Learning Monocular Reactive UAV Control in Cluttered Natural Environments

Andreas Wendel

Joint work with Stéphane Ross, Narek Melik-Barkhudarov, Kumar Shaurya Shankar, Debadeepta Dey, J. Andrew Bagnell, Martial Hebert (CMU), and Horst Bischof (TU Graz)

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Abstract

Autonomous navigation for large Unmanned Aerial Vehicles (UAVs) is fairly straight-forward, as expensive sensors and monitoring devices can be employed. In contrast, obstacle avoidance remains a challenging task for Micro Aerial Vehicles (MAVs) which operate at low altitude in cluttered environments. Unlike large vehicles, MAVs can only carry very light sensors, such as cameras, making autonomous navigation through obstacles much more challenging. In this paper, we describe a system that navigates a small quadrotor helicopter autonomously at low altitude through natural forest environments. Using only a single cheap camera to perceive the environment, we are able to maintain a constant velocity of up to 1.5m/s. Given a small set of human pilot demonstrations, we use recent state-of-the-art imitation learning techniques to train a controller that can avoid trees by adapting the MAVs heading. We demonstrate the performance of our system in a more controlled environment indoors, and in real natural forest environments outdoors.

Contents

1 Introduction

In the past decade Unmanned Aerial Vehicles (UAVs) have enjoyed considerable success in many applications such as search and rescue, monitoring, research, exploration, or mapping. While there has been significant active research in making the operation of UAVs increasingly autonomous, obstacle avoidance is still a crucial hurdle towards this task. For MAVs with very limited payloads it is infeasible to carry state-of-the-art radars [1]. Many impressive advances have recently been made using laser range finders (lidar) [2–4] or Microsoft Kinect cameras (RGB-D sensors) [5]. Both sensors are heavy and active, which leads to increased power consumption and decreased flight time. In contrast, passive vision is promising for producing a feasible solution for autonomous MAV navigation [6–8].

Figure 1: We present a novel method for high-speed, autonomous MAV flight through dense forest areas. The system is based on purely visual input and imitates human reactive control.

Our work is primarily concerned with navigating MAVs that have very low payload capabilities, and operate close to the ground where they cannot avoid dense obstacle fields. We present a system that allows the MAV to autonomously fly at high speeds of up to 1.5 m/s through a cluttered forest environment (Figure 1), using passive monocular vision as its only exteroceptive sensor. We adapt a novel imitation learning technique [9] to train reactive heading policies based on the knowledge of a human pilot. Visual features extracted from the corresponding image are mapped to the control input provided by the expert. In contrast to straightforward supervised learning [10], our policies are iteratively learned and exploit corrective input at later iterations to boost the overall performance of the predictor, especially in situations which would not be encountered by a human pilot.

This is an important feature, as the purpose of any reactive controller is to provide a reliable, low-level layer for autonomous control, which works on minimal visual input and can handle situations where 3D mapping [8, 11] or high-level trajectory planning [12] fails. Our novel method is evaluated in a constrained indoor setting using motion capture, as well as in several forest environments. In total, we successfully avoided more than 680 trees during flights over a distance of more than 3 km.

2 Related Work

An impressive body of research on control and navigation of MAVs has been published within the last few years. Several state-of-the-art approaches for MAV control would be ideal to fly through a forest, as they feature impressive aggressive maneuvers [13] or can even be used for formation flight with large swarms of MAVs [14]. However, these methods still require the real-time, accurate state feedback delivered by a motion-capture system and are therefore unsuitable for our purpose.

The most popular sensors to carry on-board MAVs are laser range finders and RGB-D sensors, as both deliver quite accurate depth estimates at a high framerate. Bachrach et al. [2] demonstrated using scanning lidars for Simultaneous Localization and Mapping (SLAM) in unknown indoor environments, and Bry et al. [3] showed how to use the same sensor for fast flight in indoor environments. The trend in indoor active sensing goes towards RGB-D sensors [5] that allow more detailed and faster scans. However, in outdoor environments, RGB-D sensors are often not applicable or suffer from very limited range. Therefore, Vandapel et al. [15] proposed outdoor planning approaches in three dimensions for UAV navigation using lidar data, and Scherer et al. [4] achieved fast obstacle avoidance using a Yamaha RMax helicopter and a 2-axis scanning lidar. For carrying outdoor lidar systems and the corresponding power supplies, larger and more expensive MAVs than what we aim for are required.

Accurate depth estimation and localization is also possible with visual sensors using stereo cameras [16] or in a moving monocular setup [17]. A single, cheap camera is enough to create sparse [11] or even dense maps [8] of the environment. While such structure-from-motion techniques are already reasonably fast, they are still too computationally expensive for high-speed flight in a forest. Additionally, pure forward motion leads to an ill-posed problem when triangulating 3D points, because the triangulation angle is very small and thus the position uncertainty is huge.

Relatively simple yet efficient algorithms can be derived when imitating

animals and insects, who use optical flow for navigation [18]. Beyeler et al. [19] as well as Conroy et al. [20] implemented systems which exploit this fact and lead to good obstacle avoidance results. Later, Lee et al. [21] proposed to use a probabilistic method of computing optical flow for more robust distance calculation to obstacles for MAV navigation. Optical flow based controllers navigate by balancing flow on either side. However flow captures richer scene information than these controllers are able to use. We embed flow in a data-driven framework to automatically derive a controller which exploits this information.

Most closely related to our approach are approaches which learn motion policies and depth from input data. Michels et al. [22] demonstrated driving a remote-controlled toy car outdoors using monocular vision and reinforcement learning. Hadsell et al. [23] showed in the LAGR project how to recognize and avoid obstacles within complex outdoor environments using vision and deep hierarchical networks. Bill et al. [24] used the often orthogonal structure of indoor scenes to estimate vanishing points and navigate a MAV in corridors by going towards the dominant vanishing point. We extend those approaches and employ a novel imitation learning technique that allows us to find a collision-free path through a forest despite the diverse appearance of visual input.

3   Learning to Imitate Human Control

Visual features extracted from camera input provide a rich set of information that we can use to control the MAV and avoid obstacles. However, programming a controller by hand using all this information would be a very time consuming and daunting task. Therefore, we leverage state-of-the-art imitation learning techniques [9, 10, 25–27] to learn such a controller. These data-driven approaches allow us to directly learn a control strategy that mimics an expert pilot's choice of actions based on demonstrations of the desired behavior, i.e., sample flight trajectories through cluttered environments.

3.1   Background

The traditional imitation learning approach is formulated as a standard supervised learning problem similar to, e.g., spam filtering, in which a corpus of training examples is provided. Each example consists of an environment (an image acquired by the MAV) and the action taken by an expert in that same environment. The learning algorithm returns the policy that best mimics the expert's actions on these examples. The classic successful demonstration

of this approach in robotics is that of *ALVINN* (Autonomous Land Vehicle in a Neural Network) [10] which demonstrated the ability to learn highway driving strategies by mapping camera images to steering angles.

While various learning techniques have been applied to imitation learning [25–27], these applications all violate the main assumption made by statistical learning approaches that the learner's predictions (actions) do not affect the distribution of inputs/states. As shown in previous work [28] and confirmed in the MAV setting here, ignoring the effects of the learner on the underlying state distribution leads to serious practical difficulties and poor performance. For example, during typical pilot demonstrations of the task, trees are avoided fairly early and most training examples consist of straight trajectories with trees on the side. However, since the learned controller does not behave perfectly, the MAV encounters situations where it is directly heading for a tree and is closer than the human ever was. As the hard turns it needs to perform in these cases are nonexistent in the training data, it simply cannot learn the proper recovery behavior.

Theoretically, [28] showed that even if a good policy that mimics the expert's actions well on the training examples is learned, when controlling the drone, its divergence from the correct controls could be much larger (by as much as a factor T, when executing for T timesteps) due to the change in environments encountered under its own controls.

Fortunately, Ross et al. [9] proposed a simple iterative training procedure called DAgger, for Dataset Aggregation, that address this issue and provides improved performance guarantees. Due to its simplicity, practicality and improved guarantees, we use this approach to learn the controller for our drone. While [9] demonstrated successful application of this technique in simulated environments (video game applications), our experiments show that this technique can also be succesfully applied on real robotic platforms. We briefly review the DAgger algorithm below.

3.2   The DAgger Algorithm

DAgger trains a policy that mimics the expert's behavior through multiple iterations of training. Initially, the expert demonstrates the task and a first policy π_1 is learned on this data (by solving a classification or regression problem). Then, at iteration n, the learner's current policy π_{n-1} is executed to collect more data about the expert's behavior. That is, in our particular scenario, the drone executes its own controls based on π_{n-1}, and as the drone is flying, the pilot provides the correct actions to perform in the environments the drone visits, via a joystick. This allows the learner to collect data in new situations which the current policy might visit, but which were not previously

Initialize $D \leftarrow \emptyset$, π_1 to query the expert and execute the expert's action.
for $n = 1$ **to** N **do**
  Sample new trajectories by executing π_n.
  Get dataset D_n of the visited information states associated with the corresponding expert's actions.
  Aggregate dataset: $D = D \cup D_n$.
  Train π_{n+1} to minimize loss on D_n
end for
Return best π_n at mimicking expert under its induced trajectories.

Algorithm 1: DAgger for imitation learning [9].

observed under the expert demonstrations, and learn the proper recovery behavior when these are encountered. The next policy π_n is obtained by training a policy on all the training data collected over all iterations (from iteration 1 to n). This is iterated for some number of iterations N and the best policy found at mimicing the expert under its induced distribution of environments is returned. This algorithm is summarized in Algorithm 1. See [9] for details.

The intuition is that, over the iterations, we collect a set of inputs the learner is likely to observe during its execution based on previous experience (training iterations), and obtain the proper behavior from the pilot in these situations. [9] showed theoretically that after a sufficient number of iterations, DAgger is guaranteed to find a policy that when executed at test time, mimics the expert at least as well as how it could do on the aggregate dataset of all training examples. Hence the divergence in controls is not increased by a factor T as in the traditional supervised learning approach when the learned policy controls the MAV.

For our application, we aim to learn a linear controller of the drone's left-right velocity that mimics the pilot's behavior to avoid trees as the drone moves forward at fixed velocity and altitude. That is, given a vector of visual features x from the current image, we compute a left-right velocity $\hat{y} = w^\top x$ that is sent to the drone, where w are the parameters of the linear controller that we learn from the training examples. To optimize w, we solve a ridge regression problem at each iteration of DAgger. Given the matrix of observed visual features X (each row is an observed feature vector), and the vector y of associated left-right velocity commands by the pilot, over all iterations of training, we solve $w = (X^\top X + R)^{-1} X^\top y$, where R is a diagonal matrix of per-feature regularization terms. We choose to have individual regularization for different types of features, which might represent different fractions of the feature vector X, so that every type contributes equally to the controls. In
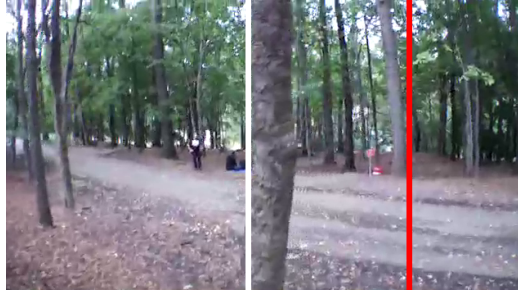
Figure 2: One frame from MAV camera stream. The white line indicates the current yaw commanded by the current DAgger policy π_{n-1} while the red line indicates the expert commanded yaw. In this frame DAgger is wrongly heading for the tree in the middle while the expert is providing the correct yaw command to go to the right instead. These expert controls are recorded for training later iterations but not executed in the current run.

other words, we regularize each feature of a certain type proportionally to the number of features of that type. Features are also normalized to have mean zero and variance 1, based on all the observed data, before computing w, and w is applied to normalized features when controlling the drone.

3.3 Using DAgger in Practice

Figure 2 shows the DAgger control interface used to provide correct actions to the drone. Note that, at iteration n, the learner's current policy π_{n-1} is in control of the MAV and the expert just provides the correct controls for the scenes that the MAV visits. The expert controls are recorded but not executed on the MAV. This results in some human-computer-interaction challenges:

1) After the first iteration, the pilot must be able to provide the correct actions without feedback of how the drone would react to the current command. While deciding whether the drone should go left or right is easy, it can be hard to input the correct magnitude of the turn the drone should perform without feedback. In particular, we observed that this often makes the pilot turn excessively when providing the training examples after the first iteration. Performance can degrade quickly if the learner starts to mimic these imperfect actions. To address this issue, we provided partial feedback to the pilot by showing a vertical line in the camera image seen by the pilot that would slide left or right based on the current joystick command performed. As this line indicated roughly where the drone would move under the current command, this led to improved actions provided by the pilot (Figure 2).

2) In addition to the lack of feedback, providing the correct actions in real-time after the first iteration when the drone is in control can be hard for the pilot as he must react to what the drone is doing and not what he expects to happen: e.g., if the drone suddenly starts turning towards a tree nearby, the pilot must quickly start turning the other way to indicate the proper behavior. The pilot's reaction time to the drone's behavior can lead to extra delay in the correct actions specified by the pilot. By trying to react quickly, he may provide imperfect actions as well. This becomes more and more of an issue the faster the drone is flying. To address this issue, we allowed the pilot to indicate the correct actions offline while the camera stream from the drone is replayed at slower speed (3 times slower than real-time), using the interface seen in Figure 2. By replaying the stream slower, the pilot can provide more accurate commands and react more quickly to the drone's behavior. The faster we're flying, the slower the trajectory could be replayed to provide good commands in time.

3) The third challenge is that DAgger requires to collect data for all situations encountered by the current policy in later iterations. This would include situations where the drone crashes into obstacles if the current policy is not good enough. For safety reasons, we allow the pilot to take over or force an emergency landing to avoid crashes as much as possible. This implies that the training data used is not exactly what DAgger would require, but instead a subset of training examples encountered by the current policy when it is within a "safe" region. Despite this modification, the guarantees of DAgger still hold as long as a policy that can stay within this "safe" region can be learned.

3.4   Features

Our approach learns a controller that maps RGB images from the on-board camera to control commands. This requires mapping camera images to a set of features which can be used by DAgger. These visual features need to provide indirect information about the three-dimensional structure of the environment. Accordingly, we focused on features which have been shown to correlate well with depth cues such as those in [22], specifically Radon transform statistics, structure tensor statistics, Laws' masks and optical flow.

We compute features over square windows in the image, with a 50% overlap between neighboring windows. The feature vectors of all windows are then concatenated into a single feature vector. The choice of the number of windows is driven primarily by computational constraints. Using a 15×7 discretization (in x and y respectively) performs well and can be computed in real-time.

Radon features (30 dim.) The Radon transform [29] of an image is computed by summing up the pixel values along a discretized set of lines in the image, resulting in a 2D matrix where the axes are the two parameters of a line in 2D, θ and s. We discretize this matrix in 15×15 bins, and for each angle θ the two highest values are recorded. This encodes the orientations of strong edges in the image.

Structure tensor statistics (15 dim.) At every point in a window the structure tensor [30] is computed and the angle between the two eigenvectors is used to index a 15-bin histogram for the entire window. The corresponding eigenvalues are accumulated in the bins. In contrast to the Radon transform, the structure tensor is a more local descriptor of texture. Together with Radon features the texture gradients are captured, which are strong monocular depth cues [31].

Laws' masks (8 dim.) Laws' masks [32] encode texture intensities. We use six masks obtained by pairwise combinations of one dimensional masks: (L)evel, (E)dge and (S)pot. The image is converted to the YCrCb colorspace and the LL mask is applied to all three channels. The remaining five masks are applied to the Y channel only. The results are computed for each window and the mean absolute value of each mask response is recorded.

Optical flow (5 dim.) Finally, we compute dense optical flow [33] and extract the minimum and maximum of the flow magnitude, mean flow and standard deviation in x and y. Since optical flow computations can be erroneous, we record the entropy of the flow as a quality measure. Optical flow is also an important cue for depth estimation as closer objects result in higher flow magnitude.

Useful features must have two key properties. First, they need to be computed fast enough. Our set of features can be computed at 15 Hz using the graphics processing unit (GPU) for dense optical flow computation. Although optical flow is helpful, we show in our experiments that removing this feature on platforms without a GPU does not harm the approach significantly. Secondly, the features need to be sufficently invariant to changes between training and testing conditions so that the system does not overfit to training conditions. We therefore refrained from adding color features, as considerable variations under different illumination conditions and confusions between trees and ground, as well as between leaves and grass, might occur. An experimental evaluation of the importance of every feature is given in the next section, along with a detailed evaluation.

In addition to visual features, we append 9 additional features: low pass filtered history of previous commands (with 7 different exponentially decaying time periods), the sideways drift measured by the onboard IMU, and the deviation in yaw from the initial direction. Previous commands encode past motion which helps to smooth the controller. The drift feature provides context to the pilot's commands and accounts for motion caused by inertia. The difference in yaw is meant to reduce drift from the initial orientation.

4   Experiments

We use a cheap, commercially available quad-rotor helicopter, namely the Parrot ARDrone, as our airborne platform. The ARDrone weights only 420g and has a size of 0.3×0.3m. It features a front-facing camera of 320×240 pixels and a $93 \deg$ field of view (FOV), an ultrasound altimeter, a low resolution down-facing camera and an onboard IMU. The drone's onboard controller stabilizes the drone and allows control of the UAV through high-level desired velocity commands (forward-backward, left-right and up-down velocities, as well as yaw rotation) and can reach a maximum velocity of about 5m/s. Communication is based on WiFi, with camera images streamed at about $10 - 15$Hz. This allows us to control the drone on a separate computer that receives and processes the images from the drone, and then sends corresponding commands to the drone at around 10Hz.

4.1   Indoor Experiments

We first tested our approach indoors in a motion capture arena. We use fake indoor trees as obstacles and camouflage to hide background clutter (Figure 3). While this is a very controlled environment that lacks many of the complexities of real outdoor scenes, this allows us to obtain better quantitive results to determine the effectiveness of our approach.

The motion capture system is only used to track the drone and adjust its heading so that it is always heading straight towards a given goal location. The drone moves at a fixed altitude and forward velocity of 0.35m/s and we learn a controller that controls the left-right velocity using DAgger over 3 training iterations. At each iteration, we used 11 fixed scenarios to collect training data, including 1 scenario with no obstacles, 3 with one obstacle and 7 with two obstacles (Figure 3).

Figure 4 qualitatively compares the trajectories taken by the MAV in the mocap arena after each iteration of training on one of the particular scenario. In the first iteration, the green trajectory to the farthest right is
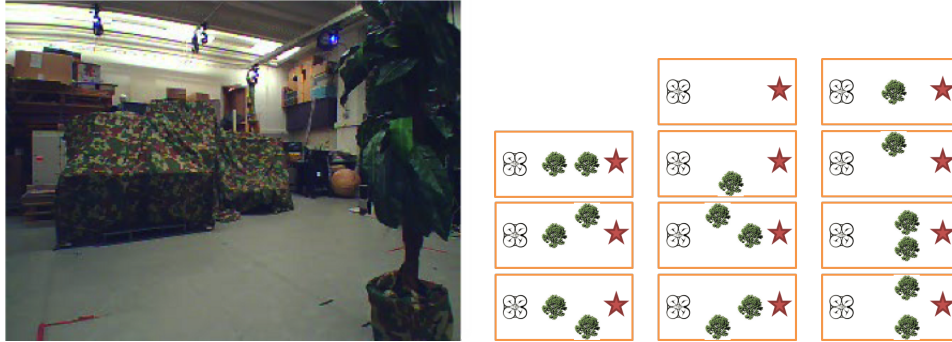
Figure 3: Left: Indoor setup in motion capture arena with fake plastic trees and camouflage in background. Right: The 11 obstacle arrangements used to train Dagger for every iteration in the motion capture arena. The star indicates the goal location.
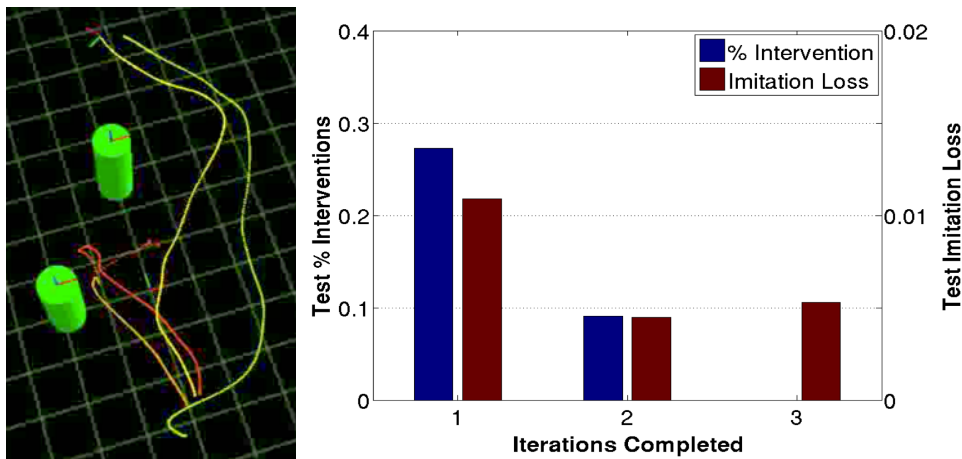

Figure 4: Left: Improvement of trajectory by DAgger over the iterations. The rightmost green trajectory is the pilot demonstration. The short trajectories in red & orange show the controller learnt in the 1st and 2nd iterations which fail. The 3rd iteration controller succesfully avoids both obstacles and is similar to the demonstrated trajectory. Right: Percentage of scenarios the pilot had to intervene and the imitation loss (average squared error in controls of controller to human expert on hold-out data) after each iteration of Dagger. After 3 iterations, there was no need for the pilot to intervene and the UAV could successfully avoid all obstacles
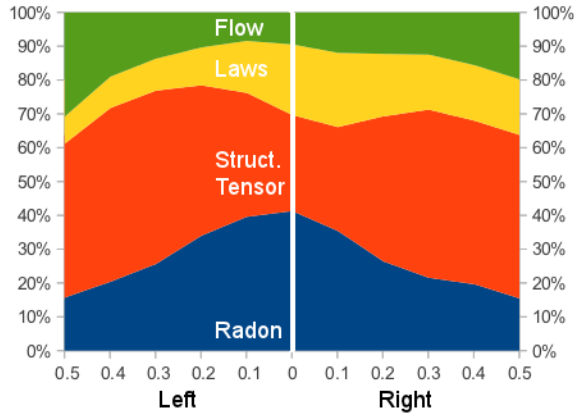
Figure 5: Breakdown of the contribution of the different features for different control prediction strengths, averaged over 9389 datapoints. Laws and Radon are more significant in cases when small controls are performed (e.g. empty scenes), whereas the structure tensor and optical flow are responsible for strong controls (e.g. in cases where the scene contains an imminent obstacle). A slight bias to the left can be seen, which is consistent to observations in the field. Best viewed in color.

the demonstrated trajectory by the human expert pilot. The short red and orange trajectories are the trajectories taken by the MAV after the 1st and 2nd iterations were completed. Note that both fail to avoid the obstacle. After the 3rd iteration, however, the controller learned a trajectory which avoids both obstacles. The percentage of scenarios where the pilot had to intervene for the learned controller after each iteration can be found in Figure 4. The number of required interventions decreases between iterations and after 3 iterations, there was no need to intervene as the MAV successfully avoided all obstacles in all scenarios.

4.2 Feature Evaluation

After verifying the general functionality of our approach, we evaluate the benefit of all four feature types. An ablative analysis on the data shows that the structure tensor features are most important, followed by Laws features. Figure 5 shows how the contribution of different features varies for different control signal strengths. Optical flow, for example, carries little information in scenes where small commands are predicted. This is intuitive since in these cases there are typically no close obstacles and subsequently no significant variation in optical flow. In fact, removing the optical flow feature on platforms without sufficient computational capabilities only results in a

(a) Radon   (b) Structure Tensor   (c) Laws
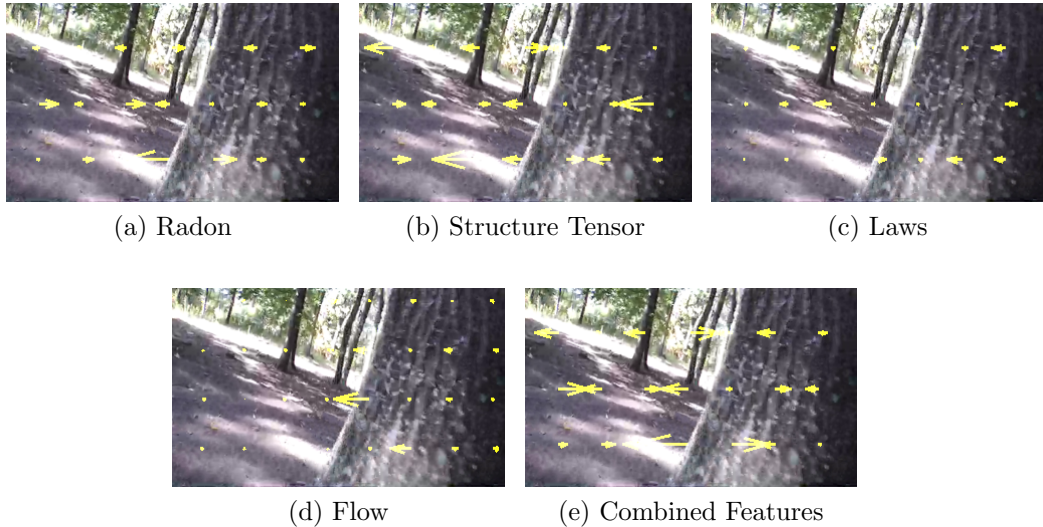
(d) Flow   (e) Combined Features

Figure 6: Visualization of the contribution of the different features to the predicted control. The overall control was a hard left command. The arrows show the contribution of a given feature at every window. Structure tensor features have the largest contribution in this example, while Radon has the least.

6.5% increase in imitation loss.

Anecdotally, Figure 6 shows the contribution of each of the features at different window centers in the image. While structure tensor features mainly fire due to texture in the background (indicating free space), strong optical flow vectors correspond to very close objects. In this example the predictor commands a hard left turn (numerical value: 0.47L on a scale of [0,1]), and all visual features contribute to this. Consistent with the above analysis, the contribution of the structure tensor was greatest (0.38L), Laws masks and optical flow contribute the same (0.05L) while Radon features provide the least contribution (0.01L). In this particular example, the non-visual features actually predict a small right command (0.02R).

4.3 Outdoor Experiments

After validating our approach indoors in the motion capture arena, we conducted experiments outdoors to test in real-world scenarios. As we could not use the motion capture system outdoors to make the drone head towards a specific goal location, we made the drone move forward at a fixed speed and aimed for learning a controller that would swerve left or right to avoid any trees on the way, while maintaining the initial heading. Training and

Figure 7: Common failures over iterations. While the controller has problems with tree trunks during the 1st iteration (left), this improves considerably towards the 3rd iteration, where mainly foliage causes problems (middle). Over all iterations, the most common failures are due to the narrow FOV of the camera where some trees barely appear to one side of the camera or are just hidden outside the view (right). When the UAV turns to avoid a visible tree in a bit farther away it collides with the tree to the side.

testing were conducted in forest areas while restraining the aircraft using a light-weight tether.

We performed two experiments with DAgger to evaluate its performance in different regions, one in a park with relatively low tree density, and another in a dense forest.

4.3.1 Low-density test region

The first area is a park area with a low tree density of approximately 1 tree per 12×12m, consisting mostly of large trees and a few thiner trees. In this area we flew at a fixed velocity of around 1m/s, and learned a heading (left-right) controller for avoiding trees using DAgger over 3 training iterations. This represented a total of 1km of flight training data. Then, we exhaustively tested the final controller over an additional 800m of flight in the training area and a seperate test area.

Qualitatively, we observed that the behavior of the drone improved over iterations. After the first iteration of training, the drone sometimes failed to avoid large trees even when they were in the middle of the image in plain view (Figure 7, left). At later iterations however, this rarely occured. On the other hand, we observed that the MAV had more difficulty detecting branches or bushes. The fact that fewer of such obstacles were seen in the training data, coupled with the inability of the human pilot to distinguish them from the background, contributed to the difficulty of dealing with these obstacles. We expect that better visual features or improved camera resolution might help, as small branches often cannot be seen in 320×240 pixel images.

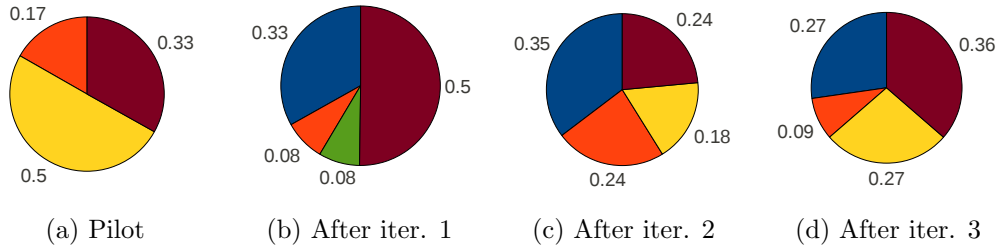(a) Pilot (b) After iter. 1 (c) After iter. 2 (d) After iter. 3

Figure 8: Percentage of failures of each type for DAgger over the iterations of training in the high-density region. Blue: Large Trees, Orange: Thin Trees, Yellow: Leaves and Branches, Green: Other obstacles (poles, signs, etc.), Red: Too Narrow FOV. Clearly, a majority of the crashes happen due to a too narrow FOV and obstacles which are hard to perceive, such as branches and leaves.
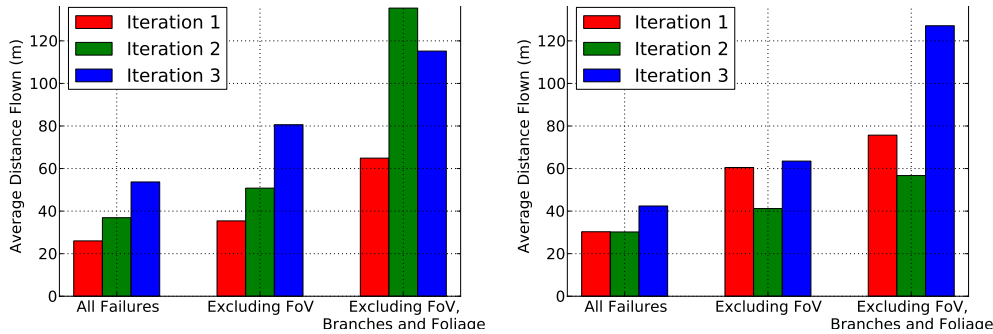

Figure 9: Average distance flown autonomously by the drone before a failure. Left: Low-Density Region, Right: High-Density Region.

As expected, we found that the narrow field-of-view was the largest contributor to failures of the reactive approach (Figure 7, right). The typical issue occurs when the learned controller avoids a tree, and as it turns a new tree comes into view. This may cause the controller to turn in a way such that it collides sideways into the tree it just avoided. This problem inevitably afflicts purely reactive controllers and could be solved by adding a higher level of reasoning [12], or memory of recent visual features.

The type of failures are broken down by the type of obstacle the drone failed to avoid, or whether the obstacle was not in the FOV. Overall, 29.3% of the failures were due to a too narrow FOV and 31.7% on hard to perceive obstacles like branches and leaves.

Quantitatively, we compare the evolution of the average distance flown autonomously by the drone before a failure occured over the iterations of training. We compare these results when accounting for different types of

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failures in Figure 9 (left). When accounting for all failure types, the average distance flown per failure after all iterations of training was around 50m. On the other hand, when only accounting for failures that are not due to the narrow FOV, or branches/leaves, the average distance flown increases to around 120m. For comparison, the pilot succesfully flown over 220m during the initial demonstrations, avoiding all trees in this sparse area.

To achieve these results the drone has to avoid a significant number of trees. Over all the data, we counted the number of times the MAV avoided a tree[1], and observed that it passed 1 tree every 7.5m on average. We also checked whether the drone was actively avoiding trees by performing significant commands[2]. 41% of the trees were passed actively by our drone, compared to 54% for the human pilot.

Finally, we tested whether the learned controller generalizes to new regions by testing it in a seperate test area. The test area was slightly denser, around 1 tree per 10×10m. The controller performed very well and was successfully able to avoid trees and perform at a similar level than in the training area. In particular, the drone was able to fly autonomously without crashing in any trees over a 100m distance, reaching the limit of our communication range for the tests.

4.3.2 High-density test region

The second set of experiments was conducted in a thickly wooded region in a local forest. The tree density was significantly higher, around 1 tree per 3×3m, and the area included a much more diverse range of trees, ranging from very small and thin to full-grown trees. In this area we flew at a faster fixed velocity of around 1.5m/s, and again learned the heading (left-right) controller to avoid trees using DAgger over 3 iterations of training. This represented a total of 1.2km of flight training data. The final controller was also tested over additional 400m of flight in this area. For this experiment however, we used the new ARDrone 2.0 quad-rotor helicopter, which has an improved HD camera that can stream 640×360 pixel images at 30Hz. The increased resolution likely helped to detect the thinner trees.

Qualitatively, in this experiment we observed that the performance of the learned behavior slightly decreased in the second iteration, but then improved significantly after the third iteration. For example, we observed more failures to avoid both thin and large trees in the second iteration compared to the

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[1]A tree is *avoided* when the drone can see the tree pass from within its FOV to the edge of the image.

[2]A tree is *actively avoided* when the controller issues a command larger than 25% of the full range, passively in all other cases.

other iterations. This is shown in Figure 8, which compares the percentage of the different failures for the human pilot and after each iteration of DAgger in this area. We can also observe that the percentage of failures attributed to large or thin trees is smallest after the third iteration, and that again a large fraction of the failures occur when obstacles are not visible in the FOV of the MAV. Additionally, we can observe that the percentages of failures due to branches or leaves diminishes slightly over the iterations, which could be attributed to the better camera that can better perceive these obstacles. A visualization of a typical sequence is given in Figure 10. Further qualitative results can be found in the supplementary material.

Quantitatively, we compare the evolution of the average distance flown autonomously by the MAV before a failure occured over the iterations of training. Again, we compare these results when accounting for different types of failures in Figure 9 (right). When accounting for all failure types, the average distance flown per failure after all iterations of training was around 40m. Surprisingly, despite the large increase in tree density and faster forward velocity, this is only slightly worse than our previous results in the sparse region. Furthermore, when only accounting for failures that are not due to the narrow FOV or branches and leaves, the average distance flown increases to 120m per failure, which is on par with our results in the sparser area. For comparison, when only accounting for failures due to tree trunks, the pilot flew around 500m during the initial demonstrations and only failed to avoid one thin tree. However, the pilot also failed to avoid thin branches and foliage more often (Figure 8). When accounting for all types of obstacles, the pilots average distance until failure was around 80m.

The increase in tree density required our MAV to avoid a significant larger number of trees to achieve these results. Over all the data, we observed that it was avoiding on average 1 tree every 5m. In this dense region, both the pilot and the drone had to use larger controls to avoid all the trees, leading to an increase in the proportions of trees that were passed actively. 62% of the trees we passed actively by the drone, compared to a similar ratio of 66% for the pilot.

The major issue of the too narrow FOV presented in this section may be addressed by two approaches in the future. First, imitation learning methods that integrate a small amount of memory may allow to overcome the simplest failure cases without resorting to a complete and expensive mapping of the environment. Second, the biologically-inspired solution is to simply ensure a wider FOV for the camera system. For example, pigeons rely mostly on monocular vision and have a FOV more than 3 times larger, while owls have binocular vision with around 1.5 times the FOV of our drone.

| MAV's on-board view | Observer's view |

Figure 10: Example flight in a dense forest area, part 1. The image sequence is chronologically ordered from top ($t = 0s$) to bottom ($t = 2.9s$) and split into the MAV's on-board view on the left and an observer's view to the right. Note the direction label of the MAV in the first frame, and the color-coded commands issued by DAgger. It can be observed that after avoiding tree A in frame 3 the vehicle still rolls strongly to the left in frame 4. This is due to the small but ubiquitous latency and should be addressed in future work to fly the MAV in even denser areas.

| MAV's on-board view | Observer's view |

Figure 11: Example flight in a dense forest area, continued. The image sequence is chronologically ordered from top ($t = 3.8s$) to bottom ($t = 6.6s$) and split into the MAV's on-board view on the left and an observer's view to the right. In frames 1-3, tree B is avoided on the left, rather than on the more intuitive right. DAgger prefers this decision based on the drift feature, which indicates that the vehicle still moves left and thus a swerve to the right would be more difficult.

5 Conclusion

We have presented a novel approach for high-speed, autonomous MAV flight through dense forest environments. Our system learns to predict how a human expert would control the aircraft in a similar situation, and thus successfully avoids collisions with trees and foliage using passive, low-cost and low-weight visual sensors only. We have applied a novel imitation learning strategy which takes into account that the MAV is likely to end up in situations where the human pilot does not, and thus needs to learn how to react in such cases. During a significant amount of outdoor experiments with flights over a distance of 3.4km, our approach has avoided more than 680 trees in environments of varying density.

Our work provides an important low-level layer for autonomous control of MAVs, which works on minimal visual input and can handle situations where 3D mapping or high-level trajectory planning fails. In future work, we want to focus on adding such higher-order layers, including receding horizon planning and semantic knowledge transfer, as well as implementing the means to handle latency and small field of view effects. This will allow us to perform even longer flights, in even denser forests and other cluttered environments.

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