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Forest Drones for Environmental Sensing and Nature Conservation

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***Abstract*— Protecting our nature and biodiversity is essential. For this purpose, remote sensing robotic platforms are increasingly explored to collect spatial and temporal data. However, there is still little attention on leveraging aerial robots to interact with trees for sample collection and targeted countermeasure deployment. In this study, we propose platforms and methodology that offer the use of aerial robots in the forests to conduct various tasks including leaf sample collection, visual sensing of forest topology and autonomous sensor placement. With the developed virtual reality (VR) interface, we show that remote environmental sensing, detection of plant pathogens, and sample collection are viable tasks that can be achieved by the proposed platforms. In this context, physical and visual sensing approaches as well as various aerial robots are introduced and discussed for forest applications.**

I. Introduction

In order to facilitate the nature conservation measures and environmental sensing, we envision the use of aerial robots for remote sensing, bio-particle sample collection, and preventive actions such as the removal of fungus-infected leaves and the deployment of disinfectants against plant pathogens. Within a single mission, an environmentally-compliant aerial robot can approach the tree, interact in a contact phase, perch on the branch, cut the spread of the infected areas and spray disinfectants. Early detection of the infections and taking a fast countermeasure are crucial for biodiversity [8]. One of the actions that awaits careful and sensitive care is the European Ash (*Fraxinus Excelsior*), a ubiquitous tree native to Britain. These species of ash tree are not only valuable in the lumber industry, but also play an important role in ensuring biodiversity. However, the European Ash is very vulnerable to the ash dieback disease (ADB). Currently, there is no cure for the disease [9] although some species of ash may possess partial tolerance to the fungal attacks. According to [10], around 80% of the UK's ash trees will eventually succumb to ADB. Therefore, devising methods to fight against ADB is a critical and active area of ash research [11]–[13]. Ash trees that are infected by ADB can be usually identified by visual symptoms on the

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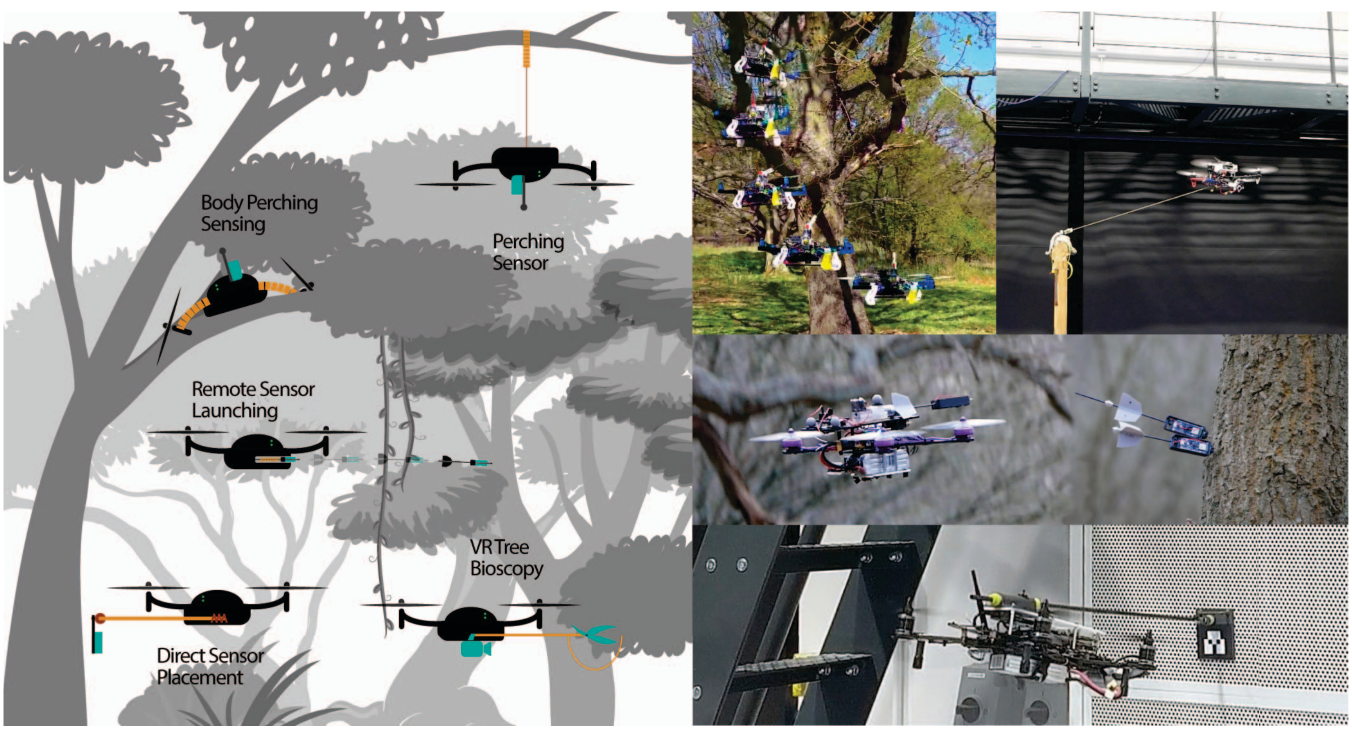

Fig. 1: Forest drones: Different platforms and approaches for remote sensing and leaf sampling. Sensor deployment methods can provide spatially sparse information on the forest. Drones capable of perching can act as a sensor for long-term data collection. The proposed leaf sampling approach provides mobility to explore the different parts of the trees including the top of the canopy for the sample collection.

tree body or crown, such as blackening patches of leaves, discoloured stems, and dieback lesion along with the tree's bark. Many of the research works involve the analysis of leaf specimens from healthy and infected ash trees. Depending on the severity of the infection, the tree could be felled to prevent further transmission.

Currently, foliar specimens are commonly analyzed by hyperspectral imaging. This technique can be used to develop an understanding of the leaf phenotype and monitor the plant's nutrient intake [14], [15]. There are several ways with which the leaf specimen can be collected from the tree. Usually, these methods are manually laborious with high associated costs and risks. The pole pruner [1] is the simplest and cheapest method. However, this method is not suitable for tall trees and it can be hard to manipulate the tools by hand for long period of time. On the other hand, tree climbing [1] allows sampling of leaf specimens from taller trees, but this requires physical fitness, additional safety equipment, and comprehensive training. Additionally, it can be difficult to sample from the extremities, that is, the branch tips. There are also more destructive sampling methods such as falling the tree or cutting down branches with ballistic projectiles [3]. However, these methods are generally undesirable as they are more dangerous to the operator as well as creating an unnecessary damage to the tree. Lastly, there are also more complex foliar sampling methods such as setting up fixed infrastructures [16] which require substantial time and cost commitment. Moreover, they can only be applied to a limited number of trees in a certain range due to the lack of mobility of the fixed infrastructure. For these reasons, they are more suitable for long-term forestry experiments for a couple of selected trees. In summary, most of the discussed leaf specimen sampling methods are manual, ineffective, destructive and may even lead to injuries to the operator. Therefore, the use of aerial robots for foliar specimen sampling may be a potential remedy to those aforementioned challenges.

One of the first examples for drone deployment of leaf sampling is a quadrotor platform with a cutting blade on an extended boom [17]. This passive mechanism cuts leaves without a method to contain the samples. Other similar but active cutting mechanism demonstrators also did not consider keeping the samples after trimming the tree [18]. These systems are more suitable to interact with the trees horizontally – they can approach from sides and collect the sampling while traversing. Recent attempts considered the use of downward tethered gripper-and-circular saw modules that are more suitable to approaching the tree canopy from above [1], [5], [19], [20]. However, these drone platforms were operated manually with the help of one or two copilots

Fig. 2: Current practices for tree sampling [1]: (a) pole pruner [2] – a long pole to collect leaf samples; (b) climber [2] – climbing on top of a giant sequoia which is one of the largest trees (220 feet) with ropes; (c) shotgun [3] – collecting by shooting cone-bearing branches from a tree; (d) line launcher [4] – setting up the tree climbing rope lines; (e) slingshot [4] – line launcher with throwing the weights; (f) hydraulic lift [5] – fork-lift sampling at various heights up to 8m; (g) helicopter [3] – collecting cones by helicopter requires additional safety equipment; (h) canopy crane [6] – tower crane built in the middle of the forest; (i) canopy raft [7] – a huge net supported by an airship and designed to be landed on the canopy.

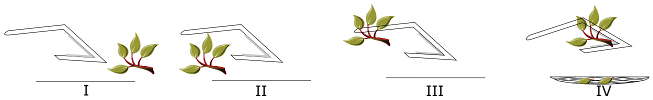

Fig. 3: VRdrone: a leaf-sampling drone in cutting sequence. The bladed mechanism can sample leaves with drone manoeuvres.

to control the sampling.

This paper summarizes the contributions of our research considering a new leaf sampling mechanism, with the use of environmentally-compliant aerial robots and computer vision algorithms for forest and nature conservation. Fig. 1 illustrates the platforms and their interaction phases. Fig. 2 shows the current field practice – our intention is to transit from these actions to deployment of our platforms.

II. Environmentally Compliant Aerial Robots

A. Leaf Sampling Aerial Robot

Our design limits the payload to allow for greater flexibility of operation in the forest. The agility of a lower payload mass aids in the movement between trees, interactions, and the deployment of countermeasures. The working configuration of the mechanism can be seen in Fig. 3 during the interaction phase. The system makes use of blades installed on the upper and lower sides to cut leaf samples while the drone moves. The first phase is based on capturing the branch in the VR view for the user. Afterwards, the drone can approach the branch while centering the branch between the hook and the basket. In the third phase, the system descends to capture the branch within the mechanism. The final phase includes controlling the pitch angle to retract the system back and cut the branch.

One of the initial configurations can be seen in Fig. 4. The mechanism is designed to be installed on the front side of the drone. The top of the sampling mechanism is connected to the hook by the rod. Different approaches, seen in Fig. 5, were tested for the sampling phase. The mechanism (a) is shaped like an oblique comb, composed of elongated teeth and slots between each tooth. The leaf petiole can pass through a slot to reach the bade which is installed at the bottom of the teeth. The mechanism (b) is a box with two rotatable blades. When the mechanism touches the branches, the inducer at the top of the blade case will be pushed away by the branches, and the leaves will be moved to the blade area. The blades on both sides squeeze each other to cut the leaf petiole. The mechanism (c) is a clip with the spring that needs to be set manually before use. The buckle is used to keep the mechanism open. The clip will close only when the trigger touches the branch.

Different materials were tested for the sample collection. As seen in Fig. 6, the first material (a) is sticky paper - when it is used in the middle of the basket, it can easily stick to leaves and twigs, and stay firm in windy conditions. The materials in (b), (c), and (e) are all rechargeable materials, which tend to attract electrons when in contact with other materials. Applying friction on these materials with wool can make them charged. The experimental results show that

Fig. 4: VRdrone: sampling drone with basket mechanism - (a) a small scale drone endowed with sampling mechanism; (b) the approaching phase; (c) homing the holding branch; (d) taking the leaf into the hook; (e) collecting the leaf phase.

Fig. 5: Leaf sampling sequences from left to right: sampling drone with basket mechanism - (a) comb-like mechanism; (b) vertical blade mechanism; (c) trap-like mechanism activated by the force.

polypropylene can adsorb some leaf fragments well, but it cannot adhere sufficiently to small branches. Errant winds would blow the leaf fragments away. The basket (d) is a fibre net, which is used to net collected leaves and is effective for different sizes of leaves and twigs.

Tests were conducted with smaller drones, seen in Fig. 7. The mechanism (a) is a hook-shaped comb. Its principle is similar to the previous hook mechanism, but it is more suitably installed in the vertical direction. An inclined blade slot is designed at the bottom of the hook and the mechanism is driven to fly upwards after the leaf enters the slots. The mechanism (b) is a clip with a magnet. There is a support rod in the middle of the shelf to keep it open. When the clip touches the branch, the support rod will be pushed, slipped off, and catch the leaves.

B. Perching on Trees

There is a growing demand for long-term spatial and temporal data collection from forests [21], but long duration navigation remains a challenge due to mobile energy storage limitations. While current aerial robots can function within the battery life limitations, a multi-modal approach has been proposed to perch and reduce or eliminate thrust requirements during data collection regimes [22]–[25]. Such perching schemes are enabled by a virtually compliant motion

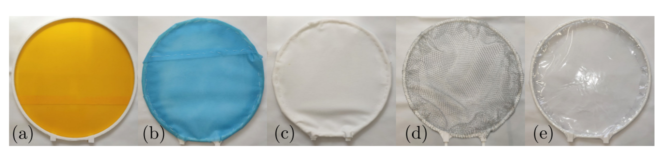

Fig. 6: Materials for basket mechanism: (a) sticky paper; (b) polypropylene; (c) PUL fabric; (d) fabric net; (e) PVC.

Fig. 7: Small drone for leaf sampling (from left to right) - (a) comb-like mechanism attached from the bottom; (b) passive trap-like mechanism for the sample collection from top.

and control scheme, allowing the aerial platforms to interact with delicate and fragile surfaces. An example of a perching application in the field can be seen in Fig. 8. The passive tensile mechanism with multiple links allows for many points of failure before an irrecoverable failure to perch. This is a robust perching hardware solution for delicate surfaces.

C. Aerial Manipulation

An aerial manipulator may facilitate precise interaction with the environment when performing inspection and sample collection. Robotic manipulators capable of stabilising the motion of an aerial platform and improving spatial positioning accuracy have been demonstrated in various applications [26] [27] including tree canopy sampling [28].

A soft system for interaction with foliage may be produced using pneumatics, shape memory alloys or electroactive polymers for actuation [29] and this can be combined with a compliant control strategy on-board the aerial vehicle [30].

D. Small and Reactive Aerial Robots

There are various platforms that are suitable for on-site forest deployment. For example, a multi-axis tilting platform can interact at different angles and apply multi-directional forces on the trees [31].

Fig. 8: SpiderMAV: A sequence of images for tensile perching [24]. With the use of microspines that holds the branches, the platform can stay in idle mode.

Fig. 9: BeeMAV: a palm-sized drone with a total weight of 158 g [32]. The platform utilizes two optical flow sensors to trigger safety actions for collision avoidance.

A palm size system that can be used to traverse in dense areas for interaction is illustrated in Fig. 9 [32]. This system leverages an on-board reactive navigation method with a lightweight sensing and computing unit (20 g). The forest provides rich sparse visual features for the optic flow sensors to sample optical flow divergence at a high rate of 160 Hz, which enables the system to react fast to the unknown dynamic environment without modelling and mapping. The inputs like visual cues, sound, light, gas, odour, and distance can help reactively traversing of these systems [33].

III. Environmental Sensing Approaches

A. Physical Sensing

Harnessing the agility of multirotor aerial robots, trees can be inspected closely by contact. By being in contact with the tree of interest, the robot can gather data directly, similar to how ecologists would do in field. Therefore, platforms for physical sensing can be incorporated to aid the ecologists during field work. In addition, sparse data acquisition can be achieved with a placed set of sensors with our sensor placement approach [34].

A commonly used tree measure is the diameter at breast height. In field, this is usually measured with large calipers or calculated from the circumference, measured with a measuring tape. Alternatively, a 200 g quadrotor with an integrated measuring wheel can measure the circumference of the tree at breast height to an accuracy of $\pm 5\%$ as compared to hand measurements.

B. Visual Sensing

A tree health monitoring pipeline was designed to provide a visual aid for the drone user during foliage sampling. As shown in Fig. 10, this pipeline features the detection of tree properties at different levels. Descriptions for the detection at each level are presented as follows:

1) *Tree-level detection:* This level of detection aims to provide a real-time tree health indicator estimation for each of the individual trees in the scene. This will act as a visual guide, telling the user which tree is potentially infected with the disease. The feasibility of real-time crown loss prediction will be explored here as many tree

diseases or pest infestations are linked to crown loss or defoliation percentage. The user can then identify which specific tree to approach based on this health indicator.

2) *Disease pattern detection:* When the drone is flying in a cluttered environment, for example, in a forest, trees are usually occluding each other. Identifying individual trees separately may not be an easy task. Hence, identifying characteristic disease patterns on the trees may be more useful for leaf sampling to avoid overlooking infected trees. For this level of detection, a case study will be carried out on the ash dieback disease to explore the feasibility of disease symptoms detection.
3) *Leaf-level disease detection:* The drone user may also wish to know the health status of leaves prior to sampling. This level of detection can help by classifying leaves based on their health status in real time.

The Plant Village data set [35] was pre-processed and used for the training of the leaf detection model. The data set consists of 54303 leaf images which were further categorized into 38 categories by species and disease. Each of the images consists of a single leaf at the centre and a label of species and health status or disease type. This form of data set is more suitable for a classification task, where a model predicts the label for a given leaf image. As a proof of concept, our focus will be on two types of common leaf diseases such as mildew and bacterial spot. Healthy leaf images are also included in the training so that the model can learn to seperate healthy and unhealthy leaves and classify the leaves based on the disease type. Several pre-processing steps were carried out to prepare the training, validation and testing data for the detection model. The high-level overview of the steps are depicted in Fig. 11, 12 and 13.

1) *Background subtraction:* This step aims to produce a black and white mask image that can be used to segment out the leaf from its background. To do this, several intensity-based foreground/background separation methods are explored. It is found out that performing *Otsu Thresholding* in the A and B channels of the LAB intensity space best separates the leaves from their respective backgrounds.
2) *Data augmentation:* Various transformations such as reflection, rotation, and translation are performed on both the mask and the original image to increase number of images in the data set by creating variations in tree leaf orientation. The masked leaf images are then pasted into different background images as shown in Fig. 12
3) *Data annotation:* By analyzing properties of the regions in the mask image, a bounding box annotation is obtained automatically, as shown in Fig. 13. Then the data set is standardized by converting it into the YOLO labelling format to enable extensive use by other researchers and practitioners.

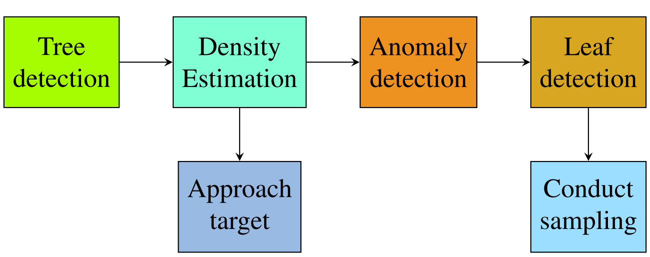

Fig. 10: Various levels of detection: the system first detects the tree to run the density estimation. If the crown loss percentage exceeds the threshold, the tree is identified as anomalous and the VR interface overlays this information for the user. The last stage is the leaf detection that will be sampled by the user.

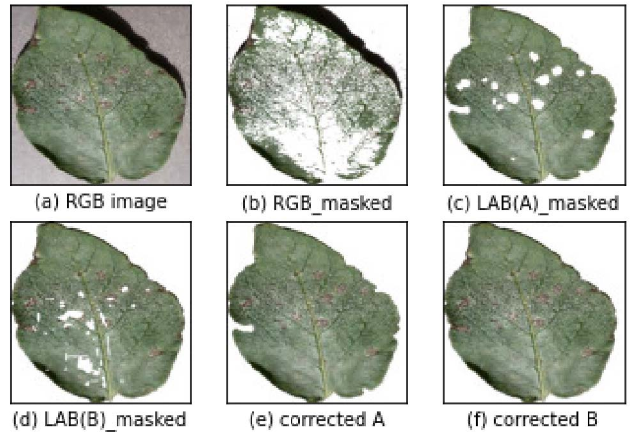

Fig. 11: Step 1: Background subtraction methods in RGB and LAB colour space: (a) Original RGB Image, (b) k-Means clustering (cluster with darker intensity), (c) Otsu thresholding on A channel, (d) Otsu thresholding on B channel, (e) corrected version of (c), (f) corrected version of (d).

Fig. 12: Step 2: Data augmentation is performed on masked leaves before pasting them into a variety of backgrounds.

For the background subtraction step, several intensity-based methods have been explored to separate the individual leaves from their background. As a reference, Fig. 11(a) shows the original RGB leaf image from the data set. In Figure 11(b) k-Means clustering (with k=2) is applied and only pixels with intensity values that are closer to the darker centroid are retained. In Fig. 11(c) and (d) the image was first converted into LAB space, Otsu's thresholding method is then applied to find the optimal threshold which maximizes inter-class (foreground and background) variance in the A and B channels respectively. The corrected versions, shown in Fig. 11(e) and (f) respectively, are the masks from Fig. 11 (c) and (d) but with holes filled by finding and filling closed contours in the mask.

The generated leaf dataset has 6000 images, it was split into 70% training, 15 % validation and 15% testing dataset by proportion. The tiny YOLO v3 model was trained on

Fig. 13: Step 3: Bounding boxes and category label are computed automatically based on where the leaves are pasted in the background images.

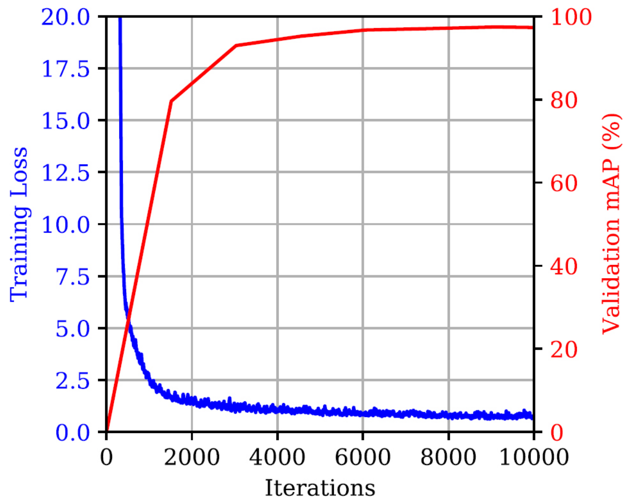

Fig. 14: Validation mAP and training loss of the leaf detection model during training.

the training dataset for 10,000 iterations. Both training loss and validation mean average precision (mAP) are kept track during training, as illustrated in Fig. 14. The trained leaf detection model was evaluated on the unseen test set. As summarised in Fig. 15, the model achieved mean average precision of 91.1%, 95.86% and 92.62% for the healthy, mildew and bacterial spot categories respectively.

For the tree-level detection, an object detection model was first trained on some tree images annotated with bounding boxes. Following the detection, the foliage density estimation model can predict the crown loss percentage for each of the detected individual trees. For this, the usage of game engine simulation is explored for two main purposes. First, synthetic data is generated using the MTree add-on in Blender for the training of the foliage density estimation model. Fig. 16 shows some examples of trees experiencing different levels of crown loss generated in Blender. The trained model will then be calibrated with annotated real tree images provided by field experts so that it can generalize well into foliage density prediction of real trees. Next, the model will also be tested in Unity VR interface where trees with known foliage density will be generated for performance evaluation as such evaluations are relatively inexpensive to run as compared to real-world deployment. Once the model's performance has reached a satisfactory level, the pipeline will be tested in the field.

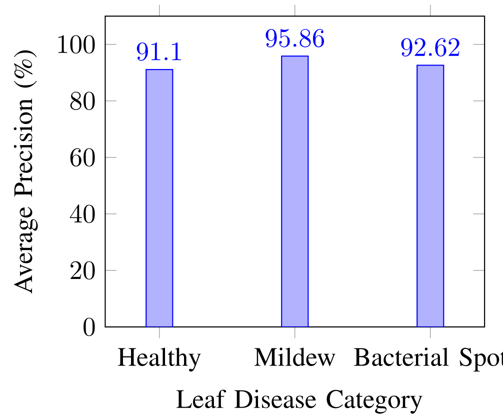

Fig. 15: Leaf detection test results: the trained leaf detection model is evaluated on an independent test dataset.

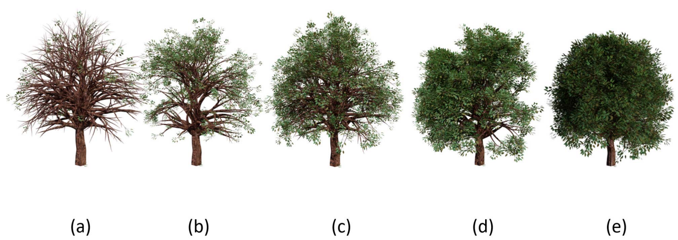

Fig. 16: Crown Loss Percentage: (a) 100%, (b) 75%, (c) 50%, (d) 25%, (e) 0%. These images are generated from Blender to train neural network for the density estimation.

C. *Virtual Reality Interface*

The VR pipeline is summarized in Fig. 17. To conduct the remote operation, a virtual private network (VPN) is used to connect the drone and the server on the same local network. Unity was the VR engine of choice for our system owing to its wide user base as an engine for VR, user interface, and game development. To enable the video stream from the platform, GStreamer is used with QGroundControl over an IP link. The platform was tested with the velocity commands given by the joystick. This was proven to perform sufficiently for remote teleoperation.

IV. Nature Conservation Measures

Considering the unaffordable cost of in-situ and ex-situ nature conservation programmes, it is crucial to take early precautions before losing the biodiversity and treat the wildlife with extreme care [36]. The ADB crisis can be mitigated if the symptoms are identified in the early stages. One of the suggestions from the forestry administration is to remove the infected leaves to save the rest of the tree. Therefore, fungus' life cycle can be disrupted, slowing down the impact of ADB [37]. In terms of more active interventions, biosecurity measures can also be applied. The guidance on the biosecurity precautions includes brush and disinfectant where they can be added to our proposed drone design similar to [26]. There are two suggested disinfectants against plant pathogens: Propellar and Cleankill Sanitising Spray [38].

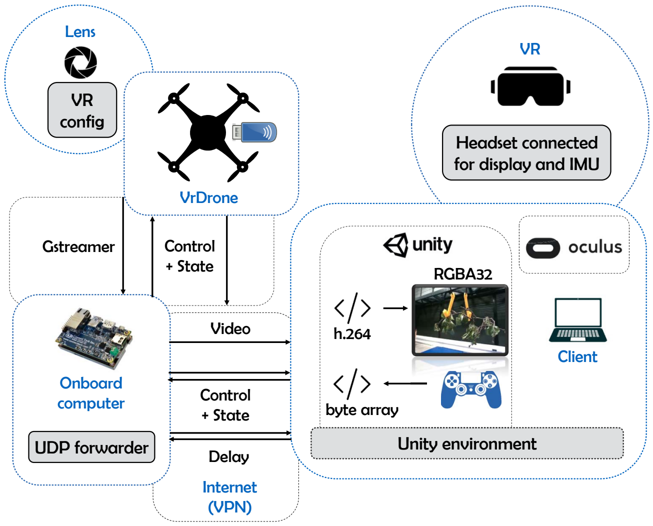

Fig. 17: VR pipeline: The system is designed for field deployment via remote teleoperation. The user and the robot share the VPN which allows them to be on the same network. The drone uses a Wi-Fi dongle and streams the video with Gstreamer libraries. The user sends the velocity commands via MAVlink, the messaging protocol for drones.

It is also possible to provide additional benefits via multi-use of the added spraying capability in our drone design. For example, oak processionary moths (*thaumetopoea processionea*) endangering the oak trees and presenting a hazard to human health can be neutralized.

Our platforms can function for various tasks including phenology monitoring [39] and pollution control [40]. Similarly; surveying, mapping and visual data collection can be achieved [41]–[48]. Handling multiple tasks require the use of more flexible control approaches, e.g, adaptive neural network [49].

V. Discussions

Considering the leaf sampling, a branch sway estimation with a more dexterous arm can also be used [28]. Furthermore, a more environment-friendly approach with a soft extension can be more beneficial [50]. One of the recent approaches is utilizing biodegradable materials for manufacturing environmental monitoring drones which can bring long-term advantages for the field deployment [51]. By using compostable and non-fossil based materials, robots can be designed that follow the circular design paradigm and ensure eco-sustainability [52], [53]. Instead of needing to dispose the robot after its application, the robot biodegrades, the stored nutrients are feed back into the nutrient matter cycle and regrowth of biomass is enabled [54]. Through strictly following this approach for the design and manufacturing, robots can be deployed in vulnerable natural environment, to which traditional e-waste represents a serious threat. Since biodiversity is one of our main concerns, there is a need for further research for the interaction phase. Since there is an intrusion to the environment during the flight, the insect reaction to this disruption could be investigated to avoid unintended biodiversity loss which is especially important as wild population sizes decline to critical levels [55].

VI. Conclusion

This paper presents our platforms and methodologies for environmental sensing and offers new possibilities with aerial robots for nature conservation. By leveraging the teleoperation approach implemented on our platforms, it is possible to traverse between trees, collect samples, and apply countermeasures. Our systems can interact with different types of trees, and operate on different parts of the trees. The laboratory and the field tests show that the proposed systems are feasible candidates for forest deployment. The data generated with the VR interface can be also used for post-processing which can help with generating new data sets for the trees.

With broadening global network connectivity, forest drones will extend from on-site control by field researchers to long range teleoperation. We would like to extend the current activities with field data collection and improve the functionalities of the platforms.

Acknowledgment

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