Aerial Perching via Active Touch: Embodying Robust Tactile Grasping on Aerial Robots

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by

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Preface

The following thesis was written to obtain my Master degree in the profile Control & Simulation at the Faculty of Aerospace Engineering at Delft University of Technology. The thesis involved the design and subsequent implementation of an aerial manipulator which uses tactile feedback to perform object localization and grasp evaluation. This research extends the foundation laid by various studies in aerial manipulation and tactile perception, with a central aim of investigating whether tactile feedback enhances the performance of aerial manipulators in perching applications. The ensuing experiments involved tasks in both open and closed-loop scenarios, providing a comprehensive assessment of the manipulator's performance.

The public presentation and defense of this thesis are scheduled for the 21st of December 2023, before a committee comprising Prof. Dr. G.C.H.E. De Croon, Asst. Prof. S. Hamaza, Asst. Prof. D. Pool. and A. Bredenbeck

I would like to express my gratitude towards my supervisor Asst. Prof. S. Hamaza who has guided me throughout the thesis to reach this important milestone.

Many thanks to A. Bredenbeck, whose support has been integral to my journey. His technical advice, assistance with experiments, and, just as crucially, ensuring my focus stayed on the right, singular track, have been invaluable.

I am extremely grateful for my family and friends who have been supporting me throughout this whole process. First and foremost, a special thank you goes to my mom and dad, Sharda Ramnathsing and Stanley Jadoenathmisier, who have provided me with all the tools I need to pursue my educational ambitions and helping my stomach remain full. To my brother Jasvant Jadoenathmisier and his wife Urmila Ramautar-Jadoenathmisier, I am grateful for opening their doors whenever I needed a space to unwind.

Lastly, but certainly not least, I express immense gratitude to my wonderful girlfriend, Julia van den Berg, whose continual motivation and calming presence have been indispensable throughout this journey.

I hope you find this thesis informative and engaging.

Anish Vidurprakash Jadoenathmisier
Delft, December 2023

Contents

1 Introduction

1.1. Background

In the ever-evolving landscape of drone technology, where these devices are finding utility in various domains such as aerial photography, agricultural monitoring, and human transport, the exploration of their versatility is a continuing endeavor. While drones have demonstrated effectiveness in passive tasks, the scientific community is increasingly drawn to a specialized variant – the aerial manipulator. Comprising drones with attached manipulators, these systems extend beyond passive roles, engaging in activities like contact-based inspection, valve turning, and the intriguing prospect of aerial perching.

Aerial perching, allowing drones to strategically land on or beneath objects, holds promise for prolonging mission durations by conserving energy. Applications range from environmental monitoring seen in research by Zheng et al.[1] to innovative recharging methods, such as using power line cables demonstrated by Iversen et al. [2].

However, the achievement of successful aerial perching comes with challenges, notably in the precise localization of suitable perching sites. Common sensors like cameras or LiDAR are employed for this purpose, but issues arise in low-light conditions or when the gripper obstructs the camera, leading to inaccuracies in object estimation. Addressing these uncertainties requires, among other methods, exploring new modalities to enhance the aerial manipulator's accuracy in perch planning.

Once such modality comes in the form of tactile perception, which has been used extensively in the world of fixed-base robotics. Tactile perception is sensing via touch and can be employed for a variety of tasks such as in-hand manipulation, grasp evaluation and object localization [3]. In the field of aerial manipulators, tactile perception has only been investigated as tactile navigation in the form of contour-following by Bodie et al [4] and Hamaza et al [5]. However, this modality can be used for much more.

Taking inspiration from fixed-base robotics, this thesis explores the possibility of extending the applicability of tactile feedback within aerial manipulation to object localization. Research on this has previously been conducted by Bredenbeck et al. [6]. To achieve this, a three-fingered, bio-inspired robotic gripper with tactile sensing capabilities is designed and affixed to a quadcopter drone. The subsequent development of a tactile navigation algorithm and a grasp evaluator aims to enhance the aerial manipulator's ability to perform object localization and subsequent aerial perching.

1.2. Research Goal

The thesis within this document seeks to illustrate the practicality of incorporating tactile feedback for drones, particularly in navigating landing scenarios. Additionally, it aims to validate the efficacy of evaluating tactile information. To substantiate these claims, the following questions have been posed:

- Does employing tactile feedback in grasping applications offer a significant advantage over remaining in open loop?
    1. To what extent does the use of tactile feedback increase the allowable object uncertainty compared to scenarios without tactile feedback?

2. How does the success rate of an open-loop perch compare with the performance of tactile-based aerial perching?
3. In what manner is the time-before-landing influenced by the utilization of tactile feedback?

- What is the magnitude of the improvement in the likelihood of a successful perch when utilizing a tactile grasp evaluator?

1.3. Report Outline

This report unfolds in three main chapters. The fist chapter presented here has given a brief background on the topic of aerial manipulators and tactile feedback. The second chapter houses the scientific paper, designed to address the research questions articulated in the project's objectives. Finally, the third chapter encompasses a comprehensive literature study conducted before commencing the actual thesis. This study delves into the intricacies of both aerial manipulators and tactile feedback, showcasing the diverse methods currently employed to achieve various objectives. The literature review concludes by identifying a knowledge gap in the existing literature, specifically centered around the use of tactile feedback in aerial grasping, aligning with the research goal.

2

Scientific Article

Aerial Perching via Active Touch: Embodying Robust Tactile Grasping on Aerial Robots

A.V. Jadoenathmisier

***Abstract*—Aerial manipulators, characterized by their ability to actively engage with the environment, are gaining popularity for their versatility in performing diverse tasks. This research focuses on augmenting the capabilities of aerial manipulators through the integration of tactile feedback, specifically employing a compliant bio-inspired three-fingered manipulator equipped with tactile capacitive sensors on each finger. The manipulator is affixed to a drone, enabling tactile-guided navigation for precise object localization, subsequent grasping, and perching.**

Additionally, a grasp evaluator assesses grasp quality, allowing the system to adapt by suggesting alternative grasp locations after an initial attempt is unsuccessful. A comparative analysis between the system's performance using tactile feedback and open-loop perching/grasping in perching scenarios demonstrates that the grasp evaluator improves the perching success rate by 55%-point and increases the allowable object uncertainty by 0.14 [m]. These findings highlight the efficacy of this approach in advancing aerial manipulator capabilities.

I. Introduction

The increasing popularity of drones across various industries, such as aerial photography, industrial inspection, and agriculture, fuels a growing interest in drone development [1, 2]. Initially employed for passive tasks without active interaction with the environment, there has been a shift towards developing aerial manipulators capable of actively engaging with their surroundings. These manipulators undertake tasks like object grasping, surface perching, and even valve manipulation [3, 4, 5].

Among actively interactive tasks, perching stands out due to its potential to help drones conserve energy and extend mission time [6]. For instance, in remote monitoring, multi-copter drones can perch on tall structures, enabling them to perform monitoring tasks without constant flight [7, 8]. Additionally, perching on power line cables offers an opportunity for drones to recharge their batteries [9].

As the demand for aerial manipulators grows, there is a pressing need to enhance their capabilities, particularly in terms of localization and precise flight trajectory towards objects [1]. Enhancing these capabilities enables aerial manipulators to perform tasks more safely and accurately.

Aerial manipulators typically consist of robotic elements, and inspiration from their fixed-base counterparts is a logical starting point for improving current designs. Object localization in fixed-base robotics has involved tactile feedback, where tactile sensors integrated within the manipulator accurately determine the object's location based on touch feedback. Tactile feedback has proven valuable in various applications, including object localization, contour following, and grasp evaluation [10, 11, 12, 13].

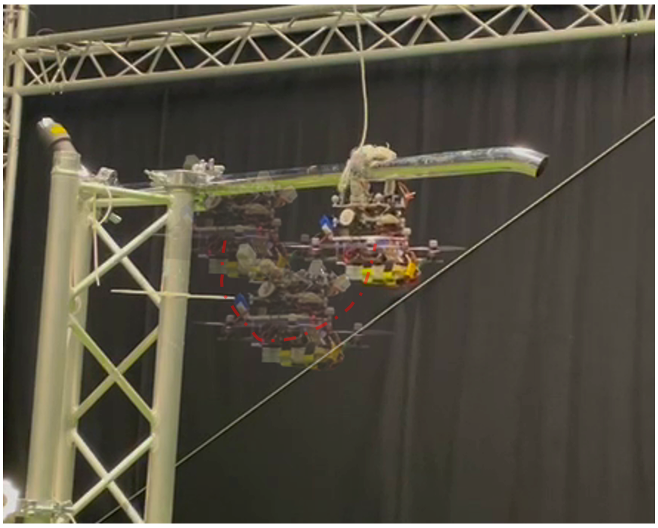


Fig. 1: The aerial manipulator using tactile-based navigation is depicted perching on an object.

In the realm of aerial manipulators, tactile sensing has found applications in contour following and surface detection [14, 15, 16]. However, the existing literature on the use of tactile feedback for object localization is relatively limited, with a modest amount of research conducted thus far, notabl by [17]. Touch localization in aerial robotics becomes particularly valuable in conditions where vision-based localization faces challenges, such as object occlusion, low-light conditions, or constrained computational power. Additionally, tactile sensing provides valuable feedback on the quality of a grasp [11].

Research into tactile feedback can involve various sensors, such as vision-based tactile sensors, piezoresistive sensors, traditional force/torque sensors, and capacitive sensing [18]. Capacitive sensing, in particular, stands out as a viable option, due to their weight and low cost[18].

While popular tactile sensors like the Gelsight tactile sensor [19] or the Syntouch Biotac[1] are commonly used in literature [18], their high price points make them less viable for all situations. In contrast, capacitance sensors such as the MPR121[2], despite providing less valuable information compared to high-end sensors, offer a cost-effective alternative that requires less data processing.

In this work, the development of an aerial manipulator that utilizes tactile feedback from an MPR121 capacitance sensor

[1] https://syntouchinc.com/
[2] https://www.adafruit.com/product/1982

to position itself for grasping or perching tasks is presented, as depicted in Figure 1. The main contributions of this work are as follows:

- Designing a semi-rigid tendon-driven manipulator with an interior structure manufactured from PLA and exterior silicon pads to enable compliant grasping behavior. Tactile sensing electrodes are embedded into the silicon finger pads.
- Developing a tactile feedback controller that utilizes touch localization to compute reference positions for the aerial manipulator to plan grasps or perches.
- Designing a grasp evaluator that utilizes tactile sensor output to assess whether a grasp will lead to a stable grip. If the grasp is deemed unsuccessful, the controller plans for a new grasp that will lead to success.
- Testing the robustness of the controller through extensive trials under varying amounts of object uncertainty. Additionally, demonstrating that the controller can perform its task until it finds a stable perch.

II. Methodology

A. Manipulator Design

The manipulator attached to the drone comprises a three-finger system designed for both stable grasping and perching.

Each finger consists of three phalanges of varying length, the sizing and shape of which was inspired by the anatomy of the human finger. The phalanges can be categorized as proximal, intermediate and distal . The proximal phalange is located closest to the base of the gripper while the distal phalange is furthest away. Having the gripper on top of the drone enables grasping objects from below and perching in the form of hanging. This design is inspired by a similar design seen in [7], other designs that involve the gripper on top of the drone include [20, 9].

The fingers are attached to a revolute joint which is in turn mounted on top of a base plate. The frame of each finger is made from PLA and was manufactured using 3D printing. On each phalange of the finger a silicon pad is attached. This combination allows the system to carry loads effectively while also offering a degree of compliance during grasping. Additionally, the silicon pads feature a rougher texture compared to PLA, which enhances grip stability due to the increased friction coefficient.

A rendering of the fingers can be seen in Figure 2 .

To optimize space allocation for the fingers, servos, and flight computer, a stacked base design was selected. This choice was driven by the constrained space available on the drone. The stacked configuration comprises three bases, with the bottom base serving to house and shield the flight computer. The second base is designed to accommodate three servos and provide ample room for electronic components. Lastly, the top base is dedicated to attaching the fingers to the system. The stacked configuration is shown in Figure 2

For controlled finger movement, a tendon-driven mechanism is employed, where each finger is linked to a servo through a tendon routed from the servo to the top of the finger. This approach, chosen over a single servo system, minimizes mechanical complexity. Passive closure is achieved by integrating torsional springs at each joint, considering the drone's passive perching capability at its maximum take-off weight and under the maximum load of the actuators. The full system in both open and closed state can be seen in Figure 2

The forward kinematics of the manipulator are used to determine the position of each phalanges at a specific joint angle. These are obtained by the matrices found in Equation 1.

$$
\begin{aligned}
T_{01} &= \begin{bmatrix} \cos(q_0) & -\sin(q_0) & 0 & 0 \\ \sin(q_0) & \cos(q_0) & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \\
T_{12} &= \begin{bmatrix} \cos(q_1) & -\sin(q_1) & 0 & L_1 \\ \sin(q_1) & \cos(q_1) & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \\
T_{23} &= \begin{bmatrix} \cos(q_2) & -\sin(q_2) & 0 & L_2 \\ \sin(q_2) & \cos(q_2) & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \\
T_{34} &= \begin{bmatrix} \cos(q_3) & -\sin(q_3) & 0 & L_3 \\ \sin(q_3) & \cos(q_3) & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}
\end{aligned} \tag{1}
$$

Each q_i represents the rotation of joint i, where joint 0 is located on the base of the gripper and joint 4 on the distal phalange. The length of each phalange is given by L_i. The forward kinematics T_{04} can then be obtained using Equation 2.

$$T_{04} = T_{01} \cdot T_{12} \cdot T_{23} \cdot T_{34} \tag{2}$$

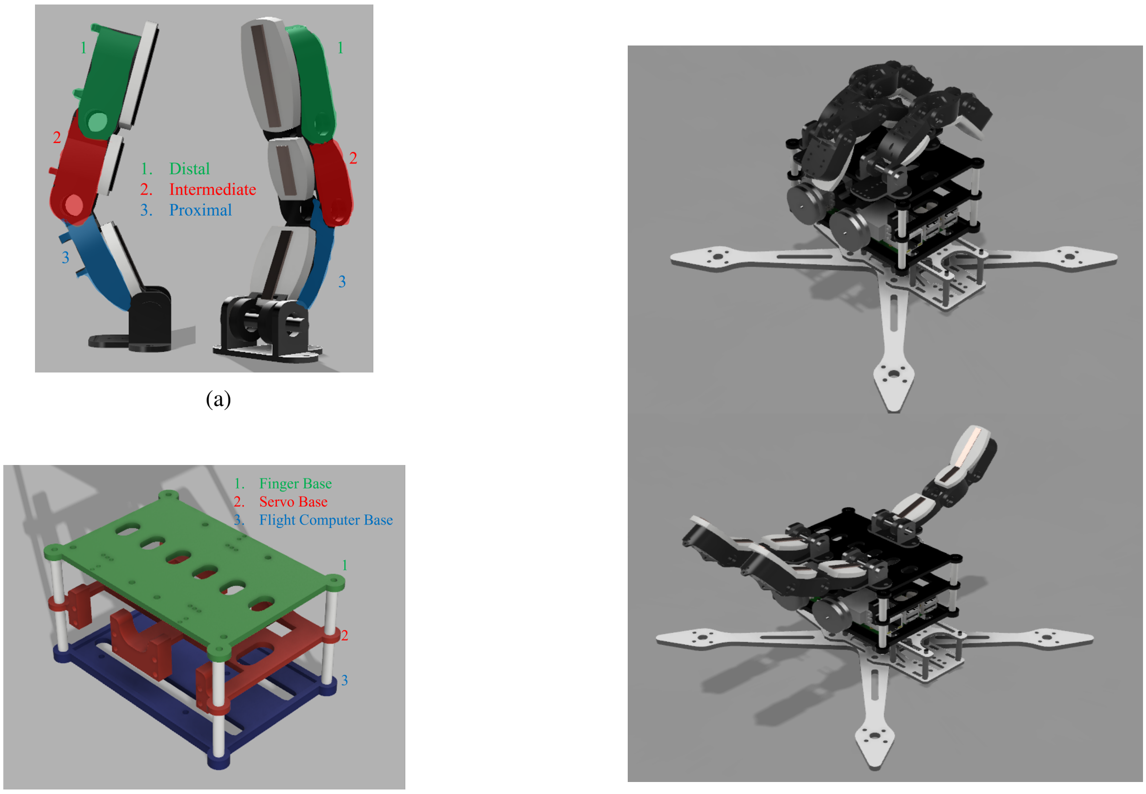
The transformation T_{04} given by Equation 3. Where c_{0123} and s_{0123} are the cosine and sine of the sum of all joint angles respectively. Using this transformation, the localization of phalanges can be obtained.

$$T_{04} = \begin{bmatrix} c_{0123} & -s_{0123} & 0 & c_{012}L_3 + c_{01}L2 + c_0L1 \\ s_{0123} & c_{0123} & 0 & s_{012}L_3 + s_{01}L2 + s_0L1 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{3}$$

B. Tactile Sensing Pads

To implement embodied sensing on the manipulator, copper electrodes are integrated into the silicon pads, enabling a tactile sensor to detect changes in capacitance and provide touch-sensing capabilities. The electrodes are connected to the sensor using electrical wiring, which are soldered on to the copper.To ensure that the electrodes do not detach of the silicon, metal pins were jointed to the copper over which the silicon could be casted. Using this method, all sensing pads were manufactured. A robotic finger with all components can be seen in Figure 3.

The tactile sensor, a MPR121, works by measuring the potential between a sensing terminal on the sensor and a



(a) (b) (c)

Fig. 2: (a) Renders of the bio-inspired fingers attached to a base, on the left is a side view showing the tendon routing needed to actuate the finger. On the right is a full view of the finger, including the sensing pads. The phalanges are numbered and color coded(b) Rendering of the stack configuration that is mounted atop the drone. Each base is numbered and color coded. (c) Renders of the drone in both closed state (top) and open state (bottom).

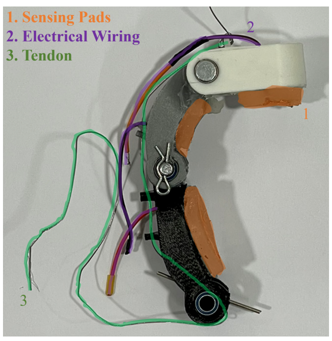


Fig. 3: The manufactured finger with sensing pads, electrical wiring and tendon.

electrode connected to it. The touch data obtained from the sensor comprises capacitive measurements that are indirectly measured by charging an electrode and measuring the resulting potential after a defined amount of time. By using a baseline capacitive measurement, a touch event can be defined as the event in which the difference between the current measurement and the baseline measurement exceeds a certain threshold. The lower this threshold the more sensitive the sensor will be. The trade-off being that false positives become more likely to occur.

C. Aerial Platform

For this research a custom built quadcopter drone was used. The drone consists of a SpeedyBee 45A BL32 4in1 ESC which controls 4 Emax ECO II Series 2207 motors. The drone is powered by a 4S battery. The full takeoff weight of the drone, with battery, is 1,01 kg.

D. Flight Stack

The flight stack onboard the drone consists of a flight controller, an onboard computer, a tactile sensor and a micro-controller for the servos.

Communication between the various subsystems is achieved using a ROS2 network, which offers a flexible way to autonomously command the drone while simultaneously giving the option to log the data in a synchronized matter.

The flight controller is a Pixracer R15 running the PX4 v1.14 autopilot software [21]. The on-board flight computer is a RaspberryPi 4.0 running Raspian Jesse. The on-board flight computer is responsible for orchestrating the flight profile of the drone. Besides being the interface between ROS2 and PX4, the RaspberryPi receives data from the touch sensor and sends commands to the motor driver of the servos.

Touch data is obtained from a MPR121 tactile sensor, which sends its data directly to the onboard computer for further processing.

The grippers are controlled by a Teensy 4.0 micro controller which communicate with the Feetech STS3032 servos over UART. The Teensy is able to send commands to the servos, but also receives position feedback. The Teensy receives commands from the onboard computer which are send over its serial port.

The full system is shown in Figure 4.

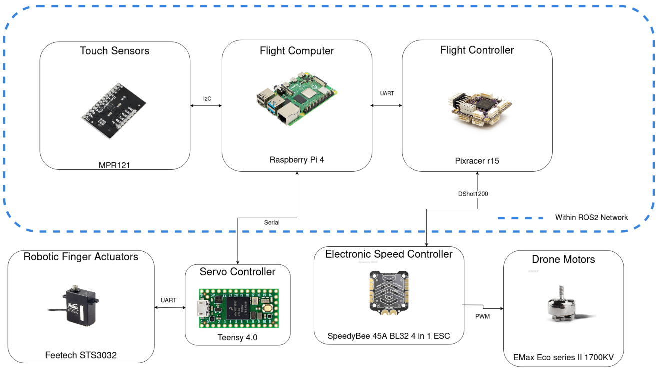


Fig. 4: Onboard drone communication depicted through the flight stack architecture. Defined communication protocols govern interactions between subcomponents, a distinction is made between components within the ROS2 network and outside of it.

E. Tactile Control Algorithm

The tactile control algorithm utilizes touch data obtained from the tactile sensor to facilitate object grasping or perching maneuvers by the drone. The algorithm involves the calculation of position set-points, taking into account the location of the drone at the touch event and an offset determined by a tactile mapping function.

The reference positions $\hat{x}_{ref}$ send to drone are calculated by first determining a goal position $\hat{x}_{goal}$ using Equation 4 .

$$\hat{x}_{goal} = \hat{x}_{touch} + \hat{x}_{offset} \tag{4}$$

Here $\hat{x}_{touch}$ is the location of the drone at the touch event, while $\hat{x}_{offset}$ is determined based on mapping $\mathcal{F}$ given in Equation 5 where τ is tactile sensor that registers a touch event. As the location of each sensor pad is know a priori, $\hat{x}_{goal}$ will be a reference position that aligns the drone with the lateral position of the object to be grasped.

$$\mathcal{F} : \tau \to \hat{x}_{offset} \tag{5}$$

The tactile mapping function $\mathcal{F}$ is determined based on the spatial arrangement of the tactile sensing pads, as illustrated in Figure 5. The corresponding distances for each pad are

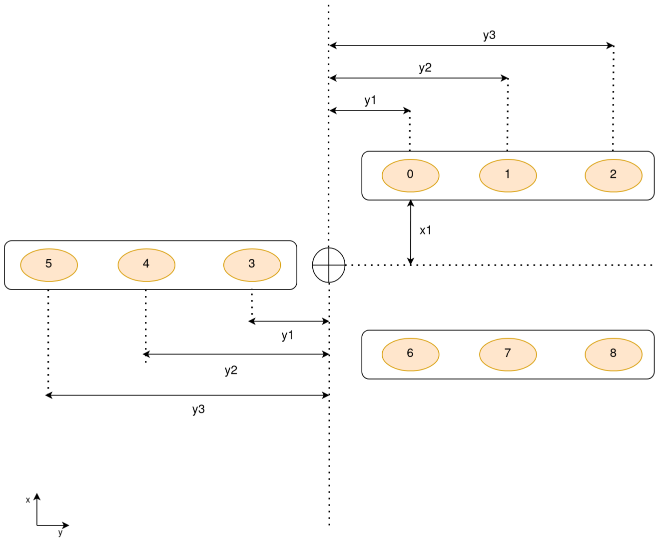


Fig. 5: The gripper configuration and the location of each sensor pad. The sensor mapping $\mathcal{F}$ for each sensor pad i, ranging from 0 to 8, can be obtained by taking the distances of each pad from the center.

TABLE I: Tactile sensor mapping

τ	Δ x	Δ y	Δ z
0	x1	-y1	z_{base}
1	x1	-y2	z_{base}
2	x1	-y3	z_{base}
3	0	y1	z_{base}
4	0	y2	z_{base}
5	0	y3	z_{base}
6	-x1	-y1	z_{base}
7	-x1	-y2	z_{base}
8	-x1	-y3	z_{base}

presented in Table I. The vertical offset Δz is based on the height of the manipulator base with respect to the drone z_{base}.

Once a goal position has been calculated, the reference positions $\hat{x}_{ref}$ are generated using the linear interpolation given in Equation 6.

$$\hat{x}_{ref} = \hat{x}_{touch} + t_{traj}(\hat{x}_{goal} - \hat{x}_{touch})v \tag{6}$$

where v and t_{traj} are the velocity and time since the start of the trajectory respectively.

F. Tactile Grasp Evaluator

Upon reaching the calculated position, the drone initiates a grasping maneuver, and the stability of the grasp is determined based on the tactile output following the grasping action.

The optimal grasp configuration occurs when all touch pads register a touched state. However, for the sake of achieving a stable grasp, it is not mandatory for all pads to be touched. During the correction maneuver, the objective is to attain a touch state Π that is sufficient for deeming the grasp as stable. It was empirically determined that the minimum required touch state should be:

$$\Pi = \begin{bmatrix}1 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0\end{bmatrix}^T$$

where each column i of Π represents sensor pad i.

If the grasp is confirmed to be stable, the drone has the option to either transition to a perching state or continue with the ongoing grasping maneuver. Conversely, if the grasp is assessed as unstable, the grasp evaluator triggers a correction maneuver.

The correction maneuver is determined based on the current tactile state obtained after the grasp.

If no tactile output is registered, i.e

$$\Pi = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}^T$$

the controller determines a new grasp position based on the assumption that the grasp manoeuvre has aligned the lateral components of the object and drone. Therefore only the vertical component needs to change. Thus, the correction maneuver involves the drone moving up towards the bar by a set amount as described in Equation 7 .

$$\hat{x}_{new} = \hat{x}_{current} + \begin{bmatrix} 0 & 0 & \Delta z \end{bmatrix}^T \tag{7}$$

If no output is registered on the either of the side fingers i.e

$$\Pi = \begin{bmatrix} 0 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 \end{bmatrix}^T$$

or

$$\Pi = \begin{bmatrix} 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}^T$$

it is assumed that the drone is at the endpoint of an object and must thus shift laterally in either the positive or negative x-direction. The correction manoeuvre is then given by Equation 8

$$\hat{x}_{new} = \hat{x}_{current} + \begin{bmatrix} \Delta x & 0 & 0 \end{bmatrix}^T \tag{8}$$

Finally if Π does not equal any of the aforementioned states, the grasp is tried again without any changes in the goal position.

G. State Machine

To facilitate the dynamic adjustments in flight behavior required across various phases of the drone's mission, a state machine is developed.

From the envisioned flight mission for this research the following distinct states are defined for the state machine: *Takeoff*, *Searching*, *Touched*, *Grasping*, *Evaluating*, and *Landing*. Each state is defined as follows:

1) *Takeoff*: In this initial state, the drone ascends from the ground, maintaining a hovering position at a specified altitude. After a predetermined duration, the drone receives an estimated location of the target object for perching or grasping, with an assigned offset. It then transitions to the *Searching* mode.
2) *Searching*: The drone undertakes a predefined search trajectory around the object's position. Throughout the search, the drone actively listens for touch events relayed by the touch sensors. Upon detecting a touch event, the state transitions to *Touched*.
3) *Touched*: Having localized the object to be grasped or perched, the drone computes an initial optimal grasp trajectory based on the tactile control algorithm's output. Upon reaching the calculated grasp position, the state transitions to *Grasping*.
4) *Grasping*: In this state, the drone executes the grasp maneuver, subsequently transitioning to the *Evaluating* phase.
5) *Evaluating*: Following an executed grasp, the drone awaits feedback from the tactile sensors. The grasp evaluator assesses this feedback, determining the success of the grasp. If successful, the state transitions to *Landing*; otherwise, the state machine reverts to *Grasping* with a newly calculated grasp location from the grasp evaluator.
6) *Landing*: With a confirmed stable grasp, the drone gradually decelerates its motors and proceeds to shut down entirely.

Figure 6 shows the state machine with the conditions that trigger a transition.

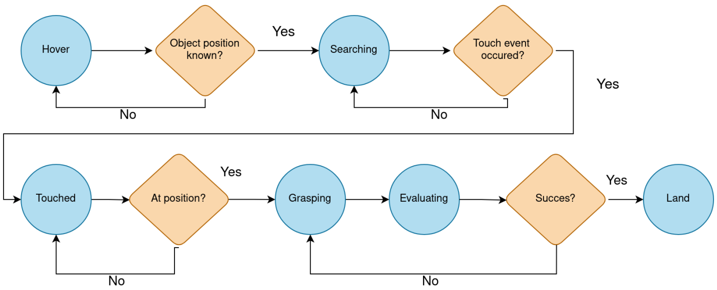


Fig. 6: Flowchart of the state machine

III. Flight Experiments

To test whether the developed algorithm led to improved perching performance various experiments are conducted in which this is evaluated.

A. Experimental Setup

Each experiment consisted of the drone having to perch on a conductive rod with a radius of 2.5 [cm]. In all experiments, Optitrack motion capture was employed for drone state estimation. To be able to search for the object using tactile feedback, the drone executed either an elliptical or zigzag trajectory around and below the perching object, as illustrated in Figure 7. The offset distances defined in Table I are given by Table II

TABLE II: Offset values used during the experiments

Offset	Value in [m]
$\Delta x1$	0.035
$\Delta y1$	0.05
$\Delta y2$	0.08
$\Delta y3$	0.11
$\Delta z1$	0.08

The offsets are obtained by assessing the distance between the base of the drone and the sensing pad. Given that the

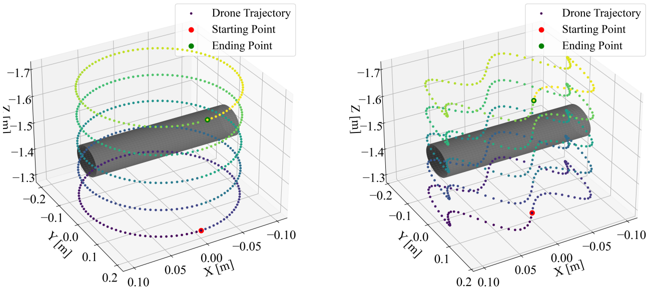


Fig. 7: Ellipse and zigzag search trajectories used in the searching state of the tactile state machine.

sensing pads cover the entire phalange, it was decided to measure from the midpoint of each pad.

B. Open and closed loop perching experiments

The perching performance assessment involved evaluating the aerial manipulator's ability to sustain a hanging position for over 10 seconds post-perch execution. Two types of experiments were conducted: an open-loop perching experiment and a closed-loop one.

In the open-loop experiment, a predefined position marked a potentially successful grasp. The aerial manipulator moved toward the perching object, and perch success was visually confirmed. Varying the offset to the goal position allowed correlating perch success rates with changing distances. The closed-loop experiment involved the manipulator utilizing tactile feedback for perching. Using the tactile controller, the drone detected the object and, based on touch localization, executed a perching maneuver. Furthermore, if the perch was deemed unsuccessful by the grasp evaluator the controller would plan for a new perch. Visual confirmation verified the perch success rate.

In Figure 8 the states during the flight mission for both the open loop and closed loop are shown.

To compare perching performance with and without tactile feedback, success rates for a given perch at a specific offset were averaged and plotted in Figure 9.

C. Touch-Based Navigation

The drones ability to align itself with an object after a touch event, was verified by running similar experiments as in the aforementioned subsection. In Figure 11, the drone's trajectory and tactile sensor outputs are plotted for a single experiment. Initially, upon touching the object, the drone plans a perch aligning with the object's position.

Multiple runs of this experiment were run to determine the behaviour of the system. In Figure 12 the convergence towards the perching object can be visualized. Here, both the location of the drone at which a touch event occurs and its location for grasping are connected to show how the drone changes its location based on touch events. This data was obtained from 28 experiments using various offsets from the center of the bar and searching trajectories.

D. Comparison between searching trajectories

Various factors influence the perching performance of the drone, these include the state estimation uncertainty and the perch location. The grasp evaluator is used to aid the drone to still reach a successful perch even after these limiting factors. In Figure 13 it is shown how the drone first performs an unsuccessful perch and then subsequently tries to perform one again. Statistical analysis is performed to determine the grasping behaviour of the system. 20 trials were run, with 10 trials using an ellipse trajectory while the other 10 were using a zigzag trajectory. This is to test whether a difference in searching trajectory led to any significant performance changes. The average amount of tries before success for the ellipse trajectory is determined to be 3.5 and the average speed is found to be 49.9 [s]. For the zigzag trajectory the average amount of tries is 2.3 and the average speed is 39.9 [s]. Both the distribution for the amount of tries and time before landing are found in Figure 10

IV. Discussion

A. Touch-based perching performance

The integration of tactile feedback significantly improves the perching performance of the aerial manipulator after a touch event, showcasing a notable advancement over its open-loop counterpart. As depicted in Figure 9, the use of tactile feedback consistently yields higher success rates across diverse offsets in object location. Furthermore, this integration extends the perching range of the aerial manipulator, effectively leveraging the full length of the gripper's fingers and accommodating uncertainties in the actual object location.

In open-loop experiments, failed perches primarily stem from instances where the manipulator engages the perching object with only the top phalanges or experiences inherent misalignments in the experimental setup. Conversely, closed-loop experiments reveal that unsuccessful perches often re-

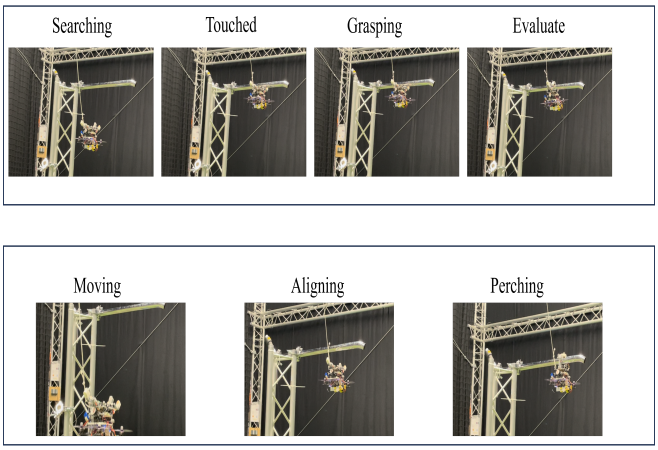


Fig. 8: Illustration of experiment trajectories and states. The top figure depicts state transitions during an experiment incorporating tactile feedback, while the bottom figure showcases the drone attempting an open-loop perch.

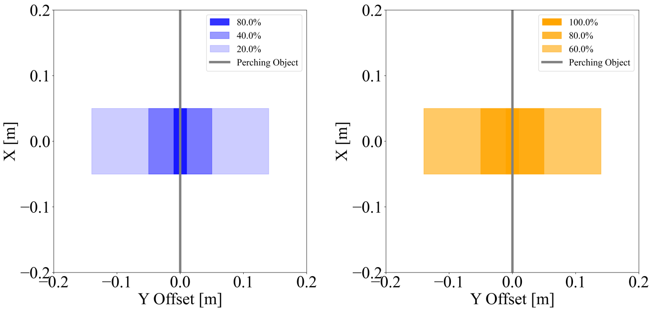


Fig. 9: The perching performance of an aerial manipulator, assessing its grasping capabilities without and with tactile feedback, is depicted. The evaluation focuses on lateral (y) uncertainty in the perching object's position. For each y offset (0, 0.05, and 0.14), five trials were conducted for both open-loop and closed-loop implementations, resulting in a total of 15 trials. The left plot illustrates performance without tactile feedback, while the right plot displays performance with tactile feedback.

sult from challenges in aligning the aerial manipulator for the initial perch. Gripper closure timing errors, influenced by state estimation inaccuracies, contribute to unsuccessful alignments and occasional collisions that necessitate additional refinement. The prospect of introducing supplementary tactile sensors, particularly on the back of the fingers, presents an avenue for collision detection and mitigation.

B. Robustness of the grasp evaluator

From the various experiments that were performed, it can be determined that the robustness of the evaluator ensured that the system was able to perch successful in various trails. From Figure 10, it can be observed that the combined probability of an initial successful perch is 20% across varying distances and searching trajectories. The aerial manipulator, upon encountering an unsuccessful perch, demonstrates an improvement in its success rate by 75% when attempting new perches. This improvement is calculated by considering the difference between the total attempts and failed attempts. Consequently, the evaluator increases the chances of achieving a successful perch by 55%-point.

While the grasp evaluator introduces enhanced robustness to grasping capabilities, it does necessitate a trade-off with speed when contrasted with open-loop grasping. In open-loop scenarios, the time until landing remains minimal and is subject to operator discretion. In contrast, tactile grasping mandates a preliminary phase wherein the aerial manipulator locates the object and subsequently plans grasps until a successful execution.This approach, while marginally slower, does augment adaptability and success rates in dynamic and uncertain environments. It can be noted that on average utilizing a zigzag searching trajectory yields a faster convergence to a stable landing compared to using a ellipse trajectory. Thus indicating that future work could focus on optimizing trajectories to find objects faster.

V. Future Work

A. Force control for increased compliance

The tactile sensors utilized in this study were limited to detecting touch events exclusively on each sensing pad, lacking information about the applied force during grasping maneuvers. The absence of force-related data could be particularly valuable, especially when evaluating the success of a grasp. Previous studies have successfully demonstrated the capability to infer forces from capacitive measurements.

Integrating force measurements into the tactile sensing system holds promise for enhancing the manipulator's compliance. This additional information not only provides insights into the force exerted during grasping but also contributes to making the manipulator more delicate in its interactions. The ability to gauge and adapt to the forces involved in a grasp adds a layer to the manipulator's control, ultimately improving its overall performance in delicate and precise tasks.

B. Pose estimation of perching object

In this study, the aerial manipulator assumes that a touch event implies the pose of the object to be grasped aligns with the front of the drone. Consequently, the current motion planning for the grasp does not account for any yaw component. Recognizing that real-world scenarios may deviate from this ideal alignment, it becomes imperative to integrate yaw movements within the tactile motion planner.

One viable approach involves leveraging a top-view camera mounted on the drone to visually servo the aerial manipulator. This allows the manipulator to align itself with the axis of the object to be perched. This method, successfully demonstrated in other research, introduces a visual feedback mechanism to enhance the precision of the manipulator's orientation.

Alternatively, expanding the degrees of freedom of the 3-hinge manipulator offers another avenue. The current design, utilizing pivot hinges, confines motion to a 2D plane. Introducing alternative joint types, such as universal joints, could empower the manipulator to perform sweeping motions. By incorporating servo feedback, these sweeping motions enable the fingers to gather information about the orientation of the object's axis, allowing for a more adaptable and accurate manipulation strategy.

C. Increased resolution of touch location

The manipulator designed for this research was equipped with sensing pads in only 9 locations, resulting in instances where the drone failed to register touch despite colliding with an object intended for grasping. To enhance touch detection reliability, an improvement can be achieved by augmenting the number of sensing pads distributed across the manipulator. This augmentation provides the drone with an increased capability to detect touch events along its manipulator.

Strategic locations for additional sensing pads include the back of the fingers. This addition addresses situations where the drone might become entangled due to the back of the fingers colliding with an object, preventing the drone from reaching a specified target position. Furthermore, incorporating

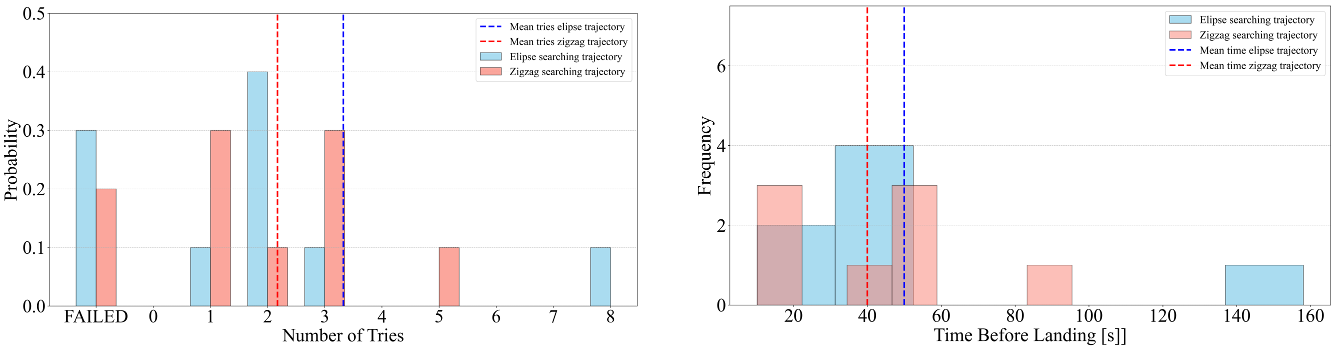


Fig. 10: Distribution plots comparing the perching performance of the aerial manipulator utilizing two distinct searching trajectories: one employing an elliptical path and the other employing a zigzag path. Each trajectory is assessed through 10 trials. The left plot illustrates the distribution of the number of attempts the aerial manipulator makes before achieving a successful perch. On the right, the plot displays the distribution of the time taken by the aerial manipulator to successfully perch.

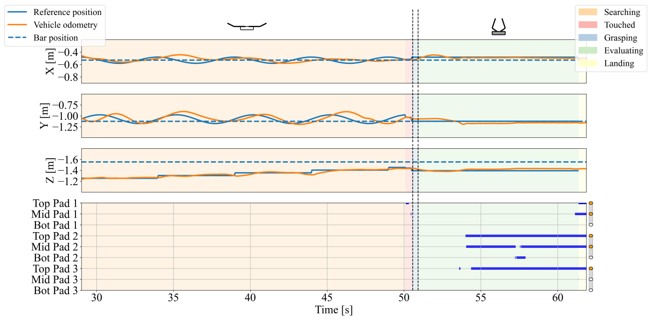


Fig. 11: The behavior of the system throughout a single trial is depicted, showcasing the dynamic changes in its state based on events. The state machine transitions are visualized, providing insights into the system's response to various cues. Additionally, the state of the tactile sensing pads at the conclusion of the trial is presented at the end of the plot.

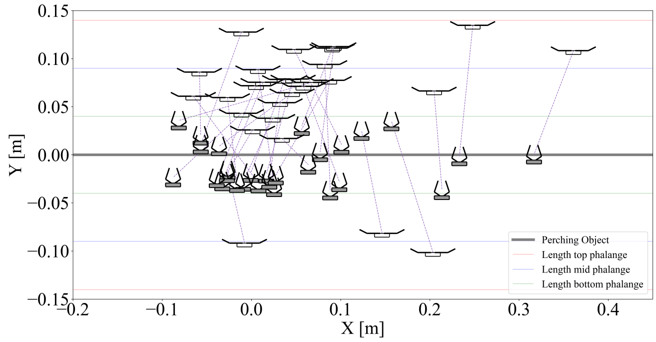


Fig. 12: The overall response pattern of the controller following a touch event is illustrated. The drone transitions to an "open" state upon detecting a touch event, and to a "closed" state when attempting a grasp. The depicted drone flight paths consistently converge toward the bar after a touch event. This data is derived from 28 individual trials involving varied offsets to the bar and searching trajectories.

sensing pads at the base of the manipulator proves beneficial, particularly for detecting objects slim enough to pass between the fingers. Without these additional sensors, such objects might escape detection.

By expanding the coverage of sensing pads, especially to critical areas like the back of the fingers and the base of the manipulator, this enhancement ensures a more comprehensive touch detection capability, minimizing instances of undetected collisions and contributing to the manipulator's overall effectiveness.

VI. Conclusion

In this study, an aerial manipulator was developed with capabilities tailored for perching. The manipulator utilized a tactile sensor to obtain tactile feedback from objects around it. A tactile-navigation controller and a grasp evaluator were designed with which the aerial manipulator was able to find objects and plan for perches.

Utilizing various search trajectories, the aerial manipulator efficiently identifies objects. Once detected, the system strategically plans perches to ensure successful outcomes. The inclusion of a grasp evaluator uses tactile feedback to assess the stability of a designated perch. In instances of compromised stability, a set of correction maneuvers has been devised, guaranteeing subsequent grasp attempts result in success.

Results demonstrated that implementing the tactile controller extended the perching range under object uncertainty by 14 [cm]. Furthermore the introduced grasp evaluator improved the reliability of perching by 55%-point.

While the platform functions as intended, opportunities for improvement exist to enhance its capabilities under uncertainty. Increasing the amount of tactile sensors on the platform provides the aerial manipulator with a more comprehensive understanding of its surroundings through embodied sensing.

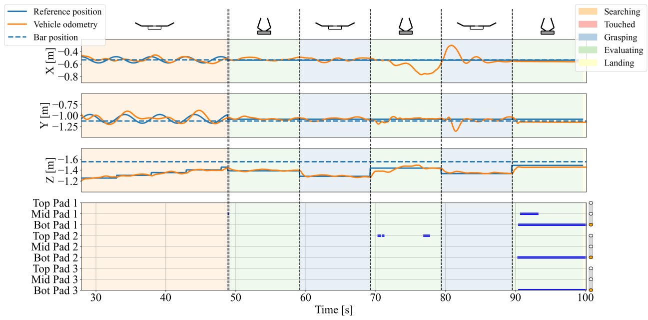


Fig. 13: The drone's capability to assess a grasp and adapt its goal position is demonstrated. Following each unsuccessful attempt, the grasp evaluator elevates the drone's altitude, continuing until the evaluator identifies a successful grasp. The concluding segment of the plot displays the final tactile configuration attained by the system.

Additionally, increasing the degrees of freedom on the fingers enables the incorporation of yaw control in the tactile controller, such that the drone is able to perch objects that are at various angles from it. Finally, the integration of force control into the design facilitates more compliant grasping, guiding the drone to handle more delicate objects.

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3 Literature Review

3.1. Introduction

This chapter serves as an introduction to a literature review on the applications of tactile feedback and aerial manipulation. Initially, background information will be provided on the current state of aerial manipulators and tactile feedback. From this overview, a research question will be formulated, which will be divided into several sub-questions to guide the literature review. Finally, an outline of the document will be presented, detailing the topics covered in each chapter.

3.1.1. Background

The growing popularity of drones in various fields such as industry, academia, and consumer use has led to an increase in demand for drones capable of performing a wider range of tasks. Drones are now being used for tasks such as food delivery, agricultural monitoring, and in various conservation projects [7]. These tasks are classified as passive interaction, as there is no physical interaction between the drone and the environment it is interacting with. Active interaction, on the other hand, is a relatively new type of interaction between drones and objects, which involves the drone physically interacting with the object [8].

Active interaction with the environment is beneficial as it expands the range of tasks that drones can perform in industry. Unlike mobile manipulators (or ground robots), aerial drones have a larger workspace, but the trade-off is that more advanced control systems are needed to ensure stability as forces and moments cannot be transferred back to the ground. Drones that perform active interaction tasks are called aerial manipulators [7].

The advancement of aerial manipulators has resulted in more sophisticated designs that enable a wider range of tasks. The first generation of aerial manipulators consisted of drones equipped with basic gripper designs that could perform simple pick and place operations [9]. However, recent advancements have introduced aerial manipulators with robotic arms capable of performing more complex tasks, such as door opening, valve turning, and pick and place operations [10, 11, 12]. The designs of both the gripper and drone have seen various changes as both under-actuated and fully-actuated systems are utilized. Furthermore, the use of more compliant grippers in the form of flexible and semi-rigid grippers has seen aerial manipulators being able to more safely interact with objects [7].

Tactile feedback, also known as haptic feedback, refers to the sense of touch that is artificially provided to a user or a robot through the use of sensors. Tactile feedback sensors are typically embedded in robotic grippers or end-effectors to provide information about the physical interaction between the robot and its environment [3].

The main function of tactile feedback is to allow the robot to detect and respond to forces and vibrations that it encounters while interacting with its environment [3]. This can include information about the surface properties of an object, such as texture, shape, and stiffness [13], as well as information about the amount of force being applied to an object [14].

Tactile feedback in robotics enhances the ability to grasp, manipulate, and navigate objects, as demonstrated by various applications. In grasping and manipulation, it helps detect object slippage and adjust the grip accordingly. Navigating with tactile feedback involves following contours on diverse shapes, or using tactile output to guide the gripper towards a desired grasp configuration through tactile servoing. In this process, the gripper's tactile output determines the offset between its current and desired configuration, enabling the robot to make adjustments to reach the target state [15, 16, 17].

Tactile feedback in the field of aerial robotics has seen limited usage. Studies performed by Bodie et al. [4] and Nava et al. [18] have demonstrated the benefits of adding a force sensor to the end-effector of drones, allowing for better regulation of force applied to objects and the tracking of complex contours. The use of tactile feedback provides aerial manipulators with a greater degree of precision in their interactions with objects, leading to improved performance and dependability.

This literature study aims to explore the integration of tactile feedback on aerial manipulators. Despite the increasing use of tactile feedback, there is still a gap in understanding the full extent of its potential applications. In particular, grasping tasks would benefit from the introduction of tactile feedback as low-light conditions can increase the difficulty for the drone to grasp an object based purely on visual input [8]. Furthermore, the gripper itself might cause occlusion of objects to be grasped, further decreasing the usability of the vision system. Tactile feedback has the potential to serve as a more robust form of navigation in these situations due to the usage of tactile servoing. Additionally, incorporating tactile feedback on a gripper can enhance the compliance of the interaction between the object and drone. Tasks that such an aerial manipulator could accomplish include compliant grasping of semi-deformable round objects (e.g. fruits).

Hence, the question that will be answered in this literature study is **Can integrating tactile sensors on a semi-rigid gripper of a quadrotor aerial manipulator improve its grasping ability on semi-deformable round objects (e.g. fruits) through enhanced compliance and grasp configuration via tactile servoing compared to no feedback grasping?**

3.1.2. Breakdown of the Research Question

To answer the question posed in the previous section, it will be broken down into several subquestions. The main question is broken down into three subquestions:

- How are the grippers, for grasping operations, currently implemented on aerial manipulators?
  - How do different designs limit or enable the applicability of the gripper?
  - What type of control systems are currently used to control these grippers on an aerial manipulator?
  - How does the type of gripper affect the performance of the aerial manipulator during grasping?
- At what stages of a grasping operation can the use of tactile feedback enhance the performance of the aerial manipulator?
  - What are the various phases that occur during grasping by an aerial manipulator?
  - How could tactile feedback be integrated on a gripper to aid in grasping operations?
  - Which feedback systems are currently used by aerial manipulators during grasping operations?
  - How do current feedback systems compare in respect to robustness and accuracy?
- How is tactile feedback utilized by mobile robots to improve their ability to grasp round and semi-deformable objects?
  - What are the benefits of incorporating tactile feedback in mobile robots for grasping round and semi-deformable objects?
  - What are the current technologies and approaches used to integrate tactile feedback in mobile robots for grasping tasks?
  - How does the integration of tactile feedback in mobile robots compare to other methods for grasping round and semi-deformable objects?

3.1.3. Document Outline

This document will explore the various research questions that were posed in this chapter. In section 3.2 various principles that should be taken into account when designing an aerial manipulator will be taken into account. A breakdown of the various uses of tactile perception will be given in section 3.3, this breakdown will include the types of sensors that are typically used and their various applications in both mobile and aerial robotics. Furthermore, the various control methods that are used to be able to have an autonomous robot perform various task will be explained in section 3.4. Finally, in section 3.5 a general conclusion will be given on the method proposed to answer the research question and how to achieve it.

3.2. Aerial Manipulator Design

Aerial manipulators are robotic devices that are designed to perform various tasks such as pick-and-place operations, assembly or disassembly, and even more complex tasks such as valve turning or door opening [7]. These devices come in various designs and sizes, tailored to suit the specific task they are meant to accomplish.

In this chapter, the different designs and types of aerial manipulators will be discussed in detail. Firstly, the various types of aerial platforms that are commonly used for aerial manipulation will be explored. This includes examining the different types of drone platforms, and the reasons for why they are used.

Next, the different design principles that are used when determining the type of gripper for an aerial manipulator will be discussed. These principles include the Degrees of Freedom (DOF), compliance, morphology, and attachment to the drone. These design principles are essential in ensuring that the aerial manipulator is able to perform its tasks effectively and efficiently.

Finally, this chapter will conclude with a proposal for the best design that can be used to answer the question that was posed in the introduction.

3.2.1. Aerial Platform Design

The use of aerial manipulators has been an active area of research for several years and various drone concepts have been experimented with. Initially, multicopters such as quadrotors and helicopters were used as platforms for the grippers [7]. Quadrotors are particularly popular as test beds because their dynamics are well understood, and a lot of literature on various control techniques is available. They have been demonstrated to be capable of performing various manipulation tasks such as pick-and-place operations and perching [8].

In recent years, there has been a shift towards the use of hexacopters and tilt-rotor drones, due to their fully actuated nature. Fully actuated drones have the advantage of being able to maneuver in any direction without changing their orientation, making them useful for tasks that require fine movement and their easier implementation of impedance control[4]. They have been used in aerial manipulators tasked with interacting with objects that are prone to move, and for contour following [4, 18]. The disadvantage of these systems is that they are usually less agile compared to quadrotor and require more complex modelling [8].

More sophisticated designs have also been demonstrated, such as morphing drones and drones that collaborate to achieve a desired task. These designs have the potential to improve the performance and capabilities of aerial manipulators [8].

3.2.2. Design Configurations for Manipulators

To enable an aerial manipulator to interact with its environment, various manipulator designs have been developed. These designs can be distinguished by their number of degrees of freedom (DOFs), the type of gripper they use (rigid or semi-rigid), and their morphology.

Degrees of Freedom

The Degrees of Freedom (DOF) of a gripper refers to the number of independent ways in which it can move. A higher number of DOF allows for a greater range of movement and increased dexterity, allowing the gripper to perform a wider range of tasks. However, this increased flexibility comes at the cost of a heavier and more complex design.

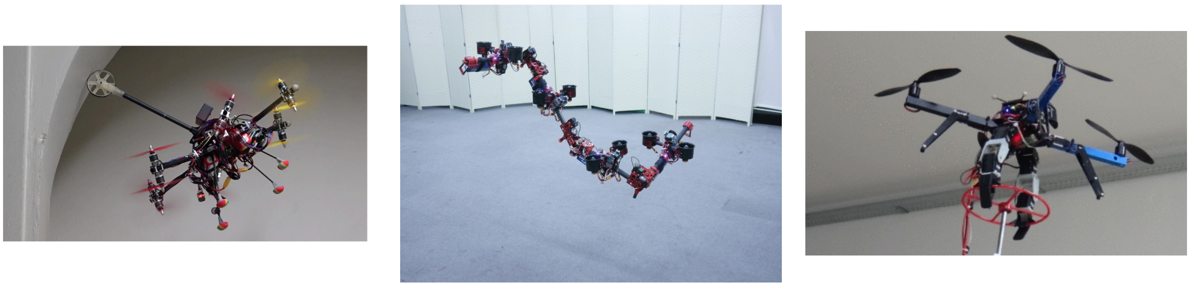


Figure 3.1: From left to right, An omnicopter developed by Bodie et al. [4] that is able to trace contours on a wall, a morphing drone developed by Zhao et al. which can be used for various applications [19] and a quadrotor manipulator developed by Korpela et al. that is opening a valve [10].

Aerial manipulators with 4- and 6-DOF have been used in various tasks such as pick-and-place operations and valve turning [20, 10]. These grippers offer a high degree of flexibility and precision, allowing them to perform a wide range of tasks.

Another type of aerial manipulator is the flying hand, which directly attaches the gripper to the body of the drone. This design significantly reduces the modeling and control efforts required to operate the gripper. However, the trade-off is that these types of grippers are limited in their workspace, and are mainly used for pick-and-place operations [21, 9].

When designing an aerial manipulator, it is important to consider the specific requirements of the task at hand and the trade-offs between the number of DOF and the weight, complexity, and workspace of the gripper. It's worth noting that, in some cases, having a lower number of DOF may not be a limitation, but rather an advantage in the sense that it can make the system more robust and less complex.

Compliance of the Gripper

Compliance refers to the ability of a gripper to adjust its shape and conform to the object it is grasping. In order to have more compliance during the interaction between the manipulator and the object, the gripper can be designed to be semi-rigid. Semi-rigid grippers have a rigid interior which can hold the load, while a softer exterior is used to increase compliance. Additionally, using a rougher material on the exterior of the gripper can increase the grip and reduce the chance of slipping [2].

Fully flexible grippers, also known as ”soft grippers” have also been developed. These types of grippers are usually made out of a form of silicon which can wrap around an object to be grabbed. They are able to adapt to the shape of the object and redistribute the force, which is beneficial for grasping delicate or irregularly shaped objects [12].

When designing a gripper, it is important to consider the type of objects that it will be grasping and the environment in which it will be operating. Grippers with a high degree of compliance can be useful for grasping delicate or irregularly shaped objects, while those with a lower degree of compliance may be better suited for task that require handling of heavier loads.

Gripper Morphology

The morphology of the gripper impacts the drones' ability to perform certain tasks. For example, a single surface magnetic gripper can be used to pick up magnetic objects, while the use of multiple surfaces allows for more manipulation of the object being grasped. Additionally, the type of gripper used can also affect the overall weight and size of the drone.

Aerial manipulators often utilize grippers that have a compact design, as they need to be able to fit within the limited space available on the drone. Some popular types of grippers for aerial manipulators include:

- Vacuum grippers: These grippers use a vacuum to suction onto an object, making them suitable for grasping a wide range of materials [11].

- Pneumatic grippers: These grippers use compressed air to actuate the fingers, allowing them to grip and release objects. They offer better compliance compared to other types of grippers and are suitable for grasping objects of various shapes and sizes [12].

- Electromagnetic grippers: These grippers use an electric current to generate a magnetic field that attracts ferromagnetic objects. They are ideal for picking up metal objects but can't grip other materials [22].
- Mechanical grippers: These grippers use mechanical fingers to grip an object, similar to how a human hand works. They offer a high degree of precision and dexterity, but they can be relatively heavy and bulky [21].

Some of these grippers are shown in Figure 3.2

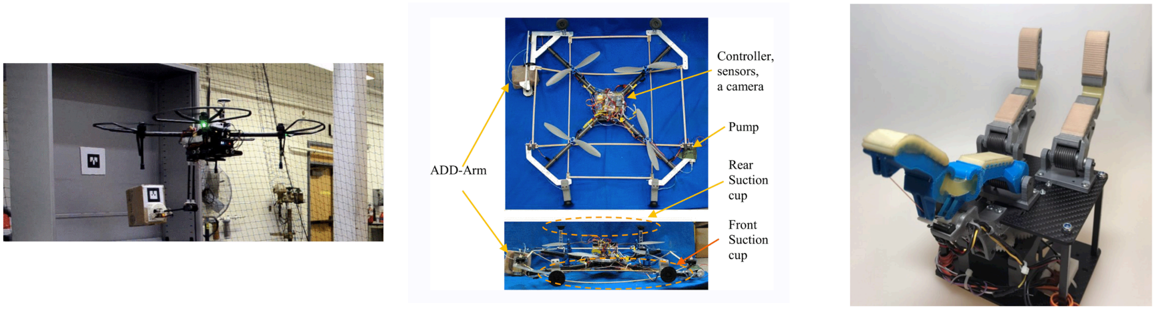


Figure 3.2: From left to right, A drone, developed by Garmella et al[22], utilizing a magnetic effector to pick up a magnetic object, The layout of a drone, developed by Tsukagoshi et al. [11] that utilizes suction cups to be able to attach itself to a door, An ultra-fast closing gripper developed by Mclaren et al. [21] that is used for both perching and handling object.

In addition to the gripper type, the size and shape of the gripper fingers also play a role in the drone's ability to grasp objects. Longer fingers provide a larger surface area for grasping, while shorter fingers are more maneuverable due to their lower inertia. A gripper with multiple fingers allows for more stability and control when grasping an object.

Integration on the Aerial Platform

Another design consideration is the location of the manipulator in relation to the drone. Some designs have the manipulator attached to the top of the drone, while others have it attached to the bottom.

Attaching the manipulator on top of the drone, as proposed in a paper by Shimahara et al. [23], can enable a drone to approach an object from below, which can be beneficial for tasks such as turning a light bulb. However, when more Degrees of Freedom (DOF) are added to the system, attaching the manipulator to the bottom of the drone can provide better stability [8].

The location of the manipulator in relation to the drone can affect the stability of the system, and it also can affect the range of motion and the ability of the drone to access certain areas. Furthermore, the location of the manipulator can also affect the payload capacity of the drone [8].

3.2.3. Proposed Design

For the purpose of this specific project, a quadrotor drone has been selected as the primary platform for the aerial manipulator. The reason for this choice is due to the well-documented and understood dynamics of quadrotor drones. In order to accomplish the task of grasping an object from below while maintaining stability, the gripper will be attached to the top of the drone. This gripper will feature a configuration that includes three fingers and one main palm. This particular design has been successfully implemented and tested in previous studies, such as by Mclaren et al. [21] and Miron et al. [24]. The finger morphology can either be interdigitated or the fingers can be spread 120 degrees apart. A concept for this is shown in Figure 3.3.

To ensure a compliant interaction between the gripper and the object being grasped, the gripper will consist of both a rigid interior and a semi-rigid exterior. The semi-rigid exterior will be made of a specific type of silicon, which will increase the friction at the point of contact and thus reduce the force required to stop the object from slipping.

The movement of the robotic fingers will be actuated by tendons, which will be driven by a servo motor. This motor will enable the fingers to open and close, allowing for the grasping of objects. A similar approach has been developed in a previous study by Mclaren et al. [21]. All tendons will be connected to a single servo motor, ensuring that the fingers will move simultaneously.

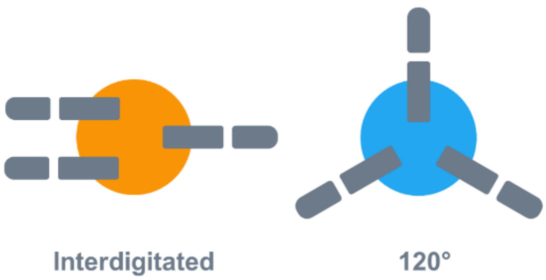


Figure 3.3: Different palm configurations that can be used during the design of the gripper [21]

In summary, the overall goal of this project is to design and develop an aerial manipulator that is capable of grasping objects from below while remaining stable. This will be achieved by using a quadrotor drone as the primary platform and incorporating a gripper that combines both rigid and semi-rigid elements, as well as a servo motor to control the movement of the fingers.

3.3. Tactile Perception

Tactile perception in robotics, also known as touch sensing, is becoming an increasingly popular modality in the field of robotics due to the enhanced capabilities it can offer [3]. This chapter aims to provide an overview of the current state of tactile perception in robotics.

First, the various sensors that can be used to obtain tactile feedback will be presented. These sensors include capacitance sensors, piezoresistive sensors, optical sensors, and whiskered sensors.

Next, an overview will be given of the tasks that are currently executed by robots utilizing tactile feedback. These applications include grasping, slip detection, object localization and classification, and surface detection. The use of tactile feedback in these tasks can greatly improve the performance and accuracy of the robot.

This chapter will also provide an overview of the use cases of tactile feedback in aerial robotics.

A breakdown of the various techniques used for tactile data processing will be given next. These techniques include principal component analysis and autoencoders.

Finally, this chapter will conclude with a concept on how tactile feedback will be incorporated in the proposed project. This will include the selection of appropriate sensors and techniques for data processing, as well as the integration of tactile feedback into the overall system design.

3.3.1. Types of Tactile Sensors

Tactile sensors are devices that detect changes in physical properties such as pressure, force, and temperature. They play an important role in robotics, automation, and human-machine interfaces, as they allow machines to perceive and respond to their environment in a more human-like way.

When selecting a tactile sensor, it is important to consider certain metrics such as spatial resolution, sensitivity, and cost. Spatial resolution refers to the ability of the sensor to distinguish between different points of contact. Sensitivity is a measure of the sensor's ability to detect small changes in the property being measured. And cost is a factor that can affect the overall budget for a project.

There are several types of tactile sensors, each with their own unique characteristics and applications. Some examples include [25]:

- Whiskered tactile sensors: These sensors mimic the tactile sensing capabilities of animals, such as rats and cats, that use their whiskers to sense their environment.
- Optical tactile sensors are specialized sensors that use light to detect changes in the proximity, position, and motion of nearby objects.
- Piezoresistive sensors: These sensors rely on the piezoresistive effect to detect changes in pressure.
- Capacitance sensors: These sensors rely on the change in capacitance that occurs when an object comes into contact with the sensor.

These sensors will be elaborated upon in the following sections.

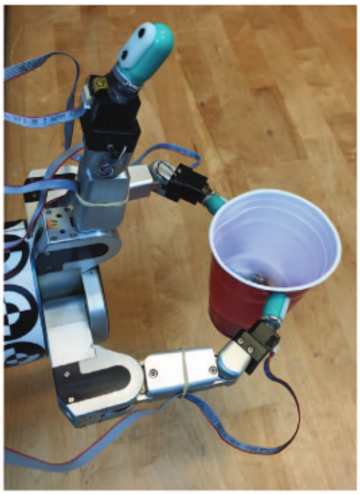
Piezoresistive Tactile Sensors

The piezoresistive effect causes some materials to change their electrical conductivity when subjected to stress [3]. This effect has seen use is various tactile sensors.

The BioTac sensor, developed by Syntouch, is an anthropomorphic finger-like device that can measure a wide range of modalities including temperature, pressure, and force. It features 19 electrodes surrounded by an elastic skin that contains an incompressible, conductive fluid. The displacement of this fluid when the sensor comes into contact with an object leads to changes in the impedance of the electrodes (due to the piezoresistive effect), which allows for the measurement of force and pressure. Temperature is measured using a thermistor embedded within the skin [14].

BioTac sensors can be used to estimate contact force as demonstrated in a paper by Su et al. [14]. Here various methods were used that map the changes in impedance to tri-axial forces (F_x, F_y, F_z). Both changes in electrical impedance and normal force were measured, and based on the assumption that only normal forces cause changes in impedance, a regression model is fitted to estimate the tri-axial forces. To fit the data, a linear regression, locally weighted projection regression, and a neural network model were used.

This sensor has been utilized in various research studies to enhance the grasping capabilities of robotic hands [14, 26, 27, 28]. However, its high cost is one of the main drawbacks of the BioTac sensor. Despite its cost, the BioTac sensor offers a highly realistic and accurate representation of the human finger and its ability to measure multiple modalities makes it a valuable tool for researchers and engineers in the field of robotics.



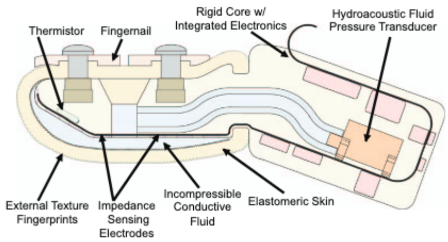


Figure 3.4: Left: A robotic hand with BioTac sensors attached to its fingertips [14]. Right: The internals of the BioTac sensor. [14]

Other sensors that utilize the piezoresistive effect are found in a paper by Li et al. [15], where a conductive foam changes its resistance when subjected to a force. Utilizing an array of tactile sensing elements (called tactels), accurate information on the forces applied, and their location could be inferred from the tactile image obtained with the output of the tactels. Similar techniques to obtain tactile images using piezoelectric sensors are found in research by Chebotar et al. [28] and Chen et al. [29]

Capacitance Tactile Sensors

A popular type of tactile sensors is the capacitance sensor, which detects touch due to changes in local capacitance [3]. The changes in capacitance can be induced due to electrodes being pushed closer together or conductive materials interfering with the electric field generated by the sensors. 2 examples of popular capacitive sensors, the ICub sensor and Adafruit MPR121, are shown in Figure 3.5

The iCub sensor is a tactile sensor that utilizes capacitive technology to detect touch [30]. The sensor is designed to mimic human skin and consists of soft dielectric transducers sandwiched between electrodes. When the sensor comes into contact with an object, the distance between the electrodes changes, resulting in a change in capacitance. This change in capacitance is then used to register touch. One of the key benefits of the iCub sensor is its flexibility. The sensor is fully flexible, which allows for greater freedom in designing the end-effector of the robot. This sensor has been demonstrated on the iCub robot, which is a humanoid robot, by having it interact with a plastic cup.

Another type of capacitive touch sensor is the Adafruit MPR121, which is a touch sensor that can be connected to microcontrollers [1]. The Adafruit MPR121 is a versatile tool that can be used to detect touch on conductive objects. When connected to a power source, the sensor generates an electric field that can be modified by the presence of conductive materials. This change in the electric field is measured via capacitance, allowing the sensor to detect touch. To ensure accurate readings, a threshold value can be set to filter out any noise. The Adafruit sensor has 12 sensing electrodes that can be connected to conductive objects via electrical wire. These electrodes are capable of detecting touch on a given conductive object, providing a reliable and efficient solution for a wide range of applications.

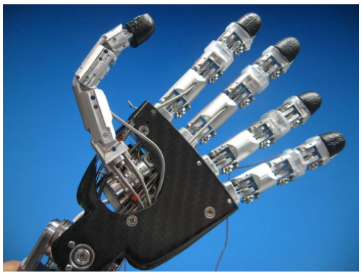
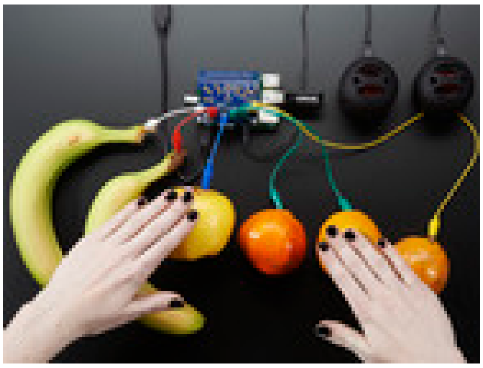



Figure 3.5: Left: The ICub sensor developed by Schmitz et al. [30] attached to a robotic hand. Right: the Adafruit sensor being utilized to detect touch when fruit are being held.

The disadvantage of these types of sensors is their low sensitivity, furthermore since different object have a different conductive measure recalibration of the sensors is needed when being used in a new environment. This can be done by collecting initial measurements whenever the robot starts operating to account for standard variations in capacitance. This calibration step is crucial for the sensor to function properly and provide reliable results [30].

Whiskered Tactile Sensors

Whiskered tactile sensors, also known as whisker-based tactile sensors, are a type of tactile sensor that mimic the sensing capabilities of animal whiskers [13]. These sensors consist of thin, flexible, and elongated sensors, similar in shape and size to an animal's whisker. They are typically made of materials such as silicon, metal, or carbon fibers

Whisker sensors work by measuring the deflection of the sensor when it comes into contact with an object. The amount of deflection and the direction of the deflection can be used to infer information about the object, such as its shape, size, and texture.

One of the main advantages of whisker sensors is their ability to sense objects in limited visibility environments. Unlike cameras and other optical sensors, whisker sensors do not rely on light to function, which makes them useful in environments with low light or complete darkness [13].

Whisker technology has been demonstrated in a paper by Huet et al. [13], where the strain of the whisker at the base is converted to tactile information that is used to navigate a robotic car.

Other whisker like technology is found in the BIOTACT whisker tactile sensors are developed in the Bristol Robotics Laboratory lab. Touch is detected due to the movement of a small magnet at the base of the vibrissae which induces a voltage due to the Hall-effect [25]. The BIOTACT whisker sensor is shown in Figure 3.6

The main disadvantage of whisker sensors is that their outputs can be prone to noise, due to humidity and airflow, and extra data processing steps are required to be able to obtain a good output. Furthermore, compared to other tactile sensors, their spatial resolution is limited [31]

Optical Sensors

Optical tactile sensors, also known as optical touch sensors, work by detecting the deflection of sensory elements using cameras [3]. The sensory elements can be made of various materials such as optical

[1] https://learn.adafruit.com/adafruit-mpr121-12-key-capacitive-touch-sensor-breakout-tutorial

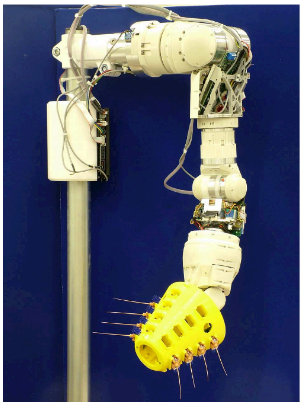


Figure 3.6: The BIOTACT Whisker Tactile sensor developed at Bristol Robotic Laboratory [25].

fibers, thin film, or transparent membranes. When a force is applied to the sensory elements, it causes them to deflect. The deflection can be detected by cameras that are typically placed behind or near the sensory elements.

The cameras capture images of the deflected sensory elements and use algorithms to analyze the images and extract information about the touch event [31]. The amount of deflection and the direction of the deflection can be used to infer the direction and magnitude of the touch. The sensor can also detect multiple touch points simultaneously and track the position of the touch points over time [32].

The Tactip sensor, created by the Bristol Robotics Laboratory, uses a camera to track the movement of pins within its membrane. When the sensor comes into contact with a surface, the position and orientation of an object can be determined based on the deflection of the pins. However, external light can sometimes interfere with the accuracy of the pin readouts, so a preprocessing step is necessary before using the data [32].

The sensor has been used by Lepora et al. [33, 16] for tactile exploration. By continuously tapping across a surface, pose estimations can be generated and from these estimations the robot is able to navigate. Both the Tactip sensor and the output it generates are shown in Figure 3.7

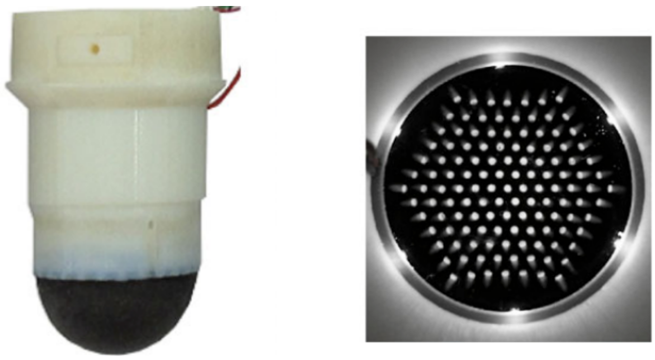


Figure 3.7: Left: The TacTip sensor as shown in [16]. Right: The corresponding output which can be obtained by tapping across various surfaces.

Optical sensors, while precise, are sensitive to lighting conditions making them not the most reliable in outdoor settings [31]. Furthermore, the added complexity that is needed to process output from the sensor might not make it the most ideal candidate on smaller robotics.

3.3.2. Applications in Mobile Robotics

The use of tactile feedback in mobile robotics is gaining popularity as it can improve the interaction between a robot and its environment. Tactile feedback allows robots to gather detailed information about the objects they are interacting with, such as shape, texture, and force distribution. This information can be used to improve a wide range of tasks, such as grasping, slip-detection, object-localization, object-recognition, and surface detection [3]. In this section, an overview will be given of these key applications of tactile feedback in mobile robotics.

Tactile-Based Grasping

Proper grasping is an important in robotics, as the ability to grasp objects securely and robustly is essential for many applications. Traditional vision-based grasping methods often lead to a high rate of failed attempts, as they struggle to accurately estimate the properties of local contact areas [3].

Tactile feedback, on the other hand, allows robots to gather more detailed information about contact points, which can be used to predict whether or not a grasp will be successful. This is usually done by using a known object model, from which successful grasps can be obtained. The classification and subsequent changes in robot pose when the grasp is deemed unsuccessful are further explained in section 3.4.

Research has shown that incorporating tactile feedback in grasping can lead to significant improvements in grasping success rate, especially in unstructured environments and with objects of unknown shape or texture [34, 35].

Tactile-Based Slip-Detection

Slip-detection is another key application of tactile feedback in mobile robotics. When a robot grasps an object, it is important to detect when the object starts slipping from its grasp, as this can lead to loss of control and potential damage to the object or the robot.

Using tactile data, researchers have been able to classify whenever an object starts slipping from a robotic hand [8]. Various modalities that are obtained from the contact location can be used to determine slippage. For example, there has been research on analyzing the vibrations at the contact location, using the Fourier Transform, to be able to predict when an object starts slipping [36]. In other research, a simple heuristic based on the derivative of tangential force at the contact location was used to determine to classify when slipping occurred [14].

Other modalities that can be used for slip detection include temperature, as changes in relative temperature can indicate slippage due to the friction heat that results from the slipping [8]. Slip-detection is an active area of research and new techniques are being developed to improve the accuracy and reliability of these methods.

Tactile-Based Object Localization

Object localization is another important application of tactile feedback in mobile robotics. The ability to localize objects during in-hand manipulation is crucial for many tasks, such as manipulation, grasping, and sorting [3].

From the tactile readings, robots are able to infer where an object is located on their end-effector and the pose it has. This information is difficult to obtain using vision-based sensors, since the gripper itself is occluding the object in is holding. The sensors used to perform object localization are typically large arrays consisting of multiple tactels [15]. The tactile data, obtained from the tactels, must be first be processed in various steps such that useful information can be obtained. These steps are explained in subsection 3.3.4. Once the data is processed, typical vision-based techniques are used to determine object pose. A demonstration of how tactile feedback can be utilized for localization is shown in Figure 3.8

Research has shown that incorporating tactile feedback in object localization can lead to significant improvements in localization accuracy, especially in unstructured environments and with objects of unknown shape or texture.

Tactile-Based Object Classification

Object classification is another key application of tactile feedback in mobile robotics. It refers to the ability of a robot to determine the type of object it is holding without relying on visual cues. Blind object classification has been demonstrated in a number of studies [35, 26, 14]

In these studies, the robot uses its tactile output as well as its joint angles, to classify the type of geometric primitive it is holding. This approach has several advantages over traditional visual-based object classification methods. For instance, it removes the need for expensive depth cameras, which can be prone to error and limited in their field of view. Furthermore, it allows the robot to obtain better grasps by classifying the object and selecting the best grasping strategy accordingly [35].

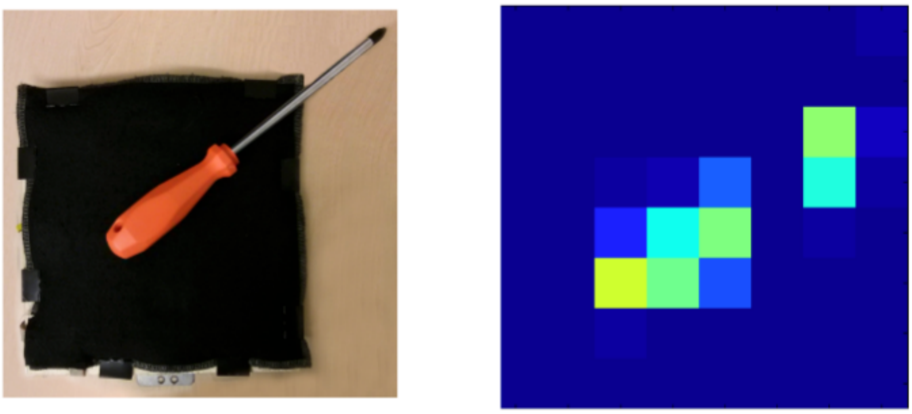


Figure 3.8: An example of how tactile feedback can be used to be able to perform tactile-based localization [15]. On the left, an image of a screwdriver on top of a tactile sensor pad is shown. While on the right the corresponding tactile image output is displayed.

Tactile-Based Surface Detection

Surface detection is another key application of tactile feedback in mobile robotics. It refers to the ability of a robot to determine the properties of a surface it is interacting with, such as roughness, texture, and friction coefficient [8].

Using tactile data, researchers have been able to infer various surface properties based on the readouts from the sensors. This can be used to aid the robot in motion planning, by selecting routes that are better suited for the surface, or to improve grasping by finding grooves or other features on the surface [25, 37].

3.3.3. Applications in Aerial Robotics

Tactile feedback within the world of aerial robotics has not been a topic that has been explored thoroughly. Most research focuses on contact-based task, where drones are tasked with remaining in contact with a surface to trace out shapes or perform Non-Destructive-Testing (NDT) [4].

In a paper by Nava et al. [18], a fully-actuated aerial manipulator is supplied with a force sensor on the end of its end-effector. By using an impedance controller, the aerial manipulator is able to remain in contact with the wall due to the fact that it is tasked to apply a specific force on the wall. In a similar work by Bodie et al. [4] a tactile force sensor is used to ensure that a drone remains in contact with a surface.

Other uses of tactile feedback, to the authors' knowledge, do not exist and there remains a knowledge gap as to the extent in which tactile feedback can be utilized. Within aerial manipulation, tactile feedback could be used to allow for finer manipulation capabilities. Since the manipulator would obtain information at the contact level, a better estimate could be obtained on the force applied and the exact location of these forces.

3.3.4. Tactile data Processing

Tactile data, obtained from various sensors located on the surface of a robotic gripper, is a valuable source of information for grasping and manipulation tasks. However, the data obtained from these sensors can be complex and highly correlated, making it difficult to extract useful information. To overcome this challenge, typically the data is mapped to a so-called latent space [38]. There exists various methods to achieve this, for example Principal Component Analysis (PCA) is commonly used to reduce the dimensionality of the data and filter out any noise [27]. Another way to extract information is by using machine learning models [39]. One popular model is the autoencoder. Both PCA and the autoencoder will be elaborated upon next.

Principal Component Analysis

PCA is a mathematical technique that finds the input variables that lead to the largest variances in the output data. The first step in PCA is to obtain the covariance matrix C_M from the output data. Then the principal components of the data can be obtained using the decomposition described in Equation 3.1 [40]

$$C_M = \mathbf{E}\Lambda\mathbf{E}^T \tag{3.1}$$

Where **E** are the unit norm eigenvectors of C_M and Λ is a diagonal matrix with the eigenvalues of C_M as its elements. By sorting the eigenvectors scaling them with their respective eigenvalues, the principal components can be found with the largest eigenvalues belonging to the 1 principal component.

By reducing the data into its principal components, a variety of object properties can be inferred from the tactile data, such as compliance, object shape, and stiffness [31]. Compliance can be quantified by using both motor joint angle and tactile sensor readings. Furthermore, an estimation of the object shape can be obtained which can be used for grasping and manipulation planning. Moreover, by analyzing the principal components of the tactile data, an estimate of the object's center of mass and orientation can be obtained. This information can be used for precise control of the object during manipulation, such as keeping it balanced or rotating it to a specific orientation.

Autoencoder Networks

An autoencoder neural network is a type of machine learning model that is designed to reduce high dimensional data into a compressed, lower dimensional representation, known as the encoded data. The encoded data is then passed through a decoder, which is trained to reconstruct the original data as closely as possible. This process is known as dimensionality reduction, and it enables the autoencoder to identify and extract the most important features of the data [41, 39].

In the field of tactile sensing, autoencoder networks have been used to extract and identify features from tactile data obtained from various sensors. For example, in a study conducted by Polic et al. [39], an autoencoder network was trained on data obtained from a TacTip sensor. The training data included tactile data from a variety of shapes, obtained from various depths and angular and radial locations, and under varying applied forces. The network was able to extract features such as object shape and applied force, as well as localize itself on different objects.

In another study conducted by Hoof et al. [41], a robot was trained to balance the pitch and roll of a rotating pole using tactile data from its end-effector. The control policy was learned through reinforcement learning, and the data input to the controller was obtained from an autoencoder. By reducing the high-dimensional tactile data to a lower-dimensional representation, the autoencoder enabled the controller to learn its control policies more effectively. This approach is similar to the one in the research by Loncarevic et al. [38], in which a robot's motor states are used to train the reinforcement learning policy, but in this case no use of tactile data is made.

3.3.5. Tactile Perception in this Project

In this project, the aim is to experiment with the capabilities that tactile feedback can offer to enhance the performance of aerial manipulators. Tactile perception has not been widely used in aerial manipulators, and this project aims to explore its potential benefits. Cost and accessibility of sensors are important factors to consider, given the time and resources allocated to this project.

After reviewing various sensors, the Adafruit MPR121 was identified as the most accessible and cost-effective option. Multiple sensors can be used to increase the amount of tactile sensing pads. However, a disadvantage of using these sensors is that they do not directly measure force. Unlike the ICub sensors, which rely on displacing electrodes, the Adafruit sensors only detect changes in the electric field generated by the sensor. The rate of capacitance change does not always scale linearly with the amount of force applied, as material properties and other factors also play a role.

In order to infer force from the Adafruit sensors, a similar technique used in mobile phones could be employed [42]. By measuring the amount of normal force applied on a mobile phone and the corresponding change in capacitance on the screen, a mapping can be obtained between changes in capacitance and changes in normal force. However, it is unclear whether it is possible for this mapping to include tri-axial forces. One way to improve this mapping could be to use the manipulator joint angles as an extra feature.

The Adafruit MPR121 sensors can be stacked together and placed on the drone. Electrical wires can then be used to connect the sensor to various sensing pads distributed around the robotic hand, such that capacitive measurements can be performed. This allows for touch to be registered on various locations on the manipulator.

In the case where more tactile sensors are needed, there may be too much data for the controller to handle. To reduce the processing load, an autoencoder could be trained to detect necessary features for stable grasping. This way, only the most relevant information is passed to the controller.

3.4. Control Frameworks

This chapter aims to provide an overview of the different control frameworks that are used in the controller design of autonomous systems, specifically focusing on aerial manipulators.

First, an overview will be given of the current techniques that are used in position control. These techniques include methods for tele-operation, off-board positioning, and on-board positioning. The advantages and disadvantages of each technique will be discussed, as well as the specific tasks that they are best suited for.

Next, force control and its implementation on both drones and robots will be discussed. Force control is an important aspect of aerial manipulation tasks and is used to ensure that the robot can apply the right amount of force to perform the task. The chapter will explore the different methods used for force control and the advantages and disadvantages of each method.

Grasping is an important task that a robot or aerial manipulator must be able to perform, and grasp control plays a crucial role in this task. This chapter will explain the various ways in which grasp control is achieved and the different estimators that are used to predict the stability and adjustment of the grasp.

Tactile feedback can also be used as a tool for local navigation, known as tactile servoing. The chapter will dedicate a section to discuss the various ways in which tactile servoing is employed on different robots, including Pose-Based and Image-Based Tactile Servoing.

Finally, the chapter will conclude with a proposed control method that can be used in both the positioning and force control of an aerial manipulator utilizing tactile feedback. This proposed method will take into consideration the different techniques discussed in the chapter and will aim to provide a comprehensive solution for controlling aerial manipulators.

3.4.1. Position Control

To be able to ensure that a gripper is able to grasp an object, the gripper and object should be aligned properly. Various methods exist to ensure a proper alignment. These can be classified in various degrees of autonomy, tele-operated, off-board and on-board positioning

Tele-operated Positioning

A common approach towards alignment is to use a human operator to move the drone to the desired position. The advantage of this approach is that no autonomous algorithms are necessary, and energy can be expended elsewhere. However, the problem with tele-operated aerial manipulators is that operators controlling the drone require training and should, of course, be paid thus increasing the operational cost. Furthermore, the telemetry signal between the operator and drone also imposes a limit on the workspace [7].

To improve the human-drone interface, research has been done on incorporating various types of haptic feedback to give the operator a sense of how the drone 'feels.' Furthermore, Head-Up Displays (HUDs) are used such that the operator is able to see what the drone is seeing. This way the operator can have a better understanding of the situation of the drone [8].

Since this study will focus on autonomous navigation, tele-operation will not be utilized for every part of the mission. However, pre-alignment could be useful in giving the drone a head start. This way the drone can reach the location faster and with a better accuracy.

Off-Board Positioning

Off-board strategies consist of methods where the processing is done off-board, meaning that a computer computes the desired locations for where the gripper should be and sends this to the drone. The drone then uses this signal as a control input and generates the necessary pose. The advantage of this approach is that the drone is not limited to calculations that normally take a long time to calculate, and thus more computationally expensive algorithms can be used [8].

A popular way to achieve motion capture is by using OptiTrack cameras [2], which are used to de-

[2] https://optitrack.com/

termine the location of the drone or an object to be grasped. By placing markers on both, software techniques can be used to obtain live locations and these are then sent to the drone such that it can align itself with an object. This technology has been demonstrated on several experiments with aerial manipulators [43]. The disadvantage of this technology is that it can break down in poor lighting conditions due to the fact that the markers will be less visible. Furthermore, the aerial manipulator is constrained to work within the field of view of the OptiTrack cameras.

Another approach could be using GPS data to locate both the drone and the object [8]. GPS has been used to perform pick-and-place operations for various research projects. GPS does not break down given bad lighting conditions, however, in the vicinity of tall buildings or when used indoors the signal can give unreliable outputs.

In this work, off-board alignment will be useful in initializing the drone location such that it can pre-align itself before the tactile feedback takes over. This way the drone can reach the location faster and with a better accuracy.

On-Board Positioning

On-board alignment strategies utilize algorithms that the drone computes on-board. Since the computational power of a drone is typically lower than that of a dedicated computer, the algorithms used are less computationally expensive. The algorithms might involve heuristics that are based on the sensor input of the drone [7].

A typical on-board strategy used by a drone is using visual input to align itself with a target object. These vision algorithms range in varying complexity. In a paper by Shimahara [23], a monochrome camera fixed to the base of the gripper was used to detect when the drone had to grasp. Since the location of the gripper tips in the camera frame did not change over time, they were used as indicators of when an object to be grasped was close. Whenever the tips were out of frame, it meant that an object was there and therefore the grasp could commence.

Image-based visual servoing relies on comparing desired visual output with the current input and minimizing the error between them. In a study conducted by Kim et al. [44] a blob detection algorithm is utilized to determine where an object to be grasped is located. Once a blob has been located, its location is compared with a desired blob location. From the error between the two images, a trajectory can be generated to minimize the error between the two. This trajectory is generated using an image Jacobian, which relates the changes in image features to changes in motor states.

Besides visual control, other sensors have been used to align a drone with an object. In a research study from Iversen et al. [2] a method is developed in which a drone uses LiDAR sensors to align itself with a power line cable. Using the feedback from 2 different LiDAR sensors, the drone is able to determine its orientation relative to a power line and from this align itself with the power line cable.

3.4.2. Force Control

Force control enables a robot to interact in a more compliant way with an object. Whenever the object to be held is known, forces can be computed beforehand so that the robot can ensure that it does not damage the object. In cases where this information is unknown, typically impedance controllers are used.

Impedance Control

In the field of aerial robotics, impedance controllers have seen their use in contact-based tasks [4, 45]. When a surface on which an aerial manipulator is applying force suddenly disappears, large disturbances can happen. To counteract these disturbances, the interaction force between the surface and the manipulator can be modeled as a mass-spring-damper system. The force can now be designed to be large when the surface is present and small when it is not. In this way, compliant interaction has been demonstrated.

An object-level impedance controller was developed in a paper by Li et al. [46]. This controller works by estimating a *Virtual Frame*, which is an estimate of both the position and orientation of an object. The frame is built using the position of the robotic fingertips as a reference. The dynamics of the contact point of the robotic finger and origin of the *Virtual Frame* is modeled as a mass-spring-damper system. The desired interaction force is calculated from the model. A schematic of the system is shown in Figure 3.9. This concept was extended upon by Li et al. [47] where tactile readings are included to obtain a better estimate for the controller gains. Using this controller, researchers were able to obtain stable grasps with both known and unknown objects.

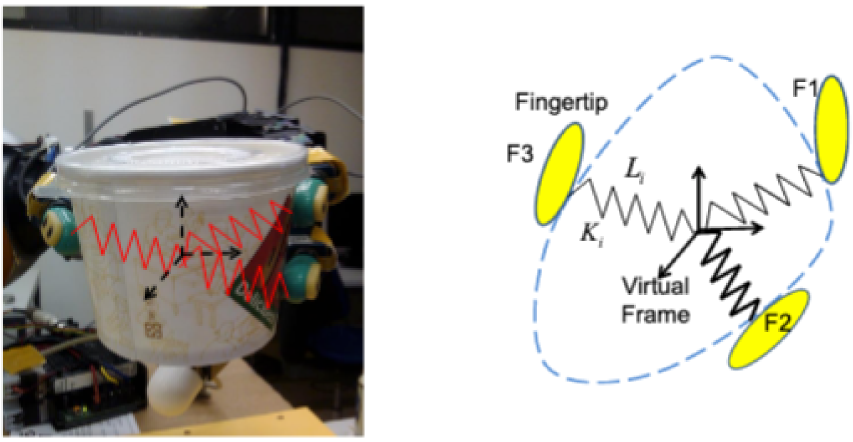


Figure 3.9: Left: The robot used by Li et al. [46] for their experiment with object-level impedance controllers. Right: A schematic showing the distribution of fingertips and the location of the defined *Virtual Frame*

3.4.3. Grasp Control

The goal of grasp control is to find a grasping configuration around an object that maximizes the stability of the object in hand.

Visual grasp control has been demonstrated in various studies [48, 49]. The goals here is to generate a bounding box around an object to be grasped. The manipulator is then tasked to ensure that its grippers remain within the bounding box. This method has shown success, however, the bounding boxes can usually only be generated when the lighting conditions are correct.

The advantage of using tactile feedback in grasp control is that there are no additional processing steps required to determine if there is contact between the gripper and object. Contact is immediately detected, and the question then becomes how to use that information to classify if the grasp was successful and if unsuccessful how to plan for adjustments [3].

This process has been formulated by Laaksonen et al. [50] using a probabilistic framework in such as shown in Equation 3.2

$$arg \max_{G} \int P(S|G,O)P(O|G_{t_0:t-1}T_{t_0:t-1})dO \tag{3.2}$$

Where S denotes the stability, G the grasp attributes (such as current grasp configuration), O the object attributes (such as object pose) and T represents the on-line tactile measurements. The conditional probabilities $P(S|G,O)$ and $P(O|G_{t_0:t-1}T_{t_0:t-1})$ represent a stability estimator and an object estimator respectively, where the subscript $t_0 : t-1$ indicates the time series information up until the current time-step. The process of formulating a grasp controller can thus be broken down into finding these two models.

Grasp Stability Estimators

Determining the stability of a grasp, using tactile feedback, has been an active area of research. One of the early works in grasp stability estimation by Ferrari et al. [51], proposes a method to infer the quality of a grasp by formalizing metrics based on the ratio between the maximum finger force and the total force applied by each finger. These metrics are termed the force and form closure, which are defined as the capability of the robot to hold the object while external forces are at work.

Using this metric Dang et al. [52], trained a Support Vector Machine (SVM) to classify whether a grasp is successful or not. A feature vector containing states of tactile sensors and the hand kinematics is used as input to the system and using this feature vector the relative force closure is calculated. Based on the value of the relative force closure, the grasp is classified as either successful or unsuccessful. Similar approaches have been proposed in a paper by Bekiroglu et al. [34] and by Li et al. [47].

Stability estimators can be trained using both simulation and real data. The GraspIt simulator [53] has been used to simulate grasps and train stability classifiers with success. The GraspIt simulator consist of various different object and grippers that can be simulated using its physics engine. Both tactile information and visual information can be simulated.

Other approaches to grasp stability estimation, includes the object-level impedance stability estimator developed in a paper by Li et al. [46]. Here, a classifier was trained on only successful grasps that were performed using an object-level impedance controller. It was argued that training a model on unsuccessful grasps would lead to unwanted noise, therefore only successful grasps are used. Based on the gain values of the impedance controller, the tactile outputs from tactile sensors and given the fact that the grasp was successful, a model was trained to classify what states resulted in a stable grasp.

Grasp Adjustment Using Object Estimators

By estimating the object attributes O from the current grasping configuration and tactile measurements, a grasp adjustment leading to a stable grasp can be obtained.

In a study conducted by Dang et al. [35], a range of stable grasps for different geometrical primitives (sphere, box, etc.) was stored in a database. When a grasp was classified as unsuccessful, the robot queries stable grasps from the database. Grasps that resemble the current configuration best are chosen to adjust the current grip. Similar grasps are found using a K-Nearest-Neighbours algorithm.

Another way of adjusting the gripper is demonstrated in a paper by Hyttinen et al [54]. Here, a probabilistic model is developed that classifies a grasp as successful or unsuccessful by using the current tactile output and the robotic hand configuration and comparing this with template objects. The probabilistic model is a kernel logistic regression model, it was trained by performing various grasps on the template objects.

During testing, an initial grasp is planned using a 3D model of the object to be grasped. The robotic hand executes the suggested grasp and subsequently uses its hand kinematics and tactile output to determine the success of the grasp. If successful, the process stops. When it is unsuccessful, new actions are simulated and the most successful action is chosen. The new actions are simulated in the vicinity of the current grasp.

Calandra et al. [37] performed an experiment where a Convolutional Neural Network (CNN) was trained to determine what manipulator adjustment would lead to a stable grasp. Using both tactile data obtained from a GelSight sensor and visual data obtained from a camera, the model was trained on classifying successful grasps. During runtime, the robot was able to use its current sensor states and simulate various random actions. The action that resulted in a stable grasp was chosen. To train the model, various trials were performed in which the robot was tasked to perform different random actions that resulted in either a successful or unsuccessful grasp. Whether a grasp was successful was determined visually.

In a paper by Chebotar et al. [28], a reinforcement learning model was trained to first detect when a grasp is unsuccessful and then adjust the current grasp to a grasp that is successful. The policies for the reinforcement learning model were learned to use the various features in spatio-temporal data. Based on the features, the grasp is adjusted. These methods demonstrate the potential of using object estimators to improve the performance of aerial manipulators by adjusting the grasp based on the object attributes, tactile feedback and grasping configuration.

Another approach was found by Schmitz et al. [30] where a simple algorithm was used for grasping with a iCub humanoid robot. The robot was tasked with grasping various objects, and it accomplished this by using its tactile sensors as an indication of when it was holding an object. The fingers on the robotic hand would only stop closing when the robot detected touch on all its tactile sensors.

3.4.4. Tactile Servoing

Tactile servoing consists of using tactile feedback on a robot such that the robot is able to align itself with an object to be grasped. It shares a lot of the concepts of visual servoing and can similarly be distinguished in visual- and pose based tactile servoing.

Pose-Based Tactile Servoing

In Pose-Based Tactile Servoing (PBTS) the pose of the sensor is estimated using the current tactile output. Based on the estimated pose, modifications are made that servo the sensor towards a desired pose. Determining the pose of the sensor from tactile feedback is not a trivial task and only recently a formalization of tactile servoing has been made [33].

A form of PBTS is demonstrated in a paper by Lepora et al. [16] where a robot was tasked to perform a contour following task using only tactile feedback. To register tactile feedback, a TacTip sensor was tasked to constantly tap across a 2D surface. A mapping between the sensor outputs and the radial and angular position of the sensor was determined on various training sets. When the sensor would output tactile information the manipulator was able to estimate its position on an object and servo its sensor accordingly based on this mapping. This was extended upon in by the same researchers [33] where a deep learning model called PoseNet is trained to map sensor outputs to the current sensor pose.

Image-Based Tactile Servoing

The basic principles of Image-Based Tactile Servoing (IBTS) are related to Image-Based Visual Servoing (IBVS) [29]. By defining a desired tactile image the controller is able to move the manipulator such that it's tactile output will match the desired image. The tactile images are obtained from the tactile sensors and their resolution depends on the type and the amount of sensors used. An example of a tactile image is shown in Figure 3.10

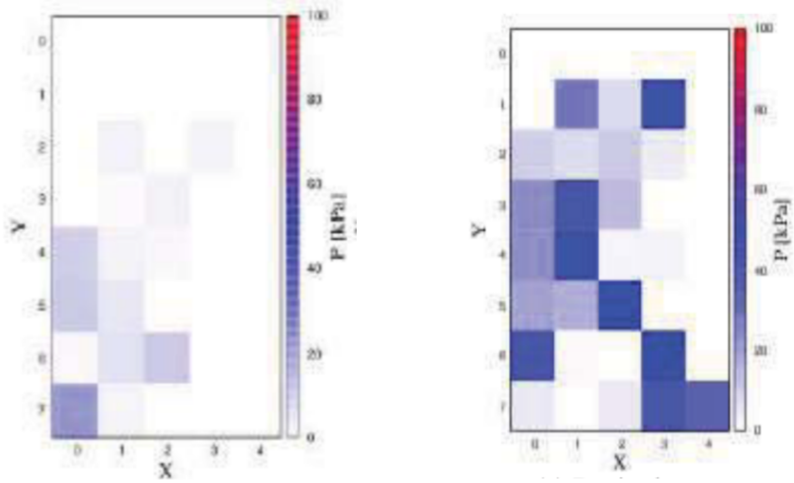


Figure 3.10: Example of different tactile images [29] Left: Current tactile output, Right: Desired tactile output

IBTS, like its visual counterpart, relies on defining a Jacobian matrix that relates the changes in joint angles (∂q) to the changes in tactile image output (∂F) as described in Equation 3.3 [29].

$$J_t = \frac{\partial q}{\partial F} \tag{3.3}$$

The Jacobian matrix, or tactile Jacobian matrix in tactile servoing, can be obtained in a variety of ways. Both in a paper by Li et al. [15] and Chen et al. [29] the Jacobian was obtained empirically by measuring both the changes in joint angles and tactile intensity and fitting the relationship using a linear regression model. Using the tactile Jacobian, the joints of the robot can be steered towards a direction of desired change.

A framework for IBTS is developed with which a variety of task can be accomplished by Li et al in [15]. Their main approach is to estimate a required sensor twist such that the robot is aligned with respect to a certain tactile feature. By utilizing a task-independent tactile Jacobian matrix and a task-dependent projector matrix, the robot is able to move itself in specific ways based on its deviation from a desired tactile image. The projector matrix ensures that only specific motors are used during the motion. Using this framework, tasks such as object tracking and rolling were achieved.

Chen et al. [29] build on the concept of IBTS and coupled it with pressure based tactile sensors. By defining a desired pressure distribution, a control algorithm was devised that took the current pressure distribution as input and gave the change in joint states that moved towards the desired distribution as output.

The work of Chen et al. [29] was further developed in [55]. Since in previous work it was assumed that the relation between the changes in intensities and joint states was linear, the control algorithms broke down when the desired tactile image was too far removed from the current tactile image. To solve this issue, instead of a tactile Jacobian, a CNN was trained to find the changes in joint states when both the current and desired tactile intensities were given.

3.4.5. Proposed Control Method

The proposed control method for this project utilizes a quadrotor drone that has a 3-fingered semi-rigid gripper attached on top. The gripper is embedded with tactile sensors that will be used for controlling the aerial manipulators' interaction with objects. The task is broken down into several subcomponents to ensure stability during each step:

- Navigation towards the object to be grasped.
- Detection of the object using tactile feedback.
- Planning of an initial grasp.
- Classification of the grasp as either successful or unsuccessful.
- Adjustment of the grasp if it is unsuccessful.
- Maintenance of a stable grasp once obtained.
- Execution of a twist-jerk motion to detach the object.
- Stability maintenance after object detachment.
- Safe landing of the drone.

Performing these steps can be achieved by defining various task vectors that contain the desired tactile output and gripper configuration states. These vectors will include n tactile sensor states ($s \in \mathbb{R}^n$) and k motor states ($m \in \mathbb{R}^k$) such as shown in Equation 3.4.

$$x_d = \begin{bmatrix} s_1 & \cdots & s_n & m_1 & \cdots & m_k \end{bmatrix}^T \tag{3.4}$$

Based on the error between the desired state (x_d) and the current state (x) the aerial manipulator must servo itself to reduce the error. Since a quadrotor is an under-actuated system, the changes in drone motor state ($q \in \mathbb{R}^4$) will be focused on vertical movement since this will make controlling the interaction easier. A mapping between the error and the drone states ($\mathcal{F}(e) \rightarrow q$) can be obtained from either a tactile Jacobian or a data-driven approach.

A tactile Jacobian can be defined as shown in Equation 3.5

$$J = \begin{bmatrix} \frac{\partial q_1}{\partial e_1} & \frac{\partial q_1}{\partial e_2} & \cdots & \frac{\partial q_1}{\partial e_{n+k}} \\ \frac{\partial q_2}{\partial e_1} & \ddots & & \vdots \\ \vdots & & \ddots & \vdots \\ \frac{q_4}{e_1} & \cdots & \cdots & \frac{q_4}{e_{n+k}} \end{bmatrix} \tag{3.5}$$

Using the definition of the tactile Jacobian the control that has to be performed by the drone can then be calculated from Equation 3.6.

$$\partial q = J \cdot (x_d - x) \tag{3.6}$$

The individual differentials have to be obtained experimentally using various grasping configurations and measuring both the motor state of the drone, motors states the gripper and the capacitive sensor states.

A data-driven approach could also be employed such as demonstrated by Chen et al. [55]. In the case of the aerial manipulator, a neural network could be trained to produce a mapping between the current drone state and the error between the desired output state and current output state to a control action. Another data-drive approach would be to use reinforcement learning to predict a control policy that reduces the output state error.

Once initial contact has been made, the aerial manipulator must start planning for a grasp. For this, two approaches can be taken. First it is possible to have the manipulator fly up until the sensor at the palm detects touch. When touch is detected, the gripper will close around the object.

Another approach that can be taken is defining a sequence of grasp adjustments that gradually lead to the final grasp. The tactile servoing approach explained above can be used to servo the aerial manipulator towards the desired final configuration. Both approaches are shown in Figure 3.11

Figure 3.11: Different approaches to grasp planning, sequence goes from top to bottom. Drone body in blue and the propellers are in black. The capacitive sensors are on when the yellow circle is filled and off when it is not. The object to be grasped is in green. Left: Once contact is established, the drone opens its grippers and moves up until the tactile sensors on the palm are triggered. It then closes its grippers around the object. Right: Once contact is established the drone only move slightly up and then does another grasp. It keeps doing this until a successful grasp is achieved.

Since the object to be grasped is known beforehand, the contact forces that are required for a stable grasp can already be known. The controller then has to ensure that the forces at the contact points are equal to this required force such that a stable grasp can be achieved.

Once the grasp is executed, and successful, the twist-jerk motion is performed to detach the object. During the twist-jerk motion, the quadrotor will perform both a yaw and pull movement. Once the object has been detached the sudden change in reaction force might lead to instabilities. To control this interaction, an impedance controller will be used for a smoother transition between detaching and detachment.

Completing the detachment of the object results in the final phase of the mission, which is landing back safely. Due to the added weight of the grasped object, some changes in the gain values of the attitude controller might be necessary.

3.5. Conclusion

In this chapter, a general conclusion will be made to answer the research question posed in the introduction of this report.

First, a summary that concludes the report will be given, with a proposal as to how the research question can be answered. This summary will provide a brief overview of the key findings and conclusions of the report, and will present the proposed solution to the research question.

Following this, an explanation will be provided as to what the next steps are that should be taken to experimentally validate the answer posed in the summary. These next steps will likely include the design, construction, and testing of an experimental setup, as well as the collection and analysis of data.

3.5.1. Summary

This work summarizes the combined research that has been done on both aerial manipulators and tactile perception, with the aim of answering the question: **Can integrating tactile sensors on a semi-rigid gripper of a quadrotor aerial manipulator improve its grasping ability on semi-deformable round objects (e.g. fruits) through enhanced compliance and grasp configuration via tactile servoing compared to no feedback grasping?**.

The current state of tactile perception research has focused on improving the grasping capabilities of robots. Tactile feedback is used to enable robots to classify objects and assess the stability of their grip. These stability estimations are typically based on data-driven models that use both the robot hand motor states and the tactile output at that particular moment. When a grip is deemed unstable, controllers exist that can move the robot to a more stable grip. These controllers can be based on policies learned through reinforcement learning or probabilistic models that estimate whether a certain action will lead to a more stable situation.

Tactile navigation can be used to move the robot to more stable holds. A tactile reference image is typically sent to the controller, and the controller must move the robot hand such that the actual tactile output better resembles that reference output. This is similar to visual navigation, where a reference feature is obtained, and the robot is tasked with moving towards that feature. Models can also be trained to determine the current pose of the end-effector based on the tactile output, allowing the robot to navigate around objects.

To interact with objects, aerial manipulators must first align themselves with the object. This can be done in a variety of ways, including tele-operation, off-board, and on-board methods. One use case for tactile feedback on aerial manipulators is in the alignment and subsequent grasping of objects. By using tactile sensors on the grippers of a drone, a drone can servo itself towards correct alignment with respect to the object, allowing for a successful grasp.

Hence, the integration of tactile sensors on the grippers of aerial manipulators will enable them to plan for better grasps that are more stable and compliant compared to when there is no feedback at all.

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