to the wheelchair. For example, if the user's input is to the sharp right, the angle would be 90 degrees. Next, a list is generated that contains an angle for each possible goal in the room. The angle is calculated between the wheelchair's orientation and the respective goal. Then, each angle in this list is compared with the input angle. The object from the list that has the closest angle to the input is identified as the new goal. After the user's intention has been recognized, the AI module will generate a new path from the wheelchair to the new goal by utilizing the optimized A* algorithm.

3 Experiments

We conducted experiments to evaluate the performance of the simulation system, specifically for the automatic and hybrid controls. The data was collected over three trial runs for each goal in each control mode.



(a) Results for the Automatic Mode



(b) Results for the Hybrid Mode

Fig. 4. Experimental Results

3.1 Performance Evaluation under the Automatic Control

To ensure the fairness of the evaluation, the starting point of the wheelchair was fixed in each experiment. We measured the time required to reach each goal using the traditional A* algorithm and our optimized A* algorithm. There were six possible goals in the training scenario, namely, tables 1 to 3, a sofa, a bookcase, and the window. As shown in Fig. 4 (a), the traditional A* generated paths that took twice as much time to traverse compared to the time required by the optimized A* algorithm.

3.2 Performance Evaluation under the Hybrid Control

The experimental procedure was the same as that in the automatic control mode. The difference was that the user did not simply choose a goal object to navigate to, but instead, the simulation system tried to identify the driving goal first. As we are still collecting data from children with severe motor impairments, a healthy adult conducted the experiment in this study. We expect that children with severe motor impairments may have poorer performance. Fig. 4 (b) shows the experimental results, which illustrate that if the traditional A* algorithm were used, even the healthy adult would find it difficult to manipulate the simulation system. In contrast, if the optimized algorithm was used, the performance was largely improved.

4 Conclusion

In this study, we presented a novel 3D wheelchair simulation system for training young children with severe motor impairments. Besides the manual control mode, we have developed optimized AI algorithms to support the automatic and hybrid control modes. The experimental results demonstrated that our system is a promising platform to provide a practical, safe, affordable, and exciting environment to train young children.

Acknowledgement

This work was supported by the Oklahoma Center for the Advancement of Science and Technology (OCAST HR12-036)

References

1. C. B. Ragonesi, X. Chen, S. Agrawal, and J. C. Galloway, "Power mobility and socialization in preschool: a case study of a child with cerebral palsy," Pediatr Phys Ther, vol. 22, pp. 322-9, Fall 2010.
2. R. Kermoian, "Locomotor experience and psychological development in infancy," in Pediatric Powered Mobility: Developmental Perspectives Technical Issues Clinical Approaches, ed Arlington, VA: RESNA, 1997, pp. 7-21.
3. H. Sveistrup, "Motor rehabilitation using virtual reality," J Neuroeng Rehabil, vol. 1, p. 10, Dec 10 2004.
4. F. D. Rose, E. A. Attree, B. M. Brooks, D. M. Parslow, P. R. Penn, and N. Ambihaipahan, "Training in virtual environments: transfer to real world tasks and equivalence to real task training," Ergonomics, vol. 43, pp. 494-511, Apr 2000.
5. M. K. Holden, "Virtual environments for motor rehabilitation: review," Cyberpsychol Behav, vol. 8, pp. 187-211; discussion 212-9, Jun 2005.
6. Available: http://unity3d.com/
7. P. E. Hart, N. J. Nilsson, and B. Raphael, "A Formal Basis for the Heuristic Determination of Minimum Cost Paths," Systems Science and Cybernetics, IEEE Transactions on, vol. 4, pp. 100-107, 1968.