# Multifingered force-aware control for humanoid robots

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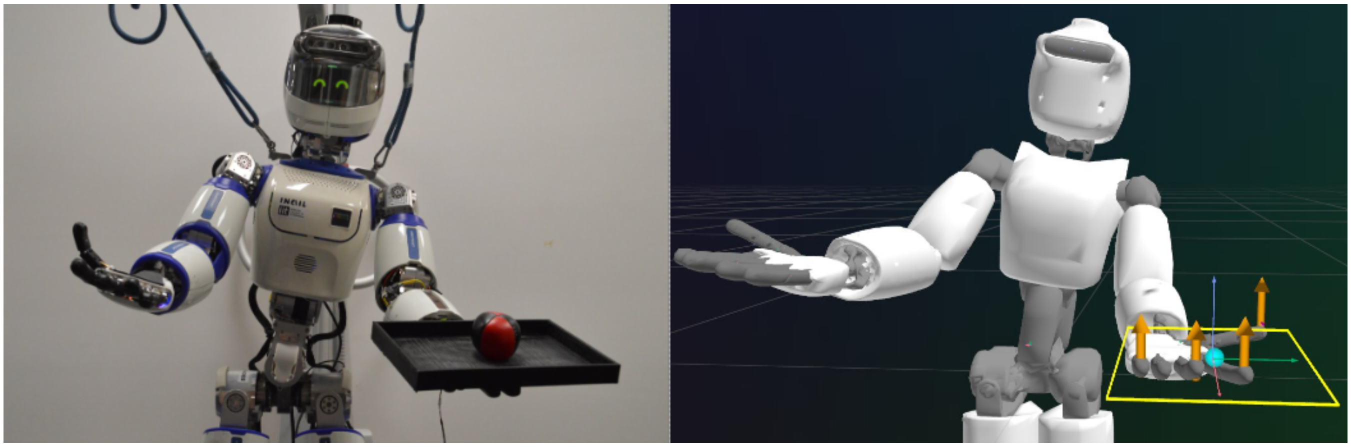

Fig. 1: Real robot (left) and its virtual counterpart [1] (right). ergoCub [2], equipped with tactile sensors, balances a tray with an unknown object by minimizing the distance between the supporting polygon center and the estimated Center of Pressure (cyan sphere), computed from normal forces (orange arrows).

***Abstract*— In this paper, we address force-aware control and force distribution in robotic platforms with multi-fingered hands. Given a target goal and force estimates from tactile sensors, we design a controller that adapts the motion of the torso, arm, wrist, and fingers, redistributing forces to maintain stable contact with objects of varying mass distribution or unstable contacts. To estimate forces, we collect a dataset of tactile signals and ground-truth force measurements using five Xela magnetic sensors interacting with indenters, and train force estimators. We then introduce a model-based control scheme that minimizes the distance between the Center of Pressure (CoP) and the centroid of the fingertips contact polygon. Since our method relies on estimated forces rather than raw tactile signals, it has the potential to be applied to any sensor capable of force estimation. We validate our framework on a balancing task with five objects, achieving a $82.7\%$ success rate, and further evaluate it in multi-object scenarios, achieving $80\%$ accuracy.**

## I. Introduction

Robots meant to live alongside and assist humans must continuously refine their actions through sensory feedback [3]. Although computer vision has reached high performance, it cannot reliably capture contact dynamics. As a result, many tactile sensors have been developed, such as magnetic [4], [5], capacitive [6], or vision-based [7], [8], enabling tasks like dynamic control [9], pose [10], [11], shape/curvature [12], [13], and texture estimation [14]. However, their heterogeneous outputs limit transferability of raw-signal-based methods. A promising alternative is to map tactile outputs into the force domain: estimating 3D contact forces yields a sensor-agnostic representation that generalizes more robustly across devices [15], [16]. Yet, although force feedback is used in manipulation, multifingered strategies are typically limited to prehensile tasks, whereas non-prehensile approaches often rely on single-finger feedback [17]. In this work, we introduce a model-based indirect control strategy to balance in-hand objects with varying mass distribution by distributing contact forces across a multi-fingered hand. To enable force feedback, we train a lightweight network to estimate 3D forces from custom magnetic Xela sensors [18] using a calibrated testbed with 3D-printed indenters. The model is deployed on the ergoCub hand equipped with these fingertip sensors. A 3D-printed tray is placed on the hand and an object of unknown mass is positioned arbitrarily on it. We validate our approach by balancing the unknown object on the tray and preventing it from falling; an example is shown in Fig. 1. In summary, the contributions of this work are threefold:

- We present a dataset containing calibrated 3D forces, relative poses, and tactile outputs for our custom finger-like Xela sensors, collected with a dedicated testbed.
- We provide a comprehensive characterization of the sensor performance and limitations, offering insights into its applicability for force estimation in manipulation.
- We propose a multifingered control algorithm for balancing in-hand objects by acting on force distribution. The controller operates directly in the force domain, making it conceptually applicable across different tactile sensors.

## II. Related works

Our work is closely related to manipulation control frameworks using tactile sensing. While there remains interest in solving manipulation tasks without tactile feedback [19], there is a growing focus on integrating tactile sensors into robotic hands control [20], [21]. Early works primarily

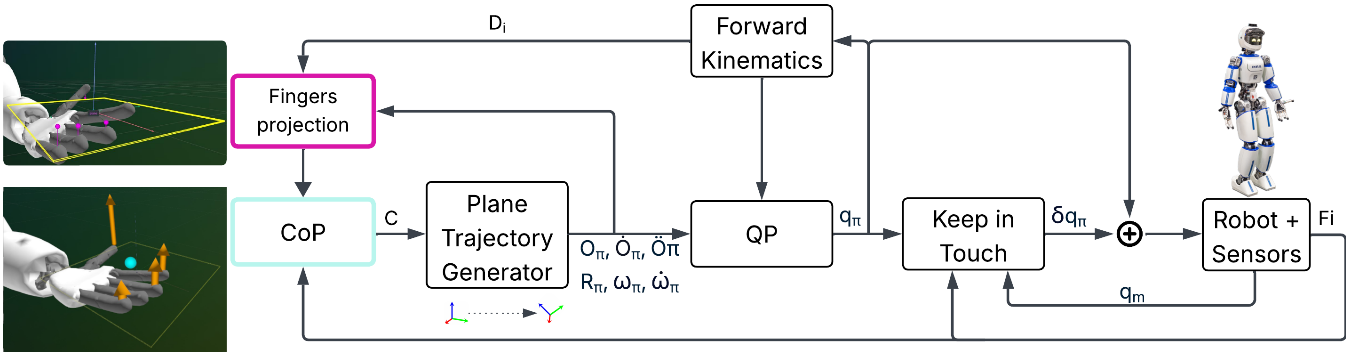


Fig. 2: Overview of the control pipeline. Finger positions (magenta spheres) are projected onto the plane (yellow rectangle), and normal force components (orange arrows) are used to compute the CoP (cyan sphere) in the plane frame. From this, a new target pose for the plane is generated, and finger and joint positions are updated with a corrective term for inaccuracies.

relied on single-finger feedback [17], [22]–[24]. More recent works explore multi-finger control for prehensile tasks [25], [26], [27]. Other approaches estimate pseudo-forces from tactile signals [28]–[30]. Whole-body controllers have been proposed for humanoid balancing and locomotion tasks [31], [32]. However, they do not control the fingers explicitly, and therefore cannot address multifingered in-hand manipulation. In [33], a tray is fixed at the end of a robotic manipulator to perform non-prehensile transportation. However, it is assumed that the object's shape and dynamical properties are known. In contrast, we develop an upper-body controller that extends the multi-joint reasoning of whole-body approaches to also include multicontact control of the fingers of a robotic hand, while making no assumption about the object. To the best of our knowledge, this is the first work to combine an upper-body controller with multifingered force distribution for non-prehensile manipulation.

## III. Method

In our scenario, a humanoid robot equipped with a multi-fingered hand and fingertip force sensors must balance an object with varying mass distribution, using fingertip force feedback to adjust its posture. Our objective is to design a control architecture (Fig. 2) that:

- controls the finger positions to establish contact with a planar base for the object;
- employs finger force measurements to adapt the pose of the hand and the overall posture.

### A. Sensor characterization and Dataset collection

*1) Sensor characterization:* To characterize the Xela sensor and collect the dataset, we use the setup shown in Fig. 3a and a set of 3D-printed indenters (similar to those in [34], Fig. 3b). We first characterize the sensor behavior with respect to three aspects most relevant to our scenario: **repeatability** of the measurements, **consistency** across different sensors, and the effect of **gravity** on tactile readings. To assess repeatability, we apply cyclic loading to the sensor, highlighting the increasing influence of hysteresis with repeated touches (Fig. 3c). To validate consistency, we perform a similar test across different fingertips: Fig. 4 shows the variability across sensors. Finally, we mount the fingers

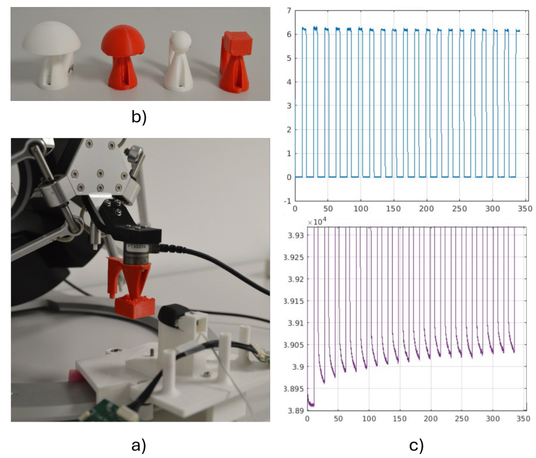


Fig. 3: a) Data collection setup. b) Indenters. c) Effect of hysteresis on the tactile readings. The graphic above shows the indented force (N) over time (s), while the bottom graphic shows the output of the sensor's taxel over time.

on the ErgoCub hand and perform random 6D movements. We observe that tactile readings vary significantly with orientation. More critically, the displacement of the taxels follows gravity.

*2) Data collection:* To collect data, we define contact points with Poisson sampling on the sensor surface, and for each point we generate random indentation trajectories. Data are collected by controlling the robot probe in position, the fingertip is fixed facing upward. To mitigate the gravity effect described in Sec. III-A.1, we augment the dataset with additional no-contact samples acquired by mounting the sensors on the robot and applying random wrist and finger motions. Results of the calibration are reported in Section IV.

### B. Finger positions control

In the following, we define two modules composing the finger positions control: the QP problem, whose unknowns are the joint accelerations $\ddot{q}$, and the *Keep in Touch* module.

*1) **QP formulation**:* we cast the finger positions control as:

$$\begin{aligned} \min_{\ddot{q}} \quad & T_1 + T_2 + T_3 + T_4 \\ \text{s.t.} \quad & c_L \leq \ddot{q} \leq c_U \end{aligned} \tag{1}$$

where the joint acceleration constraints are defined as in [35].

TABLE I: Results of the experiments. Force estimation uses different networks for each finger (first five rows) and one network for all the fingers (last row). Each metric is evaluated at different positions (1–5) and on average.

| | Time (s) | | | | | | Distance CoP (cm) | | | | | | Success rate (%) | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Position* | *1* | *2* | *3* | *4* | *5* | *Mean* | *1* | *2* | *3* | *4* | *5* | *Mean* | *1* | *2* | *3* | *4* | *5* | *Mean* |
| **Object 1** | 9.2 | 6.5 | 6.4 | 42.1 | 40.5 | 20.9 | 35.0 | 13.2 | 13.6 | 33.4 | 31.9 | 25.4 | 66.7 | 100.0 | 100.0 | 100.0 | 100.0 | 93.3 |
| **Object 2** | 8.8 | 9.5 | 5.2 | 24.6 | 28.9 | 15.4 | 14.1 | 6.4 | 3.1 | 12.6 | 15.0 | 10.2 | 100.0 | 100.0 | 66.7 | 100.0 | 66.7 | 86.7 |
| **Object 3** | 9.0 | 7.4 | 5.1 | 29.3 | / | 12.7 | 9.3 | 2.3 | 6.7 | 21.7 | / | 10.0 | 100.0 | 100.0 | 100.0 | 66.7 | 0.0 | 73.3 |
| **Object 4** | 12.3 | 28.4 | 11.9 | 22.2 | 22.8 | 19.52 | 44.0 | 168.0 | 15.2 | 93.2 | 25.0 | 69.1 | 66.7 | 66.7 | 33.3 | 100.0 | 66.7 | 66.7 |
| **Object 5** | 42.3 | 20.94 | 39.7 | 5.7 | 43.0 | 30.3 | 34.6 | 21.7 | 10.3 | 21.0 | 33.2 | 24.2 | 66.7 | 100.0 | 100.0 | 100.0 | 100.0 | 93.3 |
| **'Object 3 (SN)** | / | / | 26.8 | 5.1 | 11.7 | 11.5 | / | / | 5.8 | 1.2 | 2.7 | 2.9 | 0 | 0 | 67 | 100 | 67 | 47 |

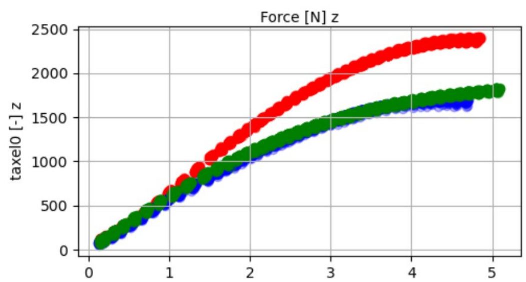


Fig. 4: Consistency validation across sensors shows variability in tactile outputs under identical applied forces.

*2) **Bring the fingers on the plane (T1)**:* we start by defining the terms of the QP. We want each fingertip position to lie on a plane $\Pi$, so as to arrange the fingers on a planar support.

*3) **Align the centroid of the finger projections to the origin of the plane frame (T2)**:* we want the position of the fingertips centroid projection to correspond to the origin of the plane frame, because this point is also the target for the CoP control (III-C).

*4) **Joint positions control (T3)**:* we further add a postural term to keep the robot joint positions close to the initial configuration.

*5) **Bound Joint Accelerations (T4)**:* this term bounds the required joint accelerations for the task and helps the solver convergence.

*6) **Keep in touch**:* in addition to the QP generated references, we introduce a contribution to compensate for small inaccuracies in the model, and mechanical imprecision due to finger tendon actuations. We call this module the *Keep in Touch* controller. This contribution is added only to the finger joints and it is evaluated from the finger force.

### *C. Plane pose evolution under the effect of the finger force measurements*

We want to implement an **indirect** control of the CoP by adjusting the pose of the plane $\Pi$. To this end, given the fingertip positions and force measurements, we calculate the CoP position relative to the origin $O_\Pi$ of the plane frame, as [36]. Then, we generate a trajectory: the idea is to move the CoP towards the plane frame origin, which is also the target position of the fingers centroid control (see III-B.3).

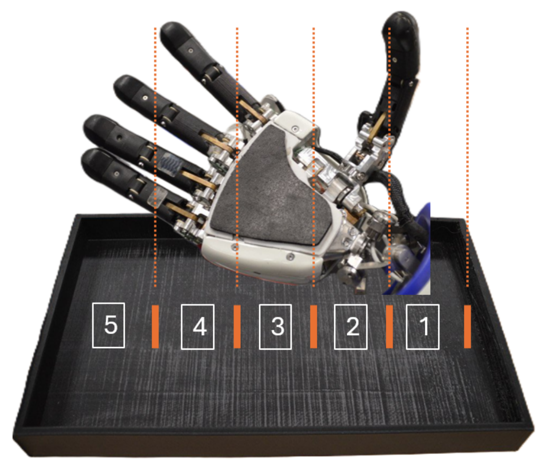


Fig. 5: Starting position on the tray. The superimposed hand shows the position of the hand under the tray.

## IV. Experimental Results

We evaluate our method in two stages: first, by validating the precision of the force estimation network, and second, by testing the controller on balancing performance on a set of objects. The task consists in balancing an object on top of a 3D-printed tray held by the ergoCub hand. We test five objects spanning different shapes, materials, and internal dynamics:

- Object 1–3: a paper tea box, filled with varying amounts of small plastic balls containing modeling clay of different weights (122.7 $g$, 152.6 $g$, 216.2 $g$), producing different mass distributions.
- Object 4: a fabric ball filled with sand (98.6 $g$).
- Object 5: an aluminum box filled with modeling clay (125.6 $g$).

Objects are chosen to weigh between 100 $g$ and 300 $g$, so that they could be reliably sensed by the Xela sensors, and they remain below the tested fingertip limit of 5 $N$ of sustainable load.

Each fingertip uses a dedicated force estimation network trained on its own calibration dataset to maximize accuracy. To assess the necessity of this choice, we conduct an ablation in which a single shared network is used across all fingers (evaluated on Object 3). In the following we report results of the force estimation, of the balancing task employing single and multiple objects.

*1) Force estimation:* We train a regressor (MLP) using the dataset described in Sec. III-A.2. Following the charac-

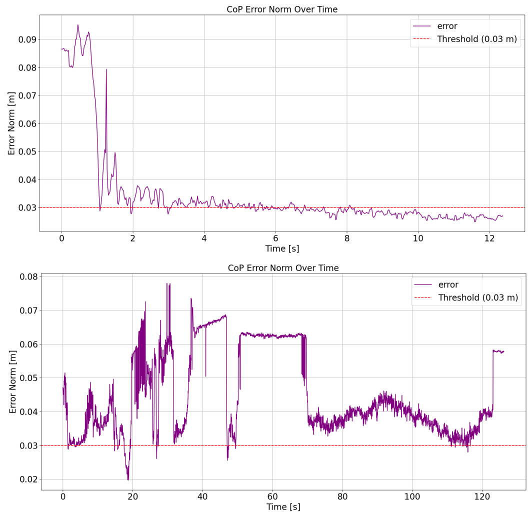


Fig. 6: CoP error for a success (top) and a failure (bottom) episode. In the failure case, the error drops below the threshold but is highly unstable.

terization study in Sec. III-A.1, we address sensor-to-sensor variability by training a separate regressor for each sensor, and validate the models on test datasets. For comparison, we also train the same architecture on the combined data from all sensors and evaluate it on all test sets. On average, the single-sensor regressors achieve a normalized MAE of $9\%$, while the multi-sensor regressor reaches $13\%$.

*2) Single object balancing experiments:* For each object, we perform 15 trials by placing it in five different positions on the tray, with three repetitions per position. The positions are chosen by uniformly dividing the tray along its major axis (Fig. 5). We evaluate performance using three metrics. First, the time to convergence. Second, the distance traveled by the CoP, indicating how many corrections are required to balance the object. Third, the success rate, when convergence is reached within $120\ s$, also accounting for those cases in which the object falls. The first five rows of Table I summarize the results. The best performance is obtained with the lightest objects (Object 1 and 5). Regarding object position, *Position 4* is the easiest to balance, being closest to the center of the support polygon (around the index/middle finger). Finally, to validate our choice of training a separate force estimator for each finger, we conduct an ablation using a single shared network (**SN**) on Object 3, shown in the last row of Table I: when force estimation is unreliable, the system struggles to converge. This outcome is consistent with the findings in Section IV-.1.

Fig. 6 shows the CoP error over time for a failure and for a success episode.

*3) Multiple objects balancing experiments:* To further check the robustness of our approach, we use two aluminum boxes filled with modeling clay (as in Object 5), for a total weight of $299\ g$. We randomly place the boxes on the tray, varying their position. The boxes are placed in three predefined configurations (opposite sides, same side, and center), with exact positions randomized across five trials each, obtaining $80\%$, $60\%$, and $100\%$ success rate respectively.

*4) Ablation on control frequency:* To assess the importance of the controller reactivity when dealing with object with varying mass, we repeat the same tests for single objects reported in Section IV-.2, lowering the control frequency to $50\ Hz$. The lower frequency reduces the system reactivity and hinders proper recovery, especially for fast-moving or rolling objects (e.g., Objects 3 and 4): on average, we experience a $9\%$ drop in success rate.

## V. Limitations

In this section, we discuss the limitations of our work. The first concerns discrepancies between the 3D hand model and tendon friction, which cause misalignment between desired and actual finger motion. Nevertheless, the approach is still able to drive the CoP in most cases, showing robustness to modeling errors. Furthermore, the *Keep in Touch* control is currently implemented as a separate module: a more systematic approach would integrate this compensation directly into the QP. The second limitation is the plane trajectory module: the trajectory generation only accounts for the angular position of the plane $\Pi$, while its linear position remains constant. Exploiting the full pose of the plane could enhance the balancing performance and also enable the execution of more complex tasks, such as trajectory tracking with the arm while balancing an object. Finally, contact with the palm represent an additional source of error: in some trials, the plane tilts and touches the unsensorized palm, breaking the assumption of fully sensorized contact surfaces. A sensorized palm would mitigate this issue.

## VI. Conclusion

In this paper, we presented a model-based force-aware control strategy for multifingered robotic hands. By operating in the force domain, our method adapts the motion of the torso, arm, wrist, and fingers to maintain stable contact with objects of varying mass, under the assumption of planar contact; we validated the approach on single-object and multi-object balancing tasks involving diverse shapes and weights, demonstrating robust performance across all scenarios. As future works, we plan to integrate the proposed algorithm as a low-level policy within hierarchical manipulation frameworks, particularly for tasks involving bimanual manipulation.

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