A Human-Inspired Real-Time Grasp Force Selection Policy Based on Load-Grip Force Coupling

Michael Stachowsky, Julie Vale, Hussein A. Abdullah, and Medhat Moussa
University of Guelph, Guelph ON, Canada
Email: {mstachow, jvale, habdulla, mmoussa}@uoguelph.ca

***Abstract*—A robotics grasp force setpoint determination policy based on coupling the load force (at the robot's wrist) to the desired grasp force (at the contact points) is presented. The policy can handle, online, changing load forces, and is able to assist in the prevention of slip and the safe grasping of objects with unknown mass, rigidity, and friction properties. Experimental results show that the policy is capable of handling unanticipated mass changes in real time with appropriate choice of controller parameters.**

***Index Terms*—grasp force determination, precision grasping, load-grip coupling**

I. Introduction

An important problem in robot grasping is estimating the grasping force required to immobilize an object. If the task is a simple pick and place and the object's shape, mass, and surface friction are known, the problem is well studied and generally considered to be solved (see, for example, [1], [2]). If the object is unknown but is rigid, a recent crop of compliant grippers (for instance [3]-[5]) have shown great promise in executing a grasp with proper grasping forces. The problem becomes more difficult if the object is non-rigid and has an unknown shape and frictional characteristics; for example, grasping a slippery, permanently deformable fruit, such as a strawberry. The robot must choose the grasping force so that it neither drops nor crushes the object. This problem is wide spread in food processing and agricultural applications where robots are being developed to perform various fruit harvesting tasks. Since fruits are nonuniform and can be easily damaged by inappropriate choices of grasping forces, fruit harvesting robots have had challenges picking fruit without damaging them [6], [7].

In a recent work, we developed a strategy for regulating grasping forces on nonrigid, fragile objects with constant mass [8]. However, robots may encounter many scenarios in which object properties change during a grasp. For instance, consider filling a paper cup with water. Although the initial grasping force may have been sufficient to grasp the cup, it is difficult to estimate the exact mass of the water being poured into the cup at any given time. Thus it becomes difficult to estimate the desired grip force as the water is being poured. The issue is further complicated if the cup is a crushable paper cup. It is not acceptable to simply grasp with the maximum possible grip force at the beginning of the task (which may be appropriate for, say, grasping a rigid object in a power grasp to ensure grasp stability), since we must avoid crushing the cup.

To that end, the problem addressed in this paper is how to choose a grasping force when grasping a non-rigid object where its mass is unknown, and can change *during* the grasp. This also includes the case where the mass remains constant but the center of mass changes. We briefly note that the choice of grip force is often a distinct problem from the actual control of those forces. Physically controlling the forces is the act of ensuring that the desired and actual grip forces agree. In this work, we focus solely on the choice of desired grip forces because, in the absence of a priori object knowledge, this problem is nontrivial, difficult, and relevant to robots operating in unstructured environments.

II. Prior Work

Romano *et al*. [9] were able to mimic human mechano-receptors to predict grasping forces during contact; however, their grasp force estimation was based on heuristics dealing with contact speed and forces, and did not include any on-line estimation of object properties. Some methods of grasp force estimation, for instance [10], [11], and early work by Cutkosky [12], propose that the estimation of grip force or friction properties can be performed by observing a signal based on object motion within the hand. Although these approaches are useful during a slip, they require grasp quality to degrade before any corrective action is taken.

Yussof *et al*. [13] and Wettels [14] both worked on estimation and control of tangential (frictional) grasping forces using shear force sensors and advanced estimation algorithms. Both solutions were able to handle the task of filling a crushable cup with water under uncertainty, although they did not control grasping forces directly.

From the above review, several open problems remain. First, it is not clear how to use the object's interaction with the hand to choose an appropriate gripping force. Second, although many researchers have studied the problem of adjusting desired grasping forces in response to slip, it is not clear how to *prevent* slip by adjusting grip forces.

Manuscript received May 7, 2015; revised September 2, 2015.

doi: 10.18178/ijmerr.4.4.336-342

We propose a policy based on the use of load-grip coupling to select grasping forces. This approach is particularly suitable for grasping fragile, uncertain objects and objects whose mass changes during a grasp. Our policy ensures that the desired grasp force increases as needed. The policy has several features that, to the best of our knowledge, are not present in the literature:

- It increases the desired grasp force to a constrained maximum value based on the mass of the object and expected friction properties.
- It can handle unexpected changes in object mass by directly adjusting the desired grasping forces in real-time.

III. Proposed Approach

A. Motivation from Human Grasping

Research into human grasping has shown that humans are able to couple the load force (i.e., the force required to lift the object) with the grip force (i.e., the force required to keep the object stationary in the hand). As the object lifts, more of its weight is shifted to the hand, which increases the load force until liftoff occurs, at which point the load force becomes constant. This increase in load force causes a simultaneous increase in grasp force. When humans encounter a new object, they use this load-grip force coupling to determine when grasping force becomes sufficient [15]. This operation is performed in real-time during the time it takes to complete the Lift-and-Hold task [16].

To compensate for inertial loads that are generated, coupling between loading and grip forces occurs during gross arm motion. This suggests that grip force and load force are not controlled independently and that “the basic coupling of the forces is a prerequisite for the sensory motor mechanisms that control adaptation of the fingertip forces" [17]. Further, it seems that the load-grip force ratio is an important variable in controlling the forces during a grasp. In essence, this ratio is related to the expected friction properties between the fingers and the object [18].

By using similar load-grip coupling structures as are present in the human sensorimotor system, a robot will be able to enhance its ability to grasp under uncertainty.

B. Using Object/Robot Interaction for Grasp Force Choice

A common approach to selecting the desired grip force in robot grasping is to do so offline, or to simply not control grip force altogether. This is a type of open-loop grip force selection that works in many cases where the object is rigid, friction characteristics and mass are known, or where it is acceptable to use a power grasp, which is typically a more stable grasp [19].

However, the above review of human grasping shows that in cases of uncertainty, when dealing with permanently deformable objects with time-varying mass, or where a precision grasp is required (for instance, if high dexterity or manipulation is necessary for future task requirements), a feedback structure is more appropriate. In closed loop, the object's interaction with the hand is used to inform the choice of grip forces, enabling a greater degree of reactivity in the grasp force controller. Fig. 1 shows this structure conceptually.

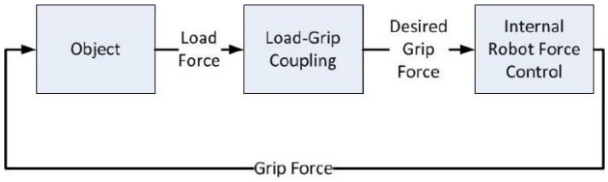

Figure 1. Feedback control structure

Another key benefit to using a feedback structure is that it alleviates the need to preprogram the task variables, which may vary considerably and unpredictably. A feedback structure enables a robot to handle many similar possibilities without the need for continual reprogramming. In this paper we develop a closed-loop approach that uses the load force sensed at the robot's wrist to select the grip force applied at the fingers during the grasp in order to leverage the benefits of feedback control.

C. Theoretical Preliminaries

In order for an object to be in a stable grasp two conditions must be met [20]:

- The sum of forces and torques acting on the object must be zero.
- The tangential contact forces must be within the friction cone at the point of contact.

In this work we assume that the object is in a grasp that *can* be stabilized by an appropriate choice of grasp forces without crushing the object, but that the final desired grasp forces are unknown. The goal, then, is, given a specific grasp, to choose contact forces that satisfy the two conditions given above. Recall that we would like to use the load force to inform our choice of grip force, so let us investigate that relationship. To that end, define F_L to be the load force, measured at the wrist, m be the mass of the object, and F_{GP} be the desired grip force for the fingers.

After the robot has made contact with the object, but before the lift begins, the robot will apply some small grip force in order to maintain contact. As the object lifts from the table, the load force will increase until one of two possible scenarios occurs:

- if F_{GP} is sufficient to lift the object, F_L will continue increasing until $F_L = mg$, at which point liftoff will occur and F_L will become constant, or
- F_{GP} is not sufficient to lift the object and at some point during the lift F_L will overcome the force of friction. At this point, termed incipient slip, F_L will stop increasing and its derivative will equal zero.

To justify this further, consider that the F_L is, in fact, due to the reaction forces due to fingertip/object friction. In general, the load forces are related to this friction force by:

$$F_L = [R_1, R_{2,} \dots R_n][F_{1,} F_{2,} \dots F_n]^T \tag{1}$$

where $F_i = [f_{i,x}, f_{i,y}, f_{i,normal}]^T$ is the contact force at contact location i, with $f_{i,x}$ and $f_{i,y}$ being caused only by friction forces. R_i is a rotation matrix that rotates the contact forces at contact location i into the coordinate frame of the load force sensor [20].

Note that the friction forces will do one of two things: either they will balance the load forces or they will reach some maximum dictated by the coefficient of friction. It is well known that, once sliding occurs, the friction forces become relatively constant with respect to velocity. Thus, during a slip, the load forces will become relatively constant (or reduce) and it is not possible to distinguish between the case of stable grasping and the case of slip.

Notice how in both cases the derivative of the load force becomes zero, so it is not obvious to a grasp force controller whether this happened due to lifting or due to incipient slip. Fig. 2 shows this behaviour for two representative scenarios: one in which the lift force is sufficient to hold the object, and one in which slip occurs during lifting.

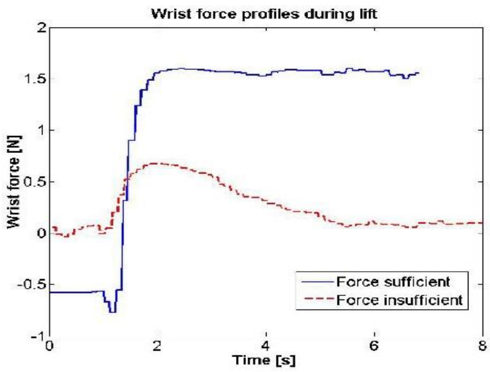

Figure 2. Wrist force response

Note: the negative wrist force indicates that the robot hand was initially pushing the object into the table slightly and is simply an experimental artifact.

The question now becomes how to choose grip force based on load force **in order to avoid this ambiguity**. Since the robot does not have any information about the final value of the load force, a naive approach would be to select a grip force that is directly proportional to F_L. However, during slip, a proper response is to *increase* the grip force, not to allow it to remain constant or to drop. Similarly, a delay would not be sufficient, since the drop in load force would still be applied, albeit after the delay period, which is not desirable. To combat this, we suggest filtering F_L through a low-pass filter. The benefit of using such a filter is that the filter output will increase with F_L; however if F_L levels out, the output of the filter will continue to increase for a short time. If the leveling off was due to slip, the increase in grip force can stop the slip, and the load force should continue to increase. On the other hand, if the leveling off was due to the object being in a stable grasp, a reasonable choice of filter parameters will ensure that the slight increase in grip force that follows will not cause a crushing problem. Thus, by closing the loop between the object's interaction with the hand and the grip force, and by designing an appropriate controller for the feedback system, we can prevent slip in situations where it otherwise would have occurred, as well as handle uncertainty.

D. *Choosing Desired Grip Forces Using Load-Grip Coupling*

Recall that our approach is motivated by human grasping. Humans use the ratio between the load force and the grip force, K_L, to assist in the choice of appropriate grasping forces [21]. We have already established in Section III. B that using K_L as a simple gain by which to multiply the load force will not be sufficient to prevent slip; instead we propose a first order low-pass filter. Let τbe an as yet unselected time constant and consider the filter

$$\frac{K_L}{\tau s+1} \tag{2}$$

which will filter the load force to produce a desired grip force. This filter has both of the desired qualities stated above. First it enables us to choose a grip force that, in steady-state, is proportional to the load force by a factor of K_L. Second, if the load force levels off the output of the filter will continue to increase for a brief time, which we have established can be used to prevent slip.

We now turn to the question of how to select K_L and τ. A typical value of $K_L$used by humans is approximately 1.3, although this can vary widely depending on the object mass and friction properties and the intended use of the object [21]. In Section V.A we will show a series of experiments that justifies that a choice of $K_L = 1.3$ is also appropriate for robot grasping. It should be noted that adapting K_L online to changing friction conditions would be desirable and more general, but that is beyond the scope of this paper.

The time constant of the filter, τ, must be chosen so that it is neither too fast nor too slow. If τ is chosen to be too fast, the filter will act like a gain, which we have already established is undesirable. If τ is chosen to be too slow then the grip force will not increase fast enough to respond to the load force increase during lifting, and slip may occur. Once again we can turn to previous research on human grasping. Humans are able to increase the grip force due to a slip response in under 100ms [22]. Using this figure as the rise time required by the filter, we can use the well-known rise-time equation ($T_{rise} \approx 2.2\tau$, where T_rise is the rise time) to determine that a reasonable choice of τ is $\tau \approx 0.05$. This value is used for the experimental setup in this paper.

Although it is intuitive to discuss the filter in continuous time, the robot will be operating in discrete time. To that end it is beneficial to re-derive the filter equations in discrete time. Let k be the current time step, $F\_L[k]$ be the current sample of the load force, $F_{GP}[k]$be the current sample of the grip force and h be the sampling time of the robot. We use the bilinear transform to obtain the following discrete-time version of this filter:

$$F_{GP}[k] = \frac{K_L h}{h+2\tau}\left[F_L[k] + F_L[k-1]\right] - \frac{h-2\tau}{h+2\tau} F_{GP[k-1]} \tag{3}$$

E. *Required Grasp Quality and Multifingered Grasping*

A fundamental assumption in this paper is that increasing the grip force will not destabilize the grasp. Ideally, then, each contact point would have its own value of K_L corresponding to both local friction *and* local contact geometry, as well as predicted directions of external wrenches that are applied to the COM. We maintain that this is impractical[1]. In the absence of any of this information, we must set the value of K_L to be equal for all fingers and refine the above assumption to assuming that *there is a maximum load force below which the increase of grip forces will not destabilize the grasp*. Since no further information is available about the object, the extension of this algorithm to the case where multiple fingers are in complex contact with the object must reduce to using the same value of K_L for all contact points.

IV. Experimental Setup

A prototype multi-fingered, under-actuated hand was designed and built at the University of Guelph and was used for all experiments. It is controlled by a Digilent ChipKit Max32 microcontroller, which is responsible for reading the tactile sensors and encoders and for controlling the grasp. Each finger has three Flexiforce sensors embedded into each of its three phalanges. The fingers are capable of changing resistance from between 1MΩ-100Ω, and read forces from 0.1N-10N. Normal forces at the contact locations were measured at a sample rate of 50Hz. A Proportional-Derivative (PD) controller was used to actuate the fingers based on the desired grip force.

The hand is attached to the robot's wrist through a Loadstar Sensors iLoad digital load cell, which is sampled at 100Hz and capable of sensing a load of 3Kg. The entire assembly is attached to a Fanuc LR Mate 200iC-5L 6 Degree of Freedom (DOF) robot arm.

Five objects were used for the study. The first is a ripe tomato, which has low friction skin and is easily damaged. The second, a boiled egg, also has low friction skin. The third was a muffin, which can be easily crushed. The fourth is a rigid ball, which was used to determine the policy's ability to prevent slip. These first four objects were used to test the policy against different object properties. The objects are shown in Fig. 3. The final object is a paper cup that was filled with water after it was lifted. The final two objects were used to test the policy's ability to handle changing grasp conditions.

Figure 3. The experimental objects with varied surface properties. From the left: tomato (mass 150g), egg (mass 75g), muffin (mass 175g), ball (mass 120g)

[1] If all of this information were available, then the amount of available information would be equivalent to having full object knowledge and thus the well-studied techniques of [20] could be used.

For all experiments, a two-finger pinch grasp was used. In particular, the contact points were chosen to be antipodal across the point where the object had maximum radius. According to [20], this grasp is force closure under minimal assumptions on contact friction for these objects. In order to control the grip forces once they were determined by the algorithm, a PD controller was used to regulate the maximum force applied to the object. The gains $K_P = 3$ and $K_d = 5$ were arrived at experimentally.

V. Experimental Results

Three experiments were run for this study:

- Lifting food items with varying K_L to justify the choice of $K_L = 1.3$
- Testing the policy against a scenario in which slip is known to occur, in order to determine slip prevention properties. Also, testing the policy against a simpler proportional controller in this slip-prone scenario for comparison
- Filling a crushable cup with water to test the policy's ability to handle unplanned object mass changes.

A. Experiment 1: K_L Validation

A preliminary experiment was run with the food items (tomato, egg, muffin) in order to explore possible ranges for K_L, and to determine if our estimate of $K_L = 1.3$, which was drawn from human grasping literature, could easily be used for a robot grasping task. The food items are challenging in that they have low friction *and* are permanently deformed by too high a grip force. Thus we can experiment with them to determine the minimum and maximum values of K_L that are appropriate, and attempt to generalize to other objects.

The experiment proceeded in three rounds: one for the tomato, one for the egg, and one for the muffin. For each item, the value of K_L that was used during a particular test was chosen from a range between 0.1 and 5.0, in increments of 0.2. Experiments were carried out five times per object per value of K_L, and a "safe" value of K_L was determined as a value for which the object was safely grasped all five times. Slippage is defined as the object being *ejected* from the grasp after the lift is complete. Object damage is defined as visible, permanent deformation as observed by the experimenter. Once the object was damaged at one set of grasping locations it was rotated for subsequent experiments if possible (hence the choice of axially symmetric objects). The range of values for K_L were chosen based on an approximate range of human values of K_L from [21].

The food item was placed on a table in front of the robot, and the robot hand was moved into a position to grasp it in a two-finger pinch grasp. The robot was commanded to close the hand and regulate the grasping forces to a low value of 0.5N in order to begin the test. The item was lifted vertically by the robot, during which time the load-grip coupling policy would regulate the desired grasping force. After the lift, whether the object slipped from the hand, was in a stable grasp without damage, or was damaged, was recorded.

The results are summarized in Table I. For brevity, wrist and grasp forces are not shown for this experiment.

TABLE I: RESULTS FROM FOOD LIFTING

K_L	Result
0.1-1.0	All slip
1.0-1.6	All safe
1.6-2.0	Muffin damage
2.0-5.0	Tomato damage
>5.0	Egg damage

Above $K_L = 1.0$, no slip was observed in any of the subsequent trials for any object, so a large range of potential values for K_L could be chosen. Research into human grasping has shown that humans tend to add a safety factor to their estimates of K_L in order to account for uncertainty, so choosing $K_L = 1.0$, the minimal value that did not lead to slip, would potentially mean that the safety factor is not ensured. As a result, we have chosen the value used in the remainder of these experiments to be 1.3, which allows for this safety factor to be included.

Surprisingly, the egg was the most durable object; likely because it was hard boiled, which made it stronger. The muffin was the most fragile object, so we choose an upper bound on K_L to be 1.6.

We acknowledge that choosing K_L experimentally may not work in all scenarios. Specifically, it is possible that there are objects for which $K_L = 1.3$ will cause either slip or crushing. Thus an adaptive approach to the choice of K_L, which is beyond the scope of this work, may be beneficial. For all remaining experiments, a value of $K_L = 1.3$ was used.

B. Experiment 2: Evaluating Slip Prevention

In this experiment a rigid ball was placed on the table and the robot grasped it with a force that was experimentally chosen to be too low to lift the object - every time a constant force was tried with this insufficient grip force the grasp would end in a slip. This set-up is identical to the one used to cause slip in Section III.

The ball was grasped by the hand with the insufficient grip force and the load-grip coupling policy was turned on. Ten trials were run for this experiment, and the final state of the ball (whether in the hand or ejected) was recorded.

A second experiment was then performed to determine if a simpler proportional controller would be sufficient to stop slip in this scenario. The procedure for this controller was identical to that for the load-grip coupler that used a first order filter. In order to ensure a direct comparison, the lift was completed five times with both the proportional controller and first order filter.

For both experiments, $K_L = 1.3$ was used.

When our load-grip coupling policy is enabled, the lift stabilizes as the grip forces increase along with the wrist forces. Fig. 4 shows typical results, with and without the load-grip coupling policy operating. All ten lifts ended in a stable grasp.

This experiment clearly demonstrates that, when using load-grip coupling, slip can be prevented despite an initial choice of grasping forces that was too low.

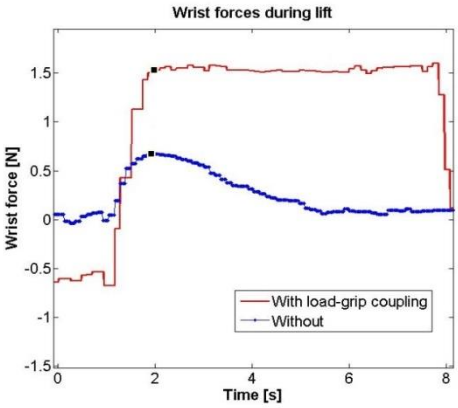

Figure 4. Load-grip stabilization

The pure proportional controller was then used. The results are summarized in Table II:

TABLE II: COMPARISON OF SUCCESS RATES

Algorithm	Result
Proportional	3/5 success
Filter	5/5 success

The pure proportional controller was able to lift the object only 60% of the time. This is due to the presence of slip in the beginning of the grasp. Since the initial grip force is not sufficient, some grasps resulted in an initial slip, which the pure proportional controller was unable to correct. This is because in an initial slip, when wrist force decreases so too does the proportional control output (reaching a minimum of the initial grip force). However, we have shown that the filter is able to prevent that initial slip by not responding immediately to any potential decreases in wrist force.

It is, of course, likely that a higher initial grip force would remove this problem entirely *for this specific object*. However, we have argued in Section I that choosing an initial grip force for every object that is sufficient to lift it is not feasible, which is why we have advocated a reactive approach in the first place.

C. Experiment 3: Handling Continuous Changes in Mass

The paper cup was placed in the hand, which was held stationary above the table. The load-grip coupling policy was activated, and the grasp forces stabilized *for the empty cup*.

After the grasp forces stabilized, 75mL of water was poured into the cup in approximately 1 second by the experimenter. The human in the experiment allowed us to test whether small random variations in pouring speed affected the algorithm's ability to compensate. The amount of water was chosen arbitrarily. The wrist forces and grasp forces were recorded during the pour, and the state of the cup (whether crushed, slipped, or safely grasped) was recorded. The experiment was repeated ten times.

Fig. 5 shows a typical profile of the wrist force sensor's response to the cup being filled with water. In each of the ten trials that were carried out the cup remained in a stable grasp without crushing, implying that the results obtained were repeatable and confirming that slight variations in pour speed had no impact on the algorithm's ability to stabilize the grasp.

To evaluate the effect of the proposed policy we conducted a second experiment where an open loop approach was used. The grip forces from this experiment are overlaid on those in Fig. 5. The grip force was held constant at approximately the final value encountered during the previous experiment. This experiment also resulted in a stable grasp and was used to ensure that appropriate choice of grasping force could indeed lead to a stable grasp without experimentation if the final mass was exactly known.

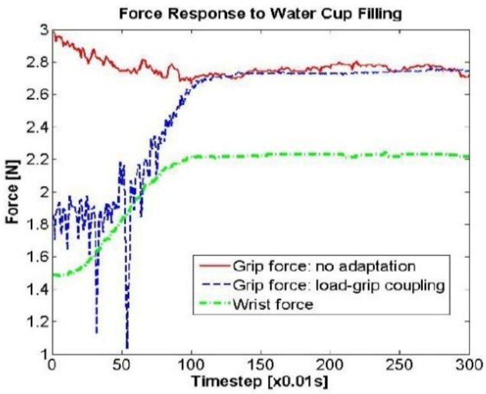

Figure 5. Continuous mass change

VI. Summary and Future Work

In this paper we presented a policy for computing desired grasp force using a load-grip force coupling controller. The policy uses the load forces sensed at the wrist to select gripping forces at contact points. Experimental results with fragile food items show that a large range of load-grip ratios could be used to safely grasp. Experimental results with an object whose mass changes in an unplanned way during the grasp have shown that the policy is robust to such changes.

The proposed policy is based on the principles of closed-loop feedback control and therefore did not require learning or training; furthermore, the policy is capable of handling changing grasp conditions in real time. We have shown that an unplanned change in mass is handled reactively, which underscores the usefulness of using a closed-loop system. By allowing the object's interaction with the hand to inform the choice of grip forces, we can alleviate the difficulty of pre-programming all grasping scenarios that can be encountered in rich, unstructured environments.

We note that this policy does not grantee a stable grasp. If the contact configuration is inherently unstable given the object shape and COM, then this policy will fail. To that end, we intend to use this controller as a base layer for a robust grasp control system. This additional layer of robustness could, for example, be equipped with a learning system that can record mass and friction properties of various objects and use that to estimate grip forces for other novel object/grasp configurations. As well, an online slip detection system can terminate grasps before failure and signal that new contact locations are necessary.

The gain $K_L = 1.3$ was chosen based on the average load-grip force ratio that humans use and experiment with a low friction, crushable object. However, since K_L is related to mass *and* friction properties, it should be tuned to suit the object and its surface friction characteristics. In the future a second layer of control could be used to adjust K_L if necessary. We further assume that each contact point must use the same value of K_L.

Finally, although the policy was only tested with a single DOF force sensor, there are no limitations on the number of DOF that can be used. For example, a six DOF force sensor, sensing both forces and torques at the wrist, would provide the robot with the ability to undergo rapid, gross arm movements or to perform more advanced manipulation tasks, including twisting. In this paper, however, inertial loads were assumed to be negligible, mainly due to an inability of the experimental apparatus used to move fast enough to provide such loading. We leave the further testing of the algorithm to future work, but note that the appropriate response to inertial loads is the same as the response to loading due to gravity.

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Michael Stachowsky is a PhD student at the University of Guelph in Guelph, Ontario, Canada. He received his M.Sc. degree at York University (Toronto, Canada) in robotics in 2010. His research interests include robot grasping, robot sensor processing algorithms, and robot autonomous exploration and learning.

Julie R. Vale, PhD, is an associate Professor at with the School of Engineering at the University of Guelph, Guelph, ON, Canada. She received the B.A.Sc., M.A.Sc., and Ph.D. degrees in electrical engineering from the University of Waterloo, Waterloo, ON, Canada, in 2002, 2004, and 2010, respectively. Her research interests include adaptive control, sampled-data control, periodic control, robust control, and nonlinear control

Hussein A. Abdullah, PhD, is a Professor with the School of Engineering at the University of Guelph, Guelph, ON, Canada. He received a B.Sc. degree in Mechanical Engineering, University of Technology, Iraq, a MSc in Mechanical Engineering from the University of Glasgow, UK and a PhD in Engineering from the University of Glasgow, UK in 1981, 1988 and 1992 respectively. His research interests include rehabilitation robotics, mechatronic systems design, manufacturing systems, and advanced automation and robotics.

Medhat Moussa, PhD, is a Professor with the School of Engineering at the University of Guelph, Guelph, Ontario Canada. He received a BASc degree in Mechanical Engineering from the American University in Cairo, Egypt, a MASc in Mechanical Engineering from the Universite de Moncton, New Brunswick, Canada, and a PhD in Systems Design Engineering from the University of Waterloo, Ontario, Canada in 1987, 1991 and 1996 respectively. His research interests include Robotics grasping, machine vision, machine learning, neural networks, and human-robot interaction. He is a member of ACM and IEEE.