Dynamic Obstacle Detection and Environmental Modelling for Agricultural Drones

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***Abstract*— Drones used in precision agricultural applications are required to fly at low altitudes where a multitude of static and dynamic obstacles are present. Real-time perception and obstacle detection are crucial to achieve collision avoidance accurately and speedily in a cluttered and dynamic environment with multiple static and moving obstacles. This paper presents a real-time obstacle detection and environmental modelling method for agricultural drones in the presence of multiple static and dynamic obstacles. A simulation experimental test bed was setup and the results of the evaluation experiments verified the capability of the proposed ellipsoidal bounding box approximation-based method for representing the environment properly with a significant reduction in volume for real-world obstacles in comparison to existing benchmark spherical bounding box approximation. Furthermore, the proposed ellipsoidal bounding box approximation method continues to perform better over benchmark spherical bounding box approximation when point clouds keep getting larger as the industry develops perception sensors of higher quality and performance.**

Keywords—Drone, Obstacle Detection, Environmental Modelling, Dynamic, Precision Agriculture

I. Introduction

Precision agriculture is a management strategy that gathers, processes, and analyzes data in real-time and uses the results to support management decision-making for improved resource utilization, productivity, and profitability.

Drones are used in many applications in the domain of precision agriculture such as, mobile data muling, crop monitoring, fertilizer and pesticide spraying and livestock monitoring etc. Apart from the inappropriate manual operation or sudden failure of the drone, the main reason for most drone accidents is obstacle avoidance failure [1]. Therefore, drones should have the capability to autonomously fly through an agricultural field while avoiding possible collisions with other entities in the field to ensure safe and reliable operation.

Furthermore, drones have to fly closer to the ground level for most agricultural applications. The environment at low altitudes in agricultural fields is complex due to the presence of a multitude of static objects such as plants, branches, fences, buildings, communication towers, lighting protectors and also dynamic obstacles such as machinery, workers, and other living beings [1]. Therefore, agricultural drones should possess an accurate and fast obstacle avoidance system that operates in real-time to avoid collisions.

Collision-free navigation of a drone in complex environments has been a widely studied research area throughout the past decade [2]. However, most drone obstacle avoidance research assume that obstacles in the surrounding environment to be either static or quasi-static [3]. At present, there are many commercial drones with obstacle avoidance features available in the market such as Skydio 2, DJI Air 2S, DJI Mavic Air 2, AUTEL Robotics - EVO II Dual 640T, etc. All of the above-mentioned drones use computer vision-based sensing systems for environmental perception. However, currently available commercial drones are also not capable of reliably detecting and avoiding moving obstacles [3]. Therefore, further research and development in the area of dynamic obstacle avoidance are required to assure collision-free navigation for autonomous drones.

Real-time perception and obstacle detection are crucial to achieve fast and accurate collision avoidance in a cluttered and dynamic environment with multiple static and moving obstacles. Furthermore, the environmental modelling system should be capable of representing the dynamic parameters of the obstacles to compute collision-free paths in the presence of dynamic obstacles. Towards these objectives, this paper presents an obstacle detection and environmental modelling system for agricultural drones in the presence of multiple static and dynamic obstacles.

The remainder of the paper is structured as follows. Section II discusses the general procedure of real-time drone obstacle detection and state-of-the-art methods and technologies, Section III discusses the related works and the common drawbacks in the existing research, Section IV describes the system architecture and methodology of the proposed system, Section V and VI present the simulation setup, results and evaluation of the proposed system. Finally, Section VII presents the conclusion on the findings of the research study.

II. Drone Obstacle Detection

The obstacle avoidance system of a drone is responsible for avoiding collisions with obstacles that appear in its flight path. Obstacle avoidance approaches for any mobile robot can be divided into two categories based on their planning stage as deliberative planning and reactive planning.

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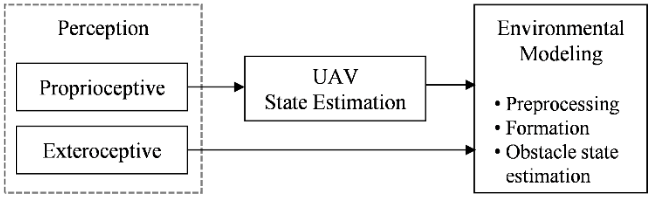

Fig. 1. General real-time drone obstacle detection procedure.

It is impractical to have an accurate map of the world with all the obstacle details including both temporal and spatial information when dynamic obstacles are present in the environment. Therefore, an obstacle avoidance system should be capable of real-time environmental perception and environmental modelling. As shown in Fig. 1, the general procedure for real-time drone obstacle detection consists of perception, drone estimation and environmental modelling.

The perception phase of the system consists of proprioceptive and exteroceptive sensors to acquire the data to estimate drone state and to model the immediate environment of the drone. The drone state estimation phase estimates parameters such as position, velocity and acceleration required in environmental modelling and also for collision avoidance planning. The environmental modelling phase is responsible for constructing a computer model that represents the obstacles and their dynamic parameters in the immediate environment of the drone. The following subsections discuss the state-of-the-art for the environmental perception and environmental modelling.

A. *Environmental Perception*

The real-time, reliable environmental perception is crucial for a drone to perform collision-free navigation in the presence of moving obstacles. Furthermore, an onboard perception layer is required for a drone to monitor its surroundings to avoid network dependency and reduce response delays. The selection of suitable sensors according to application requirements is crucial as different types of sensors have their operational advantages and performance limitations.

A comparison among sensor types taking response rate, accuracy, field of view (FOV), range, processing requirement, power consumption, size and weight as criteria is shown in Table I. The priority order of these criteria is based on the criticality of requirements in a drone dynamic obstacle detection system [3]–[6].

Response rate and accuracy of the sensor are critical when selecting an environmental perception sensor for dynamic obstacle avoidance systems. A review of technical specifications shows that event camera, millimeter wave radar and LiDAR have higher response rates and high accuracy in comparison to other sensors.

In a static environment, collision risk can be narrowed down towards the heading direction of the drone. However, when the environment consists of dynamic obstacles, they can be in collision course with the drone in any direction. Therefore, FOV has high importance when selecting a perception sensor. Among sensors that are highly accurate and fast, LiDAR has the highest FOV (Table I). Although LiDARs have a lower range than MMwave radar, their range is sufficient for low altitude applications.

TABLE I. STATE-OF-THE-ART ENVIRONMENTAL PERCEPTION SENSOR COMPARISON

Perception Sensor	Type	Response rate	Accuracy	Field of View	Range	Processing requirement	Power consumption	Size, weight
Conventional Camera	Passive	L	M	H	L	H	L	L
Event Camer (DVS)	Passive	H	H	L	L	H	L	L
Thermal Camera	Passive	L	M	L	M	H	L	L
Radar (MM wave)	Active	H	H	L	H	L	M	L
LiDAR	Active	H	H	H	M	L	M	M
Sonar	Active	L	M	L	L	L	M	L

Computational complexity should be a consideration while selecting a sensor for real-time drone obstacle avoidance applications due to limited onboard resources and the requirement of minimum response delays. In this context also LiDAR sensors including other active sensors have an advantage over passive sensors listed in Table I.

However, LiDAR sensors in standalone operating mode have a few limitations such as the inability to detect transparent obstacles that can be overcome by sensor data fusion of multiple sensors. It should be noted that sensor fusion inherently leads to higher computational and power demands, complex algorithms and an increase in payload size and weight.

B. *Environmental Modelling*

The environmental modelling or the computer representation of obstacles in the local environment of a drone is required to detect the obstacles and obstacle-free areas. A drone can be in collision course with obstacles even though they are currently situated at different altitudes when the environment consists of dynamic obstacles. Therefore, 3D environmental representation is required to ensure collision-free navigation in a dynamic environment. Furthermore, the environmental model should be updated continuously throughout a drone's journey.

While many different methods have been used for environmental modelling, most of the classical mapping techniques do not consider the dynamic nature of objects in the environment [7]. Among the few approaches that are capable of dealing with dynamic obstacles, the obstacle bounding box approximation method and dynamic occupancy grid map method are the key approaches. These two methods were reviewed for the selection of an environmental modelling method.

Dynamic occupancy grid map methods represent the environment as an occupancy grid and include dynamic information of obstacles by means of tracking each cell instead of tracking the obstacles as separate units. Each cell of a dynamic occupancy grid map stores the probability of that cell being occupied by an obstacle and the information regarding its dynamic nature such as velocity, movement and orientation. While ease of use with sensor data fusion is an advantage of the dynamic occupancy grid map method, it has inherent disadvantages of discretization errors, high computational costs and high memory requirements.

TABLE II. SUMMARY OF THE OBSTACLE DETECTION AND ENVIRONMENTAL MODELLING IN THE RECENT LITERATURE IN THE DRONE DYNAMIC OBSTACLE AVOIDANCE DOMAIN.

Research	**UAV Type**	**Altitude**	**Obstacle**			**Perception Sensor**	**FOV**		**Environmental model**		**Obstacle Velocity Estimation**
			Multiple	**Static**	**Dynamic**		**Azimuth**	**Altitude**	**2D/3D**	**Method**	
[2]	Quadcopter	NM	✓	✓	✓	EI			3D	Spherical bb	EI
[13]	Fixed wing	High	✓	✓	✓	Monocular Camera	<360°	×	2D	Circle bb	×
[9]	Quadcopter	Low	✓	✓	✓	EI			3D	Spherical bb	EI
[10]	NM	Low	✓	✓	✓	EI			2D	Circle bb	EI
[14]	Fixed wing	High	×	✓	✓	Radar	<360°	×	3D	Spherical bb	×
[22]	Hexacopter	NM	×	✓	✓	Lidar	360°	<360°	3D	Spherical bb	✓
[21]	Hexacopter	NM	✓	✓	✓	NM	360°	360°	3D	Spherical bb	✓
[3]	Quadcopter	Low	✓	×	✓	Event Camera	<360°	<360°	3D	Ellipsoidal bb	✓
[11]	Fixed wing	High	✓	✓	✓	EI			2D	Circle bb	EI
[15]	Quadcopter	Low	×	✓	✓	EI			2D	Circle bb	×
[12]	NM	NM	✓	✓	✓	Ultrasomic	<360°	<360°	2D	Circle bb	EI
[16]	Quadcopter	Low	✓	✓	✓	Lidar	360	×	2D	Circle bb	×

Obstacle complexity or the amount of information stored in a computer model to represent the obstacle affects the computational complexity. This can be measured in terms of the number of obstacle edges [8]. A common practice to reduce the complexity of computer models is to represent obstacles by bounding box approximation.

III. RESEARCH GAP

The summary on state-of-the-art in drone obstacle detection and environmental modelling for dynamic obstacle avoidance systems is shown in Table II. The absence of real-time obstacle detection [2], [9]–[12] and obstacle state estimation [13]–[16] is a common drawback in a majority of the research. A majority of drone dynamic obstacle detection and modelling systems have used obstacle bounding box approximation method due to its less computational complexity and ability to represent obstacles as separate units. However, the selection of geometric shape is important and most have selected the sphere which is the least complex model (circle in 2D case). However, a sphere is incapable of optimally representing most real world objects, which in turn can lead to limited ability for collision-free navigation in environments with narrow gaps. Falanga et al. [3] have used an ellipsoid, which is a better approximation. However, their system only detects dynamic obstacles.

IV. METHODOLOGY

As the first step in the development of obstacle detection and environmental modelling system, a technology framework for research simulation was created as shown in Fig. 2 with PX4 used as the autopilot flight stack with ROS API to develop the system. As shown, PX4 on software in the loop (SITL) was used with Gazebo as the simulator where 3DR Iris quadcopter was selected as the drone model and LiDAR as the perception sensor for the simulation. The simplified methodology diagram for the proposed obstacle detection and modelling system is shown in Fig. 3.

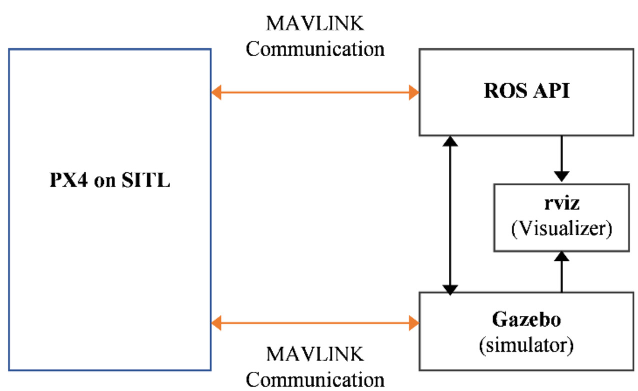

Fig. 2. System architecture

A. *Point Cloud Pre-processing*

Initially, the statistical outlier removal technique from Point Cloud Library (PCL) was used to filter out noisy data. Agricultural drones have to fly at low altitudes to support their application requirements. However, to represent obstacles as separate units with obstacle bounding box approximation, the points that represent the ground should be filtered out from the initial point cloud. A simple approach was used to segment these ground points based on the distance from the drone to ground level (obtained from a downward depth sensor). As a drone in flight has to maintain a certain safe distance from the ground level, this filtering would not eliminate the informative data required for further obstacle avoidance steps.

B. *Point Cloud Clustering*

When an environment consists of multiple obstacles, the system should cluster the pre-processed point cloud to separate the point clouds for each obstacle for an ellipsoidal bounding box approximation. This study adopted a distance connectivity based hierarchical clustering approach to group the point cloud

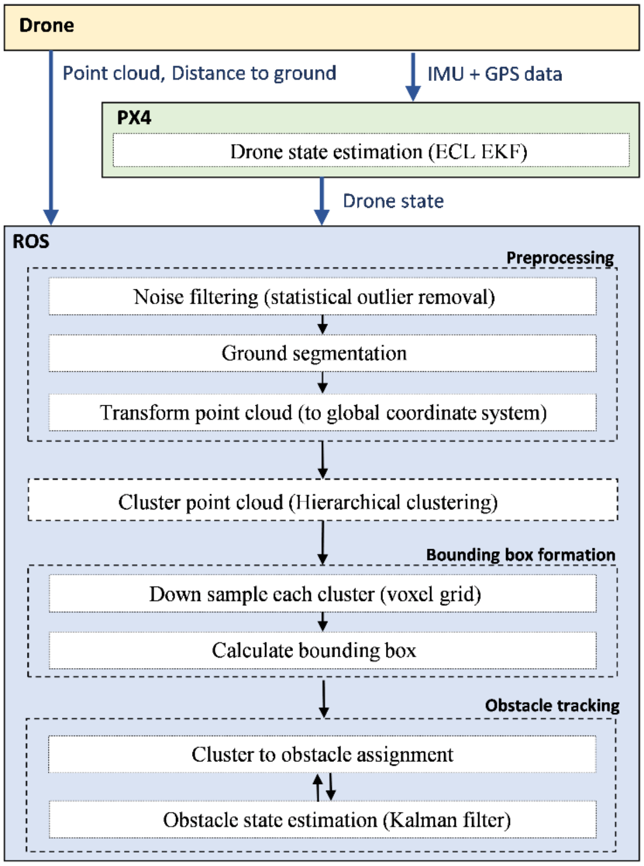

Fig. 3. Methodology

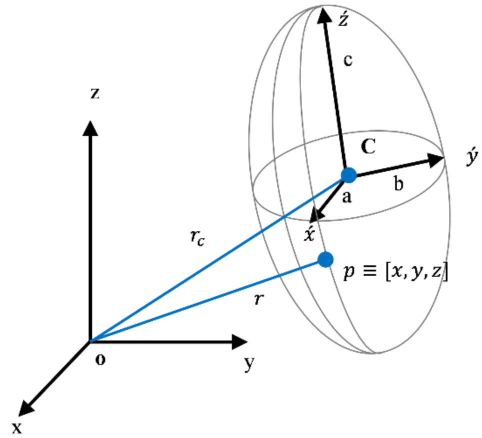

Fig. 4. Ellipsoid Notation

into clusters. The cutoff threshold was selected based on the drone size with safety distance (1m is used for the simulation). The system considers each cluster as an individual obstacle and the clusters move in space according to the movement of corresponding obstacles.

C. Bounding Box Formation

Different types of 3D geometric shapes can be used as the bounding box to represent the obstacles in the bounding box approximation based environmental modelling method. Sphere, ellipsoid, and box are a few examples of 3D bounding boxes with sphere being widely used as it is the least complex 3D model [17]. However, sphere is incapable of representing the environment properly when the obstacles are more elongated along one dimension. This may cause faulty collision risk identification, resulting in lengthy escape routes or even systems failing to plan collision-free navigation in the presence of narrow gaps.

Ellipsoid is a better approximation in the presence of elongated obstacles [8] and most obstacles found in agricultural fields such as trees, plants, poles, support structures, workers etc are typically tall and narrow in shape. Therefore, ellipsoids are a better approximation for obstacles in agricultural applications in comparison to spheres.

Multiple circumscribed ellipsoids can be defined for a finite point cloud. However, since it is preferable to have bounding boxes closely fitting to obstacles, the volume of each ellipsoid should be minimized. Furthermore, for a finite point cloud (with n points) $C = \{r_1, r_2, \dots, r_k, \dots, r_n\}$, there exists a unique minimum volume circumscribed ellipsoid known as the Löwner-John ellipsoid [18].

$$\varepsilon = \{r \mid (r - r_c)^T A (r - r_c) = 1\} \tag{1}$$

The standard form of the ellipsoid equation is (1), where *r* is a position vector of a point on the ellipsoid surface, r_c is the position vector of the centre (c) of the ellipsoid and A is a positive definite matrix (refer Fig. 4). The volume of the ellipsoid is directly proportional to the $\sqrt{(\det A^{-1})}$. Which leads to the optimization problem shown in equation (2) where r_k are the points of the point cloud. The Khachiyan's algorithm was adopted to solve this problem and approximate the r_c and A for the Löwner-John ellipsoid [19], [20].

$$\begin{aligned} &\mathit{minimize} \quad \log(\det(A)) \\ &\mathit{subject\ to} \quad (r_k - r_c)^T A (r_k - r_c) \leq 1, k = 1,2,..n \end{aligned} \tag{2}$$

Furthermore, the scale and the orientation of the ellipsoid was obtained by singular value decomposition of matrix *A*.

D. Obstacle tracking

The system should be capable of estimating the dynamic parameters of the obstacles to tackle environments with dynamic obstacles. Since the system considers each cluster as an individual obstacle, they move in space according to the movement of corresponding obstacles. However, in the presence of multiple obstacles, assigning these clusters to corresponding obstacle tracks is required to estimate the dynamic parameters of the obstacles in real-time. The standard Kalman filter was used to estimate the velocity of the obstacle tracks. The already identified obstacle tracks were associated depending on their predicted trajectory based on estimated state parameters from the Kalman filter. When a new cluster is detected by the system at an instance, then they are assigned to a new obstacle track. If multiple tracks are in the transient stage of the Kalman filter estimation, then a distance threshold is used to associate them with their respective track until the Kalman filter estimate converges. Furthermore, all obstacles are assumed to be dynamic in nature until the Kalman Filter of that corresponding track converges.

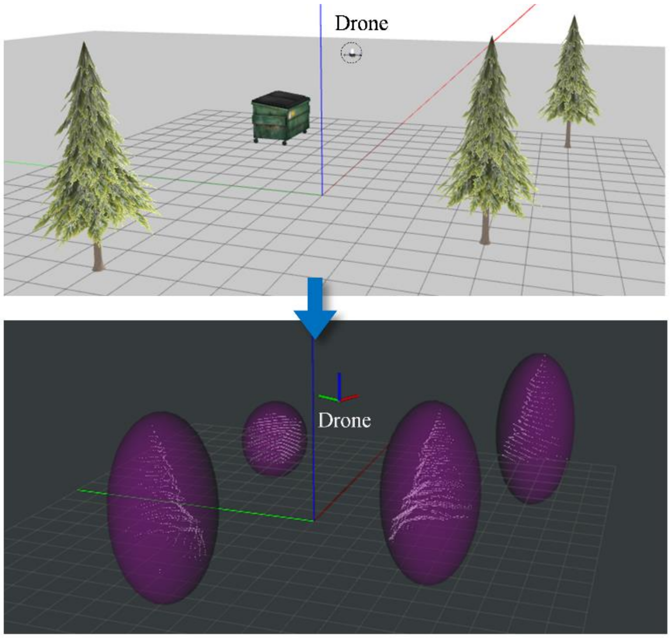

Fig. 5. Environmental model with ellipsoidal bounding box approximation

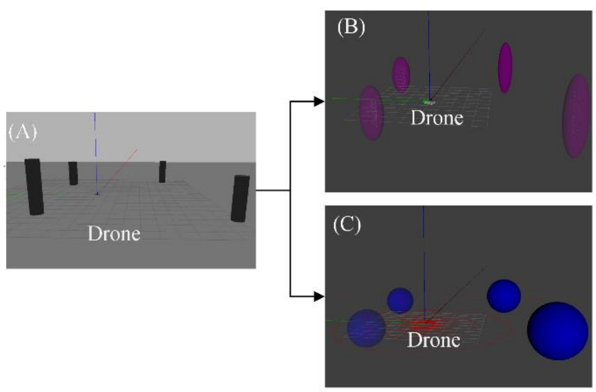

Fig. 6. Environmental model (A) with spherical bounding box approximation (B) and ellipsoidal box approximation (C).

V. Simulation Setup

The 3DR iris was used as the drone model for the simulations. The Velodyne HDL-32E sensor was used as the perception sensor for the simulation while assuming the vertical FOV of the sensor to be 180˚. Fig. 5 shows the environmental model which represents the obstacles in the immediate environment of the drone with ellipsoidal bounding box approximation.

VI. Evaluation

As discussed in the research methodology, the ellipsoid was used as the geometric shape for the obstacle bounding box as it is a better approximation for real-world obstacles over a sphere which is the least complex 3D bounding box (refer Fig. 6). A time-based analysis was carried out to check the added complexity to the obstacle detection and modelling system by this selection.

Fig. 7. Obstacle models used for the evaluation; Pine tree(A), Dumpster(B), Human(C)

TABLE III. Results of Time Based Complexity Analysis for Ellipsoidal and Spherical Bounding Box Approximation Methods.

Obstacle	No of points	Volume reduction in bb* (%)	Computational time (s)	
			Spherical bb*	**Ellipsoidal bb*** (Tol = 0.01m)
Pine tree	489	59.9	1.246	0.078
Dumpster	315	43.2	0.497	0.039
Human	42	87.4	0.011	0.026

Based on the comparison shown in Table II, the research work proposed by Park et. al [21] was selected as the benchmark research for the study. This research has used a spherical bounding box approximation-based environmental model. The position vector of the centre ($\vec{r_c}$) and radius r of the sphere was calculated using Equation (3) and (4) respectively where, ($\vec{r_1}$) and ($\vec{r_2}$) are the position vector of two points with the longest pairwise Euclidean distance and d_s is safety distance [22].

$$\vec{r_c} = \frac{\vec{r_1} + \vec{r_2}}{2} \tag{3}$$

$$r = \frac{\|\vec{r_1} + \vec{r_2}\|_2}{2} + d_s \tag{4}$$

The obstacle bounding box approximation for 3 obstacles; pine tree, dumpster and human (refer Fig. 7) were carried out by placing them at a 10m distance from the drone for time-based complexity analysis. The simulation results in Table III shows that as the point cloud gets larger, the ellipsoidal bounding box formation performs better in comparison to the spherical bounding box formation. Further, the volume of the bounding box has reduced significantly for all 3 obstacles, which gives the capability to the obstacle avoidance system to navigate the drone through narrow gaps due to obstacle bounding boxes closely representing the real shape of obstacles.

Two cylindrical objects, which are 0.3m, 0.5m in radius and 2m, 1m in height, respectively, were used to test the system's capability to tackle environments with multiple dynamic obstacles. The velocities of the obstacles were set to < 1.5, 0.5, 0 > ms^{-1} and < -1, 1, 0.5 > ms^{-1} respectively for the experiment. The system was capable of assigning the obstacle tracks accurately and estimating the velocities of the obstacles with greater accuracy as shown in Fig. 8.

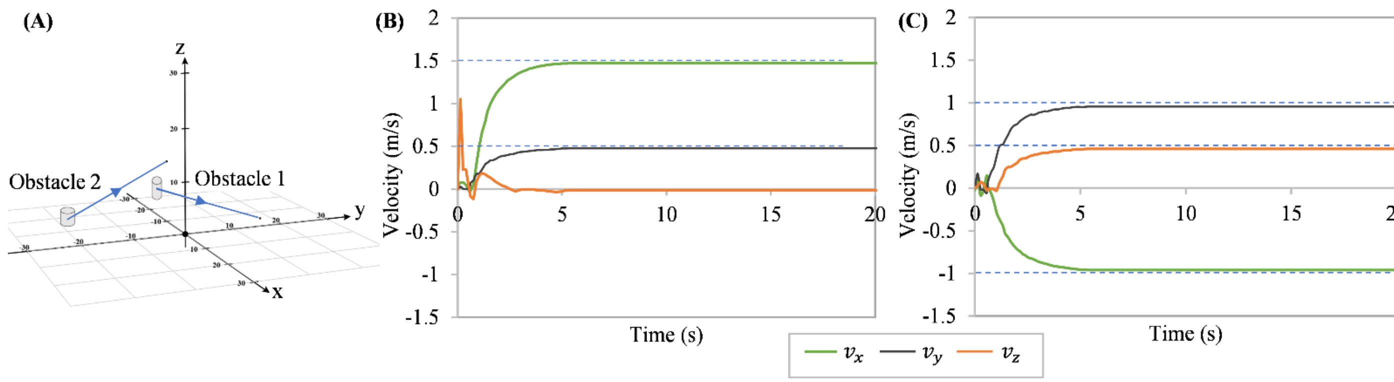

Fig. 8. Obstacle state estimation results. (A) Obstacle path. (B) Velocity estimation for obstacle 1, (C) Velocity estimation for obstacle 2.

VII. Conclusion

This paper presented a real-time obstacle detection and environmental modelling method for precision agriculture drones in the presence of multiple static and dynamic obstacles. The proposed system adapts the obstacle bounding box approximation method as the obstacle modelling method due to its multiple benefits over most other classical mapping techniques that do not consider the dynamic nature of the obstacles and computational simplicity requirement. The proposed system has selected ellipsoid as the geometric model for bounding box approximation considering its capability to represent the real world objects more accurately over the widely used spherical model.

A time complexity based analysis was carried out to evaluate the added complexity to the proposed environmental model due to the selection of ellipsoid as the bounding box over much simpler shape of a sphere. However, the results verified that the proposed method can perform better with large point clouds which is an added advantage when working with high-quality perception sensors. Furthermore, a significant reduction in bounding box volume could be achieved which increases the system's capability to navigate in environments with narrow gaps and multiple obstacles. Moreover, the system could estimate the velocity of multiple dynamic obstacles accurately.

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