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iChair: Intelligent Powerchair for Severely Disabled People

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***Abstract*—Development is underway on an intelligent powerchair (iChair) for people with severe disabilities. Research is focused on developing the software that gives a power chair equipped with computing hardware and state-of-the-art sensors, and the intelligence to assist people who cannot use their arms or legs or eyes, to live a high-quality, independent lifestyle.**

After a brief overview in the introduction we describe how the iChair was conceived and the various advancements it has undergone to optimize the human computer interaction model (Sec. II). In order to accomplish its tasks when assisting quads with their activities of daily living (ADLs), the iChair is programmed with the following capabilities: localization (Sec. III), object detection & tracking (Sec. IV), object classification (Sec. V), event anticipation (Sec. VI), and autonomous navigation (Sec. VII). Finally we conclude (Sec. VIII) our discussion of the iChair with an optimistic look at a future where quads are on a level playing field with their able-bodied peers, to make a significant contribution to society and maximize their human potential.

Keywords: Smart wheelchair, Co-robot, Autonomous navigation

I. Introduction

People who cannot use their arms or legs or eyes (quads), whether it be due to an accident or disease, rely on motorized wheelchairs for their mobility needs. Since quads cannot use a traditional joystick to navigate their wheelchairs they use alternative control systems like head joysticks, chin joysticks, sip-n-puff, and thought control. In many cases power wheelchair users have difficulties with daily maneuvering tasks (Fig. 1) and would benefit from an automated navigation system. Mobility aside, quads are heavily reliant on their caregivers for eating and drinking, handling items, and communicating with others, especially in large groups.

To accommodate the population of individuals who find it difficult or impossible to operate a motorized wheelchair, several researchers have used technologies originally developed for mobile robots to create smart wheelchairs (see [1], [2] for historical review). A smart wheelchair typically consists of either a standard power wheelchair base to which a computer and a collection of sensors have been added or a mobile robot base to which a seat has been attached [3]. Pineau et al. 2011 argue that the transition to wheelchairs that cooperate with the user is at least as important as that from manual to powered wheelchairs possibly even more important since this would mark a paradigmatic rather than merely a technological shift [4].

II. Human-iChair Interaction

The objective is to develop an intelligent power chair for severely disabled people (iChair) to help them with activities of daily living (ADLs). There are many challenging tasks

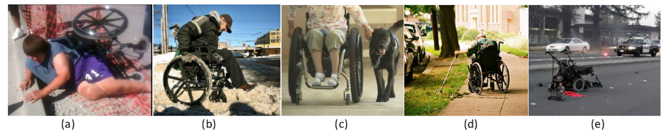

Fig. 1. Navigation problems for wheelchair users: (a,b) Accidents with manual navigation for visually impaired wheelchair users; (c) Service-dog for navigation support; (d) Navigation with cane holder; (e) Accident happened due to poor navigation.

in developing the iChair system. One of these challenges is to build an efficient human-iChair interaction model that all types of disabled people can feel comfortable using. The next challenge is to design it to work for any make of motorized wheelchair. This means the entire robotic system is mountable on any wheelchair a quad would use, and removable for maintenance and travel. One of the most sophisticated features of the iChair is that disabled people can interact with the iChair through intelligence and the slightest head movements. Leaman became a quad after a spinal cord injury in 1996, and has been designing assistive technology (AT) to reduce barriers, improve quality of life, and overall efficiency for quads using power wheelchairs ever since.

In 1998 the first iteration of what was to become the iChair, the Gryphon Shield, was born at NASA's Marshall Space Flight Center. The primary motivating factor for the Gryphon Shield was to have rearview capability, since most motorized wheelchair users, especially those with quadriplegia, are unable to turn around to see what is behind them. The first Gryphon Shield consisted of a small voltage converter that supplied power from the wheelchair's batteries (24V) to a black and white analog video camera (5V), and a 2 inch LCD display (12V). Subsequent advances came with the addition of a laptop computer and a larger LCD display. By 2007 the system was recognized as one of the top 25 inventions of the year by the History Channel and the National Inventors Hall of Fame [6]. The next advancement included storage space and a solar panel powered trickle charge system. By 2010, however the system had grown too large, and heavy for the wheelchair base, and had become difficult to maintain.

From 2011-2014 a new system was designed using 3D CAD, to be lightweight, functional, and easily removable for travel and maintenance. The current Human-iChair Interaction model (Fig. 2 & 3) includes the Head Tracking Mouse [7], that follows the user's head movements, and gives users the ability to mouseclick by dwelling on a particular location on the screen for a few seconds. This assistive technology is plugged in via USB cable to the laptop, which in turn is attached to the motorized wheelchair with the Mount-n-Mover [8].

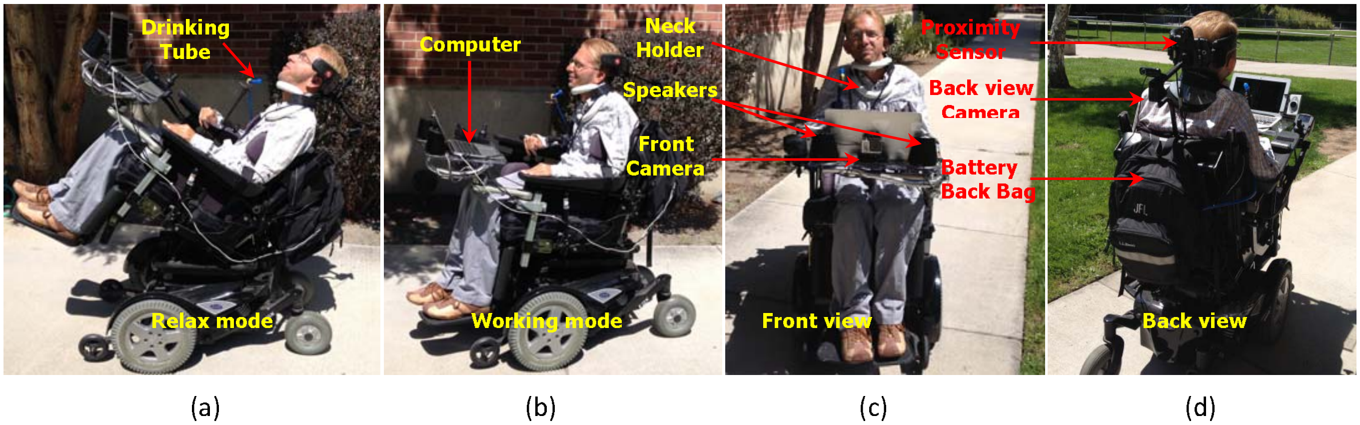

Fig. 2. Current iChair in action: (a) iChair in relax mode; (b) iChair in working mode; (c) Front view of the iChair; (d) Back view of the iChair. The iChair is equipped with various sensors including front and back cameras, proximity sensor, computer and speakers to help user to easily interact with the environment. The user operates the iChair by head movement using a proximity sensor from Assistive Switch Laboratories (ASL) [5]. This feature provides a vital role in allowing users, who are paralyzed from the shoulders down, to control the movement of the chair efficiently.

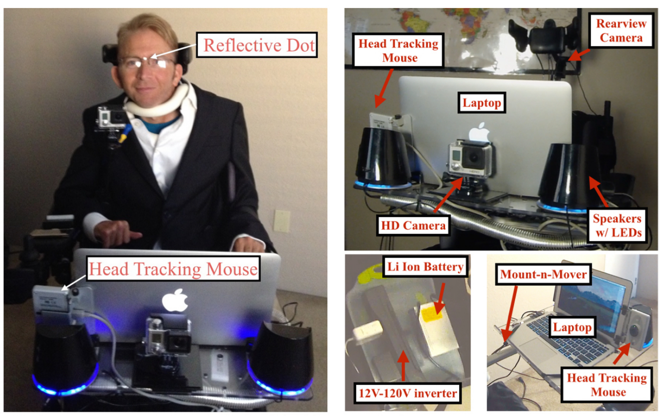

Fig. 3. Invacare FDX serves as the wheelchair foundation and the Human-iChair Interaction Components include: Laptop, Head tracking mouse, Forward camera, Speakers with LEDs, Mount-n-Mover, Rearview camera, Lithium-ion battery, Power adapter, Voltage converter. This system enables users to interact with the iChair using intelligence and the slightest movement of their head.

A. *Efficiency improvement*

By default a quad is bedridden because without assistance from people and/or technology there is no way to get up. That being said, with the right combination of human and technological resources, a quad can have an extremely rich life and make a major contribution to society. With the right tools and the right attitude you can accomplish anything, a philosophy we hope to share with people who have just experienced the onset of disability. For the purpose of quantifying the efficiency of a human being we suppose that all ADLs (Table I) fall into three categories: Survival (S), Quality-of-life (Q), and Maximize your potential (M). Without assistive technology quads can only perform survival related ADLs, except watching television. Even with AT quads will always need some human assistance, especially for S and Q ADLs, but the burden on caregivers is much less. AT for quads is usually an 'all-or-nothing' tool that either gives the person the ability or not. With the right combination of AT quads can spend 6-8 hours a day, depending on commute time, pursuing employment, maximizing their potential. With the iChair, users will be able to perform tasks unimaginable a few decades ago.

TABLE I. ACTIVITIES OF DAILY LIVING (ADLS) *on a typical day for a quad. Columns 2 and 3 indicate approximate start and stop times. Column 4 shows the percentage of assistance a quad needs to perform these ADLs. Column 5 shows the percentage of assistance needed for each activity for an iChair user. The types (Column 6) of ADLs fall into three categories: Survival (S), Quality-of-life (Q), and Maximize your potential (M). Without AT like the iChair Quadriplegics are destined to perform only Survival ADLs, and those only with the assistance of a caregiver.*

Activity	t_{start}	t_{end}	w/o (%)	w/ (%)	type
Unlock door	08:00	08:01	100	0	S
Prepare tea	8:01	08:05	100	100	S
Drink tea	08:05	08:10	100	0	S
Exercise	08:10	8:40	100	100	Q
Bladder Care	8:40	8:50	100	100	S
Bowel care	8:50	9:00	100	100	S
Shower	9:00	09:30	100	100	Q
Transfer to bed	09:30	09:40	100	100	Q
Get dressed	09:40	10:00	100	100	Q
Transfer to chair	10:00	10:10	100	100	Q
Prepare breakfast	10:10	10:30	100	100	S
Eat breakfast	10:30	10:45	100	0	S
Cleanup kitchen	10:45	10:55	100	100	S
Open door	10:55	10:56	100	0	S
Go to busstop	10:56	11:00	100	0	M
Ride bus	11:00	11:30	100	0	M
Work with AT	11:30	13:00	100	0	M
Go to busstop	13:00	13:05	100	0	M
Ride bus	13:05	13:28	100	0	M
Open door	13:28	13:30	100	0	S
Prepare lunch	13:30	13:45	100	100	S
Eat lunch	13:45	13:55	100	0	S
Cleanup kitchen	13:55	14:00	100	100	S
Open door	14:00	14:01	100	0	S
Go to busstop	14:01	14:05	100	0	M
Ride bus	14:05	14:30	100	0	M
Work with AT	14:30	18:30	100	0	M
Go to busstop	18:30	18:35	100	0	M
Ride bus	18:30	18:59	100	0	M
Open door	18:59	19:00	100	0	S
Prepare dinner	19:00	19:30	100	100	S
Eat dinner	19:30	19:40	100	0	S
Cleanup kitchen	19:40	19:45	100	100	S
Transfer to bed	19:45	19:55	100	100	Q
Exercise	19:55	20:45	100	100	Q
Undress	20:45	20:55	100	100	Q
Bladder care	20:55	21:00	100	100	S
Watch TV	21:00	22:00	0	0	Q
Sleep	22:00	08:00	0	0	S

III. LOCALIZATION

Since the iChair needs to safely navigate on roads and sidewalks, it is required that the localization and navigation accuracy be within a range of a few centimeters.

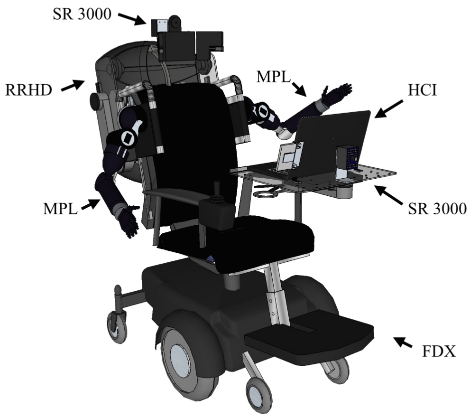

Fig. 4. 3-D sketch of the iChair 2015. Labels indicate various components, including 2 Swiss Ranger 3000 (SR 3000) 3-D cameras, the human computer interface (HCI), the retractable roof & heads up display (RRHD), and two modular prosthetic limbs (MPL), mounted onto an Invacare FDX Power wheelchair.

The iChair is equipped with two Swiss Ranger 3000 [9] 3-D cameras mounted on the front and rear of the chair (Figure 4) and an integrated inertial measurement unit (IMU), the MicroStrain IMU 3DM-GX3. We evaluate our localization algorithm with indoor map building, scanning our lab. The range data and the iChair's pose (position and orientation) are used as the inputs of the SLAM (Simultaneous Localization and Mapping) algorithm [10], [11]. We conducted two experiments: SLAM using pose from the wheel encoders only; and another one using pose estimated using an extended Kalman filter (EKF).

A. EKF for Accurate Localization of the iChair.

The EKF is implemented using realtime sensory data on the iChair and we test localization accuracy both indoors and outdoors. The RTK GPS [12] can output the position of the chair with 2cm accuracy. The update frequencies of the robot wheel encoders and IMU are more than 20Hz, therefore, we set the update frequency of the Kalman filter to 18Hz to make sure that the filter can update all data information from these sensors.

We define an inertial frame $\mathcal{I} : XYZ$ on the ground with the X-axis along the traffic flow direction and the Z-axis vertically upwards. The IMU is mounted around the center of the robot, and we use Euler angles $\Phi = [\phi_r \ \varphi_r \ \theta_r]^T$ to define the vehicle's attitude, where ϕ_r is the roll angle, φ_r pitch angle and θ_r yaw angle. We define a two-dimensional position vector of the iChair center in $\mathcal{I}$ as $q_r = [x_r \ y_r]^T$. We denote the yaw rate of the iChair as ω_θ.

To estimate the iChair's attitude, we use the IMU measurements. We denote the angular rate measurements of the IMU as $\Omega = [\omega_x \ \omega_y \ \omega_z]^T$ in the IMU frame. The kinematic models describe the relationship between the attitude vector Φ and the IMU gyro measurements Ω. Now, the dynamic motion of the iChair which is incorporated with IMU motion is modeled as

$$\begin{cases} \dot{x}_r = v_r cos(\theta_r) - \phi_r v_r sin(\theta_r) + \frac{T}{2} a_x \\ \dot{y}_r = v_r sin(\theta_r) + \phi_r v_r cos(\theta_r) + \frac{T}{2} a_y \end{cases} \tag{1}$$

where v_r is the magnitude of the linear velocity p_r, T is the sampling time, and a_x, a_y are the accelerations of the iChair motion along the X and Y directions, respectively. This model includes the acceleration of the iChair to enhance the accuracy. We define the state variable

TABLE II. EKF ALGORITHM

Stage	Calculation
Prediction	
	$X^-(k) = A(k)X(k-1)$
	$P^-(k) = A(k)P(k-1)A^T(k) + Q(k)$
Kalman Filter	
	$K(k) = P^-(k)H^T(k)[H(k)P^-(k)H^T(k) + R(k)]^{-1}$
Correction	
	$X(k) = X^-(k) + K(k)[Z(k) - H(k)X^-(k)]$
	$P(k) = P^-(k) - K(k)H(k)P^-(k)$

$$X(k) = [x_r(k) \ y_r(k) \ v_r(k) \ \omega_\theta(k) \ \phi_r(k) \ \varphi_r(k) \ \theta_r(k)]^T \tag{2}$$

and linearize the kinematic motions to obtain the dynamic model.

$$X(k+1) = AX(k) + BU(k) + w(k), \tag{3}$$

$$A = \begin{bmatrix} 1 & 0 & Tcos(\theta_r) & 0 & 0 & -Tv_r sin(\theta_r) & 0 \\ 0 & 1 & Tsin(\theta_r) & 0 & 0 & Tv_r cos(\theta_r) & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 + T\dot{\varphi}_r tan(\varphi_r) & \frac{T\dot{\theta}_r}{cos(\varphi_r)} & 0 \\ 0 & 0 & 0 & 0 & -T\dot{\theta}_r cos(\varphi_r) & 1 & 0 \\ 0 & 0 & 0 & 0 & \frac{T\dot{\varphi}_r}{cos(\varphi_r)} & T\dot{\theta}_r tan(\varphi_r) & 1 \end{bmatrix}$$

$$B = \begin{bmatrix} \frac{T^2}{2} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 \frac{T^2}{2} & 0 & 0 & 0 & 0 & 0 & \end{bmatrix}^T \tag{4}$$

Table II shows the EKF algorithm where $H(k)$ is an $n \times n$ identity matrix, $R(k)$ and $Q(k)$ are measurement and process noise covariance matrices, assumed to be zero mean Gaussian white signals namely, $v(k) \sim \mathcal{N}(0, R(k))$. The measurements are obtained as follows: positioning information (x_r, y_r) are obtained from the RTK GPS, the iChair's linear velocity v_r and the yaw angular velocity ω_θ are obtained by the lower-level iChair controller. The covariance matrix for the measurements $Z(k)$ are given as:

$$R(k) = diag(\sigma^2_{x_{gps}}(k) \ \sigma^2_{y_{gps}}(k) \ \sigma^2_{v_{odo}}(k) \ \sigma^2_{\omega_{odo}}(k))$$

Once the iChair travels to an outdoor environment, an advanced localization and navigation will be developed to accurately localize the iChair. GPS measurements are integrated with attitude information from the onboard IMU to enhance the localization accuracy. Moreover, the developed navigation system also fuses the GPS/IMU measurements with the wheel odometry information through an EKF design [13], [14]. The accuracy of the wheel odometry of the all-wheel steering platform is much higher than those of other types of mobile robots (e.g., car-like mobile robots) due to the small wheel slippages in operation [14], [15]. With the proposed odometry-enhanced fusion, the iChair will feature high-accuracy localization even in GPS-denied environments.

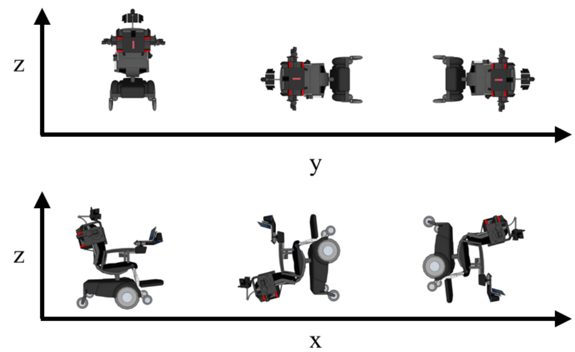

Fig. 5. Top: 3 potential pitch angles ($\varphi_r = 0, -90^o, 90^o$). Bottom: 3 potential roll angles ($\phi_r = 0, -90^o, 90^o$).

B. Autonomous Emergency Signal (AES)

The AES is a simple algorithm that utilizes data from the IMU and bluetooth biosensors to continually make sure the wheelchair has not fallen over, and that the user's health has not changed for the worse. This is an experience many wheelchair users experience in their lifetimes (Fig. 1). The IMU continually collects information about wheelchair status, including pitch (φ_r) and roll (ϕ_r). A significant change in either of these angles from normal status, to one that is critical, would indicate a fall (Fig. 5). The algorithm also processes data from sensors embedded in the wheelchair's backrest and armrest, that continually collect the user's heart rate, aspiration, and blood pressure. If the IMU and bluetooth biosensors indicate an emergency, a text message is sent to the authorities, who will then initiate a phone call to check on the user.

IV. Object Detection & Tracking

As in [16], we combine 3D shape, color (when available), and motion cues to detect and accurately track moving objects in real-time. Starting with a coarse approximation to the posterior, the tracker successively refines this distribution, increasing in tracking accuracy over time. The longer we collect data the more refined the map becomes, and the easier it is to identify new or dynamic objects.

Methods like Normal-Enhanced Range Image (NERI) and Singular Value Decomposition (SVD) provide the edge enhancement necessary to accurately and consistently identify objects with the Swiss Ranger 3000 range finder [9]. Objects within the sensor's immediate surroundings ($< 5.6m$), serve to accurately describe a location and obstacles, building a 3-D map that can be used later as a template for image subtraction and new object discovery. We are aiming for an uncertainty in object size of $< \pm 5mm$ at a range of < 30 inches, within the reach of our robotic arms.

V. Object Classification

In order to give the computer the ability to anticipate the behavior of objects we adopted the control time method for logging positive detections and determining the rate at which they occur in certain locations [17], [18]. This is a technique used by astrophysicists to compute the rate of cosmic events like supernovae depending on the type of explosion and the environment in which it occurred. In the terrestrial, every day context that we anticipate the iChair to encounter, objects are categorized in a 4×6 matrix (Table III) that will serve to give us correlations between object type and the probability (P) that the object will be at a certain location (X, Y, Z) at a particular time (t).

TABLE III. Object categories: *stationary objects help build a 3-D map template. Movable objects are easily discovered by subtracting the template from the most recent observation. Life forms are a special type of movable object that introduce an uncertainty into every scene. Depending on their size, certain lifeforms can be their independent decision-makers and have an impact on their surrounding environment. Events involve one or more objects interacting at a particular location at a given time.*

	1	2	3	4
	Stationary	Mobile	Life forms	Events
A	walls	furniture	trees& plants	sunrise
B	pathways	decorations	aerialists	sunset
C	stairs	appliances	amphibians	daily
D	ground cover	doors	ground animals	crime
E	driveways	vehicles	water animals	rush
F	signs	barricades	humans	annual

TABLE IV. Object subcategories: *are linked to libraries which hold observation logs, which are used in the object detection rate and event prediction calculations.*

Type	Name	Linked Library
1A	Wall	floor plans: buildings
1B	Pathway	floor plans: property maps
1C	Stairway	floor plans: elevator records
1D	Ground cover	navigation: maps in the cloud
1E	Driveway	navigation: maps in the cloud
1F	Sign	navigation: library of signs
2A	Furniture	room floor plans
2B	Decoration	calendar of holidays
2C	Appliance	environmental control
2D	Door	maps in the cloud
2E	Vehicle	library of vehicles
2F	Barricade	library of signs
3A	Tree or plant	fixed in at least 2D
3B	Aerialist	airborne most times
3C	Amphibian	near water
3D	Ground animal	moves along 2D most times
3E	Water animal	found in water most times
3F	Human	many known limits and abilities
4A	Sunrise	beginning of the day
4B	Sunset	end of the day
4C	Daily	once or more every day
4D	Crime	malicious human decision-making
4E	Rush	lifeforms in a hurry
4F	Annual	once every year

The stationary objects of category 1A-F are always at the same fixed location, while all other objects will have $P < 1$ of being at the same location at a different time. Mobile objects and events can thus be cataloged with locations referenced to the nearest stationary object. Over time the stationary objects make up an increasingly accurate 3-D map, that serves as a reference point for previously discovered mobile objects, and makes it much easier to detect new objects and notice the absence of previously catalogued objects.

Certain mobile object types have a higher probability of reoccurring at the same place than others. For example category 2A may include a bookshelf that remains fixed most of the time, while a chair may have a much lower probability of being found at the same location a few hours later or the next day. A category 3A object like a rose bush is fixed in two dimensions, but fluctuates in the third dimension, depending on the age of the plant, current and past environmental conditions, and whether or not any roses have been removed lately. Events are a special category of object, because they involve more than one object and the outcome depends on their relationship to each other at any given time. For example, just before the lunch rush, chairs in the cafeteria are orderly and near a table. After lunchtime there is a low probability that the chairs will be in their usual location.

VI. Event anticipation

Event prediction is vital for making new object discoveries and to notice absent objects, because it helps to minimizes the amount of time and processing power needed to make near real-time discoveries. The algorithm includes the following steps:

1) Each time the range sensor engages, a basic 3-D map is built.
2) Previously identified objects are confirmed to be in their last known location.
3) Known quantities that are rediscovered are used to update the library of objects.
4) The average values of all the objects in the field are fused together to produce a template.
5) New, unidentified objects are discovered by subtracting the template from the current image.
6) Calculate the location of the new object with respect to known quantities.
7) Classify objects by searching the library of models and receiving human input.
8) Update event logs as often as possible given memory and processing constraints.
9) Calculate the rate of events of various types (table III) depending on their time, location, and objects involved.
$$\nu_{Ev} = \frac{N_{Ev}}{T_{Ev,S}} \quad (5)$$
where N_{Ev} is the number of events that occurred during the total control time $T_{Ev,S} = \Sigma(ct_{Ev,S})$ for a certain volume of 3-D space $S = [X; Y; Z]$ during the course of the overall data collection campaign. Individual control times $(ct_{Ev,S})$ are determined by the time the measured probability $p_{Ev} > \theta$, and the detection threshold.
10) Calculate the probability that an event will take place at a particular location at a certain time.

$$P_{Ev} = 1 - exp(-\nu_{Ev} T_{Ev,S}) \quad (6)$$

VII. Autonomous navigation

Autonomous navigation requires both cm-level localization precision and real-time object detection, ideally with gesture recognition and trajectory prediction. Based on the success of the EKF for iChair localization, the team is going to develop a novel navigation algorithm to allow the iChair to autonomously and safely navigate in complex environments. The developed navigation algorithm will inherit the advanced performances of our previous work on autonomous navigation for robots [19]–[21].

The iChair will implement path planning [22] to navigate from the wheelchair accessible entrance of the Applied Research Facility at the University of Nevada, Reno (Fig. 6) to the ARA Laboratory. In the course of the experiment the iChair has to complete six stages and autonomously navigate in three different operating modes.

1) Ramp/Doorway: While navigating a ramp, or passing through a doorway, the system must allow the iChair to come close to objects to pass through narrow doorframes, at the expense of travel speed and user control [1].
2) Wall following: [23] demonstrated a safe, reliable guide following algorithm. Laser scan images of a guide by an in-vehicle laser range sensor based on Kalman filter and data association, estimate the guide's footprint. Based on position data of the footprint, a cubic spline generates a target path for the iChair.
3) Docking: safe docking locations at rectangular and circular docking structures with proper alignment information are automatically detected using 3D point cloud data [24]. Based on geometric information, computed from depth data, the method is invariant to scene or lighting changes, ideally suited for path planning, and in this experiment, for riding the elevator.

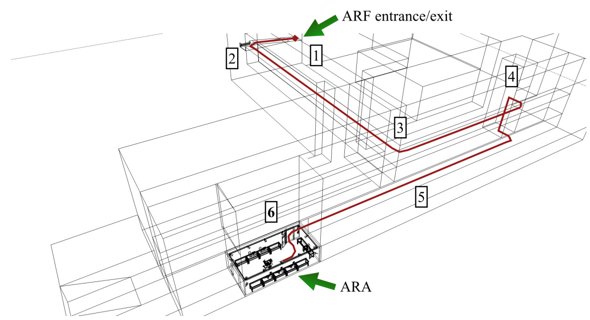

Fig. 6. Diagram of the path planning experiment in the Applied Research Facility (ARF) at the University of Nevada, Reno. The iChair's first task is to navigate a ramp (1), enter through the building's two sets of doors (2), follow the hallway on the second floor (3), until it reaches the elevator (4). After docking with the elevator and riding down to the first floor, the iChair follows the hallway (5), until it reaches the doorway (6), and enters the Advanced Robotics and Automation (ARA) lab.

A. Future developments

Thanks to rapid advancements in robotic arm hardware and control software the next generation of iChair will be equipped with the following upgrades.

- The Retractable Roof (RR) is compact, sturdy, lightweight, stylish, and designed to provide shelter, safety, and the structural foundation for the Heads up Display.
- The Heads up Display provides real-time visual alerts and helps identify potential targets within reach of the robotic arms.
- The Robotic Arm Assistant (RAA) will be integrated with the iChair (Fig. 4) to enable various ADLs to be performed independently, reducing the burden on caregivers and boosting spirits of quads, and their loved ones alike. We use two modular prosthetic limbs (MPL) developed at Johns Hopkins University [25] under a grant from the DARPA, mounted onto the motorized wheelchair with an in-house fabricated Aluminum & Carbon fiber bracket. The object detection and classification method described in the previous sections provides the data necessary to identify objects.

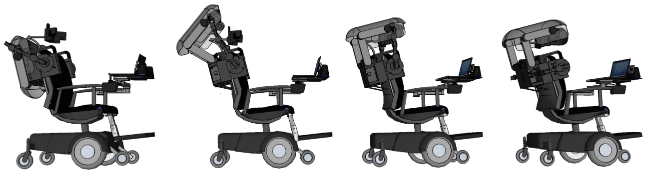

Fig. 7. 3-D rendering of the iChair raising its roof. Left to right: Robotic Arm Assistant (RAA) reaches back and unlocks the Retractable Roof (RR); 2 Mount-n-Movers rotate assisted by 2 12V servos and aided by the robotic arms; RR locks into position and the heads up display (HD) rotates into the user's field of view.

We have the following research objectives for the RAA on the iChair, that will give the user abilities unimaginable for a quad in years past.

1) Eating
2) Drinking
3) Retrieving/Depositing items
4) Pressing buttons
5) Raising/Lowering RR
6) Nonverbal communication
7) Remote control

VIII. Conclusion

The iChair is a Smart wheelchair and a co-robot that will greatly improve the lives of quads and contribute to the integration of robots into everyday society, to safely work and interact side-by-side with humans in public spaces. This research has produced Human-iChair Interaction models that enable quads to access many more employment opportunities and a high quality independent lifestyle. The iChair reduces the need for human caregivers, and helps level the playing field for quads to work in high paying influential jobs.

Autonomous navigation will prevent the iChair from colliding with objects and allow users to travel along predefined paths, independently or by tracking a companion. The control algorithms developed for the iChair such as localization, object classification and event prediction are relevant not only to the Smart wheelchair research community, but present a fundamental research challenge in computer science that has the potential to drastically change a robot's ability to learn over time and anticipate events.

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References

[1] R. Simpson. Smart wheelchairs: A literature review. *JRRD*, 42(4):423–436, 2005.

[2] J. Leaman and H. M. La. A comprehensive review of smart wheelchairs: Past, present and future. *Transactions on Human-Machine Systems (THMS)*, 2015.

[3] R. Simpson. Smart Wheelchair Component System. *Journal of Rehabilitation Research and Development*, 41(3B):429–442, 2004.

[4] O. Pineau. On the Feasibility of Using a Standardized Test for Evaluating a Speech-Controlled Smart Wheelchair. *National Science and Engineering Research Council Canada*, 2011.

[5] Adaptive Switch Laboratories. Head joystick with proximity sensor. *http://www.asl-inc.com*, 2015.

[6] M. Chandler. America's next great inventions. *Mercury News, Available at: http://www.mercurynews.com/c-i5485125*, March 2007.

[7] NaturalPoint. Head tracking mouse. *http://www.naturalpoint.com/*.

[8] BlueSkyDesigns. Mount-n-mover. *http://www.mountnmover.com/*.

[9] G. HEGDE and C. YE. Singular value decomposition filter: an effective method to enhance the swissranger sr-3000's range images. *Int. J. Intell. Control and Syst*, 2008.

[10] W. Burgard, D. Fox, and S. Thrun. An efficient fastSLAM algorithm for generating maps of large-scale cyclic environments from raw laser range measurements. In *IEEE/RSJ Inter. Conf. on Intel. Robots and Sys. (IROS)*, pages 2006 –211, Oct. 2003.

[11] S. Thrun, Y. Liu, D. Koller, A. Y. Ng, Z. Ghahramani, and H. Durrant-Whyte. Simultaneous localization and mapping with sparse extended information filters. *International Journal of Robotics Research*, 23(7-8):693–716, Aug. 2004.

[12] Differential Global Position System. http://www.novatel.com/.

[13] K. Ohno, T. Tsubouchi, B. Shigematsu, and S. Yuta. Differential GPS and odometry-based outdoor navigation of a mobile robot. *Advanced Robotics*, 18(6):611–635, 2004.

[14] E. North, J. Georgy, U. Iqbal, M. Tarbochi, and A. Noureldin. Improved inertial/odometry/GPS positioning of wheeled robots even in GPS-denied environments. *Global Navigation Satellite Systems - Signal, Theory and Applications*, 11:257–278, 2012.

[15] L. Wei, C. Cappelle, Y. Ruichek, and F. Zann. Intelligent vehicle localization in urban environments using EKF-based visual odometry and GPS fusion. *the 18th IFAC World Congress, Milano, Italy*, pages 13776 – 13781, 2011.

[16] D. Held, J. Levinson, S. Thrun, and S. Savarese. Combining 3-d shape, color, and motion for robust anytime tracking. In *Proceedings of robotics: Science and systems*, Berkeley, USA, July 2014.

[17] F. Zwicky. Types of novae. *Reviews of Modern Physics*, 12(1):66–85, 1940.

[18] J. Leaman, W. Li, R. Chornock, and A. V. Filippenko. Nearby supernova rates from the lick observatory supernova search - i the methods and data base. *Monthly Notices of the Royal Astronomical Society*, 412(3):1419–1440, 2011.

[19] H. M. La, R. S. Lim, B. B. Basily, N. Gucunski, J. Yi, A. Maher, F. A. Romero, and H. Parvardeh. Mechatronic and control systems design for an autonomous robotic system for high-efficiency bridge deck inspection and evaluation. *IEEE Trans. on Mechatronics*, 18(6):1655–1664, April 2014.

[20] H. M. La, R. S. Lim, B. B. Basily, N. Gucunski, J. Yi, A. Maher, F. A. Romero, and H. Parvardeh. Autonomous robotic system for high-efficiency non-destructive bridge deck inspection and evaluation. *IEEE Inter. Conf. on Auto. Sci. and Eng. (CASE)*, pages 1065–1070, 2013.

[21] H. M. La, N. Gucunski, S. H. Kee, J. Yi, T. Senlet, and L. Nguyen. Autonomous robotic system for bridge deck data collection and analysis. *IEEE Inter. Conf. on Intel. Robots and Sys. (IROS)*, 2014.

[22] R. Tang, X. Chen, M. Hayes, and I. Palmer. Development of a navigation system for semi-autonomous operation of wheelchairs. In *2012 IEEE/ASME International conference on Mechatronics and Embedded Systems and Applications (MESA)*, 2012.

[23] K. Miyazaki, M. Hashimoto, M. Shimada, and K. Takahashi. Guide following control using laser range sensor for a smart wheelchair. In *ICROS-SICE International Joint Conference 2009*, Fukuoka International Congress Center, Japan, Aug 2009.

[24] S. Jain and B. Argall. Automated perception of safe docking locations with alignment information for assistive wheelchairs. In *Automated Perception of Safe Docking Locations with Alignment Information for Assistive Wheelchairs*, pages 4997–03, Chicago IL, Sep 2014.

[25] J. Burck, J. Bigelow, and S. Harshbarger. Revolutionizing prosthetics: Systems engineering challenges and opportunities. *JOHNS HOPKINS APL TECHNICAL DIGEST*, 30(3):186–197, 2011.