Autonomous Vision-based Rapid Aerial Grasping

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Abstract—In a future with autonomous robots, visual and spatial perception is of utmost importance for robotic systems. Particularly for aerial robotics, there are many applications where utilizing visual perception is necessary for any real-world scenarios. Robotic aerial grasping using drones promises fast pick-and-place solutions with a large increase in mobility over other robotic solutions. Utilizing Mask R-CNN scene segmentation (detectron2), we propose a vision-based system for autonomous rapid aerial grasping which does not rely on markers for object localization and does not require the size of the object to be previously known. With spatial information from a depth camera, we generate a point cloud of the detected objects and perform geometry-based grasp planning to determine grasping points on the objects. In real-world experiments, we show that our system can localize objects with a mean error of 3 cm compared to a motion capture ground truth for distances from the object ranging from 0.5 m to 2.5 m. Similar grasping efficacy is maintained compared to a system using motion capture for object localization in experiments. With our results, we show the first use of geometry-based grasping techniques with a flying platform and aim to increase the autonomy of existing aerial manipulation platforms, bringing them further towards real-world applications in warehouses and similar environments.†

I. INTRODUCTION

A. Motivation

Over the last five years, drones have gained significant popularity as tools to observe and capture the world around us through photographs and videos both for consumers and industry alike. With the rise of soft gripping technology, drones are gaining increased capabilities for physical interaction with their environments. However, these capabilities will only find use if the drones have a way of efficiently perceiving the environment around them. The capabilities of an autonomous robotic system are always going to be limited by the information the system receives: for instance, a drone which can grasp objects but has no way of locating its target objects is rather limited for any real-world autonomous use cases.

A common solution in research is to use motion capture systems as a quick and precise solution to provide localization data. However, it is infeasible for industrial use to attach markers to every object that a robot should grasp. Solutions for object localization using fiducial markers like ArUco markers [1] exhibit the same problem. Vision-based localization solutions that solely rely on monocular vision also do not have the capability of perceiving depth and cannot provide us with sufficient spatial information for rapid grasp planning.

To solve these challenges, we present a vision-based, marker-less system for object localization and grasp planning. Using a stereoscopic camera (Intel RealSense D455 [2]) for color and depth information, Mask R-CNN-based [3] scene segmentation (detectron2 [4]), and efficient point cloud processing for grasp planning (Open3D [5]), our system gives robots the ability to perform marker-less autonomous grasping. The use of mobile platforms, especially when in air, is accompanied by major challenges such as a substantial increase in tracking uncertainty making it difficult to execute precise grasps. Furthermore, in the case of mobile manipulation, target objects can be much further away compared to static manipulation scenarios, which reduces the pixel size of the objects in the image and therefore increases the importance of precise scene segmentation.

We use RAPTOR [6] as a platform for deploying our system. RAPTOR combines a quadcopter with a soft Fin Ray® gripper which passively adapts to the shape of the objects that are being grasped. It is a platform that is capable of dynamically picking up different objects at high speeds. Using RAPTOR as a platform also allows us to compare the grasping performance against the grasping performance using a motion capture system for object localization.

Our solution allows a mobile platform to quickly and autonomously detect possible grasping targets (without any markers attached to them), localize them, and execute a grasp. This capability presents a step towards bringing mo-
bile robotic platforms for grasping and manipulation, such as RAPTOR, further towards large-scale industrial applications.

B. Related Work

1) Aerial Grasping: Multiple works on aerial grasping exist that use marker-based target designations. The dynamics of aerial grasping [7], [8] have been examined in-depth previously. With traditional manipulators, Lippiello et. al [9] and Buonocore et. al [10] have shown a marker-based visual-servoing approach for manipulation. More recently, rapid aerial grasping using soft gripping mechanisms has been shown using a motion capture system for estimating the pose of the target object by Fishman et. al [11], [12] and Appius et. al [6]. There is also work on marker-less target designation using monocular vision: Luo et al. [13] perform feature matching for detection while Lin et al. [14] have used a custom object detection algorithm to achieve aerial grasping. We present a marker-less system for aerial grasping which uses stereoscopic vision and performs more extensive grasp planning. Our approach generalizes across different objects using Mask R-CNN segmentation [4]. We also explicitly decouple our segmentation and grasp planning pipeline from the motion planning of the platform such that the vision system itself remains platform-agnostic.

2) Grasping With Statically Mounted Manipulators: For statically mounted manipulation platforms such as robotic arms, previous works show a number of different approaches for grasp planning that have yet to be deployed on aerial platforms. One of the proven strategies is geometry-based grasp planning [15], [16]. While in recent years learning-based approaches [17], [18] for grasp planning have risen in popularity, they require comprehensive datasets. Methods using reinforcement learning [19] have also been explored, however, they have a high complexity in implementation and their generalization remains a challenging task. We aim to demonstrate the use of of geometry-based grasp planning approaches with a highly mobile platform that is much farther away from its targets, placing an increased importance on clean segmentation of objects.

C. Contribution

In the following, we lay out the main contributions of this work.

1) Marker-less Aerial Grasping: We propose a system that enables rapid aerial grasping using a flying platform without the use of any markers or previously known object sizes. We enable these abilities by using real-time scene segmentation and geometric grasp planning based on stereoscopic vision.

2) Mobile Grasp Planning: Instead of using a statically mounted robotic arm for grasping objects, we use a highly mobile flying platform. We present the necessary system architecture to enable the required dataflow from the flying platform to an onboard computer. To the best of our knowledge, we are the first to bring stereoscopic vision-based grasp planning to a flying platform.

3) Real-world Performance Validation: We conducted real-world experiments evaluating the localization performance of object centroids and comparing our marker-free grasping performance against the performance of the previously used marker-based motion capture approach.

II. OBJECT SEGMENTATION AND GRASP PLANNING

A. Creating the Object Point Cloud

We use Mask R-CNN (detectron2 [4]) for segmenting the RGB images from the camera. R-CNN-based architectures have proven themselves to handle small objects in the frame well compared to more lightweight architectures [20], [21]. In addition, the ability to generate segmentation masks allows for much more precision for grasp planning compared to object detection [22], [23]. Once a target object is segmented from the scene, we apply the segmentation mask to the RGB image. We then combine the masked RGB image with its corresponding depth image to create a cropped point cloud of the scene. Next, we remove all points in the point cloud which are black due to having been masked out in the previous step. This preprocessing yields a point cloud of the surface of the object that is visible to the camera. Finally, we apply radius outlier removal (as implemented in Open3D [5]) to correct for any possible outliers that the mask might have accidentally included as part of the object and apply voxel downsampling to reduce the computational load for further computations. A visual representation of this process is given in Figure 2.

![Image](350x221 to 521x387)

Fig. 2. The grasp planning pipeline. In a), we see the point cloud as it was created from an unmasked RGB frame and the corresponding depth frame. In b), we see a point cloud created from a RGB frame that is masked around the bottle in the center of the frame. Then, c) shows the full point cloud we get by removing all masked points and applying radius outlier removal. Finally, d) shows the downsampled point cloud fused with a copy of itself that is rotated around the main axis of the point cloud. Grasping candidates are highlighted in red, e) shows the same point cloud in full resolution for better illustration.

B. Conditions for Grasp Planning

We acquire a point cloud of the object and then perform grasp planning using the degrees of freedom available to us with RAPTOR: the 3D position and yaw of the drone. There
are multiple other aspects to consider for successful grasp planning:

- The drone will be executing grasps in the direction of the detected object. Only the visible surface of the object will be considered for grasp planning. The gripper on the drone actuates along the same direction that the drone is flying in - thus, one side of the gripper will grasp the back surface of the object which we do not capture for grasp planning.
- Fusing different views of the object together for a more complete point cloud requires repositioning the drone. Repositioning takes significant time and directly contradicts the concept of rapid aerial grasping.
- There is tracking uncertainty from the drone and localization uncertainty from the vision system. The actual position the drone will fly to will differ from the one sent within the command to grasp the object.

We compensate for the uncertainty and unknown surface on the back of the object with the soft gripper. The passively compliant fingers can successfully grasp most geometries, given that the gripper can close around the object. In most cases, for a successful grasp, we do not need to grasp the exact points we were targeting, but rather simply make contact in an area close to the targeted points.

C. Computing a Grasp

We choose a relatively simple geometry-based strategy for selecting grasping points which is inspired by previously shown strategies [15]. The algorithm can be summarized into four major aspects:

1) Estimate the centroid of the point cloud and determine its pose.
2) Duplicate the point cloud and rotate it around the axis with the largest extent.
3) Determine the new centroid and the new pose of the combined point cloud.
4) Determine a set of candidate points by taking the intersection of the point cloud and a cutting plane that goes through the estimated centroid and is normal to the axis with the largest extent. These candidates mark the possible contact spots for our gripper on the front and the back.

III. Mobile Vision Architecture

A. Compute Platform

All expensive computations are running on an offboard computer for faster compute times per iteration of the system compared to using an onboard computer. The offboard computer is an HP Omen 30L Desktop PC with an AMD Ryzen 7 5800X CPU (central processing unit), an Nvidia RTX 3070 GPU (graphics processing unit) and 32 gigabytes of RAM (random access memory). We use an Nvidia Jetson Nano [24] onboard the drone to capture, compress and send the RGB and depth frames from the Intel RealSense D455 [2] camera. We have also equipped the Nvidia Jetson Nano with an Intel AC8265 wireless networking card which is much faster than the wireless networking hardware on simpler single-board-computers like a Raspberry Pi 4.

B. Data Pipeline and Processing

We send color and depth frames to the offboard computer over the local network, do the most intensive computations there and then forward the result to the RAPTOR system over the local network as shown in Figure 3.

1) Dataflow: We start with the camera image publisher running onboard the drone on a Nvidia Jetson Nano which compresses both RGB and depth frames from the Intel RealSense D455 camera and sends them to the offboard computer. On the offboard computer, we run scene segmentation with detectron2 [4] and object localization and grasp planning using Open3D [5]. Since trajectory planning for RAPTOR happens in the global motion capture frame, we transform the target coordinates of the computed grasp to the global motion capture reference frame using the pose of the drone in the motion capture system. The pose of the drone is received from a bridge process which publishes the pose to the grasp planning process and receives the position and yaw for the resulting grasp in turn. Once the position and yaw of the grasp is forwarded from the bridge process to the trajectory generation process of RAPTOR, using MAVlink [25], it will be sent to the flight controller of the drone, a Pixhawk 4 [26], which then handles all lower levels of control to fly the drone to the target position.

2) Synchronisation of Processes: We use a request-reply communication pattern within ZeroMQ. Using this request-reply pattern means that both the bridge process and the camera image publisher send the drone pose and the images to the main object detection and grasp planning process and then wait for a reply from that process before they send the next pose or image. In case one process fails, this failure will interrupt the request-reply scheme and the other processes will not keep operating on old or invalid data as it would be the case with the Fast DDS publisher-subscriber model.

3) Transport and Serialization: Transport mechanisms are as shown as well in Figure 3: in between the processes in our vision system and the bridge process to RAPTOR, we use ZeroMQ (ZMQ) [27] for transport. For the serialization of our ZMQ messages, we use Protobuf [28] and for sending the images, we use imagezmq [29]. All ZMQ connections are configured as REQ-REP (request-reply) connections, which means that a sender will only send further messages to a receiver after receiving a reply from the receiver. This mechanism helps with the synchronisation of all of our processes, which is crucial for synchronising the images we are receiving with the pose data that is incoming. All ZMQ connections also use TCP (Transmission Control Protocol) for reliable transport of messages. To establish communication in between the vision system and the RAPTOR system, there is a bridge process that both implements ZMQ and Fast DDS [30] communications, which is used on the RAPTOR flying platform.

4) Image Streaming and Compression: We access one stream of RGB frames and one stream of Z16 depth frames
from the *Intel RealSense* [2] camera, both with a resolution of 640 by 480 pixels. It is imperative to transport these frames in a synchronized manner. For compression of the camera frames, we use multi-processing to compress the two frames concurrently, which saves from 10% to 40% in processing time compared to a sequential implementation. For compressing the color frames, we use lossy JPEG compression with a quality of 95, resulting in a size reduction to approximately 15% of the size of the uncompressed image on average. For compressing the depth frames, we cannot use lossy compression like JPEG since the encoding of the depth information is very sensitive to even small changes due to compression and precision cannot be sacrificed when grasping objects. Hence, we use lossless PNG compression with a compression factor of 2, resulting in a size reduction to approximately 19% of the original size on average. The runtimes for each process are considered in Section IV-A.

IV. RESULTS AND DISCUSSION

A. Performance Analysis

In the following, we analyze the system performance of the vision system. Particularly for real-time robotic systems, identifying runtimes and delays is crucial to ensure that all data, which the system is operating on, is synchronized.

1) Process Timings: The camera image publisher running on the *Jetson Nano* takes 100 ms on average to get, compress, and send a pair of RGB and depth frames. Scene segmentation and grasp planning on the offboard computer takes approximately 170 ms on average. The *RAPTOR* processes for trajectory generation and data transfer run at a speed of 20 ms per iteration.

2) Networking Latency: All offboard processes run on the same computer and the time messages spend in transport is on the order of nanoseconds. However, there is considerable networking latency when sending the image frames from the *Jetson Nano* on the drone to the offboard computer. For transport, the TCP implementation of *ZMQ* is used. A showcase of the transit times of images is given in Figure 4.

B. Localization Performance

In the following, we give an overview of the localization performance of our system compared to the ground truth using motion capture. We first describe our evaluation methodology and then the test results.

1) Evaluation Methodology: We have conducted localization tests using a teddy bear and a 0.51 PET bottle as test objects (shown in Figure 5). Both objects fulfil all criteria of being grasped by our system. Furthermore, it is noted that the bottle is perfectly symmetrical and the teddy bear is slightly asymmetrical towards its camera-facing side. Both objects were mounted on a stand (see Figure 6), which was equipped with motion capture markers. The center of the frame of the stand was calibrated to be exactly on top of the aluminum extrusion that provides the mounting point for the objects. The objects were placed on the stand shown in Figure 6 to provide the best approximation for their centroids.

We recorded performance measurements by positioning the drone for its start in a specific x- and y-coordinate on a virtual grid. The grid ranges from $-0.5$ m to $-2.0$ m in increments of $0.25$ m. In the y-axis, the values range from $-1.5$ m to $1.5$ m in increments of $0.5$ m. These values are denoted $x_k$ and $y_k$. Position estimates are denoted by $p$. As
Fig. 6. The experimental setup used. On the left side, the bottle is mounted on a stand equipped with motion capture markers to allow us to perform localization tests. On the right side, the teddy bear is mounted without any markers for the grasping tests.

an error metric, we use the error

\[ e(x) = p_{\text{MoCap}} - \hat{p}_{\text{Vision}} \]

\[ = p_{\text{MoCap}} - \frac{1}{n} \sum_{k=1}^{7} p_{\text{Vision}}(x, y_k) \]  

where \( e(x) \) is a three-dimensional function that contains the error in x-, y- and z-axis. In addition, we use the absolute mean error

\[ e_{\text{abs}}(x) = \frac{1}{3} \sum_{k \in \{x, y, z\}} \| e(x)_k \| \]

as error metric. For \( e(y) \) and \( e_{\text{abs}}(y) \), we simply swap the x- and y-axis. A visualization of the axis assignment is given in Figure 6.

2) Localization Results: We show figures of our localization test results for the bottle and the bear in Figures 7 and 10. Notably, we see that errors in x- and y-coordinates are mainly within two centimeters of our ground truth for the bottle. Real-world grasping tests show that the error in the z-axis does not appear to be posing a determining factor for successful grasping performance since the fingers of the gripper are sufficiently long to allow for some uncertainty in positioning. However, the x- and y-error greatly determine whether a grasp is successful. While the error in the x-coordinate for the teddy bear is of seemingly substantial magnitude, it did not reduce the grasping efficacy. We can see that to minimize the x-error, a translation of \(-1.3\) m in the x-axis and no translation in the y-axis is ideal and minimizes the error.

C. Validation with Grasping Tests

Finally, we validate the grasping performance of our system. We first explain the choice of test objects, then introduce our evaluation methodology, and finally present the test results.

1) Test Objects: We conducted the grasping test with the same teddy bear from the error analysis shown in Section IV-B and a slightly larger and heavier bottle shown in Figure 5. The choice falls on these objects since any objects that are to be grasped have to be in the COCO (Common Objects in Context) dataset, they have to fit in the gripper, and their
weight has to be below 500 grams to be suitable for lifting by the drone. Furthermore, while we also tried other objects like a handbag, they were prone to be either easily blown away by the wind generated by the propellers of the drone or easily deformed by the wind. We refer to Appius et al. [6] for a showcase of the grasping abilities of RAPTOR with a wider variety of objects.

The main objective of these real-world grasping tests is to show that we can achieve with a marker-less approach similar grasping efficacy for similar types of objects compared to the motion capture implementation that was previously used [6]. We would like to use onboard vision to not require an external marker-based system to determine the object’s location.

2) Evaluation Methodology: We placed both objects on top of a weight on a metal plate (shown in Figure 6) without any markers attached. This setup ensured a stable pose of both of our objects even with the drone flying close by. The stand was placed in a position where the camera would pick up the teddy bear - about 1.2 m offset in x-direction and 1.2 m offset in y-direction. The drone executed the following mission plan:

1) Fly to the center of the room and get a view of the object.
2) Hover for 5 seconds and gather a first grasp estimate for the target object.
3) Reposition to execute the swooping maneuver for the grasp in a straight line.
4) Execute the swoop and grasp the object, then drop the object and land again.

We only stopped the drone to exchange the battery, otherwise, the testing circumstances remained equal for all tests. For each object, we completed a total of 36 grasping attempts.

3) Grasping Tests Results: For the teddy bear, we saw a success in 32 out of the 36 attempts, yielding a success rate of 89%. This success rate is a slightly worse performance compared to the baseline. The RAPTOR system as baseline previously used a marker-based stationary motion capture implementation on a similarly sized styrofoam object (shown in Figure 5) (100% grasping efficacy over 36 attempts).

Similarly, we saw for the bottle as test object 23 out of the 36 successful grasp attempts. This success rate of 64% slightly outperforms the motion capture implementation (61% over 36 attempts). Note that the new bottle used was about 2 centimeters larger in diameter than the bottle used in the localization experiments (as shown in Figure 5). We conclude that we do not have a significant loss in performance compared to a motion capture implementation when grasping objects while completely eliminating the necessity to equip the objects with markers.

The results indicate the potential of our vision-based system as an alternative for the previously used marker-based localization systems. With this solution, the drone could be used outside a motion capture space.

V. Conclusion

We have demonstrated our vision-based system for real-time scene segmentation and grasp planning and its capabilities as a replacement for motion-capture-based target localization solutions. Our system eliminates the need for objects to have any markers on them or to be of a predefined size as it would be the case for other vision-based solutions that have been previously tried on aerial robots. We have shown that our system can precisely localize objects for grasping and have validated the performance in real-world grasping tests with different objects, showing that there is nearly no loss in grasping success and demonstrating a successful transfer of geometric grasp planning to a mobile platform. We detailed our system architecture including how we synchronized processes running at different speeds and deployed them on the RAPTOR platform. This work shows how we achieved real-time localization and grasping and serves as a foundation for future work that will extend our system’s capabilities and use case scenarios.

Furthermore, we also showed the limitations of our system when it comes to grasp planning on partial point clouds. Particularly, for localizing centroids of larger objects, exclusively working with the visible surface of the object induces localization errors as shown in Figure 10.

For future work, we propose a learning-based approach to learn the three-dimensional shape of different objects. Once a partial point cloud is acquired, we would then generate an estimate of the full three-dimensional point cloud of the object. Such an approach would enhance spatial awareness through learning instead of gathering more data from different angles. This solution would be an important step towards giving robots a true understanding of the shape of objects and how to interact with these objects. Interaction based on vision is something humans and animals have mastered long ago, giving robots a similar perception of space and objects through learning will be a major achievement for any kind of autonomously acting robotic systems.

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