User Intent in a Shared Control Framework for Pedestrian Mobility Aids

Glenn Wasson*, Pradip Sheth†, Majd Alwan‡, Kevin Granata††, Alexandre Ledoux†, Cunjun Huang†
{ wasson | pns7q | ma5x | kpg8n | ledoux | ch8me } @virginia.edu
* Computer Science Department, University of Virginia
† Department of Mechanical and Aerospace Engineering, University of Virginia
‡ Medical Automation Research Center, University of Virginia
†† Department of Engineering Science and Mechanics, Virginia Tech

Abstract

This paper presents a novel approach to infer navigational intent of the user of a walker, based on measuring forces and moments applied to the walker's handles. While there are many types of "intent" that could be inferred for a given user action, the experiments conducted here focused on the determining user's navigational intent, i.e. their desired heading. Our experiments used two 6-DOF force/moment sensors on the walker's handles and a digital motion capture system to correlate applied force with actual motion. Results revealed that the intent to turn, represented by changes in the heading angle, highly correlates with the overall turning moment around the vertical axis as well as the side forces applied by the user. Other force/moment components reveal additional information, such as support needs. The inferred user intent will be incorporated into a passive shared steering control system for the walker.

1. Introduction

One of the most important factors in quality of life for the elderly is their ability to move about independently. Not only is mobility crucial for performing the activities of daily living (ADLs), but for maintaining fitness and vitality. Lack of independence and exercise can lead to a vicious cycle. Decreased mobility due to a perceived lack of safety can cause muscular atrophy and a loss of the feeling of empowerment (both of which contribute to further decreased mobility).

We are developing a pedestrian mobility aid for elderly users. The primary goal of this work is to augment a user's ability to walk, not replace it. In this sense, we are seeking to help those who *can* and *want to* walk perform this task more safely and easily. As the world's elderly population rises (doubling in the US alone in the next 30 years [3]) and the cost of healthcare skyrockets (to $4 trillion over the same period [1]), robotic mobility aids increase in importance.

This work proposes a shared control framework for a wheeled walker, which provides situation-dependent synthesis of control signals from both human and machine. Our work concentrates on walkers because they are the most commonly used mobility aid, except for the cane [6]. Our framework attempts to ascertain user intent, that is, the user's desired goal as opposed to their actual moment-to-moment control input. Based on this goal and relevant safety concerns, the walker may attempt to influence the motion of the walker-human system. Our control framework must synthesize these signals in such a way that assists the user, but does not jeopardize their stability. The remainder of this paper is organized as follows. Section 2 describes the shared control framework while section 3 describes our approach to measuring user intent. Section 4 discusses related work and section 5 describes the results of our experiments. In section 6 we draw our conclusions.

2. Shared Control Framework

Our shared control framework is based on the notions of passive robotics and *user intent*. Passive robotics means that the walker's control system is not thought to be continuously active nor can it provide motive force. It is capable of controlling only the angle of the walker's front wheel and it will only attempt to bias that angle in response to concerns about the ease and safety of the user's movement. When no such concerns arise, the control system is completely passive, allowing the user full control of the walker. User intent reflects the control system's estimation of the human user's desired goal. The gap between the user's intent and the human-walker system's actual motion (based on the force placed on the walker frame by the user) is where the control system has an impact. For example, consider a human pushing a walker through a doorway that is narrow relative to the width of the walker frame. Slight errors in the control of the walker frame by the user may cause one of the wheels to impact the side of the doorway. This can result in a twisting motion of the entire frame, destabilizing the user and possibly leading to a fall. If the walker's control system could "understand" that the user's intent was to go through the doorway, it could bias the movement of the walker frame toward this goal. If the control system is successful, it is hoped that the user will not necessarily be aware that they did not perform the maneuver themselves. A block diagram of the walker control system architecture is shown in Figure 1.

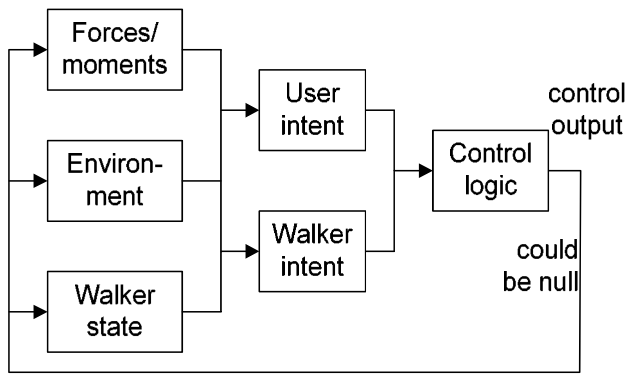

Figure 1. Walker Control System Architecture

The control system determines user intent from three factors, the forces and moments placed on the walker frame by the human user, the current state of the environment as measured through sensors (e.g. to determine possible user goals) and the state of the control system (to reflecting historical data). Similarly, the "walker intent", i.e. the bias that the control system wishes to introduce into the walker's wheel angle, is based on the same three variables. However, the environment and state data are now used to detect safety hazards to the path indicated by the force data. The control logic then must balance the notion of the user's intent with the control system's own intent of keeping the user safe and produce a control signal to the walker frame's wheel.

3. Approach to User Intent

"User's intent", in the context of a shared control framework for a robotic walker, is a complex multi-tier concept. The navigational intent of young healthy users of the walker will be reflected by the forces and moments they apply to the handles of the walker to provide the necessary propulsion and steering. This is due to the fact that these users correctly perceive the environment, and apply motor controls that are accurately executed to attain these goals. However, when the user is an older adult suffering from some condition that affect their perceptual or motor control abilities, the forces applied to the walker's handles may no longer reflect the user's true intent. In this case, if the walker is to infer the user's intent, it must also take into account the environmental context (e.g. the distance to obstacles detected by the perception system) and the historical state of the walker. In addition, user specific conditions, such as consistently applying more downward force on the left hand grip than the right hand grip must also be factored into the inference process. Perceptual information can help identify possible passable paths or goals. The environmental context distinguishes between obstacles that the user may be trying to approach to perform a certain activity (such as sinks, desks, tables and closed doors they could open) from high collision risk obstacles that should be avoided. The (historical) state of the walker includes the velocity and direction. It is believed that contextual distinction between obstacles can be gleaned from both the historical state of the walker and the perception of the environment, for example a slower approach to an obstacle possibly indicates that the user is aware of its presence and that the intent is to dock, whereas a faster approach to an obstacle possibly indicates that the user is unaware of its presence, and hence there is a higher collision risk. In these cases, the control logic would intervene to divert the walker from the obstacle or safely guide the walker into position next to the obstacle. Moreover, disagreement between user's real intent and walker's action may also be sensed by measuring the current withdrawn by the steering motor, in addition to measurements of handle forces and moments. However, if the walker moves in a way that, while safe, is inconsistent with the user's perceived force input, the response measured at the handles may be completely different than when the walker moves as the user believes it should. In other words, the mapping between forces applied to the walker and the user's navigational intent may not be the same when the walker is active as when it is passive. The work carried out thus far focuses the attention on inferring user's navigational intent in the case of a passive walker. The results will be used in incrementally building up the walker estimation of a user's intent.

4. Related Work

The "user's intent" concept, required for the shared control design paradigm discussed here, was introduced in [8] and [10] . Similar concepts have also been encountered in the assistive robotics literature employing various sensing techniques. However, the scope of this review is limited to published research work that used the measurement of forces and/ or moments for the inference of user's intent. A walker that provides guidance implemented on top of a commercial omni directional mobile robot platform equipped with two force-sensing handlebars that play the role of a haptic interface to the system is described in [8]. Each handle bar is equipped with two independent force sensing resistors, one before and one after the gripper handle, and measure the force only along the handle bar's axis. The force readings are then transformed to planar translational and rotational velocities of the platform. The intent is intuitively translated as follows: a forward push on both handles results in forward motion, a differential push-pull combination results in rotary motion, and a pull on both handlebars stalls the robot. User-intended motion is determined through a user-specific motion model that represents a mapping of force sensor readings recorded to trajectory commands. The model is used to compute the user's desired translational and rotational velocities from force input data to drive and steer the platform. PAMM is another mobility aid based on a cane supported by a mobile platform with non-holonomic drive capabilities that is designed to support and guide a person using ceiling signposts distributed in the environment [4]. The cane moves in response to the forces and torques applied to a force/torque sensor. The inference of the user's intent requires distinguishing forces and torques applied to the handle for support from those applied by the user to indicate directional intent to control both the steering and propulsion of the cane. Currently the research team is studying learning algorithms to identify the support forces from training data collected from an individual user.

5. User Intent Experiments

To identify user navigational intent, an experiment using able-bodied human subjects is underway and the initial data are reported in this paper. The goal is to determine navigational intent from measured forces and moments recorded at the handles of the walker. Specifically, it is hypothesized that the forces and moments recorded from the walker handles will correlate with the intended direction and rate of movement of the walker. Subjects include young-healthy (college-age) and active elder adults (greater than 50 years of age). Future research will investigate subject populations that require use of assistive devices. The walker is a standard three-wheel commercially purchased walker without any modifications, except for those required for the installation of the load cells. The motion model (walker/user) is computed from the test data by using reflective markers and the Vicon system 612 connected to six 120Hz video cameras [8]. The Vicon system creates a 3-D motion model by using the positions in the (x-y-z) space of particular real points (markers) placed on the human and the walker frame. In this model, seven markers represent the walker and twelve are used for the human body. A capture from the video of a trial and its corresponding kinematic model (skeleton form) are shown at the Figure 2.

The motion kinematics data can be complemented by the kinetic data and also the corresponding force/ moment time traces. These values can be obtained by using two force plates at the ground level, which provide the ground reaction forces, and two six-axis force and moment sensors from *ATI Industrial Automation* (US120-160) mounted in the left and the right handle respectively, as shown in Figure 5.

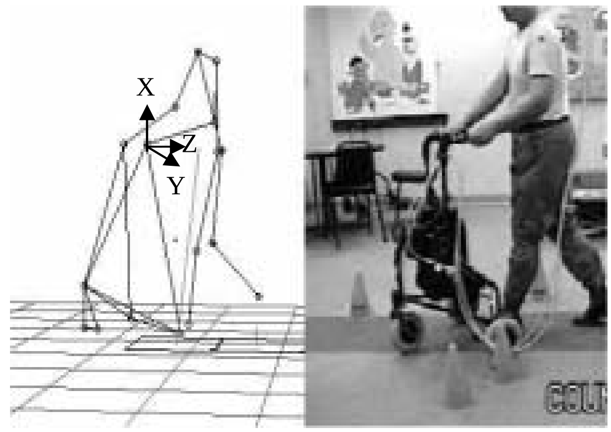

Figure 2. Walker/User kinematics model represented by Vicon Motion Capture System

These sensors provide the load/moment transfers between the walker and the user. The initial data collection trials have focused on the elemental tasks: go straight (St), turn left 45° (L), turn left sharp 90° (LS), turn right 45° (R), turn right sharp 90° (RS), and rearward (Rw). With the position of each marker of the walker in the x-y-z coordinate system provided by the Vicon system, the radius of curvature r and the angle θ created between two successive positions of the walker are computed from a simple kinematic model of a three-wheel walker adapted from [1] and shown in Figure 3.

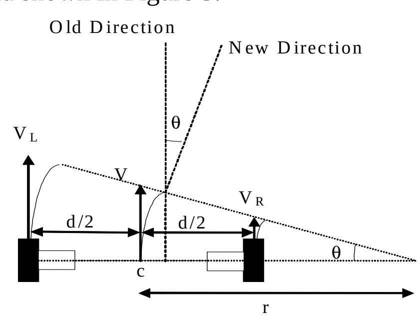

Figure 3. Simple kinematic model to compute *r* and *θ*

Assume different linear velocities at the right and left wheels, V_R and V_L respectively, and that $V_L > V_R$. After a short period of time, equal to the sampling time T_S, the right wheel would trace an arc of length $V_R .T_S$; likewise, the left wheel would trace an arc of length $V_L .T_S$. If the sampling time is small (corresponding to 120hz in our case), the linear velocities of both wheels can be assumed to remain constant during the interval, and thus the wheels would trace arcs from circles centered on the turning center, as illustrated in figure 3. The equations describing the change of direction are:

$$\theta = \frac{V \cdot T_S}{r} \quad (1), \qquad r = \frac{V \cdot T_S}{\theta} \quad (2)$$

where r is the distance between the center of the wheels' axle and the instantaneous center of turning. Further:

$$\theta = \frac{V_R \cdot T_S}{r - \frac{d}{2}} = \frac{V_L \cdot T_S}{r + \frac{d}{2}} \quad (3)$$

where d is the distance between the two driving wheels. By substituting equations (2) in (3),

$$V_R = V - \frac{d \cdot \theta}{2T_S} \quad (4), \quad V_L = V + \frac{d \cdot \theta}{2T_S} \quad (5)$$

The change in direction during one sampling period from Equations (4) and (5) is:

$$\theta = (V_L - V_R)\frac{T_S}{d} \qquad (6)$$

The linear velocity of the center of the wheels' axle is given by:

$$V = \frac{V_R + V_L}{2} \qquad (7)$$

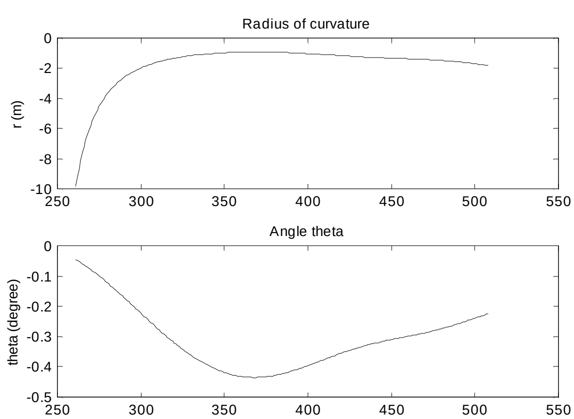

Figure 4. (r, θ) values for a left sharp turn (LS)

This model is valid if T_s is short, such that the change in the linear velocity of the vehicle is negligible. The computed (r, θ) associated with a motion trajectory for a left sharp turn captured by the Vicon system is presented in Figure 4.

Note that the radius of curvature undergoes a quick change from a large value to a relatively small value that remains almost constant during the turn. The corresponding variation in angle θ is shown in the bottom half of the figure. Because the radii of curvature can indeed shift from very large values in positive or negative sense (indicating a somewhat straight motion trajectory) to small values and hence exhibit sharp changes, the force/ moment traces are correlated with the relatively "smoother" trajectories of θ in the analyses presented in this paper.

For the interpretation of force/ moment directions, note that in Figure 2 the X-axis is vertically up, the Y-axis is sideways and the Z-axis is positive toward the rearward direction of the walker. These same axis orientations apply to the load cell in each of the two handles.

Thus, F_{XL} represents vertical left-hand force, F_{YL} represents sideways left hand force, and F_{ZL} represents fore-aft left hand force. The corresponding moments M_{XL}, M_{YL}, M_{ZL} represent the *local* left handle moments about the three axes. M_{XL} represents the local left-hand grip moment about the vertical axis, M_{YL} represents the local left-hand moment about the Y-axis indicating a moment due to the vertical support force on the left-handle, while M_{ZL} represents the twisting moment or torque applied by the left-hand grip onto the handle. The subscript L can be replaced by R to symbolically represent the right handle. For the left and the right handles, therefore, a total of twelve channels of data are acquired (six at each handle). In a previous study [3], a single 6-axis load cell was mounted midway between the two handles and a composite or an overall resultant of three force components and three moment components were experimentally acquired for correlation with the walker's trajectory. With the two load cells, one in each of the two handles, more data and more information regarding the *localized* gripping forces/ moments exerted by each hand are available. This additional information, which cannot be elicited from a single load cell or single axis force sensors (such as those employed in [3][4]), may include the user's support needs in the X direction on the two handles, the desire to brake or reduce speed, or certain user specific information such as negotiating a turn by modulating side-way forces in the Y direction on the two handles instead of or complementing the modulation of the fore/aft Z direction forces on the two handles to achieve a turn. Correlation analysis was employed to determine the relationship between the forces/ moments acquired from the two load cells and the computed angle changes θ of the walker. The twelve channels of data were also consolidated to a point midway between the handles in a resultant 6-component force/ moment vector to characterize more global effects of the individual handle forces/ moments. Correlation Coefficients were calculated in this analysis using functions built into Microsoft EXCEL. Correlation Coefficient is defined as the result of the division of covariance of any two signals over the standard deviation of each signal.

The consolidated 6-component resultants at the center and the separate force/ moment data from the two load cells were used to compute the Correlation Coefficients to the θ *time-series*. For the resultant force/ moment, the overall turning moment M_X traced in Figure 9 has the highest correlation coefficient (Figure 6). We also note that there is a relatively high correlation with the side force F_Y indicating that the user is applying side forces to turn the walker. While the support force, F_X, is also highly correlated, it is orthogonal to the walker's plane of travel. Although F_X is not a component of navigational intent, it may contain useful information about the user's continuing support needs while negotiating the turn. The two load cells, the turning moment on the left handle M_{XL}, the side force on the left handle F_{YL}, the bending moment on the left handle M_{YL}, and the turning moment on the right handle M_{XR} are the four largest correlation coefficients in the 12 signals shown in Figure 7. Figure 8 depicts the time variation of the left handle turning moment in relation to the corresponding θ .

Statistical consolidation of these data over a broader spectrum of test subjects, and also including the shared control of a motorized front caster as a test parameter, are currently underway in our lab. This consolidation is expected to guide in the design of the controller logic, including a dynamic model of the walker. Further, applicability of these data for training or customizing user-specific parameters of the walker and the controller is also under investigation.

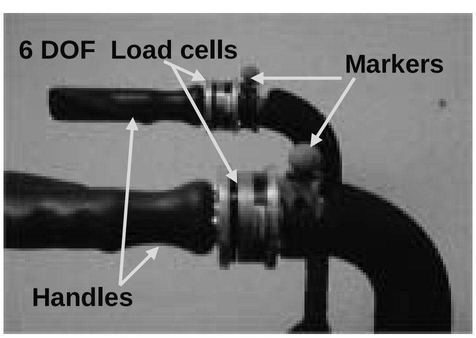

Figure 5. Load cells for measurement of user forces and moments

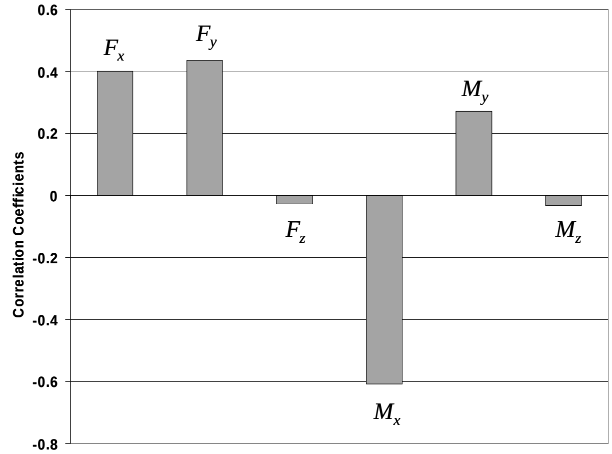

Figure 6. Correlation Coefficients of 6 resultant force/ moment components to θ

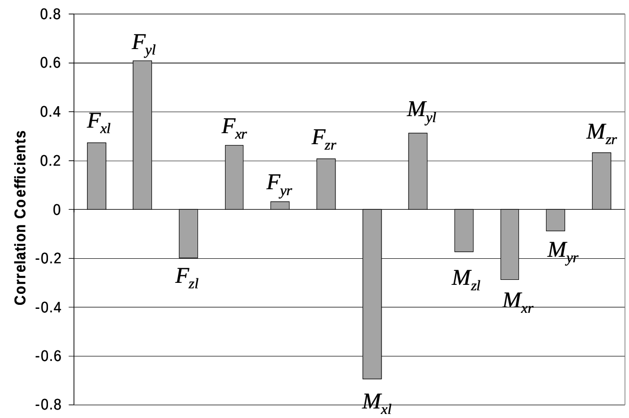

Figure 7. Correlation coefficient of the 12 force/ moment components from two load cells to θ

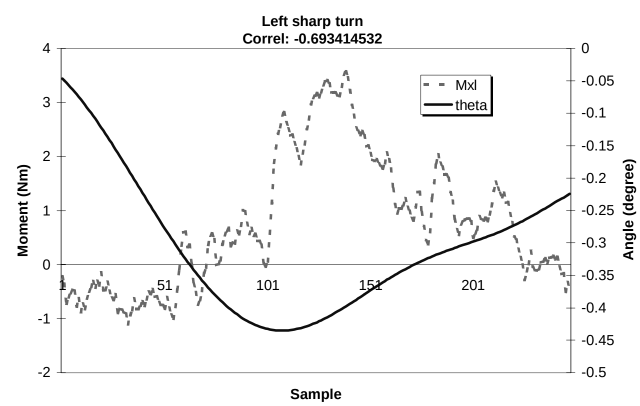

Figure 8. Turning moment in left handle M_{YL} vs. θ

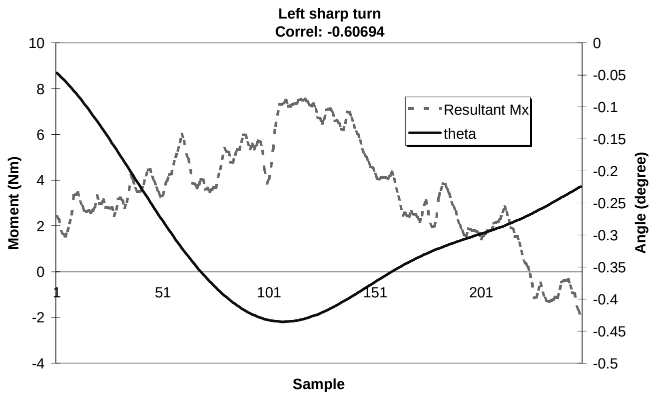

Figure 9. Overall walker turning moment M_X vs. θ

6. Conclusions

For a shared control of a mutually collaborative system, such as a human supported by a walker, the controller must use integrated information from a number of sources, including the intent of the user. A testing program and the associated test protocol are presented here for the collection and analysis of the user intent data. A digital motion capture system and two independent, 6 dof load cells, one each in each of the two handles, is utilized for test data collection. A simple kinematic model of the walker is utilized to post process the motion capture data and time-series. Correlation Coefficients are computed to ascertain the strength of correlations between the various handle forces/ moments and the motion trajectory. The two load cells provide detailed localized information, much more than a single 6 dof load cell for overall resultants. The turning intent is strongly correlated with the turning moment, while it is also noticed that the turning moment is created by the application of side forces—perhaps an inefficient way to provide such moment when the actual kinematic constraints of the walker used in the tests. The support force and moment variations during turning show a strong correlation as well, indicating a strong cross coupling between the navigational intent related forces/ moments and the support force/ moment. These data and tests are being further developed for use in the design of a shared controller.

7. Acknowledgement

This research was funded by the National Science Foundation (NSF award ID 0004247). The authors would like to thank the staff at the Gait and Motion Analysis Lab, Kluge Children's Rehabilitation Center at the University of Virginia, where experiments are conducted.

8. References

[1] Alwan, M. 1997. Planning and Navigation of an Autonomous Wheelchair. Ph.D. Dissertation, University of London, Imperial College of Science, Technology, and Medicine.

[2] Ciole R. and Trusko, B. 1999. HealthCare 2020: Challenges for the Millennium, Health Management Technology, August 1999: 34-38.

[3] Danek, K. 2002. The First Steps Toward Automatic Aid: An Exploration into the Feasibility of Intuitive User Control. Mechanical Engineering Senior Thesis, University of Virginia.

[4] Dubowski, S., et al. 2000. PAMM – A Robotic Aid to the Elderly for Mobility Assistance and Monitoring: A “Helping Hand” for the Elderly, Proceedings of the IEEE Conference on Robotics and Automation: 570-576.

[5] Kramarow, E., Lentzner, H., Rooks R., Weeks, J. and Saydah S. 1999. Health and Aging Chartbook, Health United States, National Center for Health Statistics. http://www.cdc.gov/nchs/data/hus99cht.pdf

[6] Morris, A.. Donamukkala, R., Kapuria, A., Steinfeld, A., Mathews, J., Dunbar-Jacob, J. and Thrun, S. 2003. A Robotic Walker That Provides Guidance, to appear in the Proceedings of IEEE International Conference on Robotics and Automation (ICRA ’03).

[7] Number of Persons Using Assistive Technology by Age of Person and type of Device. 1994. National Center for Health Statistics. http://www.cdc.gov/nchs/about/major/nhis_dis/ad292tb1.htm

[8] Vicon612 Technical Specifications. http://www.vicon.com/main/downloads/VMS009S_60_TechSheet.pdf

[9] Wasson, G., Gunderson, J., Graves, S., and Felder, R. 2001. An Assistive Robotic Agent for Pedestrian Mobility. International Conference on Autonomous Agents: 169-173.

[10] Wasson, G., Gunderson, J., Graves, S., and Felder, R. 2001. Effective Shared Control in Cooperative Mobility Aids, Proceedings of the Florida Artificial Intelligence Society (FLAIRS ’01): 509-513.