Door Delivery of Packages using Drones

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Abstract—In this work, we present a system that enables delivery drones to autonomously navigate and deliver packages at various locations around the house. The objective of this to reach a specific location in the house where the recipient wants the package to be delivered by the drone without the use of any external markers as currently used. This work is motivated by the recent advancements in semantic segmentation using deep learning that can potentially replace the specialized marker used by the current delivery drone for identifying the place where it needs to deliver the package. The proposed system is more natural in the sense that it takes an instruction input on where to deliver the package similar to the instructions provided to the human couriers. We propose a semantic segmentation-based lowering location estimator that enables the drone to find a safe spot around the house to lower from higher altitudes. Following this, we propose a strategy for visually routing the drone from the location where it lowered to a specific location like the front door of the house where it needs to deliver the package. We extensively evaluate the proposed approach in a simulated environment that demonstrates that the delivery drone can deliver the package to the front door and also to other specified locations around the house.

I. INTRODUCTION

In recent years, the use of drones for the delivery of packages and food has gained significant interest. The drones are used for the delivery task primarily due to their operational efficiency and ability to reach remote areas. Therefore, the use of drones for delivery has been prevalent amongst the logistics undertakings due to the ability of drones to reduce the cost and also speed up the delivery process [1]. The delivery of packages using drones involves various challenges such as the design of the robot, navigation, safety, and delivering the package at a location desired by the recipient. Previous researches have primarily focused on the design [2, 3], navigation [4–6] and the safety [7, 8] aspects of the delivery drones. But, there has been less investigation on delivering packages at specific locations around the house as desired by the recipient, which is a critical part of automating deliveries using drones.

Currently, many e-commerce retailers and fast-food chains have been investigating on utilizing drones for their delivery. Most of these drones fly to the destination and then, drop the package far away from the doorstep. This requires the human recipient to pick up the package as soon as the package has been delivered by the drone. The delivery drones from Amazon [9], UPS [10], Dominos [11] and Walmart [12] use a similar approach where the packages are placed on the ground over a specific landing pad or lowered and dropped using a string. These methods require human intervention in receiving the package. But, in most of the real-world scenarios, the human courier delivers the package at the doorstep where the recipient is not available to receive the package. The need for the presence of the recipient during the delivery can potentially limit the large-scale deployment of this technology.

Further, the literature contains several interesting studies on the impact of delivery drones in terms of ethics and privacy [13], economic impacts [14] and the threats imposed by these drones [15]. But, there has been very limited field studies regarding the practical aspects of delivery drones. Prior work focused on delivering packages in the balconies of apartment houses [6]. The delivery drone uses visual markers to detect the balcony and also to localize. However, this approach is limited to apartments with balconies only. There are various types of residential housing, including not only apartments but also detached houses and townhouses. Especially, the majority of the population in the United States reside in a detached single-unit house that does not usually have a balcony [16]. Hence, so as to enable large-scale deployment of package delivery using drones, the robots should be able to deliver the packages at the doorstep or at any other preferred location like a human courier.

Another field study on the user acceptance of delivery drones in a campus environment found that people have a positive attitude towards delivery drones [17]. However, human interventions were involved in the safe landing of the delivery drones that may not be well suited for complete autonomous delivery. To this end, methods for autonomous

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safe landing of Unmanned Aerial Vehicles (UAV) have been proposed. Neural networks capable of identifying flat regions that are suitable for the UAV to land have been used for estimating safe landing spots [18, 19]. Other approaches for the identification of safe landing s include Fuzzy Logic’s [20], Naive Bayes Classifiers [21] and optical flow analysis [22]. But these methods are oriented towards safe landing during emergencies and are not applicable for a safe landing in the proximity of a house during delivery tasks.

In this paper, we present an autonomous system for the last-mile delivery of packages using drones. Unlike the previous works, the proposed system delivers the package at a location in the house as desired by the recipient. For instance, some people might prefer the drone to deliver the package at the doorstep like a human courier, and some might prefer the package to be delivered in their backyard, and so on. The approach enables the drone not only to deliver the package at the desired location but also to perform the task without the use of any external markers like a landing pad or a fiducial marker. The proposed system enables the drones to find a safe lowering spot based on the aerial image of the delivery site. The drone uses the features perceived from aerial images to estimate the lowering spot. Then, the drone lowers itself at that location and then performs vision-based navigation to find its way to the final package delivery spot.

Fig. 1 shows the drone navigating to the front door of the house where the drone needs to deliver the package.

The main contributions of this paper are the following:

- A novel external marker-free autonomous delivery drone capable of delivering packages anywhere around the house.
- A semantic segmentation-based lowering location estimation that enables the drone to identify a safe spot to lower the altitude in the vicinity of the house that is close to the final package delivery spot.
- The design of a real-time path planner that can route the drone from the lowering location to the final delivery spot.

- Extensive experimentation and evaluation of the proposed system with respect to the real-world variations the drone might encounter during a delivery task in a photo-realistic simulator.

II. PROBLEM DESCRIPTION

The overall problem considered in this paper is to autonomously deliver packages using drones to locations such as the front door and the backyard of a house. The drone delivers the package to a specific location in the house as specified by the recipient and does not use any additional specialized markers. The core assumption of this work is that the drone delivers the package to a typical single-unit house (the most common house type in the United States) and the delivery location specified is a feasible one. The last-mile delivery problem considered in this work begins once the drone is over the top of the recipient’s house. The navigation to the top of the house can be achieved effortlessly using autopilot systems that allow for point-to-point navigation at higher altitudes where good Global Positioning System (GPS) reception is available [23]. The challenge is to empower the drone to navigate from the top of the recipient’s home to a specific location like the front door where the drone needs to deliver the package. We also assume that the drone delivers the package during conditions with good visibility such as under bright daylight and that the visibility is not affected by external factors such as the weather. We formulate this as a vision-based navigation problem, where the drone navigates to the final delivery location based on the visual perception. The design aspect of the drone involved in actually delivering the package at the delivery location is not considered within the scope of this work. For simplicity, in this work, we only consider the following delivery locations: front door, backyard, front yard, and front paved area.

III. SYSTEM OVERVIEW

The proposed system enhances the automation of the delivery drones by facilitating them to deliver packages
at a specific location similar to human couriers. In other words, the proposed system routes the drone from the top of the house to a very specific delivery spot. The drone can potentially use GPS-based navigation to reach the top of the house since the GPS remains accurate at the higher altitudes [23]. The specific location where the drone needs to deliver the package is given as input to the system. This is similar to the instruction given to the logistics firm about where exactly the recipient wants the package to be placed.

As shown in Fig. 2, the proposed system consists of two key components: 1) lowering to the house through semantic-segmentation, and 2) vision-based navigation to the delivery spot. The lowering to house component computes a safe spot for the drone to lower itself from the top of the house. The lowering location estimated is also such that the drone can easily reach the final delivery spot from that lowering location. For instance, if the drone needs to deliver the package to the front door of the house, it may not be feasible to reach the front door if the drone lowers in the backyard of the house. Ideally, the drone should lower in the front yard or at some paved areas in front of the house. Semantic segmentation is performed on the aerial images to identify the features present such as the roof, grass, trees, paved area, and so on. Based on these features observed and the final delivery spot, the drone estimates a feasible location where it can lower itself. In case, the lowering location is the delivery location itself (like backyard), then the drone completely lands and delivers the package. The complete details on the implementation of the lowering to house system are explained in Section IV.

The vision-based navigation system assists the drone in autonomously navigating from the lowering location to the final delivery spot during scenarios where the lowering location and the delivery spot are not the same. The drone first tries to identify the final delivery spot such as the door using visual perception. If the final delivery spot is not evidently visible, the drone performs a search until it finds the delivery location. Then, the drone navigates itself to that location and lowers itself to drop the package. The drone while searching or navigating to the final delivery spot maps the environment and also dynamically routes itself. The complete details about the functioning of the navigation system are described in Section V.

The drone platform considered for this paper is equipped with a camera and a range sensor facing downward. The downward-facing camera is used to obtain an aerial view of the house and estimate the location to lower the drone. The range sensor is used to estimate the height from the ground plane and assists the drone in the lowering process. The drone is also equipped with a front-facing stereo camera. The front-facing stereo camera enables the drone to map and navigate in the proximity of the house post lowering. The perception sensors for the drone have been selected based on the sensors that are commonly used with the drones for various applications.

IV. LOWERING TO THE HOUSE

In this section, we describe the method used by the delivery drone for identifying a safe lowering position based on the semantic segmentation of aerial view images obtained from the drone’s downward-facing camera. The various steps involved in computing a safe lowering position from the aerial images are shown in Fig. 4.

A. Semantic Segmentation

Dataset. Semantic Drone Dataset [24] was used to train the segmentation model to extract the various features present in the vicinity of the delivery site. The dataset contains aerial images of over 20 houses obtained from an altitude of 5 to 30 meters above the ground. The dataset has pixel-accurate annotations of 22 class labels: paved area (road and pavement), dirt, grass, gravel, water, rocks, pool, vegetation, roof, wall, window, door, fence, fence-pole, person, dog, car, bicycles, tree, bald-tree, ar-marker and obstacle (objects other than mentioned earlier) that are critical in deciding a safe spot for the drone to lower its altitude. To train and test the model, we used the public dataset split which contains 400 images. The dataset was split in the ratio of 90:10 for the train and the test images.

Semantic Segmentation using Unet. A semantic segmentation model based on Unet [25] with VGG-16 [26] as initialization was trained on the dataset. In the implementation, the following classes from the dataset only were considered: roof, paved area, grass, vegetation, fence, car, and tree. The classes were selected based on the objects that are available in the simulated test environment. The model was trained for 50 epochs using Adam optimizer. An initial learning rate of 10−4 was used. Fig. 3 shows aerial images obtained from the drone (left) in the simulation environment and the segmented images (right) alongside the class labels. Classification accuracy of 83.6% was obtained on the test images using the model trained.

B. Lowering Location Estimation

Lowering location estimation is performed once the drone reaches the GPS coordinate of the recipient’s house. The GPS coordinate to which the drone arrives can be anywhere over the house, and hence, the drone cannot lower itself right away. The drone captures an aerial view of the recipient’s house using the downward-facing camera. The camera follows a pinhole model and captures an image of size $W \times H$. In the image frame, the drone is located at the center of the image, and its location is given as $p_{drone} = (W/2, H/2)$. In Fig. 4a the position of the drone, $p_{drone}$ is marked using a red dot.

Semantic Segmentation of Aerial Image. Semantic segmentation is performed on the aerial image captured. The result of the semantic segmentation yields the locations of different regions and also the various objects present around the house in the image frame. From the results, the locations of the roof, paved area\(^3\) and grass are extracted. The

\(^3\)Note: The semantic classifier considers both roads and pavements as paved area.
The drone identifies the roof of the house to which it needs to deliver the package based on the color labeling shown in Fig. 3. The results of the semantic classification can have multiple segments corresponding to roof class in the segmentation output for the aerial image shown in Fig. 4a and are not distinguishable from the results in the image labeled as grass and grass are classified as: 

$$\vec{v}_{front} = c_{roof} - c_{paved}. \quad (2)$$

Fig. 4d shows the direction of the house’s estimated orientation in red arrow, along with the actual orientation marked in yellow.

Front and Back Categorization. In scenarios where the drone needs to deliver the package to the front or the back yard, it is ideal if the drone lowers in the corresponding yard. But the regions corresponding to both the yards will be labeled as grass and are not distinguishable from the results of semantic classification. Now, the angle between the pixels in the image labeled as grass and \( \vec{v}_{front} \) is used to classify whether they lie in the front or back of the house. Let \( n_{grass} \) be the total number of pixels in the image labeled as grass and \( g_i \in \{1, \ldots, n_{grass}\} \) be the coordinate of those pixels. Now, the angle these pixels form with the orientation of the house is computed as:

$$\theta_i = \arctan2(g_{iy}, g_{ix}) - \arctan2(v_{front_x}, v_{front_y}). \quad (3)$$

where \( v_{front_x} = c_{roof_x} - c_{paved_x}, \) and \( v_{front_y} = c_{roof_y} - c_{paved_y}. \)

Then, the angles are normalized to be in the range \([-\pi, \pi]\] as:

$$\theta_i = \begin{cases} 
\theta_i - 2 \pi, & \text{if } \theta_i > \pi \\
\theta_i + 2 \pi, & \text{if } \theta_i \leq -\pi \\
\theta_i, & \text{otherwise.}
\end{cases} \quad (4)$$

Based on the normalized values of \( \theta_i \), the pixels labeled as grass are classified as:

- front, if \(-\pi/2 \leq \theta_i \leq \pi/2\)
- back, otherwise. \quad (5)

Fig. 4e shows two random pixels \( g_p \) and \( g_q \) labelled as grass. Based on the angle these pixels form with \( \vec{v}_{front} \), \( g_p \) is classified as front and \( g_q \) as back.
The drone can be flying over any region around the house based on the GPS coordinate of the delivery site provided. The region above which the drone is currently flying can be identified using the semantic class label of the pixel \((p_{drone}, p_{drone})\). Now, the drone needs to move to the region where it needs to lower. Based on the final delivery spot \(\star \in \{\text{front door, front paved area, backyard, front yard}\}\), the lowering region \(\in \{\text{front paved area, back yard, front yard}\}\) is decided as:

- \textit{front paved area}, if \(\star = \text{front door or front paved area}\)
- \textit{backyard}, if \(\star = \text{backyard}\)
- \textit{front yard}, if \(\star = \text{front yard}\).

In other words, the drone lowers in the paved area if the final delivery spot is the front paved area or the front door. The drone lowers in the corresponding yard if the front or the back yard is specified as the final delivery spot. If the drone is currently not flying over the region where it needs to lower, it moves towards that region. Let \(c_{lower}\) be the centroid of the region where it needs to lower, then the direction of motion of the drone \(\vec{v}_{drone}\) is computed as:

\[
\vec{v}_{drone} = p_{drone} - c_{lower}. \tag{6}
\]

Fig. 4f shows the direction \(\vec{v}_{drone}\) (red arrow) for the sample environment considered. The drone moves in the direction \(\vec{v}_{drone}\) while maintaining a fixed altitude. The drone keeps moving in that direction until it is over the lowering region. The drone segments the new images obtained from the downward-facing camera as it moves and stops the motion once the region below the drone at pixel \((p_{drone}, p_{drone})\) is labeled as the region where the drone needs to lower.

**Safe Lowering.** Now, that the drone is above the region where it needs to lower, the drone needs to estimate a safe spot in that region where it can lower itself. Fig. 4g shows the updated position of the drone where it is flying over the paved area region which is the region where it needs to lower. First, the drone measures its flying height \((h_{drone})\) over that region using the range finder. The height is measured so as to build a back-projection model to find the correspondences between the pixels in the image frame and its actual 3D coordinate in camera frame. A pixel \((u, v)\) in the image frame can be mapped to corresponding location in the camera frame \((U, V, W)\) as:

\[
U = h_{drone} \times (u - O_x)/f_x,
V = h_{drone} \times (v - O_y)/f_y,
W = h_{drone} \tag{7}
\]

where \((O_x, O_y)\) is the optical center of the camera, and \((f_x, f_y)\) is the focal length of the camera along x and y axes.

Safe lowering location is selected such that the lowering coordinate is close to the footprint of the house and also at a safe distance from the obstacles. Prior research has found that the drone can drift up to 2 meters while lowering due to errors in the GPS reception and estimation [17]. Hence, in the implementation, it was set such that the lowering location is at least 2.5 meters from the house’s footprint and the other obstacles such as cars, vegetation and so on.

Using the image frame to camera frame mapping as shown in Eq. 7, the distance to the closest point on the roof and other obstacles from the drone is measured. Let \(d_{roof}\) be the distance between the drone’s current position and the closest point on the roof. Let the number of obstacles in the proximity of the drone be \(n_{obstacles}\) and the \(d_{obstacles}, l \in \)
\{1, \ldots, n_{\text{obstacles}}\} be the distance to the closest point on the boundary of each obstacle from the drone. If any of these distances are less than 2.5 meters, the drone cannot lower at its current position and a new lowering position must be computed. The new lowering position is computed by iteratively searching for a point along the neighboring regions of the drone’s current position. The search is done until a point that it at least 2.5 meters away from the roof and obstacles is found. The search is done only in the area corresponding to the lowering region of the drone. The lowering position computed for the sample environment considered is shown in Fig. 4h.

Once a safe lowering point is found, the drone moves to that point while maintaining its current height. Then, the drone begins to lower itself until it reaches a height of 2 meters from the ground.

V. Vision-based Navigation to Door

This section describes the mapping and the routing methods used by the drone to navigate itself to the door of the house after lowering. The implementation of this section is used only when the drone needs to deliver the package at a location that is not the lowering space. For instance, if the final delivery location is specified in the front or the backyard, the drone can lower itself further to land and then, drop the package.

Door Dataset and Detection. DoorDetect dataset [27] was used to train the door detection model that can identify doors in the image. The dataset contains 1,213 images of various objects such as door, handle, cabinet, and refrigerator door collected from various public datasets along with their bounding boxes. In our work, the images of the door (refers to any room door) alone were used to train the detection model. A Convolutional Neural Network (CNN) model based on YOLOv3 [28] was used to train the door detection model. The model was trained following an 80:20 split on the dataset. A mean Average Precision (mAP) of 46.3\% was obtained on the test dataset.

Mapping. Once the drone lowers itself, the drone maps the environment in addition to searching for the door. The drone maps the environment using the front-facing stereo camera. The environment is mapped as an OctoMap using the point cloud data obtained from the stereo camera. The mapping is performed so as to compute a path from the drone’s current location to the door (once the door is found). In the implementation, RTABMAP [29] was used for estimating the odometry and for building the OctoMap.

Door Search. The drone searches for the door right from the spot where it was lowered. In case the door is not visible to the drone right away, the drone performs slight yaw on both sides to extend its viewing range (in the implementation, yaw range of \([-\pi/4, \pi/4]\) was used). In most of the cases, the door should have been detected by now, since the drone lowers close to the footprint of the house. In case, the door of the house is still not detected, the drone uses the segmented aerial image as a reference to route itself along the footprint of the house. Segmented aerial image captured right before the decent is converted to an occupancy grid. The areas corresponding to the roof and other obstacles are considered as occupied region and the paved area and the grass are considered as open spaces. The height from which the image was captured is used to estimate the resolution of this occupancy grid. From the occupancy grid map, a path to traverse along the boundary of the house’s footprint and open space is computed. Now the drone moves along this path until it finds the door.

Path Planning to Door. Once the door is found, the 3D coordinate of the door in the OctoMap of the environment is estimated. The doors 3D coordinate is estimated by mapping the center of the detected doors bounding box to the point cloud of the environment. To maintain, a safe distance from the door during delivery, the point on the door is offset by a distance of 1 meter along the normal direction at that point. This gives a point right in front of the door that is suitable for delivering the package and also resembles the way human couriers deliver a package. In the implementation, Point Cloud Library [30] was used for estimating mapping between the image and the point cloud and also for estimating the normal.

Finally, the drone computes a path to the point in front of the door. Once the drone reaches that point it lowers itself completely so that the package can be delivered.

VI. Experiments

The proposed system was experimented using AirSim [31], a photo-realistic simulator from Microsoft. Robot Operating System (ROS) was used for the entire implementation. The simulated drone was set up as per the configuration mentioned in Sec. III. The neighborhood environment provided as a part of Airsim simulator was used for the experiments. Houses with various layouts were used in the experiments to show the effectiveness and the robustness of the proposed system. The experiments were repeated by varying the delivery locations and the initial GPS coordinate.

The first experiment presented consisted of lowering the drone to the backyard of the recipient’s house. In this given scenario, the drone was able to distinguish the backyard from the front yard and find a safe location to lower itself. Fig. 5a shows the drone lowering into the backyard along with the trajectory traced by the drone marked in purple. The top part of the trajectory corresponds to the drone aligning itself with the lowering location and the following straight line corresponds to the path traced by the drone while lowering. Changing the initial GPS location of the drone did not contribute to any major changes in the lowering behavior of the drone. The drone was always able to deliver the package somewhere close to the footprint of the house. Similar results and trajectories were obtained when the final delivery location was specified as the front yard or the front pavement. For brevity, the result of lowering to the backyard is only presented.

The second experiment presented consisted of the drone attempting to deliver the package to the front door of the house. In this scenario, the drone lowered itself to the front
paved area and routed itself to the door. Here, changes in the initial GPS location caused significant differences in the way the drone reached the door of the house. Fig. 5b and 5c shows the drone landed at front of the door following the lowering over the paved area. In the experiment shown in Fig. 5b, the drone lowering close to the door, and the door was detected following a minor yaw motion performed by the drone. But, in the experiment shown in 5c the drone lowered itself close to the garage and was far away from the main door of the house. The door was not detected even following a yaw motion. The drone routed itself along a path following the footprint of the house until it detected the main door. One of the two behaviors of the drone was observed for during multiple delivery attempts to front door of the different houses from various initial GPS coordinate.

A. Discussions

Overall, our method was successfully able to route the drone to various locations around the house so that it can deliver the package. Following numerous experiments, the method was found to be robust to the numerous variations that the drone might encounter in the real world. The drone was able to find a safe lowering location and also route itself to the door. A safe lowering location was estimated until there exists a location on the desired lowering region that is at a safe distance from the objects and vegetation’s around. Hence, the expectation of the system is that the lowering region of the drone should not too cluttered that there is not any location safely distanced from the objects around. The system also identified the front door of the house and reached it provided the house follows a typical structure of a single unit house or a townhouse. With a deeper understanding of the various house architectures, the system can be enhanced to deliver the package to any type of house. Potentially, the system can be used for delivering packages to apartment-type houses where they can lower on the open spaces around the apartment building. But human intervention might be needed to pick the package as soon as the drone leaves it.

As discussed above, the GPS coordinate from which the drone begins the delivery process was found to have a key role in deciding the lowering position and also the strategy used by the drone to find the front door of the house. Until the GPS coordinate was close to the proximity of the house, the drone was able to detect the correct roof of the house and the delivery attempts were successful. When the GPS coordinate provided was close to the outer bounds of the house, the roof of the neighboring house was detected as the roof of the recipient’s house and subsequently, the whole delivery attempt failed. Hence, it is important that the GPS coordinate provided is not close to the outer bounds of the house, and closer the GPS coordinate is to the center of the house the better it is.

At times the system suffered from misclassifications in the semantic segmentation. During the experiments misclassification commonly occurred over the shadowed regions in the image. In the experiments, it was commonly noticed that the shadowed regions on the roof were often misclassified as paved areas. These misclassifications can potentially lead to the estimation of lowering locations that may not be safe and can cause damage to the package or the objects around. Such issues can be potentially fixed by training the model using a larger dataset and also investigating the development of semantic segmentation models that are more specifically developed for classifying drone’s aerial images. During the experiments, the initial height of the drone at the starting GPS coordinate was randomly set between 20 to 30 meters. In most of the cases, the downward-facing camera of the
drone was able to observe the entire house (house and other open spaces around it). But, at times the entire house was not covered in the aerial image and the height of the drone needs to be increased to capture the entire house. But, the increase in the height affected the accuracy of the semantic classifier. Hence, in the development of new aerial image datasets, it is better to capture the images from a wide range of height.

VII. CONCLUSION

In this paper, we present an integrated system that allows drones to autonomously deliver packages at various locations around the recipient’s house. The proposed system does not require any direct human interaction during the delivery of packages. The drone autonomously delivers the package at the location specified by the recipient like a human courier. Although autonomous delivery drones are still futuristic, our work provides a working proof of concept that addresses the various challenges involved in the last-mile delivery of packages using drones.

Future work will focus on conducting real-world experiments using an actual human input for the delivery location. We are developing an end-to-end system that allows the recipients to specify delivery instructions in natural language, and the drone will be able to deliver the package as per the instructions specified. In our current implementation, the drone cannot search for the house’s door in case of a complex house design where the door is not clearly visible. We intend to add intelligent search strategies that enable the drone to identify the door when the door is not evidently visible.

Furthermore, we also intend to improve the accuracy of the aerial image semantic classifier. We plan to develop a larger dataset of aerial images covering different housing environments. Additionally, a novel semantic segmentation neural networks capable of segmenting aerial images with higher accuracy will be developed.

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