

NRI-SMALL: A ROBOTIC FACTORY ASSISTANT FOR KITTING, TRANSPORT AND DELIVERY

1 INTRODUCTION

While many tasks within modern factories has benefited from robotic automation, the mundane and repetitive task of part retrieval is candidate for automation. It is desired to create a robot that is capable of autonomously navigating a factory among humans to retrieve parts from various stock locations, populating trays (kits) with the correct components, and delivering these kits to assembly stations. Developing a robot capable of such a task will require advancing three of the areas of robotics identified as needing further research: “manipulation”, “awareness of people”, and “social interaction”[1]. *A Roadmap for US Robotics: From Internet to Robotics* asserts similar elements crucial for increased presence of robotics in manufacturing; “adaptable and reconfigurable assembly”, “autonomous navigation” and “human-like dexterous manipulation”[2]. In this project, we propose to develop a robot that is easily trained by humans to retrieve and assemble kits for delivery to factory personnel. This robot will safely navigate autonomously through the factory to stock locations and interact safely and elegantly with human it encounters. We will assemble this robot from existing, high volume, commercial parts to create a mobile manipulation platform for a cost similar to that of most mobile platforms alone.

A significant challenge of this effort will be to perform reliable manipulation of kit components. Developing robots capable of reliable, dexterous and “human-like” manipulation of unstructured elements within an unstructured environment will continue to be a research challenge well into the future. Further, dexterous hands are too pricey and too unreliable for manufacturing applications. An approach to this problem with immediate applicability is to use component packaging that is designed for automation, thus, leveraging the inherent structure of a factory setting. Extending this position, “Smart Payloads” should inform a robot of helpful details, including payload contents, how to recognize the payload (identity and pose), handling instructions and restrictions, and recommended grasp sites and strategies.

Within this project, we will focus on three main tasks: safe operation among humans, programming by demonstration, and reliable manipulation of smart payloads. Also as part of this project, we will build a relatively low-cost but competent and robust mobile manipulator from commercial, off-the-shelf components to create a platform useful for manufactures. We will also leverage the existing community of robotics research via use of the Robotic Operating System (ROS) and through compatibility with the DARPA ARM-S program software. The products of our research will be released back to the community making this robot platform accessible to the research community as well.

2 SAFE OPERATION AMONG HUMANS

2.1 Background

The greatest value of a mobile manipulator will be realized when it can operate safely in environments with people. Conventionally, robots operating in factories are sequestered from workers through various means to prevent direct interactions. Mobile robots in factories typically have been limited to following marked routes which general required costly factory infrastructure upgrades. More recent developments have allowed for greater flexibility, as in the case of Kiva robots (Kiva Systems, Inc. North Reading, MA), that move pallets

on demand within factories. The Kiva system converts the warehouse paradigm from one where humans search for bins to a paradigm where (mobile) bins find humans. The Kiva robots, however, never “interact” with humans.

Autonomous Guided Vehicle (AGV) fork-lifts have also been introduced, although they present greater hazards, and they have limited acceptance to date.

Safety remains a top priority, and additional work is needed. Reflexive collision avoidance may be invoked to prevent collisions with known, static obstacles. Interacting with pedestrians, though, presents greater challenges. A problem observed in motion planning of mobile robots through dynamic environments is the “freezing robot” problem[3]. When the environment includes dynamic agents, a robot may not be able to compute an assured clear path from start to goal and if such a path is found, it may be quickly invalidated by unexpected changes in anticipated trajectories of the other agents. This causes the robot to stutter and fail to make progress as paths are constantly being recomputed and constantly being invalidated. Early approaches to addressing planning in crowds utilized physics models [4, 5]. Later approaches incorporated the assumption that the dynamic agents would react cooperatively to alter their trajectories, *e.g.* as described in [3], which used interacting Gaussian processes describing “social forces”. A recent cognitive-science based approach to the problem involved modeling human behavior in crowds [6]. These latter works were encouraging in simulations, including exhibiting human-like dynamics, such as “laning.” However, these techniques need to be evaluated experimentally. Further, the dynamic models attempted to describe pedestrians interacting with pedestrians, not pedestrians interacting with wheeled, kinematically-constrained vehicles. In implementation (in contrast to simulation), a challenge is to distinguish dynamic agents from static obstacles. Works confronting this problem include [7], which considered separate tracking of static, semi-static and fully dynamic entities, as well as [8, 9], which describe interaction dynamics in the context of tourguide robots.

2.2 Approach

Our mobile manipulator will be relatively heavy (100kg) and powerful (*e.g.*, capable of driving its own weight plus a payload > 100kg up a steep grade at > 2m/sec). (See Section 5.) Making the mobile manipulator substantially lighter would not be an option, as the arm and vehicle must possess a useful payload and power life. Instead, the system must navigate fluidly among human coworkers and operate with assured safety through software protections.

This task will exploit previous work by co-PI Newman in artificial reflexes[10, 11]. Formerly applied to industrial robot arms, this collision-avoidance approach is applicable to mobile manipulators. As a starting point, we will re-use code developed for “Dexter,” Case’s entry in the 2007 DARPA Urban Challenge, (Newman, project leader, [12]), and subsequently extended for smart wheelchairs. Dexter was able to navigate streets in a city with human and robotic traffic, while obeying all rules of the road. This capability is applicable to safe and effective navigation of vehicles in buildings, avoiding collisions with static objects and other mobile robots.

In the presently proposed work, we will be building on earlier development of “Otto,” Case’s smart wheelchair. (See Section 5.) Otto and our other Case mobile robots use existing ROS nodes to implement path planning, simultaneous localization and mapping (SLAM), as well as localization based on *a priori* floor plans. We have developed precision steering software applicable to wheelchair-style wheeled kinematics, which will be useful in the present work.

Interacting safely and efficiently in shared spaces with pedestrians will require additional work,

including identifying and tracking pedestrians and behaving interactively in a manner that is conducive to smooth and safe traffic flow. We will build on existing people-tracking methods and behavioral models of pedestrian-interaction dynamics, modified to take into account human interaction dynamics with wheeled vehicles, and augmented with the option of utilizing building sensors.

2.3 Methods

In interacting with humans, it is essential that the mobile manipulator can do no harm. Accomplishing this will require multiple layers of safety hierarchy. At the lowest level, we will emulate the servo-level safety system already incorporated in industrial arms. At this level, power is disconnected from the motor drives if the servo error becomes excessive. Such errors can result from low-level failures, such as a faulty encoder, broken cable or failed power semiconductor.

At the next layer up, the platform must be commanded to come to a halt safely before possibly colliding with any person or object in its environment. This level, a reflexive intervention, must override any trajectory plan that would lead to collisions. If the reflexive layer is failsafe, then errors in higher-level software will not pose a threat[13].

While a reflex controller must be failsafe, this cannot be achieved by being overly conservative. The robot must still be capable of passing through doorways, for which the clearance is small and a conservative obstacle map would prevent traversal. Successful reflexive collision avoidance depends crucially on reliable obstacle sensing. Since no one sensor is infallible, sufficient reliability requires integration of multiple sensing modalities. For example, laser range finders do not detect glass walls, and some dark fabrics absorb the laser light, rendering them invisible to LIDAR. Sonar sensors can detect glass walls, but they provide poor resolution. Three dimensional vision is valuable, but easily fooled. Since these behaviors cannot be characterized as unbiased Gaussian noise, Kalman-filter integration cannot be used. Rather, integration requires a probabilistic approach, which must be based on detailed characterization of the sensors involved.

Beyond creating a reliable map of a static environment, it is also crucial to identify dynamic entities. Great care must be taken if the vehicle moves close to a person, who might suddenly move into the vehicle's path. We will utilize the Kinect camera to help identify humans, and build on prior work in people trackers. For factory use, in particular, the task of tracking pedestrians can exploit connectivity of a situated robot exploiting assets of a smart building. Anticipating smart buildings of the future, the building should always have an awareness of how many people are contained, who they are, and where they are. Cameras and other sensors distributed throughout the building would make this task easier than depending on mobile sensing alone. However, the situated robot can also provide its sensory data to the smart building, thus augmenting overall sensing.

Even with a perfect map of all pedestrian locations, a mobile robot would still be challenged to move safely among pedestrians. The pedestrian dynamic models described in Moussaïd et al. show promise, and this approach will be applied to robots moving among pedestrians. We will acquire additional data of pedestrian dynamics in the presence of a human-controlled power wheelchair. We expect a different pedestrian dynamic model, as people will recognize the kinematic constraints of the wheelchair. Further, the wheelchair will be driven by a human, using our own internal model of how to interact with pedestrians. This data will be analyzed to yield new models, both for pedestrians interacting with wheelchairs and for wheelchair drivers interacting with pedestrians. The former will be used within a model-based prediction of pedestrian dynamics, and the latter will be used to design a human-like interaction controller for the mobile robot. Our expectations are that a mobile robot that behaves like a human wheelchair driver will be

compatible with human pedestrian traffic.

2.4 Management Plan

Year 1 will consist of data acquisition concerning pedestrian interaction with mobile robots. Experiments will be conducted using our existing robots and wheelchairs, and rules concerning the navigation of the mobile robot among humans will be developed. Navigation functionality will be extended extended to create “Follow Me” functionality over years 2 and 3 (“Follow Me” is primarily an element of the “Program by Demonstration” aspect of the project. See Section 3.) Fully autonomous navigation that incorporates smooth and safe interaction among humans will be implemented in year 4. (See Section 8.)

3 PROGRAMMING BY DEMONSTRATION

A significant obstacle to the adoption of new robotic technology is the expense associated with updating and changing the programming of the robot. An intelligent robot interacting with people should be capable of being retasked without requiring users (*e.g.* shop-floor personnel) to make software edits. Rather, we advocate for programming by demonstration.

3.1 Background

Programming by Demonstration is a naturally appealing proposition for retasking robots without the need to edit code. It has been approached in various specific instances [14–16], including Newman’s own prior work in the context of mechanical assembly [17–19]. The challenge of programming by demonstration is to infer abstracted goals from specific examples, and to use these goals in the context of available sensors and actuators to auto-generate strategies to realize these goals. In general, this problem is overwhelmingly hard. However, in specific environments and contexts, the complexity can be reduced to inferring a set of unknowns within an *a priori* model. That is, teaching a robot by demonstration is manageable if one can restrict consideration to a limited context, for which goal states can be reasonable inferred from specific examples. Additionally, the context must offer the possibility of sensing the crucial variables (analogous to observability in control theory) and the possibility of influencing the environment appropriately (equivalent to controllability in control theory).

Specifically in the context of kitting, we propose that the programming-by-demonstration problem is approachable. Both observability and controllability in the context of manipulation will be enabled by “smart payloads” (See Section 4.).

3.2 Approach

The scope of our task will limit the scope of the “Programming by Demonstration” aspect of the proposed robot. The robot will extract goals (acquisition of specific kit elements from approximate depot locations, comprising a specific collection to be delivered to a specific site). Obstacles (including people) may be encountered along the way, and the robot must look for and respond to such obstacles appropriately. (See Section 2.) Pick-up (and possibly drop-off) locations cannot be specified precisely by example. For example, if the robot is steered to acquire a package from a shelf, the observed location will not be valid subsequently, since the part that was at that location originally is no longer present.

More generally, the robot should infer that a particular part type should be available at some approximate spatial coordinates. The robot should navigate to these coordinates, responding appropriately to unexpected obstacles along the way, and it should identify and acquire the object of interest. Object acquisition will be made more complicated due to the fact that the robot will not be able to navigate to a precise, pre-established location. Rather, once in the approximate vicinity of a part depot, the robot must use sensors to recognize and locate the desired part. (See Section 4.) Typically, the robot would never retrace the example demonstration verbatim, but it would achieve the same sequence of desired outcomes, ultimately resulting in kits being correctly populated and delivered.

3.3 Methods

Inferring goals from the demonstration, the robot should carry out autonomous actions that achieve the desired outcomes (acquisition of identified parts, organized and delivered as kits to observed workstation destinations). Abstracting from a specific example to the general case is required. Achieving a sequence of subgoals would require path planning, trajectory following, recognition of specific payloads, acquisition (grasp) of desired payloads, placement of payloads in an orderly array within kits, and delivery of such kits to desired assembly stations. From a single training example, the robot must extract the desired sequence of goals and, subsequently, be able to replan dynamically to achieve the sequence of goals.

Before integrating the entire system, we will make progress on sub-elements of the training task. We will use one of our mobile robots to develop a leader/follower behavior for use in the programming-by-demonstration process. This capability must be compatible with our parallel effort in safe navigation among pedestrians (to be integrated subsequently).

Separately, an ABB IRB-140 arm and accompanying sensors in the Case Mechatronics Lab will be used to learn manipulation from demonstration, taking advantage of *a priori* payload manipulation and payload descriptive information. (Such information will subsequently be embedded in web-based object descriptions, pointed to by digital markers on payloads. See Section 4). Known (modeled) objects, visible to the robot system, will be moved by a human from an initial location to a final location. From observation of this action, the robot will extract the goal that an object of the type moved is to be transferred from some approximate feed location to a specific destination location. Success in this task will be demonstrable. When a human places an instance of the desired part within an approximate feeding zone, the robot will recognize the part, recognize its pose, associate the pre-established grasp strategy (or choose the most appropriate option), plan an approach, acquire the part, and place the part at the desired destination.

Mobility training and manipulation training will be integrated on our new mobile-manipulator platform. (See Section 5.) Our mobile manipulator will be trainable to: follow a leader to a destination, observe the trainer placing an identifiable object on a tray carried by the robot, and follow the leader to a drop-off location, and observe the trainer transferring the part to a destination location. Subsequent to this training, the robot will be instructed to acquire another kit, causing it to plan a route to the feeding location, find and acquire an instance of the desired object, plan and execute a route to the drop-off location and deliver the part to the desired final destination.

Ultimately, the system will be extended to integrate safe and effective motion among pedestrians—including in the training stage. (See Section 2.) Manipulation strategies will be generated on the fly using information provided by smart payloads. Training will be extended to assembling complete kits, and kitting tasks thus encoded will be executable by reference to prior training examples.

3.4 Management Plan

During year 1 we will develop leader/follower behavior on an existing mobile robot. We will develop manipulation training using an ABB IRB-140 arm during the second year. In year 3, mobility training and manipulation training will be integrated on our new mobile-manipulator platform.

By the end of year 4 (conclusion of the program), we will have completed integration of all tasks within this program, enabling simple and effective programming by demonstration for kitting operations.

4 SMART PAYLOADS

Completely autonomous manipulation in unstructured environments is beyond the scope of this proposal. The mobile manipulation task of retrieving kit elements for kit assembly and delivery will happen in a factory setting. We propose to leverage the structure inherent in a factory to simplify the manipulation by creating “Smart Payloads”, (*e.g.* we propose to impose structure on the kit elements by specifying aspects of the kit element packaging as delivered by the supplier). (See Figure 1b.)

Humans interact with Smart Payloads daily. Typical packaging often display symbols to communicate to humans, such as which way is up, *etc.* There is also an implied grasp point where the cardboard is cut to provide a handhold. (See Figure 1a.) It is common for packaging to use symbols to communicate to humans information concerning the proper package handling. It is also quite common for packaging to display computer readable information. Bar codes located on the bottom half of the box communicate shipper information. Even small, products sold from bins contain barcodes for sales purposes.

Using computer vision to determine how to pick up the package in Figure 1a is beyond the scope of this project. Using open source software and optical code standards, computers can easily read specifically designed labels and markings. Quick Read codes (QR codes are the two dimensional equivalent of bar codes) and other types of markings can provide invaluable information to simplify the recognition and grasp operation. Markings and labels can greatly simplify the problem, in essence, having the package tell the robot how to manipulate it (See Figure 1b.)

4.1 Background

Robotic grasp has been researched intensively over the last several decades. A good summary of progress up to year 2000 is reviewed in [20–22]. Some key contributions include development of the Salisbury hand Salisbury, the MIT-Utah hand [24], Mason and Salisbury’s text on the mechanics of manipulation [25] and Cutkosky’s seminal study of grasp in humans, resulting in a taxonomy of 16 types of power and precision grasps [26]. Mathematical analysis of grasp quality distinguishes between form closure and force closure [see *e.g.* 20–22, 27], the former being more desirable but seldom achievable.



Figure (a) Side of a package

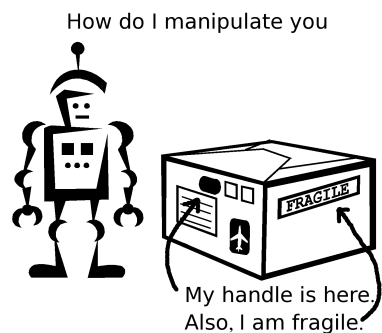


Figure (b) Smart Payload

Figure 1: Typical packages contain instruction for correct manipulation. These markers can be used by robots, also.

Research in grasp has largely followed two approaches: a planning approach and a control approach. For the planning approach, knowledge of an object’s shape and pose is assumed to be known, and a time series of locations and forces/torques of contact points is computed for optimal grasp and manipulation. In contrast, a control approach assumes little or no knowledge of the object to be grasped, and contact points and forces are an emergent property of interaction between the object and hand under the influence of a compliant-motion control law.

One notable success, attributable to our team (Newman) is the first installation of force-controlled robotic assembly in Ford Motor Company [28, 29]. This success derived from Newman’s previous research in Natural Admittance Control (NAC) for mechanical assembly [18, 30–33], and subsequent collaboration with ABB Robotics to create a high-reliability system that was installed in assembly-line operation. Additional extensions of NAC included application to kinematically redundant manipulators [34], use of NAC for performing snap-fit mating operations [35], and use of NAC for compliant grinding and deburring tasks [36, 37]. Natural Admittance Control was used successfully as a foundational layer for the execution of manipulation strategies. Synthesis of manipulation strategies included computed interpretation of sensed contact forces [38], transfer of human skills [17], and autonomous exploration for learning assembly skills [39, 40].

One of the barriers to practical mobile manipulators is dexterous manipulation. In manufacturing, custom grippers are designed to handle specific components. More generally, it would be desirable to have a gripper capable of general-purpose manipulation. Sophisticated human-like hand designs have included [23, 24]. However, these and similar manipulators are prohibitively expensive, insufficiently robust, and are still limited in their capacities. The Barret gripper achieves a somewhat better compromise among cost, generality and robustness, although it is still limited and expensive (over \$40,000).

Radio Frequency Identification (RFID) has been used to inform manipulation tasks. Deyle et al. have used UHF RFID tags to facilitate the discovery of objects in unstructured environments. The tags allow object detection at distances of five meters and simplified object location and recognition. Möller et al. expanded this to create “Cognitive Objects” which are objects that contain information about themselves, such as an object’s use.

4.2 Approach

The range of complexity can extend from a specifically designed package that includes a handle matched to the robotic manipulator. The location of the grasp point conveyed using either RFID or optical markings. More complex information could be provided to a manipulation robot with a dexterous hand via an external reference which describes how and where to grasp a package (perhaps using an unaltered handle designed for human hands).

In the present context, we must realize useful, reasonably general manipulation, although the daunting task of general-purpose gripper design, will continue to be a research challenge for many years to come. Our approach to circumventing this barrier for the near term (with immediate industrial applicability) is the innovation of “Smart Payloads”. In this concept, we will provide the robot with a few options of simple grippers (*e.g.* vacuum cup, electromagnet, parallel-jaw gripper) that are capable of grasping a set of useful payloads (*e.g.* with magnetic surfaces, smooth, airtight surfaces or a graspable handle). A “smart” payload would be one that is capable of describing a robot how to grasp it.

A robot could much more easily determine how to manipulate a payload that announces what type(s) of grippers may be used, what surfaces or features may be used for grasp, and how to locate these surfaces on

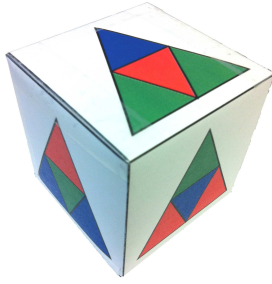


Figure (a) Cube with uniquely identifiable faces



Figure (b) A computer readable QR Code.

Figure 2: Computer readable information can be easily printed on packages faces or in RFID information (either directly or through indirect reference). (a) shows a cube with machine vision adapted graphics to uniquely identify the cube face. (b) provides information concerning the handling of the document

the object. Finding these grasp points or surfaces typically would require sensing the object, e.g. by vision. It would thus be useful if the object could inform the robot how to recognize the object and its pose. This may include a description of fiducials, prominent features or a suitable template for recognizing faces of the object.

4.3 Methods

We propose to use RFID technology and machine readable symbols (optical codes and other similar mechanisms) to provide information to robotic manipulators such as orientation, form factor, mass, grasp point location and grasp description. RFID can provide small amounts of very useful information about the object to which it is attached, including providing a “homing beacon” to simplify object recognition, localization and grasp. (See Section 2 and Section 3.) Optical codes present another simple to implement means to provide critical information to a robot. (See Figure 2.)

We assert a set of assumptions concerning the factory environment and kit elements upon which to create “Smart Payloads” which will assist an autonomous robot manipulate the payload:

1. Kit elements will be packaged individually and the individual elements will be packaged together in an organized fashion. (Analogous to a palette of cereal boxes at Costco.)
2. Suppliers will accommodate small changes to packaging (such as adding RFID devices and adding graphics to packaging).
3. Individual packaging will be compatible with the desired manipulator
4. Elements will not need to be removed from the individual packaging by the robot
- OR-
5. Packaging will facilitate extraction of the contents by the robot (such as via quick release lids on boxes).

Low-cost RFID (Radio Frequency Identification) devices can communicate some of this information—or could communicate a web pointer for a more detailed description on-line. RFID badges which contain up to 256 KB of user defined data plus unique identification numbers cost less than \$0.50 each in bulk,

and badges without less to no user writable storage can cost around \$0.15. This small amount of data can be used to communicate information about the physical nature of the object to be grasped, including a description of how to grasp the object. Such information will greatly reduce the complexity of the grasping and manipulation task. For instance, the grasp type and handle location can be described, or a URL for much more detailed data can be communicated. In addition to providing information, RFID tags can be used to facilitate the localization of objects. Specifically, UHF RFID tags can be detected from a distance of up to five meters.

Markings may be placed on every face of a package to identify each individual face. Other computer readable information can communicate the physical description of the object, including the size and location of the graphic itself. This information can be used to significantly reduce the complexity of the required computer vision to recognize the package. Essentially, once an optical code is scanned, a three dimensional model of the package may be constructed and its location in space known, include the grasp point. Autonomously or by further instruction derived from optical code or RFID, either directly or via reference, the robot will be able to manipulate the package.

4.4 Management Plan

In year one, information requirements for the manipulation will be determined. A minimum set for manipulation of structured packaging will be determined in year 1. The development of the theoretically required information for an arbitrary manipulator to manipulate an unstructured object will also be created.

A package specification to simplify autonomous grasping in unstructured environments (of structured objects) will be developed during year 2. Size and placement of packaging surface finished which accommodate suction grasps, reusable inserts to facilitate grasp using magnetic graspers, reusable handle addons and package break away elements which yield useful handles will all be developed.

Packaging elements will be generated in simulation for testing the ease of autonomous grasping using a simulation of the robot hardware. This will begin during the end of the package development process during year 2 and continue through the beginning of year 3. Grasp of packaging elements using hardware under increasingly real circumstances will be well developed by the end of year 3.

During year 4, methods to allow the robot to generate package descriptions and grasp points from arbitrary packages will be developed. (See Section 8.)

5 MOBILE MANIPULATION PLATFORM

5.1 Background

A wide variety of robot arms and mobile platforms exists already, although pricing of these is typically a barrier for both research and applications. A more limited set of robots exist that are capable of both mobility and manipulation. A popular example was the RX4000 mobile platform by the now defunct Nomadic Technologies, hosting a PUMA 560 robot arm [43]. The cost of the RX4000 platform alone was approximately \$36k, before addition of a robot arm. In 2003, DARPA, under the Mobile Autonomous Robot Software (MARS) program, provided Segway RMP mobile platforms to 12 research institutions, some of which were augmented with manipulators. Platforms by Segway Inc. of Bedford, NH are also pricey (*e.g.* an RMP400 base costs approximately \$40k), plus there is the cost of adding an arm. Barrett Technologies Inc. of Cambridge, MA produces a platform popular with researchers. The the Barrett WAM (whole-arm

manipulator) costs \$100k for the arm alone and with a 7-DOF WAM arm, 4-DOF wrist and BarrettHand costs nearly \$170k.

DARPA and NASA created a mobile version of Robonaut, combining an anthropomorphic torso with a Segway base[44]. This system is not commercially available, and therefore it is difficult to estimate price, though it is certainly beyond reach of all but a few research laboratories. Currently, one of the most sophisticated commercial mobile manipulators is the PR2 from Willow Garage Inc. of Menlo Park, CA[45]. While highly sophisticated, the cost of this system (at about \$400k) is prohibitive, and the system is unlikely to be sufficiently robust for hard use (*e.g.* manufacturing). The DARPA ARM-S developed a standardized mobile manipulation platform consisting of two 7-DOF Barret WAMs, each with a BarrettHand. The manipulation system alone approaches \$500k. The M1 by Meka Robotics LLC of San Francisco, CA is a dual-armed robot, like the PR2, priced at \$340k. The Packbot by iRobot of Bedford, MA, is a remote-controlled (non-autonomous), tracked manipulator priced at over \$100k. Recently, Kuka Roboter GMBH of Augsburg, Germany introduced the youBot, a mobile manipulator priced at approximately \$33k. However, this system has a mere 0.5kg payload capacity, and thus has limited practical utility. Additional commercial mobile-base options (without arms) include the RWI/iRobot B21 from iRobot of Bedford, MA at approximately \$20k, a MobileRobots “PowerBot” by Adept Technologies of Amherst, NH at \$20K, and the “Husky A200” by Clearpath Robotics of Kitchener, ON, at approximately \$10k. In our own work, we have used a variety of arms and mobile platforms, including an “Andros” by Remotec, originally of Oak Ridge, TN (now a subsidiary of Northrop Grumman Corp. of Fall Church, VA) tracked vehicle (originally \$50k), and “Dexter” – full-scale road vehicle run in the DARPA Urban Challenge constructed at Case Western Reserve University.

5.2 Approach

A more practical alternative that we have used for mobile-robot research consists of wheelchair bases by Invacare of Elyria, OH. For the present project, we propose to use an Invacare wheelchair base, for multiple reasons. First, we are already thoroughly familiar with this platform, which will enable us to make rapid progress with this project. This base has a large battery capacity and can carry heavy payloads at appropriate (walk-speed) rates. Further, we have several of these on hand available for use in the project, which helps to reduce the budget needs. Another virtue of this chassis is that it incorporates decades of development and testing to assure safety and reliability in the context of working closely with people. Introduction of this platform into additional human-interactive tasks will benefit from inheriting the safety and reliability of wheelchair development.

Further, our steering solution interfaces to Invacare wheelchairs via existing cabling and connectors, thus enabling low-cost, modular retrofits to stock wheelchairs.

Our specific system will integrate a low-cost laser-triangulation ranger (from a “Neato” robot vacuum cleaner, \$400), multiple sonar sensors, and a “Kinect” 3-D imaging system (\$120). *The Neato and Kinect sensors, being relatively new, will require detailed characterizations and development of appropriate probabilistic models suitable for optimal sensor fusion. – Still true?*

We have provided Otto with a modular, yet relatively powerful, compact and economical computer retrofit that provides capacity for growth as well as wireless communications. Otto also incorporates an array of competent but low-cost sensors, including encoders, mouse optics, a scanning laser triangulator, an inertial measurement unit, sonar sensors and a Kinect camera. These sensors are all mass produced and are relatively inexpensive. Fusion of the various sensors offers the opportunity for dependable sensing.

Unlike mobile-robot companies that have had short lives, leaving their customers abandoned with pricey but obsolete platforms, Invacare, Inc. has been in operation since 1985, rising to become the world’s leading manufacturer of battery-powered wheelchairs (delivering nearly 40,000 wheelchairs annually). This volume allows achieving economies of scale that have not been realized by robot manufacturers. A complete Invacare power wheelchair can be purchased for under \$4k, and this could be substantially lower cost if the base is purchased without the chair, cushions, footrests, joystick, and associated hardware specific to operation as a wheelchair.

We have enjoyed Invacare research support in the past, which has included both equipment donations and student fellowship support. Working with Invacare, we have developed means to interface to existing controllers with a plug-and-play retrofit, thus making it simple for researchers or remarketers to extend the functionality of these generic, powerful and economical bases. (See Figure 3.)

5.3 Methods

To convert our chosen mobile platform into a practical mobile manipulator, we will use an IRB-120 robot from ABB Ltd. of Zurich Switzerland. This model is a 6-axis arm with a 3 kg payload. It weighs just 25 kg and has a compact controller, suitable for mobile use. The IRB-120 is a dependable, factory-automation grade robot that is unusually economical, at under \$15k. (See Figure 3.). Further, discounts are available for educational institutions, making this arm an attractive choice for academic researchers. As with the Invacare base, we additionally have a preference for ABB robots since we have enjoyed sustained support from ABB, both through equipment donations and through student fellowship support. Already being familiar with ABB robots and controllers will enable us to make rapid progress with the mobile-manipulator task. Additionally, ABB has expressed interest in supporting this work through donation of an IRB-120, which will further help extend our resources.



Figure 4: ABB IRB-120 industrial robotic manipulator.

By integrating the Invacare mobile base with the IRB-120 robot arm, we will create a platform that is unusually robust and economical. Within this task, we will need to design specific mechanical, electrical and communications interfaces that are comparably robust and economical. It is our objective to publish details for performing this integration, which will make this technology available to other researchers and developers.

Manipulation demonstrations performed in Newman’s lab have included: assembling gears and splines washing a window with a squeegee, carrying an egg between steel tool flanges with two arms, pouring liquids (with a robotic bartender), playing air-hockey, manipulating of levers, dials and switches, sliding rigid objects along rigid kinematic constraints, sliding paper across a surface, using power tools (grinders, Dremel tools), fitting a key into a lock, and performing snap fits (e.g. pneumatic quick-connects). This experience will benefit our team’s ability to create and demonstrate the functionality of the mobile-manipulation robot. In addition, Prof. Newman is currently engaged in NSF-sponsored research in robotic surgery, focusing on compliant manipulation of compliant objects and Prof. Lee has been developing an autonomous manipulation system based on the DARPA ARM-S Community Outreach program. This parallel work will be useful in addressing the challenges tasks in object manipulation in

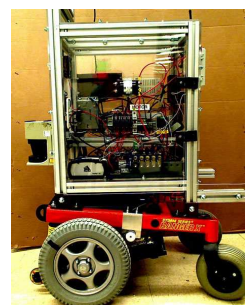


Figure 3: “Harlie” is a robot based on an Invacare wheelchair.

unstructured environments.

Use of NAC is consistent with control-based grasp, as described above, with autonomous learning, and with schema-based behavioral control. It has shown its worth outside of the laboratory under harsh industrial demands of throughput and reliability. It has been demonstrated as a retrofit to a spectrum of robot arms (including Robotics Research Corp’s first compliant-motion control instantiation, the ParaDex robot, and industrial robots from Motoman, Seiko, Kawasaki and Adept). NAC has been retrofitted to the ABB IRB-140 manipulator.

Concurrent with the hardware integration, ROS based simulations of the hardware will also be constructed. Software development for the factory kitting assist robot can begin once a simulated robot is complete. ROS packages available for navigation, localization, mapping and SLAM will further speed the development process.

The DARPA ARM-S program also uses ROS to facilitate the development for autonomous manipulators[46]. The ARM-S program established a standardized reference hardware, government-furnished equipment (GFE), that was developed using ROS. DARPA provided ARM-S program awardee with the hardware and a software simulation. That simulation has also been released to the public in a Community Outreach program to spur public participation similar to that observed during the DARPA Grand Challenge. The software environment will leverage this package as well to integrate well with the current state-of-the-art development in autonomous manipulation.

5.4 Management Plan

The mobile manipulator developed in this task, integrating the Invacare base with the ABB IRB-120 arm, will be completed within the first year of this project. While incremental improvements will be incorporated through the program, a functional system can be completing within this time due to our existing experience with the components. By the end of year 1, our system will execute ROS nodes that drive our system through hallways of a building, performing LIDAR-based localization, and motions of the arm will be controllable via ROS messages.

The integration of the Invacare wheelchair and ABB IRB-120 arm and ROS interface will be complete at the end of year 1. Work concerning hardware development in year 2 will include interfacing the ROS components to the DARPA ARM-S infrastructure and development of simulation components. All ROS and DARPA ARM-S development will be released to the public by the end of the second year. (See Section 8.)

6 INTELLECTUAL MERITS

The proposed work will contribute to robotic science in three areas of research: programming by demonstration, navigation among humans, and autonomous manipulation.

“Programming by Demonstration” is an area of significant current research. The proposed work will not solve the issue, however, adequate background exists to allow the limited scope of work for the robotic assistant to be programmed by demonstration by factory floor personnel instead of software reprogramming by robotics engineers. We aim to simplify the process to the point that demonstrating new programs to our robot will be as complex as showing “the new guy” where to get kit elements and where to drop them off.

The robot will still need to travel autonomously through the factory to acquire kit elements and deliver to assembled kits. Our robot will take advantage of observed behavior of humans interacting with autonomous

robots. To be functional, autonomous robot must not only be safe, but they must be able to complete the specified task within a certain time frame. The research proposed for this project will further this area of knowledge for the benefit of several areas of robotics.

The autonomous manipulation problem is a daunting one. We have proposed to leverage the existing structure in the apparently unstructured environment of the factory floor. Our robot will use this structure to facilitate autonomous manipulation. The research to establish in our robot the ability to reliably manipulate an object in an unstructured environment will facilitate the adoption of robots like the one proposed in many applications. It will also help to further research into autonomous manipulation in unstructured environments.

7 BROADER IMPACTS

The proposed mobile manipulator and the methods for development has been designed to leverage and contribute back to the robotics community and to expose many students to robotics research.

7.1 Dissemination

The proposed project will design software interfaces to leverage existing open-source software. Specifically, we further our existing ROS (Robot Operating System) interface for the Invacare mobile platform and develop an interface for the IRB-120 arm. These interfaces will support the existing ROS code library, including routines for interfacing sensors, performing path planning, mapping, localization, steering, and an ever-growing suite of capabilities. We will also incorporate our own routines for precision steering and navigation, developed previously for both the DARPA Urban Challenge (TeamCase/Dexter) and for our ongoing research in smart wheelchairs. We have already contributed robotics code to the ROS repository, and work under this task will expand our contributions, notably in support of the new mobile-manipulator system.

Robot hardware and software development will leverage the Robotic Operating System (ROS). ROS is specifically a mechanism to facilitate community development of robotics[47]. We will use ROS to more quickly develop a software system for controlling our hardware, as well as develop a simulation of our platform. The Community Outreach element of the DARPA ARM-S program provides a ROS based interface to the hardware and simulation of the Government-Furnished Equipment (GFE). The ultimate goal of the DARPA ARM-S program is to develop autonomous manipulation software for an arbitrary mobile manipulator. We will incorporate the DARPA ARM-S Community Outreach environment to allow software addressing the challenges in the DARPA ARM-S program to use the simulation we develop, and ultimately our hardware as well.

7.2 Education

The development process described for the robotic hardware will be used to expose students in the mobile and manipulator robotics course to the development of actual robot hardware and software. The development process will leverage course work, independent projects, and outreach programs to provide education opportunities for many students interesting in robotics and engineering to interact with active research in these fields.

Integration of Research and Education:

Case Western Reserve University encourages undergraduate participation in research, and we intend to utilize the NSF REU opportunity to promote undergraduate involvement. We also engage students in our ongoing research through senior projects. Additionally, this research will feed into courses taught by the principal investigators, including our courses in mobile robotics, robotic manipulators, computational intelligence and cognitive robotics.

Integrating Diversity and outreach to K-12:

The present research will involve high-school students through participation in the research and through high-school competitions that we host and coach. Prof. Newman has organized CWRU's annual high-school Lego competition for the last 3 years. As part of this competition, we have offered tours and tutorials on robots and robot programming. Future Lego competitions may explore intelligent wheelchair challenges (appropriately scaled to Lego robots). Additionally, Dr. Newman has advised FIRST robotics teams for the last 5 years, specifically targeting underrepresented groups in engineering. He founded an all-girls high-school robotics FIRST team, specifically to promote more women in engineering, and also advised a predominantly-minority, inner-city high-school robotics team, for which he won the Woody Flowers mentoring award. Prof. Newman also has regularly advised high-school students participating in his robotics research. Finally, Prof. Newman participates in Case's ACES program, most recently hosting a student from a HBCU during summer 2010 to work on speech recognition for smart wheelchairs. NSF support of this project will help to maintain Prof. Newman's outreach efforts.

8 PROJECT MANAGEMENT

This project will be conducted over a four year period. The breakdown of the project into constituent element can be seen in the Gantt chart in Figure 5.

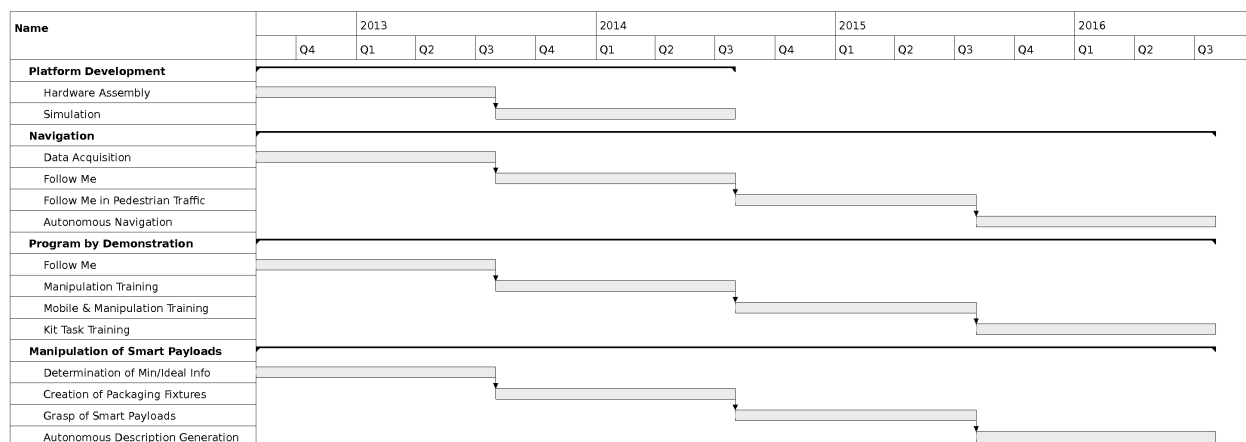


Figure 5: This Gantt chart indicates how the proposed project will deconstructed into elements, the relationship between elements, and the approximate time to complete elements.

9 RESULTS FROM PRIOR NSF SUPPORT

Dr. Wyatt S. Newman, a former NSF Young Investigator in robotics, is currently a co-PI on an NSF grant in robotic surgery. Under this grant, Dr. Newman developed a hybrid control means that merges his

prior work in Natural Admittance Control with kinematic constraint satisfaction for access of tools through portals. A thesis and a submitted publication are both currently under review.

Dr. Newman was also a co-PI (with Dr. Çavuşoğlu, PI) on a recently-concluded NSF equipment grant (CISE CNS-0423253, 09/04-09/09, \$159,945). This equipment grant fulfilled its goals in enabling new research (ultimately leading to the latest robotic-surgery NSF award) and bringing research into the classroom (including Prof. Newman's mobile-robotics projects course).

Dr. Newman also recently supported a small company, Western Robotics (founded by one of his former students) in developing a compliant-motion controlled robot system for material removal. After completion of a successful NSF phase-I SBIR, Western Robotics was awarded a Phase-II grant. Through subcontracts to CWRU, Dr. Newman continues to provide research support to Western Robotics.

The most recent NSF award in which Newman was the PI was "Computer-Aided Manufacturing of Laminated Engineering Materials: Machine Design and Process Control" (ENG CMMI-9800187, 06/98-6/01, \$185,000). This work resulted in 6 publications, 1 Ph.D. and 2 M.S. theses, 3 U.S. patents awarded, and the foundation of a company, CAM-LEM, Inc., which is still in operation.

Dr. Gregory S. Lee has not received funding from the National Science Foundation.

10 TEAM QUALIFICATIONS

Wyatt S. Newman, Ph.D. is a Professor in the Electrical Engineering and Computer Science Department at Case Western Reserve University in Cleveland, OH. His research is in the areas of mechatronics, robotics and computational intelligence, in which he has 12 patents and over 120 technical publications. He received the S.B. degree from Harvard College in Engineering Science, the S.M. degree in Mechanical Engineering from M.I.T. in thermal and fluid sciences, the M.S.E.E. degree from Columbia University in control theory and network theory, and the Ph.D. degree in Mechanical Engineering from M.I.T. in design and control. Dr. Newman spent 8 years in industrial research at Philips Laboratories, Briarcliff Manor, NY, engaged in electromechanical design and control. He joined Case in 1988, and in 1992 he was named an NSF Young Investigator in robotics. Wyatt also holds an adjunct appointment at the Cleveland Clinic and the Cleveland V.A. Medical Center. Additional professional appointments and experience include: visiting scientist at Philips Natuurkundig Laboratorium, Eindhoven, The Netherlands; visiting faculty at Sandia National Laboratories, Intelligent Systems and Robotics Center, Albuquerque, NM; NASA summer faculty fellow at NASA Glenn Research Center; and visiting fellow at Princeton University.

Gregory S. Lee, Ph.D. is a Research Assistant Professor at Case Western Reserve University in Cleveland, OH. He has studied force feedback haptics, image recognition, robotics, and secure teleoperation. He received his B.A. in Physics from Whitman College in Walla Walla, WA and M.S. and Ph.D. degree from the University of Washington in Seattle, WA. Dr. Lee joined Case Western Reserve University in 2010.