In-Hand Object Stabilization by Independent Finger Control
Filipe Veiga, Benoni B. Edin, and Jan Peters

Abstract—Grip control during robotic in-hand manipulation is usually modeled as part of a monolithic task, relying on complex controllers specialized for specific situations. Such approaches do not generalize well and are difficult to apply to novel manipulation tasks. Here, we propose a modular object stabilization method based on a proposition that explains how humans achieve grasp stability. In this biomimetic approach, independent tactile grip stabilization controllers ensure that slip does not occur locally at the engaged robot fingers. Such local slip is predicted from the tactile signals of each fingertip sensor, i.e., BioTac and BioTac SP by Syntouch. We show that stable grasps emerge without any form of central communication when such independent controllers are engaged in the control of multi-digit robotic hands. These grasps are resistant to external perturbations while being capable of stabilizing a large variety of objects.

Index Terms—in-hand manipulation, modular control, reactive control, tactile feedback, independent finger control, slip prediction.

I. INTRODUCTION

Robotic grasping and in-hand manipulation are traditionally viewed as monolithic planning and control problems. As such, control policies determine the approach strategy and finger placement (contact forces and contact locations) for the entire hand, while considering finger trajectories, force and contact profiles throughout the entire manipulation task [1]. This monolithic formalization requires accurate kinematic and dynamic models of the hand and object along with precise sensing of hand and object position as well as interaction forces. In practice, however, control eventually becomes largely data-driven as such models are rarely available and due to the uncertainty associated with the joint use of all these models [2].

Data-driven approaches do not come for free. They either require large training data sets [3]–[5], restrict the tasks to sufficiently similar scenarios [2], [6], or rely on low-dimensional representations such as synergies [7] and motion primitives [8], that encode the considered manipulation task. Consequently, learned policies inherently couple the employed degrees of freedom, resulting in solutions that are task- and platform-specific. Furthermore, incorporating tactile feedback from all fingers into a control policy quickly becomes intractable given the dimensionality of the feedback signals. In short, low-level control policies that both deal with uncertainty (e.g., in contact locations and forces) and generalize well beyond a limited set of cases, need to be both data-driven and modular.

Ensuring grip stability is central to both stabilizing an object in the hand and moving an object between stable grip configurations. Classical robotics approaches often rely on measures such as form- or force-closure for assessing grip stability — but with imperfect models and contact/force sensing, using such measures is very challenging. As a result, many researchers have proposed alternative grasp stability measures [9]–[13] and developed accompanying control strategies.

In contrast, human grasping and manipulation appears to be largely data-driven [14] despite relying on feedback signals of huge dimensionality and relatively low precision when control compared to robots. As deduced from several behavioral studies [15]–[18], human grasp control strategies seem to be modular and based on local sensing and actuation, rendering the control of the fingers largely independent from each other, i.e., Independent Finger Control [15]. Specific grasps and force distributions appear to emerge from tactile feedback as the fingers interact with objects. Clearly, such an approach would be desirable for robotic grasping and manipulation.

Inspired by progression from one-finger over two-fingers to the whole hand proposed by [19] in the context of tactile object exploration, by early studies of grasp stability using tactile feedback [20] and by the independent control hypothesis in human grip control by [15], [16], we have developed independent control policies based on tactile feedback for each finger that in conjunction generalize from one-finger to five-finger gripping and in-hand manipulation.
To achieve this, we equipped the robotic fingertips of two hands with multimodal fingertip sensors (BioTac and BioTac SP for the four finger Allegro and five finger Wessling Hand, respectively; Figure 1), each with a learned predictive model of future slips based on the tactile feedback acquired during finger-object interactions. The local control laws in each finger counteract future slips, ideally preventing them. The resulting control law is capable of stabilizing objects against other objects (such as a table or a wall), jointly stabilizing objects with more robotic fingers (as in in-hand object stabilization or gripping) or against the hand of a human operator (human-robot joint stabilization). It can also be employed for in-hand manipulation by stabilizing an object with several fingers while one or more fingers move the object within the stable grip. The coordination between modular finger controller occurs only indirectly through the tactile signals observed by each finger.

This modular approach enables a higher-level planning system to operate with less object knowledge while requiring simpler models for control than analytical approaches. In contrast to monolithic data-driven approaches, the proposed reactive control framework therefore can be expected to generalize across multiple tasks, a variety of objects and different reactive control frameworks. Here, we depict a PA10 with a finger equipped with multimodal fingertip sensors (BioTac and BioTac SP) as one of the classes in the set \( c_{t+\tau_f} \in \{\text{slip, contact, \neg contact}\} \). For an in-depth study of how the feature function affects the detection and prediction of slip, the reader is referred to our previous work [22].

2) Force adjustment: is accomplished through a control law that converts the predicted slip state, \( c_t \), at time \( t + \tau_f \) into adjustments in the applied normal force. Most robotic hands are controlled in joint or end-effector positions rather than applied forces. To make the controller applicable across a range of robotic hands, our controller therefore adjusted the desired task space velocities, \( s_t \), rather than controlling force explicitly. Hence, whenever \( \text{slip} \) was predicted, we increased the normal force, \( F_N \), alternatively slowing decreasing the force while keeping the object stable, in line what has empirically been found during human grasping. This behavior was achieved by using a leaky integrator

\[
y_t = \alpha y_{t-1} + (1 - \alpha) L
\]

(2)

to control the task space velocity in the contact normal direction, i.e.,

\[
s_t = N_t y_t.
\]

(3)

Here, \( \alpha \) is the leakage at each time step and \( N_t \) is a unit vector pointing in the contact normal direction. The integrator input signal \( L \) changes with the predicted contact state \( c_{t+\tau_f} \), increasing the accumulated response when \( \text{slip} \) is predicted and allowing the integrator to leak if \( \text{contact} \) is predicted, i.e.,

\[
L = \begin{cases} 
1 & \text{if } c_{t+\tau_f} = \text{slip}, \\
0 & \text{otherwise}
\end{cases}
\]

(4)

This integrator thus operated as a smoothing filter which was important given the discrete nature of the slip predictor outputs. In multi-fingered scenarios, any oscillations in the
controller response would propagate to other fingers engaged in the grasp and cause instability. While still allowing the fingers to react to all oscillations, the integrators manage the intensity of the response, slightly changing the applied force for instantaneous perturbations or greatly increasing the applied force for more persistent perturbations.

Finally, a minimum integrator response \( y_{\text{min}} \) is required to avoid oscillations around low integrator responses values where slip is imminent. However, instead of specifying \( y_{\text{min}} \), each finger estimates its minimum response by observing the first slip transient following a first stable period. The minimum response is then defined as the the response \( y_t \) where the first transition from contact to slip occurs

\[
y_{\text{min}} = y_t \text{ if } \Delta c = \text{contact} \rightarrow \text{slip}.
\]  

This minimum response implicitly defines the minimum fingertip normal force necessary to prevent slips and makes the controller responsive to the prevailing friction at its digit-object interface.

### B. Multi-Finger Gripping by Single-Finger Slip Control

When progressing towards in-hand stabilization and in-hand manipulation, more fingers are required and the complexity of the tasks quickly scales accordingly with hand dexterity. Generally, a higher dimensionality can be coped with either by identifying a lower-dimensional manifold for the problem or by decomposing the problem. Following the core insight in [15] that human multi-finger grip stabilization appears to be accomplished by separate neural circuits that interact through the object instead of via the central nervous system, we hypothesize that multi-finger robot gripping can be accomplished using the same single-finger stabilization controller on each finger independently. As a first scenario, we reproduce the scenario from [15], where two humans jointly hold an object using one finger each with the same apparent ease as if a single person use the index finger and thumb of one hand or one finger from both hands. The underlying neural control appeared to be unaffected by the precise task condition. We reproduce this experiment in a human-robot joint stabilization task as shown in Fig. 2: the single finger controllers of both the human and the robot worked well together without any precautions.

To fully utilize the dexterous capabilities of the hand, we propose that each hand should be considered a set of independently controlled fingers pertaining specifically to stabilization. This independent control approach obviously still requires a higher level planning approach for fingertip placement, as well as making and breaking of contact with the object.

A set of independent fingers – in contrast to a fully connected manipulator – allows decomposing the object stabilization control problem such that each finger separately predicts future slip based on tactile sensing, counteracting it by independently adjusting the applied forces. While synchronization only through the tactile feedback may appear counterintuitive, it actually greatly reduces the dimensionality of the control problem while ensuring that the fingers affect each other only when necessary for object stabilization. As a result, it not only becomes more straightforward to design stabilizing control laws but the synchronization becomes more robust.

## III. EXPERIMENTAL EVALUATION

The proposed independent finger control law (from Sec. II) is evaluated both to constructively verify the independent finger control hypothesis as well as to show that the proposed approach works sufficiently well in practice. We begin by stabilizing several objects with a varying number of fingers, using the Allegro hand, without any external perturbations (Sec. III-D1), and demonstrate that a control strategy working under the proposed hypothesis is able to re-stabilize objects in-hand throughout sequences of externally applied perturbations (Sec. III-D2). The presentation of the results is preceded by a detailed description of the experimental setup, i.e., robotic platform and an account of the tactile sensors mounted on the platform as well as the sensors used to measure the external perturbations (Sec. III-A), and a detailed outline of the procedure used to acquire the ground truth data for the slip classifiers (Sec. III-C).

### A. Experimental Setup: Testing Platform & Tactile Sensors

To demonstrate the independent finger control, the control scheme was implemented on two robotic hands: The four finger Allegro Hand and the five finger Wessling Robotic Hand.

The Allegro Hand (Wonik Robotics GmbH, www.simlab.co.kr, Fig. 1), is a lightweight four fingered hand with four joints per finger, for a total of 16 actuated degrees of freedom. The thumb has an abduction joint, two metacarpal joints (rotation and flexing) and a proximal joint. The remaining fingers do not have abduction joints and instead have a distal joint. A PD controller was used to control the robot joint positions. One end-effector was defined for each fingertip and their positions were controlled by estimating the desired joint velocities, by means of the Jacobian Pseudo-Inverse, and integrating the estimations to acquire the desired joint positions.

The Wessling Robotic Hand has five modular fingers, each with four joints where two of these four joints are coupled and cannot be moved independently (Wessling Robotics, www.wessling-robotics.de; Fig. 1). A PD controller is used for joint position control and a Pseudo-Inverse Jacobian controller is used for controlling the end-effector position of each finger. The control signals are sent to a real-time machine where the conversion to torque is performed by an joint impedance controller from Wessling Robotics [23].

While the Allegro Hand has one finger fewer than the Wessling Robotic Hand, it is more compliant and its workspace is larger than that of the Wessling Hand. The base control loops of each hand operate at different frequencies, i.e., 300 Hz and 1 kHz for the Allegro and Wessling Hand, respectively. However, despite these differences, the slip prediction based controllers were the same, each controller trained on data from the respective fingertip sensors.

BioTac and the BioTac SP tactile sensors (SynTouch Inc., www.syntouchinc.com; Fig. 1) were mounted on the Allegro and Wessling Hand, respectively, and served as fingertips.
Both provide multi-modal responses composed of low and high frequency pressure ($P_{dc}$ and $P_{ac}$), local skin deformations ($E$), temperature and thermal flow ($T_{dc}$ and $T_{ac}$). The sensor consists of a conductive fluid captured between a pliable skin and a rigid core. The core surface is covered with impedance sensing electrodes (19 for BioTac; 24 for BioTac SP). The pressure signals are acquired by a pressure transducer, skin deformation is measured through local impedance changes measured by the electrodes and temperature is regulated by a thermistor. All data channels of the sensor are sampled at a rate of 100 Hz. The high frequency pressure signal is acquired internally by the sensor at a rate of 2.2 kHz, but is available for readout at 100 Hz, producing batches of 22 values every 10 ms. Considering all channels and the Pac batch data, the sensors output a total of 44 or 49 values every 10 ms.

Finally, the Optoforce OMD-D20 3D (Optoforce Ltd., www.optoforce.com) is an optical force sensor (insets of Fig. 7) that was used to measure the magnitude of external perturbations applied on the objects during in-hand re-stabilization experiments. The Optoforce reconstructs the magnitude and direction of the applied force from the values of four light sensitive photo-diodes that detect the amount of reflected light by interior surface diodes. The sensor has a nominal sample rate of 100 Hz.

**B. Test and Training Objects**

Our set of 38 test objects belonged with two exceptions (a tea box and a plastic cup) to the YCB object set [24], shown in Fig. 3. Among the test objects, the weight varied from 10g to more than 400g and grasp width from less than 10 mm to more than 100 mm. Specifically, the plastic cup (cf., Fig. 2) was included to assess the performance of the control system when faced with highly deformable objects.

Only 4 objects were used during training: a tuna can, a plastic cup, a ball, and a tea box (arrows in Fig. 3). Successful manipulation of all test objects thus implied that the method generalized across grasps and object properties.

**C. Tactile Training**

As our independent finger stabilizers reacted to slip-based feedback, it was necessary to train the classifiers responsible for slip prediction. This training required data collected on the real system and ground truth labels for the slip events.

To start data collection, one of the training objects was fixated by a support in the hands work space (Fig. 1). All fingers were positioned in an initial configuration and subsequently flexed until they made contact with the object. Then the pressure applied by each finger was adjusted by a PID controller until a target pressure was reached on each finger. Finally, the fingers moved along the tangential contact plane, surveying the object surface. Acquiring data from three sensors simultaneously reduced the necessary number of training trials. All data from each of the fingers was concatenated into a single data set that was used to train each of the individual slip predictors. The data collection setup is exemplified in Fig. 1.

Fig. 4 shows a representative, single training trial with data from the index finger. Slip labels were generated automatically from the fingers end-effector location and the recorded pres-
Fig. 5. Stable grasps of a variety of objects. The specific grasp configurations varied from trial-to-trial but always resulted in stable grasps. The panels show (A) two-finger, (B) three-finger and (C) four-finger grasps with the Allegro Hand and (D) two-finger, (E) three-finger and (F) four-finger as well as five-finger grasps with the Wessling Robotic Hand.

sure values. The total shift in Cartesian position was calculated from the end-effector position. Since the object was fixated during training, we defined slipping as the state when the finger was in contact (i.e., the recorded pressure was above a certain threshold \( T_{\text{Contact}} \)) and the finger was moving (i.e., the finger velocity exceeded the movement threshold \( T_{\text{Movement}} \); both thresholds are indicated with dashed lines in Fig. 4). This procedure relied on randomly selected velocities in task space for the object surface surveying. Target pressures were selected from 9 possible values in sensor grounded pressure units: \( P = [20, 40, 60, 80, 100, 150, 200, 250, 300] \). Spanning the data across multiple pressures in conjunction with randomly selecting the velocity and having distinct contact locations across the three fingers, allowed for training slip classifiers that were not specifically correlated with certain pressures, contact locations or fingertip velocities. In addition, all sensor values concerning pressure or finger deformation were grounded before training, preventing parametric differences in the sensors (for example nominal fluid pressure) from correlating to slip. Three trials were executed for each value of \( P \) on four training objects (Fig. 3) for a total of 108 trials. The resulting data set thus comprised 324 single finger trials across the three engaged fingers and was acquired in less than 15 minutes.

D. Grip Stabilization Evaluation

For the multi-finger grip stabilization scenarios, finger pressure was analyzed and used to make behavioural comparisons across objects (reported in Sec. III-D1). In addition, we assessed the in-hand re-stabilization capability of our approach as the grip was perturbed by an external agent (Sec. III-D2). Since each finger was controlled independently, the approach was scalable with respect to the number of fingers. In this study, however, we considered grip configurations involving two and three fingers across all test objects (Fig. 3) including the four objects used in the slip predictor training data collection experiments.

1) Multi-Finger Grip Stabilization with Independent Finger Control: To test the validity of our independent finger control hypotheses for grip stabilization, we attempted to stabilize multiple objects with varying number of fingers. We place the robotic hand in an open-hand configuration with an object positioned such that it could be held in an opposition grasp, and then closed two or more fingers (up to four with the Allegro Hand and up to five with the Wessling Robotic Hand). Immediately after all fingers have made contact with the initially supported object, the grip stabilizers were activated and the independent finger stabilization process began, while the object support was removed. To ensure that the object would not be dropped during the activation transient of the grip stabilizers, each controller was initialized to generate a predefined fraction of the maximum output. For deformable objects such as the white plastic cup, this activation resulted in an initial surface deformation that was subsequently automatically reduced.

The control based on independent finger control was able to reliably and consistently stabilize all 39 test objects (Fig. 5). For each object and grasp configuration (two-, three- and four-finger grasps with the Allegro Hand and up to five-finger grasps with the Wessling Hand), we recorded five trials each lasting 10 seconds with every object. A grasp was considered stable if the object was not dropped. Since no desired hand configuration was enforced, the hand
adopted slightly different configurations for each object and across repetitions. To study this variability in more detail, we analyzed the grip forces applied by the fingers to different objects. Figure 6 shows the pressure profiles and estimated forces for the Allegro and Wessling Hand, respectively, for trials with the lightest and one of the heaviest objects, i.e., the white plastic cup and the cracker box. The pressure profiles applied in the Allegro experiments were recorded directly from the BioTac sensors while the estimated forces applied in the Wessling experiments were calculated from joint torques and angles. The data illustrates two important emergent properties of the grasp control. First, finger pressures and forces converged to lower values when gripping the lighter plastic cup than when gripping the cracker box. Second, there was a substantial variability in force sharing between the digits across trials, particularly obvious in the profiles recorded during trials with the cracker box. Both of these observations can be explained straightforwardly through the design of the controller. Notably, an uncountable number of grip force distributions could result in stable grasps but the control system did not explicitly enforce a specific distribution. Instead, pressure applied by each finger propagated through the object to the other fingers, dynamically impacting the grip force distribution while each controller minimized the risk for local slips keeping the fingertip forces low. The ability to adapt the overall grip force by reactively changing the force applied by each finger contributed to the high generalization capability of our approach, even though no specific object orientation, weight or weight distribution was expected by the stabilizers.

2) Grip Stabilization under External Perturbations: To further test the validity of our underlying control hypothesis, we investigated responses to externally applied perturbations (Fig. 7). Once the object was stabilized in the robotic hand, the experimenter held an Optoforce sensor and used it to disrupt the object state by applying sequences of irregular disturbances, either to the different surfaces of the objects or to the fingertips, during 30 second recording periods (insets in Fig. 7).

For the entire duration of these experiments, the stabilizers invariably counteracted the perturbations successfully by adapting the finger pressures. With every perturbation, we observed a change in the fingertip forces and an increase in the accumulated value of the integrator that regulated the applied velocity. As a result, the individual fingers applied slightly different steady-state forces after each perturbation. For instance, the 1st, 4th and 8th perturbation in Figure 7 were applied in a similar fashion (i.e., from top) but in response, the independent finger controllers generated different stable grip force distributions. Indeed, while the object was held in a similar position throughout this trial, the pressure distributions across the fingers differed following each perturbation. Changes in fingertip forces due to slip prediction noise or re-stabilization were also frequently observed (e.g., around 16 and 21 second mark).

3) Master-Slave Operation: From the perspective of the independent fingertip controllers, there was no conceptual difference between external perturbations and those caused by the actions of other fingertips. This interaction was further explored in master-slave experiments during which the experimenter manually pushed or pulled a finger to increase or decrease the force it applied while the controllers of the remaining fingers jointly stabilized the grasp. Indeed, three- and two-digit grasps remained stable even when one of the digits was lifted off the surface of a grasped object. In contrast
Fig. 7. Responses to external perturbations. The panels show (A) the pressure applied by the experimenter on the surface in the manner shown in the insets, (B) the integrator response of the controller that drives the fingertip velocities (C) the observed fingertip velocities and (D) the applied fingertip pressures by the thumb, index and middle fingers (yellow, blue and red lines). As each controller continuously predicted the contact state 100 ms in the future, the output of their leaking integrators increased whenever a slip was predicted, otherwise allowing the integrator output to decrease slowly to a minimum value. The integrator response determined the necessary fingertip velocity, thereby implicitly managing the applied pressure against the object surface.

to more traditional solutions for manipulation control, force sharing between the engaged fingers varied substantially from trial-to-trial due to the emerging nature of the independent finger control policy. Such variability is, however, typical in human manipulation [15]–[17], [25]. While it could be easily removed by additional regularization, it could actually be beneficial in practice as it allows a wider range of potential solutions (e.g., for use in a manipulation planner). The master-slave experiments are shown in Figure 8.

In grasping and in-hand manipulation, instability is synonymous with slip [26]. In this study, we have focused on low-level control of grasp stability rather than finger positioning and re-positioning. However, the results suggest that independent fingertip control at the base level of a hierarchical control framework may enable higher level control policies to perform complex manipulations. In a basic scenario, rotating an object, for instance, would simply require that one of the fingers introduce a desired perturbation to the object, while the remaining fingers keep it stable.

IV. CONCLUSION AND DISCUSSION

The proposed independent finger grip stabilization control approach, inspired by neurophysiological findings, was able to stabilize a wide range of objects by taking advantage of the generalization capabilities of the slip feedback signals. The resulting grasps not only kept the objects stable within the hand but were also robust to perturbations. The adaptability of the approach may also enable higher level control policies to manipulate objects in-hand, as demonstrated by the master-slave experiments.
A. Summary of the Contribution

We have corroborated the hypothesis that stable grasps emerge from a set of independent finger controllers. Indeed, the synchronization between fingers emerge from the tactile feedback of each finger controller and enable stable gripping despite disturbances caused by poor contact distribution on the fingertip surfaces, introduced by other fingers action on the object, or external disturbances. Each finger thus automatically compensated for changes that jeopardized grasp stability. Moreover, our modular control approach was shown to be generalizable across multiple objects, even objects that were substantially different from the objects in the training set.

B. Recognized Shortcomings

Using the low dimensional slip signals defined in previous work [22], enabled the design of the controller used in this paper. As the full tactile state is much richer than the slip signals, we may potentially have discarded relevant information.

Additionally, in the proposed approach we focused on 'low-level' control of grasp stability. As such, the objects tested were provided to the hand in configurations where the stabilization would be possible, requiring neither finger gating nor re-positioning.

The implemented controller is reactive, albeit that upcoming slips are predicted by the controller. The temporal limitations in this respect have not been analyzed. For comparison, it takes human as much as 60-80 ms to initiate force responses to incipient and overt fingertip slips and at least 50-100 ms to generate substantial counteracting forces [27], [28], i.e., these delays are too long for preventing the loss of a stable grasp once overt slippage occurs.

C. Future Work

Partitioning the hand into a set of independent fingers allows the manipulation problem to be viewed as a distributed problem where each finger solves the task locally and coordination only emerges by interaction through the object. This setting invites simpler control models than when considering a complete model for the full hand. Specifically, we consider it realistic to use data driven approaches that take into account a richer sensor space, as the dimensionality of the problem is distributed across the fingers. Our future work will focus on exploring the high dimensionality of the feedback signals and learning stabilization controllers using reinforcement learning approaches in these high dimensional spaces.

Our results invite further exploration of master-slave paradigms. In a simple scenario, rotating an object would simply require that one of the fingers introduce a desired perturbation to the object, while the remaining fingers keep it stable.

Finally, for complex manipulations, we posit that independently controlling the fingers will be necessary but not sufficient to achieve robust performance. Using the independent control as the base level in a hierarchical control framework is expected to enable higher level control policies to perform these manipulations, effectively creating a robust control hierarchy, where the task complexity is distributed across the several levels of the hierarchy. Building such a hierarchy is thus a potentially interesting future work.

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