The Complex Structure of Simple Devices: A Survey of Trajectories and Forces that Open Doors and Drawers

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***Abstract*— Instrumental activities of daily living (IADLs) involve physical interactions with diverse mechanical systems found within human environments. In this paper, we describe our efforts to capture the everyday mechanics of doors and drawers, which form an important sub-class of mechanical systems for IADLs. We also discuss the implications of our results for the design of assistive robots. By answering questions such as "How high are the handles of most doors and drawers?" and "What forces are necessary to open most doors and drawers?", our approach can inform robot designers as they make tradeoffs between competing requirements for assistive robots, such as cost, workspace, and power.**

Using a custom motion/force capture system, we captured kinematic trajectories and forces while operating 29 doors and 15 drawers in 6 homes and 1 office building in Atlanta, GA, USA. We also hand-measured the kinematics of 299 doors and 152 drawers in 11 area homes. We show that operation of these seemingly simple mechanisms involves significant complexities, including non-linear forces and large kinematic variation. We also show that the data exhibit significant structure. For example, 91.8% of the variation in the force sequences used to open doors can be represented using a 2-dimensional linear subspace. This complexity and structure suggests that capturing everyday mechanics may be a useful approach for improving the design of assistive robots.

I. Introduction

Little is known about the statistics of real-world mechanical systems in human environments nor the implications of these statistics for robot design. In this paper, we describe progress towards capturing and characterizing real-world mechanical systems that are relevant to assistive robots. With the example of doors and drawers, we show that even ostensibly simple real-world devices relevant to instrumental activities of daily living (IADLs) have complex structure that can be captured and characterized (see Fig. 1). We also present evidence that this structure can be used to inform the design of assistive mobile manipulators, both in terms of hardware and software.

Recently, researchers have developed a number of robotic systems to operate doors between rooms [1, 2, 3, 4], and open cabinet doors and drawers [5, 6, 7]. Other work in service robotics has used observations to estimate kinematic parameters of doors and drawers and articulated rigid bodies [5, 8, 9]. Robots have also estimated mechanical parameters to perform tasks, such as friction coefficients when pushing objects [10].

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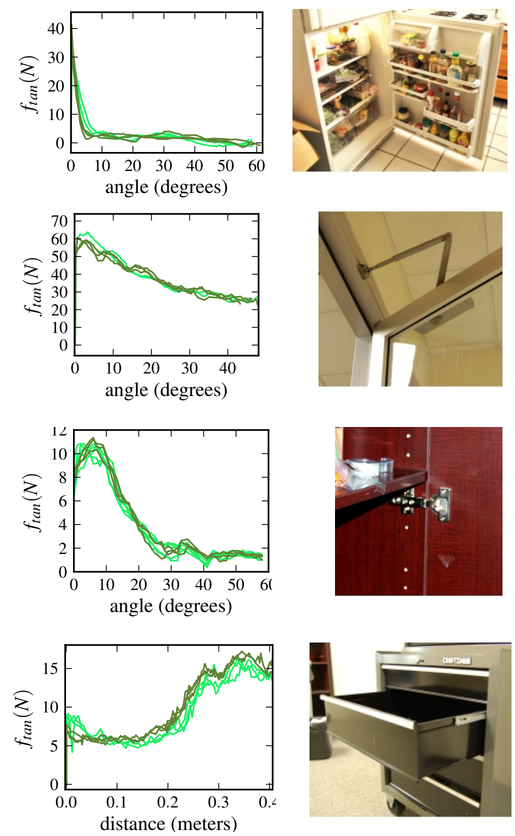

Fig. 1. Forces recorded while opening four mechanisms. Left plots show forces tangential, f_{tan}, to the motion of the handle as a function of the device's configuration. Lighter green indicates trials with higher average velocity. Pictures on the right highlight a key mechanical element of each mechanism. **Top:** refrigerator, 6 recordings, avg. velocities of 17.8°/s to 26.8°/s. High initial force due to low pressure interior. **Upper Middle:** springloaded door, 5 recordings, avg. velocities of 6.5°/s to 13.5°/s. Large forces throughout movement due to linkage at top. **Lower Middle:** kitchen cabinet, 9 recordings, avg. velocities of 7.4°/s to 16.3°/s. Non-linear spring keeps it closed with max force at about 4°. **Bottom:** toolchest drawer, 6 recordings, avg. velocities of 0.07m/s to 0.15m/s. Larger force halfway due to 2nd stage of telescoping rail.

These efforts have focused on algorithms for control and estimation, not on capturing the statistics of everyday mechanics. As such, their empirical evaluation has been limited to a relatively small number of mechanisms. Despite progress towards assistive robots capable of opening doors and drawers, basic questions remain unanswered, such as, "How hard does a robot need to pull in order to open most doors?" and "How high does a robot need to reach in order to open most drawers?".

In this paper, we describe our efforts to address these questions by capturing kinematic trajectories and forces

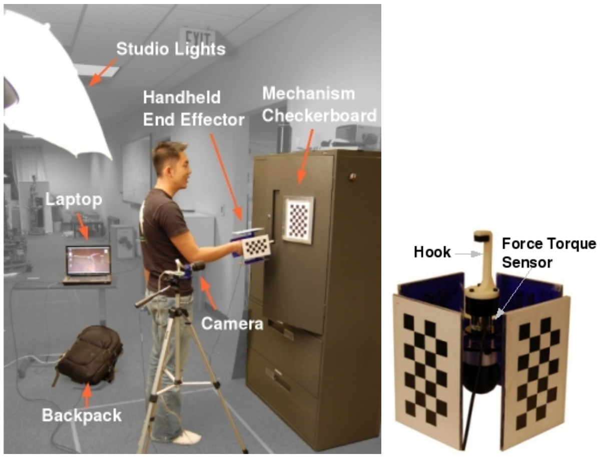

Fig. 2. **Left:** The different components of our capture setup. **Right:** The handheld end effector consists of a 3D printed hook with a force-torque sensor at its base and four checkerboard patterns.

while operating 29 doors and 15 drawers in 6 homes and one office building in Atlanta, GA, USA. We have also hand-measured the kinematics of 299 doors and 152 drawers in 11 area homes.

We have organized the rest of this paper, as follows. First, we describe our capture setup and capture procedure in Sec. II, and present simple mechanical models for doors and drawers in Sec. III. We then analyze the kinematic and force data in Sec. IV. In Sec. V, we give examples of how our captured data could be used to inform design decisions for assistive robots. We then conclude with sections Sec. VI and Sec. VII.

II. Methodology

A. Capture Setup

We designed a capture system to log the kinematic trajectory through which mechanisms move and the forces used to operate them. Fig. 2 shows the components of our capture system which consists of: (1) a checkerboard pattern that we attach to the mechanism (2) a handheld end-effector that consists of a hook, a force-torque sensor (ATI Nano25), and four checkerboard patterns (3) a camera (Point Grey DragonFly2) to capture video of the operator (4) studio lights (5) a backpack containing hardware for the force-torque sensors, and (6) a laptop to log the data. The handheld end-effector consists of a 3D printed hook with a force-torque sensor at its base, four laser cut acrylic pads with checkerboard patterns, and a handle for the operator to grasp. The four checkerboard patterns allow us to ensure that one checkerboard is visible given typical hook orientations.

We have used open source code for this capture setup, including ROS [11], OpenCV [12], and have released our code and hardware designs (see Sec. VIII).

B. Capture Process

Research in the field of haptics, has attempted to capture and model everyday mechanics to produce realistic haptic simulations in virtual environments [13, 14, 15, 16, 17].

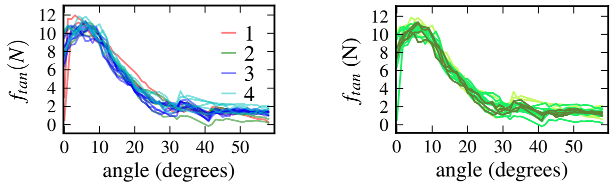

Fig. 3. Forces recorded when four different operators open the same mechanism. The forces are dominated by the configuration of the mechanism and not by the operator. **Left:** Trials colored by the operator. **Right:** Trials colored by average velocity. Lighter green indicates trials with higher average velocity.

This body of work emphasizes high-fidelity models of single objects for realistic haptic feedback.

In contrast, we wish to capture statistics that can inform the design of assistive robots. Since robots operating at moderate to slow speeds would have value, we create quasi-static models and characterize the statistics of real-world mechanisms. We capture data relevant to quasi-static models by instructing the operators to open the doors and drawers at slow speeds. We then throw out recordings of trials with large average velocities. For each mechanism we first find the lowest average velocity across all the trials. We then throw out all trials whose average velocity is larger than this lowest average velocity by more than 10°/s or 15cm/s.

To capture data, we use the handheld hook to pull the door or drawer open and record force-torque sensor readings and video. The operator for any mechanism in our dataset was one of four different people. We also conducted trials for four operators on one mechanism and found that the measured force exhibited no clear variation due to the user and was strongly dependant on the quasi-static forces due to the configuration of the mechanism (see Fig. 3).

C. Mechanisms that we surveyed

We collected data in six homes and one office environment in Atlanta, Georgia, USA. At each location, we tried to capture data for all the different kinds of mechanisms subject to the constraints of our capture setup. First, we were unable to collect data for mechanisms whose trajectories are not parallel to the ground (e.g. dishwashers) or would occlude the checkerboard patterns. Second, we were limited to mechanisms that can be operated by hooking then pulling. This excludes all the doors between rooms at the locations we visited, except two spring loaded doors in the office environment. Third, drawers in the kitchens of two of the six houses had a tendency to fall down as they are pulled out (Fig. 9). We did not capture data for these drawers.

If there were multiple mechanisms with the same hinge type, we collected data for one of them. For example, we collected data for one drawer out of a set of identical looking drawers. We logged 10 trials for each mechanism.

In addition, we hand-measured kinematic properties of every mechanism in 11 different homes (a total of 451 doors and drawers). We measured the height of the handle of the mechanism above the ground and the distance of the hinge of the mechanism from the hooking location (for rotary joints), and the opening distance for drawers.

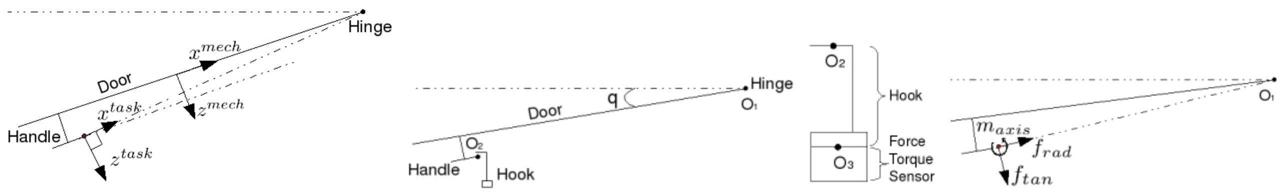

Fig. 4. **Left:** The orientation of the task frame at the handle can be different from the mechanism coordinate frame. **Middle Left:** Top view of a mechanism as we use a hook to open it. O_1 is a point on the axis of rotation of the mechanism. O_2 is the point of contact between the hook and the handle. **Middle Right:** Hook with the force-torque sensor at its base. The force-torque sensor measures the wrench at point O_3. **Right:** Components of the wrench $W^m(O_2)$ computed using Eq. 2. f_{rad} and f_{tan} are the components of the force in the plane of the trajectory of the hook and m_{axis} is the moment parallel to the axis of the rotary mechanism.

D. Estimating Kinematic Parameters

1) Estimating the mechanism angle/position: We denote the angle or position of a mechanism as q. For a rotary mechanism, q corresponds to the angle of the door, and for a drawer, q corresponds to how far the drawer has been pulled open. For each frame of the captured video, we estimate the 6D pose of the mechanism checkerboard pattern in the coordinate frame of the camera with [18]. We then fit either a rotary or a linear model to this trajectory using [8] and use that to compute the configuration q of the mechanism for each frame of the video.

2) Estimating a Task Frame at the Handle: As detailed in Sec. III, we factor the forces measured using the force-torque sensor into a component that is responsible for opening the mechanism and a second component that produces only constraint forces. To do this, we estimate a task frame at the point of contact between the handheld end-effector and the mechanism handle [19].

For a linear mechanism, we assume that this task frame is the same as the coordinate frame of the mechanism checkerboard pattern. This is the same as assuming that the mechanism checkerboard pattern is mounted such that the normal to the surface of the pattern and the direction of motion of the drawer are identical.

The orientation of the task frame for a rotary mechanism is shown in Fig. 4. It is important to note that if the handle sticks out from the surface of a rotary mechanism, the orientation of this task frame will be different from the orientation of the coordinate frame of the mechanism checkerboard pattern. We fit a circle to the trajectory of the point on the handheld end-effector that makes contact with the mechanism handle. We assume that this point is fixed relative to the hook. We then use the radial direction of the circle for our estimate of x^{task}, and the normal to the plane of the circle as the estimate of y^{task}. We compute z^{task} as $x^{task} \times y^{task}$.

E. Time Synchronization

We log the data from the force-torque sensors at around 100Hz, and video from the camera at 30 frames per second. To synchronize the two data streams we smooth the force data independently for each channel, and resample at 33Hz.

III. Measuring the Opening Forces

We would like to use the captured data to compute statistics that will be useful for the design of robots. In this section we model drawers as prismatic joints and doors as rotary joints, and use basic mechanics to estimate the forces that open the doors and drawers in our dataset. These models can be violated in the real world. For example, there can be some amount of motion in the joint of a door and some drawers have a tendency to fall down as they are pulled out (Fig. 9).

A. Notation

We use the tuple $W(A) = (f(A), m(A))$ to denote the force $f(A)$ and moment $m(A)$ due to wrench W at a point A on a rigid body. The value of the wrench W at a different point B on the same rigid body can be computed as

$$\begin{pmatrix} f(B) \\ m(B) \end{pmatrix} = \begin{pmatrix} f(A) \\ m(A) + P(BA) \times f(A) \end{pmatrix}, \quad (1)$$

where $P(BA)$ is the vector from point B to point A.

B. Mechanics of a Rotary Joint

Fig. 4 shows a rotary mechanism with a hinge at point O_1, opened by an angle q using the hook which makes contact with the handle at point O_2. Let the wrench applied to the force-torque sensor by the hook measured at the base of the hook be $W^s(O_3)$. Using Eq. 1, we can compute the value of W^s at the point of contact between the hook and the handle of the mechanism O_2, denoted by $W^s(O_2)$. Now, let W^m be the wrench applied to the mechanism by the hook. Assuming that the mass and moments of inertia of the hook are small enough for us to ignore dynamic effects, we get

$$-W^m(O_2) - W^s(O_2) + W^g(O_2) = 0, \quad (2)$$

where W^g is the wrench due to gravity on the hook. At the start of each trial, when we know that W^m is equal to zero, we compute W^g by measuring W^s from the force torque sensor. We then assume that W^g is constant for the duration of the trial, although the hook orientation might change.

Eq. 2 allows us to compute the wrench applied on the mechanism by the hook, W^m. We then compute the forces f_{tan} and f_{rad} and the moment m_{axis}, shown in Fig. 4. For our capture setup, m_{axis} is almost zero indicating that contact between the hook and the handle of the mechanism

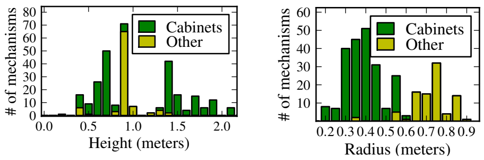

Fig. 5. **Left:** Histograms of height of the handles of rotary mechanisms in our kinematic dataset. Each bin represents a range of 10cm. Frequencies of heights of cabinets are in green, and of other mechanism classes (doors, freezers, and refrigerators) are in yellow. **Right:** Distributions of door radii using the kinematic dataset with each bin having a range of 5cm. Cabinets are in green and all other rotary mechanisms are in yellow.

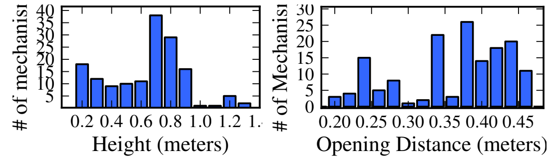

Fig. 6. **Left:** Histogram of height of drawer handles above the ground. Each bin has a range of 10cm. **Right:** Histogram of maximum opening distance for drawers. Each bin has a range of 2cm.

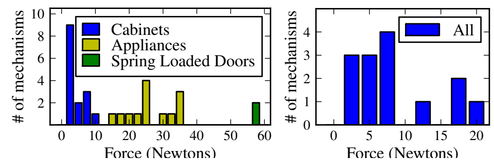

Fig. 7. **Left:** A histogram, colored by category, of the minimum tangential forces that were necessary to initiate motion while opening 31 different rotary mechanisms in our dataset. "Appliances" include refrigerators, freezers, and a microwave. **Right:** A histogram of the minimum forces that were necessary to start opening the 14 drawers in our dataset.

can be approximated by a pin joint. We assume a pin joint model for the point of contact and set m_{axis} equal to zero.

To compute f_{tan} and f_{rad}, we estimate a task frame at O_2, see Sec. II-D. f_{rad} points in the radial direction and will only result in constraint forces at the hinge of the mechanism. f_{tan} is the only component of the force that contributes to a moment about the mechanism axis. The moment about the hinge axis due to W^m will be equal to $f_{tan} \cdot r$, where r is the distance of O_2 from the mechanism axis.

C. Mechanics of a Linear Joint

We model drawers as a prismatic joint whose direction of motion is along z^{task}, as explained in Sec. II-D.2. Using this model, the only component of the wrench W^m that is responsible for opening the drawer is the force along z^{task}. All the other components will result in constraint forces.

IV. Statistics of Doors and Drawers

We now present statistics of the forces and kinematics from our dataset.

A. Kinematic Analysis

Fig. 5 shows the distribution over heights of the door handles. We divide this distribution into two with the first containing the handle heights of cabinets, and the second containing the handle heights of all other mechanisms.

There are few cabinet handles between a height of 0.9m and 1.3m. Often in kitchens in the US, countertops are 91.4cm (36") high, and cabinets sit 18" above countertops or 124.2cm above the ground [20]. The most frequent non-cabinet rotary mechanisms are doors between rooms. The standard height for the handles for these doors, 91.4cm (36"), corresponds to the peak in the yellow histogram in Fig. 5. Other doors such as storage and coat closet doors occur at lower frequencies. In Fig. 5, we also show the distribution of the radii, split into cabinets (green) and all other mechanisms (yellow). Cabinets come in a variety of standard sizes starting at 22.5cm (9"), increasing in increments of 3" up to 122cm (48") [21].

From Fig. 6 we observe that most drawer handles are less than 1m above the ground. Thus, if a mechanism handle is at a height greater than 1m, there is a strong prior that the mechanism is not a drawer. Alternately, if a robot has a specific controller or behavior for opening drawers, it might be sufficient for that behavior to work at a maximum height of 1m above the ground.

B. Force Analysis

As detailed in Sec. II-B, we capture data relevant to quasi-static models by instructing the operators to open the doors and drawers at slow speeds and then throw out recordings of trials with large average velocities. Fig. 1 shows that there are only modest changes in the forces for the remaining trials indicating that the data are dominated by configuration dependent forces, and thus agrees with our quasi-static assumptions. Furthermore, average velocity is a reasonable way to model the variation across trials, since all the doors and drawers were closed and at rest at the start of each trial, and the mechanism configuration increased monotonically during all trials.

For the data we use in our analysis, the angular velocities for door opening had a mean (standard deviation) of 19.6°/s (8.2°/s). The mean (standard deviation) of the average linear velocities for drawer opening was 0.14m/s (0.068m/s). Moreover, the structure of the forces relates to the configuration-dependent mechanics, rather than other aspects of the trajectory. As shown in Fig. 1 the forces when opening the cabinet were dominated by the non-linear spring that holds the cabinet closed and has a peak force at around 4°of opening. Likewise, when opening the drawer the forces were dominated by the effects of the telescoping rail.

Fig. 7 summarizes the minimum force that was required to start the motion of a door or drawer. We compute this as

$$f_{motion} = \min_{i \epsilon \{1 \dots N_i\}} \max_{q \epsilon [0, q_0)} f_{tan}^{q,i}, \quad (3)$$

where q is the mechanism configuration, N_i is the number of trials for the i^{th} mechanism, and $f_{tan}^{q,i}$ is the tangential force at q for trial i. q_0 is a threshold that we used to determine when the motion of the mechanism began. We set it to 1° for rotary joints and 1cm for drawers. Fig. 7 shows that there is a clear separation in the force required to initiate the motion of cabinet doors, freezers and refrigerators, and spring loaded doors in our dataset. We found that drawers tend to require

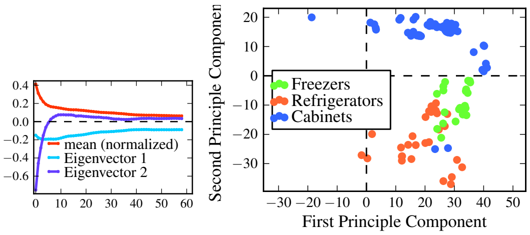

Fig. 8. **Left:** The mean vector and the first two principal components of the force profiles. **Right:** Scatter plot showing the projection of all the force profiles onto the first two principal components.

less force to operate than rotary mechanisms. The maximum force required to start opening any drawer in our dataset was around 20N.

C. Principle Components Analysis

We now present trends in the data for rotary mechanisms revealed using Principle Components Analysis (PCA). We first convert the force profiles into a vector v^i for every trial i as

$$v^i \quad = \quad \left[\begin{array}{cccc} v^i_1 & v^i_2 & \ldots & v^i_{50} \end{array} \right]^T, \tag{4}$$

where

$$v^i_j \quad = \quad \max_{q \;\epsilon\; [j-1, j)} f^{q,i}_{tan}, \tag{5}$$

and q is the angle of the mechanism in degrees. We selected a maximum angle of 50° so that we could use data from almost all the force profiles. We then compute

$$V = \left[\begin{array}{cccc} v^1 & v^2 & \ldots & v^M \end{array} \right], \tag{6}$$

which is the matrix of all trials for all mechanisms combined, a total of M trials. In our dataset, we have a total of 146 trials on 29 rotary mechanisms.

Fig. 8 shows the first two principal components and a scatter plot of these 146 trials projected onto the 2D subspace. Points are colored by mechanism type. The first two principal components together account for 91.8% of the data's variance (83% and 8.8%) and 8 principle components represent 99% of the variance over the 146 force profiles for 29 doors.

The scatter plot of Fig. 8 shows that even after projecting to two dimensions, there is some separation between refrigerators, freezers and cabinets. These clusters appear to reflect common attributes of the mechanisms that keep the doors shut, see Sec. IV-D. The blue scatter points in the refrigerator cluster are from the only microwave in our dataset. Qualitatively, the microwave is similar to refrigerators as the forces that keep it closed decay rapidly as the mechanism is opened.

D. Illustrative Examples

In this section, we present examples from our dataset that illustrate that the non-linear behavior of doors and drawers is consistent across multiple trials for the same mechanism. Fig. 1 shows f_{tan} as a function of the mechanism configuration for all trials of four different mechanisms in our dataset.

Fig. 9. Three different types of drawers that we encountered – drawers with telescoping rails, rollers, and drawers with nothing preventing them from falling down as they are opened.

We can get some intuition about the shapes of the force profiles by looking at the mechanisms that keep them shut.

Refrigerators require a large initial force to open them due to the suction from the low pressure inside the refrigerator. However, once opened the doors swing easily due to bearings on the door. The force profile thus has a high peak when the door is closed and is very small after that.

Spring loaded doors require a large force to open. However, the tangential force required to open this spring loaded door is non-linear and decreases as the door is opened. Almost all cabinet doors also exhibit a behavior similar to the spring loaded doors. Most cabinets have a spring-like mechanism in their hinge that ensures that the door remains closed.

We observed that many drawers have rollers or telescoping rails. Telescoping rails can introduce a change in the amount of force required to open the drawers as different sections of the telescoping rail can have different mechanical properties, see Fig. 1. Finally, we also encountered some drawers that have neither rollers nor rails. These drawers tend to fall down as they are pulled out and might require more complex control methods compared to the other types of drawers. Fig. 9 shows images of the three different types of drawers that we encountered.

V. Implications for Robot Design

By answering questions such as "How high are the handles of most doors and drawers?" and "What forces are necessary to open most doors and drawers?", our approach can help support the rational design of assistive robots. In this section, we discuss how our data could be used to inform design decisions for assistive mobile manipulators.

A. Related Approaches to Robot Design

Current approaches to the design of mobile manipulators for human environments fall into two main categories.

The first is to design robots by emulating aspects of human form and function [22]. The majority of human environments have been built to enable able-bodied humans to perform everyday tasks. If a robot were to perfectly emulate the capabilities of an average adult human, it would be capable of performing IADLs and providing assistance. The main problem with this approach is that humans represent an exceedingly high-bar for robot design. This is coupled with a lack of clear guidelines on how to simplify the human model, while producing an effective system.

Second, many designers attempt to design robots by understanding the tasks the robot would perform. The main advantage of this approach is that it opens up the possibility for robot designs that differ dramatically from humans. For example, this could result in designs for robots with limited capabilities that are achievable in the near term, and designs for robots with super-human capabilities in the long-term.

Designers following this approach use qualitative assessments of the task constraints [23, 24, 25] or government and industry standards to guide their designs [3]. In the US, for example, public and commercial spaces are legally regulated by the Americans with Disabilities Act to conform to accessibility guidelines (ADAAG) [26]. Among other specifications, these guidelines dictate that doorways need to be at least 36" wide and doors need to be equipped with lever handles. There are also industry standard dimensions for some home features, such as cabinets, drawers, and countertops. However, in spite of these efforts at standardization, significant variation remains in the real world. For example, residential homes are exempt from the ADAAG and older buildings may be out of compliance. Additionally, guidelines and requirements can change over time, allow for non-trivial variation, and leave critical mechanical properties unspecified, such as the forces that operate devices.

The strength of our approach is that it has the potential to quantitatively assess the statistics of real-world mechanics, instead of following intuition, heuristics, or written design standards. Challenges to our approach include factoring the mechanics specific to IADLs from the mechanics of the capturing process. Moreover, for this approach to be well-justified, the real-world statistics must be sufficiently complex to negate the possibility of simple specifications, and sufficiently structured for the captured data to be informative. Recent research by Aaron Dollar et al. has pursued a similar approach in the context of objects [27], which we have found inspiring.

B. Influencing Robot Design Through Captured Kinematics

We now discuss ways in which the captured kinematic data could be used to inform the design of an assistive robot that opens doors and drawers. Kinematic data provides necessary conditions that the robot must meet in order to quasi-statically operate doors and drawers by interacting with the handle. If we assume that the robot's end effector makes contact with the handle, then the end effector must be able to traverse the trajectory the handle follows when opening the door or drawer to a desired configuration.

For a conventional mobile manipulator, this immediately implies constraints on the workspace of the arm, and the interplay between the motion of the arm and the motion of the mobile base. For example, if the end effector can not reach a range of heights, the robot would be unable to operate doors and drawers at those heights, see Fig. 5. Likewise, the distribution for different radii of doors (Fig. 5), and the distance drawers can be pulled out (Fig. 6) imply particular trajectories that the end effector would need to traverse, either by movement of the arm, movement of the mobile base, or a combination of the two.

One of the main opportunities provided by this data, is the potential to rationally tradeoff features such as the arm's workspace, the agility of the mobile base, the cost, and the robot's success at operating various doors and drawers. One extreme design would use long arms that can traverse these trajectories without moving the base. For this design, a simple base might be sufficient, but the arms would probably be more complex, since a longer reach implies higher joint torques and greater positional errors due to joint angle errors. Likewise, a design that combines very short arms with an agile base might be feasible. Given the statistics, these tradeoffs could be considered relative to the desired performance over various doors and drawers. For example, an assistive robot that only operates low drawers and doors of moderate size might improve quality of life sufficiently to be desirable, especially if the cost were substantially reduced.

Kinematic data could also be used to improve software design. For example, prior knowledge can improve estimation of the kinematics of mechanisms [28]. Robots might also use this information to infer the type of door or drawer based on an observed trajectory. For example, a large radius with a handle one meter above the ground is unlikely to be a kitchen cabinet.

C. Influencing Robot Design Through Captured Forces

We now discuss how the captured forces could be used to inform the design of an assistive robot that opens doors and drawers. If we assume that we have accurately captured the quasi-static forces associated with opening doors and drawers, then we can define necessary conditions for an assistive robot to open these same mechanisms. In other words, the data defines a lower bound on the required forces. Any increase in velocity or acceleration would result in an increase in the force. Likewise, our quasi-static assumption implies that reductions in velocities or accelerations would not lower the forces significantly.

Consequently, the captured forces can be used to provide guidelines for a robot's power. For the given end effector velocities, a robot must be able to generate the necessary forces at the end effector. The implications of these constraints are particularly evident with respect to different classes of doors and drawers. For example, from Fig. 7, springloaded doors, refrigerators and freezers require much greater force to open than cabinets, so a robot that only opens cabinets would have much lower power requirements. Likewise, we found that drawers require less force to operate than rotary mechanisms.

Researchers have demonstrated that dynamically stable mobile manipulators can apply more force when pushing by leaning into the action. For example, in [29] a dynamically stable and statically stable version of a small-scale mobile manipulator attempted to push a drawer closed. The statically stable version failed, while the dynamically stable version succeeded. The authors used this result to argue for the superiority of dynamically stable mobile manipulators, but they neglected other engineering challenges associated with dynamic stability, such as increased complexity and safety concerns. By capturing the forces required to close drawers, we could estimate the value of this additional force. For example, if the greater forces provided by dynamic stability were unnecessary for a particular assistive robot design, then a statically stable base might be more appropriate.

Finally, force data can be used to improve the robot's software. Although the mechanics of operating real doors and drawers is non-linear, the structure exhibits consistency within classes across houses, such as kitchen cabinets, freezers, and refrigerators. This suggests that a robot could use similar data to better detect anomalous conditions, such as collisions, locks, or obstructions. Likewise, the robot might use this data to decide how much force to apply when opening a door or drawer for the first time. In addition, robots might be able to haptically infer characteristics of doors and drawers. For example, the forces associated with opening a refrigerator are highly distinctive.

VI. Future Work

There are many opportunities for additional research in this area. Further analysis and better estimation of the hook's velocity and acceleration could help validate our quasi-static assumptions. Faster operation of doors and drawers might be preferred by users of assistive robots, which would require methods to capture and characterize highly-dynamic mechanics. For example, we have observed humans "throwing and catching" doors and drawers by initially applying an impulsive force and then decelerating the door or drawer at a desired configuration. Variation in mechanisms over time is another complexity that could be addressed. For instance, the mass of a drawer changes based on its contents, and some doors have objects that hang from them.

VII. Conclusion

Using a custom motion/force capture system, we have shown that operation of seemingly simple mechanisms like doors and drawers involves significant complexities, including large initial forces and non-linear forces. We have also shown that relevant kinematic parameters, such as handle height and the distance drawers can be opened, exhibit large variation. We have demonstrated that in spite of these complexities, the data exhibit structure that can be used to inform the design of assistive robots.

Based on our results, we are optimistic that everyday mechanics associated with other aspects of IADLs can be captured, characterized, and used to improve assistive robots. We expect that collecting large scale datasets will become easier as robots are deployed in human environments and interconnected through the internet.

VIII. Supplementary Material

Supplementary material, including a video, source code, and hardware designs, can be found at the following address:
`www.hsi.gatech.edu/hrl/mechanics-biorob10.shtml`

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