



Precision Agriculture Plantation Monitoring Using A Quadcopter

¹R.vishnuvardhan,²R.Arunkumar,³G.Gowthamprasad,⁴S.Kamalesh,

¹Assistant professor, ^{2,3,4}Student Scholars

¹Department of Electronics and Communication Engineering,

¹P.A College of Engineering and Technology, ¹Pollachi, ¹India.

Abstract: Quadcopters have become an essential aspect of precision agriculture due to their advanced sensors and imaging capabilities. In this paper, we offer a framework that uses supervised learning to perform plantation monitoring and yield estimation while autonomously traversing along a plantation's inter-row path. The suggested navigation system, which has been integrated with ROS (Robot Operating System), supports the quadcopter in following a sequence of collision-free GPS route points. The navigation framework's trajectory planning and control module uses convex programming techniques to build a minimum time route between waypoints and generates appropriate control inputs for the quadcopter. A new 'Mango dataset,' which includes plantation surveillance video and annotated frames showing the many stages of pomegranate growth as well as the nascent pomegranate, has been released.

Keywords – Robot, Plantation, Quadcopter, Agriculture, Imaging.

I. INTRODUCTION

Current farming approaches for yield estimation are time consuming and costly. They are inconsistent and do not scale well for large commercial farms. Precision agriculture, on the other hand, uses real-time processing of site-specific farming data to reduce input costs, increase efficiency, and is scalable for big farms. Satellite pictures have played a significant part in such real-time deployments and are widely used in today's agricultural infrastructure. However, we have recently seen an increase in the usage of quadcopters in agricultural help.

They were able to overcome some of the usual limitations of satellite photography, such as low resolution, sporadic revisit durations, and cloud-induced distortions. In the near future, quadcopters are viewed as one of the viable platforms for precision agriculture.

Currently, plant monitoring, particularly of tea leaves, is still done manually, with the foreman as supervisor of each garden block going straight to the field to inspect the tea leaves' condition. Problems such as uneven leaf colour maturity and tree loss are common in manual monitoring, resulting in a drop in the quality and quantity of tea plantations. However, with the advancement of technology, such things may now be monitored more easily in real time, one of which is the usage of UAVs or drones. Tea plantations also require a control system to aid the UAV in determining the monitoring path and assessing the findings of the tea garden monitoring.

One of the most significant contributions of our work is that it specifically addresses these issues by using colour and texture cues as feature vectors calculated over each of multiple generated candidate objects and employing a supervised learning framework for detection using SVM (Support Vector Machine). Furthermore, a quadcopter flies autonomously through the inter-row path utilising GPS waypoints at the average height of pomegranate plants while employing a monocular camera to estimate the yield of pomegranates and flower buds.

I. Drone or UAV

A UAV (Unmanned Aerial Vehicle) is a flying device that uses an autopilot and GPS coordinates to fly a pre-determined course. In the event of a malfunction or a risky scenario, the device can also be piloted manually. The word UAV is sometimes used to refer to the entire system, including ground stations and video systems, but it is most usually used to refer to model planes and helicopters with fixed and rotary wings.

What is the basic principle of drone operation?

A drone's or quadcopter's four propellers are fixed and oriented vertically. Each propeller has its own changeable and independent speed, allowing for a wide range of motion. The following are the main components of a drone:

A. Chassis

The drone's skeleton, to which all componentry is attached. The chassis design is a compromise between strength (particularly when additional weights like cameras are added) and weight, which necessitates longer propellers and stronger engines to lift.

B. Propellers

The load the drone can carry, the speed it can fly, and the speed it can manoeuvre are the most important factors. The length of the propeller can be changed; longer propellers can produce more lift at lower rpms, but they take longer to accelerate up and slow down. Shorter propellers are more manoeuvrable because they can change speeds faster; but, they require a higher rotational speed to provide the same power as longer blades. This puts too much strain on the motors, shortening their lifespan. A faster movement is possible with a more aggressive pitch, but hovering efficiency is lowered.

C. Motors

Drone motors are rated in "kV" units, which equal to the number of revolutions per minute they can achieve when supplied with a voltage of 1 volt and no load. A quicker motor spin provides more flight power, but it also consumes more battery power, resulting in a shorter flight time.

D. Electronic Speed Controller (ESC)

It feeds each motor with a regulated current to achieve the desired spin speed and direction.

E. Flight Controller

The onboard computer that reads the pilot's signals and sends the appropriate inputs to the ESC to control the quadcopter.

F. Radio Receiver

The pilot's control signals are received by this device.

G. Battery

Because of their great power density and ability to recharge, lithium polymer batteries are commonly used. Sensors such as accelerometers, gyroscopes, GPS, and barometers can also be utilised for positional measurements. Aerial photography and navigation are also common uses for cameras.

II. Drone mechanism

A drone is piloted using a handheld radio control transmitter that controls the propellers manually. The controller's sticks allow you to go in different directions, while the trim buttons let you to modify the trim to balance the drone. Screens can also be used to display sensor data and receive live video feed from the on-board camera.

In addition, on-board sensors can give useful options such as Auto altitude, which keeps the drone at a fixed altitude, and GPS hold, which keeps the drone at a fixed GPS position.

Modern flight controllers can employ software to indicate GPS waypoints that the vehicle will fly to and land or advance to a defined altitude, allowing the drone to fly independently.

III. Agriculture

Farmers and agriculturists are always looking for low-cost, effective ways to check their crops on a regular basis. Drones' infrared sensors can be programmed to assess crop health, allowing farmers to react and improve agricultural conditions on the spot with fertiliser or insecticide applications. It also enhances crop management and results in higher yields. Drones will account for roughly 80% of the agriculture business in the next few years. Inspection of power lines and pipelines: Drones can inspect a variety of systems, including electrical lines, wind turbines, and pipelines.

IV. Agricultural applications of drone

A. Soil and field analysis

Drones can be extremely useful in the beginning of the agricultural cycle. They create exact 3-D maps for early soil analysis and seed planting pattern planning. Drone-assisted soil analysis gives data for irrigation and nitrogen management after planting.

B. Planting

Drone planting solutions developed by startups have a 75 percent uptake rate and 85 percent lower planting expenses. These systems fire pods containing seeds and plant nutrients into the soil, giving the plant everything it needs to live.

C. Crop monitoring

The biggest challenge in farming is the size of the fields and the inefficiency of crop monitoring. Weather conditions that are becoming more unpredictable worsen monitoring issues, increasing risk and field maintenance costs.

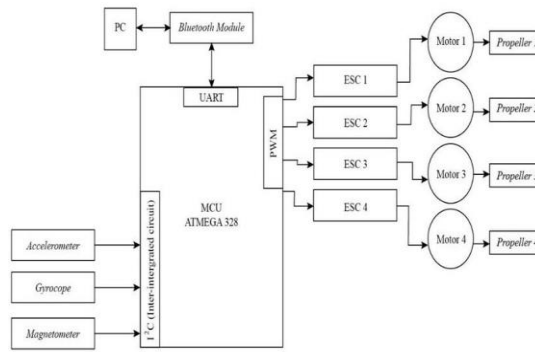


Fig.1. Block diagram of the developed quadcopters

D. Plantation Monitoring and Yield Estimation

For yield prediction, the suggested framework uses three primary stages: segmentation, feature extraction, and classification. Algorithms for segmenting fruits that are currently available work on colour or shape, both of which are affected by lighting and occlusion. Furthermore, object identification algorithms use either the sliding window method or segmentation techniques to extract several candidate items that are then analysed. Philipp et al. used automatic segmentation to generate several candidate objects N . This research inspired our suggested methodology. The current state of the art method computes superpixels and a boundary probability map that associates a boundary probability with each superpixel edge for each image. Seed superpixels are calculated among them, and foreground and background masks are created based on these. Then, across the masks with critical set among them, a signed geodesic distance transform is performed, resulting in candidate objects, which are later employed for recognition in our paper. These candidate items are fed into the trained system, which classifies them as fruit, flower bud, or other, and outputs a label L and a confidence index CI .

To make detection resistant to lighting, occlusion, and direction, our approach captures monocular cues from each candidate item, such as colour and texture traits, and saves them in the form of a histogram called the Color and Edge Directivity Descriptor (CEDD). The histogram has 144 bins, each of which is represented by 3 bits ($144 \times 3 = 432$ bits).

The textural information taken from the histogram is used to partition the histogram into six areas. Each region is further subdivided into 24 subregions, each with $624 = 144$ colour information. To get colour information, the HSV colour channel is fed into a fuzzy system. The texture data is made up of edges that are classified as vertical, horizontal, 45°, 135°, or non-directional. This histogram is used to describe the candidate item and is fed into the learning system as a feature vector.



Fig.2. Detected fruits

Real quadcopter monitoring video was used to construct a comprehensive training and testing set. The framework labels the dataset using a semisupervised strategy that involves annotating every fourth frame and propagating the findings to the remaining frames. 5000 frames are manually tagged, and the annotations are then transmitted to the remaining 15000 frames. Adjustments to the annotations (if any) are made by going back to each frame's annotations and double-checking them.

For each positive annotation, extra annotated boxes are generated by moving them by 3 pixels across 8 directions surrounding the original bounding boxes to strengthen the resilience of the training data against occlusion. As a result, a dataset of partially occluded fruits and flower buds is constructed.

Our dataset contains 25400 'pomegranate' labels, 5000 'buds' labels, and 54000 'NA' labels; we employ a 4:1 split for training and testing purposes in experiments. The many candidate objects identified by are used as an input to the supervised learning system for a given frame of an input video. Following that, the candidates are categorised as pomegranate, flower bud, or other labels. L_i , where $i = 1, \dots, N$. Candidate objects labelled as fruit or flower bud are represented by a bounding box

$Pos_j, Ar_j, L_j, CI_j, j = 1 \dots K$ and $K = N$, where K is the number of objects classified as pomegranate or flower bud, Pos_i is the top-left corner position bounding box for candidate object, and K is the number of objects classified as pomegranate or flower bud. where Ar_j is the box's area, L_j is the object's label, and CI_j is the label's confidence index. To decrease false positives, candidate objects that fall below a confidence index threshold are rejected. NMS (non-maxima suppression) is used on overlapping regions with comparable labels, with only the highest score boxes kept

V. CONCLUSION AND FUTURE WORK

A unique approach for mango plantation monitoring and yield estimation is described. Over ROS, an efficient and robust autonomous navigation framework was created that generates a shortest time trajectory between a sequence of GPS waypoints using convex optimization. The proposed approach is demonstrated in the research on a mango plantation, but it has intriguing capabilities that can be applied to a variety of plantations. The Mango dataset, as well as a navigation framework that will aid future research, will be released to the open source community. Integration of a Near Infrared Sensor (NIR) over a quadcopter to make more diverse and accurate forecasts, as well as livestock monitoring in a plantation, are two more enhancements.

REFERENCES

- [1] Chia-Che Hung, John Nieto, Zeike Taylor, James Underwood, and Salah Sukkarieh. Orchard fruit segmentation using multi-spectral feature learning. In (IROS). IEEE, 2013.
- [2] Cihan Akin, Murvet Kirci, Ece Olcay Gunes, and Yuksel Cakir. Detection of the pomegranate
- [3] John F Federici, Robert L Wample, David Rodriguez, and Suman Mukherjee. Application of terahertz gouy phase shift from curved surfaces for estimation of crop yield. Applied Optics, 2009.
- [4] N. Smolyanskiy and M. Gonzalez-Franco, "Stereoscopic First Person View System for Drone Navigation," *Frontiers in Robotics and AI*, vol. 4, no. March, pp. 1–10, 2017. [Online]. Available: <http://journal.frontiersin.org/article/10.3389/frobt.2017.00011/full>
- [5] Roberto Benedetti and Paolo Rossini. On the use of ndvi profiles as a tool for agricultural statistics: the case study of wheat yield estimate and forecast in emilia romagna. *Remote Sensing of Environment*, 1993.
- [6] Stephen R Dunn, Gregory M. Yield prediction from digital image analysis: A technique with potential for vineyard assessments prior to harvest. *Australian Journal of Grape and Wine Research*, 2004.
- [7] Savvas A Chatzichristofis and Yiannis S Boutalis. Cedd: color and edge directivity descriptor: a compact descriptor for image indexing and retrieval. In *Computer vision systems*. Springer, 2008

