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A Literature Review on the Usage of mmWave Radar in UAV's Detect-and-Avoid Applications

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Abstract: In the implementation of obstacle avoidance mechanisms in Unmanned Aerial Vehicles (UAVs), many researchers have focussed on the use of sensor fusion technology, but this method indeed requires more on-board sensors, and hence limiting the allowable payload on the UAV. The advancement in chip fabrication technology has further improved the performance of mmWave Radar sensors, enabling it to be one of the states-of-the-art sensors in UAV application. Thus, this paper aims to study the various methods used in detect-and-avoid (DAA) algorithm of a UAV and explore the use of mmWave Radar as the only perception sensor for obstacle avoidance operations on a UAV. In this paper, the DAA methods studied are categorized based on the three stages in DAA: obstacle detection, obstacle state estimation, and obstacle avoidance path generation. Based on the survey performed, some researchers have started exploring the possibility of using only mmWave Radar sensor on a UAV, while there exists certain trade-offs among the common methods used for obstacle state estimation. Meanwhile, mmWave Radar can be used with various obstacle avoidance algorithms including those AI-based and geometric-based. In short, work that solely based on mmWave Radar is still relatively unexplored, and it should be studied more to realize it as a standalone perception sensor on UAVs.

Keywords: mmWave Radar, Unmanned Aerial Vehicles, detect-and-avoid, obstacle detection, obstacle state estimation, obstacle avoidance.

1. Introduction

An Unmanned Aerial Vehicle (UAV) is an aircraft that flies without carrying any human pilot or passengers. Typically, a UAV is also known as a drone. In recent years, numerous possible applications of UAVs have been researched and developed as it brings many benefits to human being. Some advantages of UAVs include reducing danger and health risks in high-altitude inspections, providing in-depth and detailed data, flexibility for quick inspections, and increasing accessibility to hard-to-reach locations [1]. For instance, Malle et al. [2] discussed onboard powerline perception systems for UAVs, whereas Yi et al. [3] researched the use of UAVs in substations and domestic power systems.

Nowadays, the applications of UAVs are extensive, including the delivery of Automated External Defibrillators (medical sector) [4], the monitoring of the coastal line (environmental sector) [5], and the automated building inspections (construction sector) [6]. Meanwhile, Norasma et al. [7] discussed the various applications of UAVs in the agriculture sector, such as monitoring the agriculture field and mapping changes to land cover. On top of that, in a survey done by Shakhatreh et al. [8], eight applications of UAV were discussed thoroughly in terms of the challenges faced, as well as the research trends and future insights. Thus, it is clear that UAVs have many applications that can bring benefits and conveniences to human life.

However, to operate a UAV in Malaysia, specific rules set by the Civil Aviation Authority of Malaysia (CAAM) must be obeyed. According to CAAM [9], the maximum altitude that a small UAV can fly in Malaysia is 400ft or 120m above ground level. However, such low-level flight activities often encounter a variety of natural and man-made obstacles like trees, hills, buildings, transmission lines and pylons [10]. Other than these static obstacles, dynamic obstacles such as birds and other UAVs can also be encountered during low-level flights. Thus, UAVs need an efficient Detect and Avoid (DAA) algorithm to avoid any collision during their flight. With the DAA approach, the UAV will not have any prior information regarding the plan for other UAVs' obstacles. This is because it focuses on reducing the computational power required in a UAV so that the UAV can make run-time decisions. Due to its quick reaction and short response time, the DAA approach is suitable for a dynamic environment, especially when dealing with sudden dynamic obstacles.

Typically, the collision of a UAV with obstacles during its flight leads to severe problems, including property damage, injuries and even death [11]. Whenever a collision happens, there is a high possibility that the UAV will lose control and fall from a high altitude. When that happens, the falling UAV might hit any person or other living organisms like dogs and cats, injuring them badly. In the most severe case, the falling UAV might take away their lives on the spot. Due to that, many researchers have been working actively to develop efficient and effective UAV DAA algorithms so that they can be deployed for a specific autonomous task without any safety concerns. Generally, a DAA algorithm consists of three main stages [11], namely obstacle detection stage, decision-making stage, and avoidance path generation stage.

In order to learn more about the recent advancement in DAA algorithms used in UAV, several related research articles have been studied and analysed. These related works studied are generally categorised into three, namely obstacle detection, obstacle state estimation and obstacle avoidance algorithms. These sections are, in fact, correlated with the stages involved in a complete DAA algorithm.

The remaining of this paper is organised as follows. Section 2 reviewed UAV obstacle detection methods that use a Radar sensor as its perception sensor. Next, several common techniques that can be used to predict the next state of the obstacle detected are discussed in Section 3. Meanwhile, Section 4 will present some of the recent works that focus on obstacle avoidance algorithms for UAV. Finally, Section 5 will conclude the work presented in this paper and provide directions for future research related to DAA algorithm in UAV applications.

2. Obstacle Detection

Recently, Radar sensor has been given much attention in being used as perception sensor in various autonomous applications such as robotic cars, surface vehicles, ground vehicles, and UAVs. In this context, only Radar based UAVs will be focused on in this section. Table 1 summarizes some of the UAV works that use Radar as its perception sensors. Some of them are solely based on Radar sensors, while the rest utilized the fusion of mmWave Radar and other sensors.

Table 1. Works that use Radar as its perception sensor

Reference	Sensor(s)	Application
Krishnan and Manimala, 2020 [12]	Radar	Obstacle avoidance, path planning
Li et al., 2021 [13]	Radar	Object tracking, path planning
Yu et al., 2020 [14]	mmWave Radar, monocular camera	Obstacle avoidance
Wessendorp et al., 2021 [15]	mmWave Radar	Obstacle avoidance
Sun et al., 2022 [16]	mmWave Radar	Object 3D reconstruction
Huang et al., 2021 [17]	mmWave Radar, monocular camera	Obstacle avoidance
Wang et al., 2021 [18]	mmWave Radar, monocular camera	Obstacle detection
Bigazzi et al., 2022 [19]	mmWave Radar, stereoscopic camera	Obstacle detection
Malle et al., 2022 [2]	mmWave Radar, RGB camera	Object detection

Krishnan and Manimala [20] have presented a new optimized path-planning algorithm for UAVs to avoid static and dynamic obstacles. In their work, the UAV manoeuvres are solely based on Radar data, and no prior terrain data is obtained. While travelling at a speed of 15m/s, the ego UAV possesses an early detection mechanism. It uses a Radar with a 10km range to capture any pop-up stationary or moving threats. In this case, they modelled a single stationary obstacle by using a sphere with a safe radius. In contrast, the dynamic obstacles are modelled using a 6-DoF UAV model.

Next, Li et al. [13] have proposed an online path-planning approach that is based on the combination of deep reinforcement learning (DRL) and transfer learning (TL). In fact, their work focuses on tracking dynamic ground targets via UAV. The real-time motion information of the target is obtained continuously through the Radar sensor. In the simulation conducted, the initial velocities of the ego UAV and the target ground vehicles are both set to 20 m/s.

On top of that, an autonomous obstacle avoidance mechanism that utilizes the fusion of Radar and the monocular camera has been proposed for UAV applications in work by Yu et al. [14]. According to them, vision-based obstacle detection that implements deep learning methods suits more in the autonomous driving application rather than the drone application as drones face more unknown flying obstacles in large outdoor environments. In their work, the visual detection part is done via feature point extraction and matching, followed by optical flow tracking to compute the displacement of the feature points between successive frames. Then, the normalized point cloud of all feature points is then clustered using Density-Based Spatial Clustering of Applications with Noise (DBSCAN) to detect different obstacles. Following that, Extended Kalman Filter (EKF) is used to fuse the data obtained from the camera and the mmWave Radar data. From the data fusion, they can obtain both the outline information and the real-world coordinates of the obstacles. One limitation of their work is that it focused on detecting static obstacles only.

Meanwhile, an obstacle avoidance scheme is proposed for MAVs that use frequency-modulated continuous-wave (FMCW) mmWave Radar as its only perception sensor [15]. According to Wassendorp et al. [15], Radar sensor is more robust in sensing the environment, as compared to cameras which fail when dust, fog or smoke present in the sensing environment. In the paper, they did mention that the data obtained from the mmWave Radar sensor is noisy. Thus, fine-tuning and filtering are needed to retrieve useful information from the Radar data for DAA applications. In their work, the range and radial velocity of the detected obstacles are obtained through the fast-Fourier transform (FFT). However, they only ran the trial tests of their proposed algorithm in an indoor environment. In order to achieve better obstacle detection, the authors have suggested the use of 77GHz FMCW radars, which feature improved bandwidth and resolution. Besides, the DBSCAN clustering technique is also recommended to enhance the accuracy further

Other than the work by Wassendorp et al. [15], Sun et al. [16] also use a similar FFT approach in processing the raw Radar signals. They have been exploring the viability of using an mmWave Radar sensor mounted on a UAV to reconstruct the 3D shapes of several objects in space. In their work, the raw Radar data is processed using FFT to get a collection of heatmaps or energy intensity maps. The heatmaps are then passed to a deep neural network model for the generation of dense point cloud. The work in [16] focuses more on the 3D shape reconstruction of static objects like cars and desks.

Another obstacle avoidance approach based on an improved A* algorithm was presented by Huang et al. [17] for plant protection UAVs. In fact, their proposed algorithm utilized the fusion of mmWave Radar data and monocular camera data. According to the authors, mmWave Radar can measure the distance of the obstacle accurately, while the camera can provide detailed image information, making them a good combination for environment perception. The information of the obstacle like distance and contour, is obtained after several processing stages, such as data fusion, Canny edge detection and morphological filter. The data fusion part can be subdivided into spatial data fusion and time fusion. In their work, the mmWave Radar used has a distance range of 1m to 30m, while the range accuracy is rated at 0.05m. In terms of angle range, the mmWave Radar can achieve $\pm 25°$ in the horizontal direction and $\pm 15°$ in the vertical direction. On top of that, the mmWave Radar sensor used operates at a sampling frequency of 90Hz. However, their work is only tested on static obstacles like trees and poles.

Another work that utilized data fusion of mmWave Radar and a monocular camera are illustrated in the work by Wang et al. [18], who research about UAV obstacle detection method. In this work, the mmWave Radar is used to detect the distance and the position angle of the obstacle, while the camera is used to capture the image of the obstacles. For the data fusion part, the target point information retrieved from the mmWave Radar is then calibrated into the image captured from the camera. Following that, the proposed Sobel operators-based edge detection algorithm is used together with the image grayscale frequency saliency map to segment the area of the obstacle in the images. This work also focuses mainly on the detection of static obstacles only.

Meanwhile, Bigazzi et al. [19] also presented another obstacle detection system UAV that is based on sensor fusion. Based on their findings, a visual system is capable of providing a high-resolution image, but it only works for short distances. In contrast, the Radar system has a lower resolution, but it covers greater range and is less sensitive to poor lighting conditions. Due to these complementary characteristics, the authors try to fuse a stereoscopic camera and mmWave Radar for obstacle detection applications in a UAV. The stereoscopic camera used can achieve an operating range of up to 40m, and the detection via this visual system is done based on the depth flow and the RGB optical flow. On the other hand, the Radar used has a range resolution of 0.5m with a maximum detection range of 120m while having 10Hz frame periodicity. In their work, the visual system and the Radar system can work independently as an obstacle detection subsystem, utilizing a Vision local map and a Radar global map, respectively.

Next, Malle et al. [2] have also developed an onboard powerline perception system on a UAV system that utilized mmWave Radar, and FPGA accelerated vision. Based on their paper, FMCW mmWave Radar can give long-range 3D measurements and can detect small cables with 1cm diameter at more than 10m. Despite the positional data obtained from the mmWave Radar, the data is very sparse, and it is difficult to retrieve the direction information of the powerline cables. Thus, an RGB camera is utilized to evaluate the powerline direction visually. The camera captures the images at a frequency of 10Hz, and they are processed using a Canny edge detector on the onboard computer. Then, the resulting grayscale image is fed into the Hough Line Transform accelerator on the FPGA to obtain the position and angle data of the line detected based on the pre-set threshold value. With that, UAVs can navigate safely near powerlines, detecting more cables at greater distances while being lightweight, low power consumption, and low cost.

3. Obstacle State Estimation

This section discusses a few common techniques that can be used on UAVs to predict the next state of the obstacles detected. Based on the prediction, a decision can be made whether to perform the avoidance manoeuvre or not. For this section, the UAV works studied are not limited to the use of mmWave Radar as a perception sensor only. It also includes works which use other sensors like 3D LiDAR and visual cameras, as summarised in Table 2.

Table 2. Common methods to predict obstacles state

Reference	Sensor(s)	Method for state estimation
Aldao et al., 2022 [12]	3D LiDAR	Polynomial regression, decision tree method
Mac et al., 2019 [21]	Camera	Cumulative moving average filter
Opromolla and Fasano, 2021 [22]	RGB Camera	Local frame-to-frame matching, multi-temporal filter, Kalman filter
Chen and Lu, 2022 [23]	RGB-D Camera	Kalman filter with feature vector
Deng et al., 2020 [24]	Monocular camera	Pixel motion estimation, Kalman filter
Wang et al., 2022 [25]	Monocular camera	Kalman filter
Malle et al., 2022 [2]	mmWave Radar, RGB camera	Kalman filter
Yu et al., 2020 [14]	mmWave Radar, monocular camera	Extended Kalman filter

Aldao et al. [12] proposed an obstacle avoidance algorithm for the navigation of UAV in dynamic indoor environments based on a 3D LiDAR sensor. In their work, whenever the sensor detects a new obstacle, the measurements of the sensors will be fit to a polynomial regression model to forecast the future position of the detected obstacles. However, note that a high-order polynomial will overfit the measurements output from the sensors, while a low-order polynomial might not give the correct representation regarding the motion of the obstacles. Thus, the authors used a decision tree methodology to determine the appropriate order for the polynomial.

Meanwhile, Mac et al. [21] have presented a method for UAVs to detect obstacles and estimate its position and velocity based on an onboard vision system. According to the authors, they cannot manage to install extra advanced sensors on the UAV to recognize unknown moving obstacles due to the weight restrictions of the UAV. Because of that, they marked the moving obstacles with coloured paper so that the obstacles could be detected by the visual camera mounted at the bottom of the UAV. In their work, the position and velocity information of the obstacles are estimated by performing various filters on the captured image. For instance, a cumulative moving average filter is applied to properly estimate the velocity of the detected obstacles. In their work, the UAV is used to detect and estimate the states of a ground robot driving at a constant speed of 0.2 m/s. Based on the results, accurate velocity estimations can be obtained for the detected dynamic obstacles when delays are considered.

Apart from that, Opromolla and Fasano [22] have discussed visual-based obstacle detection, tracking and conflict detection in small Unmanned Aerial System (UAS) for sense and avoid applications. In their work, the obstacle tracking part consists of tentative tracking and firm tracking. The tentative tracking is performed via local frame matching and multi-temporal filtering. In fact, the frame differencing technique used for the transition to firm tracking requires lower computational effort as it uses only two consecutive image frames in each operation. Meanwhile, the firm tracking depends on two linear Kalman filters, which extracts the azimuth and elevation information of the intruder in North-East-Down (NED) coordinate system.

Next, the use of the Kalman filter is also seen in the work by Chen and Lu [23], which focused on UAV navigation. They managed to perform real-time identification and avoidance of both stationary and moving obstacles at the same time. The method that they proposed uses the point cloud data generated from an RGB-D camera. According to them, most existing works that use point cloud data from a depth camera match the obstacle based on the centre point of the obstacles only. Thus, it depends heavily on the Kalman filter in predicting the position of the dynamic obstacles as time elapsed. Hence, they introduced the feature vector, which is much better in terms of matching robustness and accuracy.

On top of that, Deng et al. [24] have proposed a global optical flow-based method to estimate the velocity of multicopters using monocular vision in GPS-denied environments. Their work first performs pixel motion estimation by identifying the global optical flow from successive images. Following that, a classical linear Kalman filter is used to fuse all data available and estimate the velocity of the ego multi-copters. Based on the paper, it is assumed that the estimation system is almost linear with the use of the classical linear Kalman filter. In order to consider the nonlinearity case, the authors have suggested using an extended Kalman filter or particle filter for velocity estimation. In addition to Deng et al. [24], the work by Wang et al. [25] has also applied the Kalman filter in its proposed sense and avoid method for UAV which uses a low-cost monocular camera. In this work [25], the position and velocity information of other dynamic obstacles can be obtained with the help of the Kalman filter.

In terms of UAV works that use mmWave Radar as its perception sensor, Malle et al. [2], who worked on the powerline perception system as discussed in Section 2 has also implemented the Kalman filter in its sensor fusion part. Specifically, it uses one Kalman filter to predict the powerline direction and another Kalman filter to estimate the position of every detected cable. In their work, these estimations are performed by utilizing the classical low-order Kalman filters, which are less computationally intensive. Other than Malle et al. [2], Yu et al. [14] has also applied an extended Kalman filter to fuse data from mmWave Radar and monocular camera, so that the exact 3D coordinates of the detected obstacles can be retrieved.

4. Obstacle Avoidance Algorithm

This section presents some of the recent obstacle avoidance algorithms that have been used on UAVs. As presented in Table 3, the algorithms discussed here are not constrained by the perception sensor used on the UAV. However, extra attention is given to work that uses mmWave Radar sensors.

Yu and Lu [26] have presented an improved artificial potential field (APF) method for a 3D environment obstacle avoidance trajectory planning of a UAV. In the traditional APF method, the destination of the UAV will exert an attractive force on the UAV while the obstacles will exert a repulsive force on the UAV. Then, the resulting force of these two forces will determine the avoidance path for the UAV. However, according to Yu and Lu [26], the traditional APF method is impractical in avoiding dynamic obstacles. In their work, they modified the traditional spherical repulsive field of the APF method into a repulsive ellipsoidal field. In their method, the UAV is surrounded by a virtual ellipsoidal repulsive field whereby the velocity of the UAV determines the magnitude of the field. With that, the obstacles appear at the edges of the ellipsoidal potential field are not having the same distance to the UAV, enabling the improved APF to provide greater repulsive influence on the obstacles positioned at region with higher collision possibilities. From their work, the improved APF method has successfully optimised the number of nodes and the total length of the avoidance trajectory. However, they did not address the local minimum problem that is commonly seen in APF approach.

Next, there are also works that used artificial intelligence (AI) optimisation-based methods in generating the obstacle avoidance path. For instance, Yu et al. [14] presented an autonomous obstacle avoidance algorithm for UAV by combining bidirectional Rapidly exploring Random Tree (RRT) algorithms and bidirectional RRT Star (RRT*) algorithms. The bidirectional RRT algorithm was introduced to improve the search speed of the original RRT algorithm by using two separate fast-expanding random trees that grow from the initial state point and the target state point, respectively. Meanwhile, the RRT* algorithm uses a cost function in the selection of parent node. Besides, the RRT* algorithm can converge to the optimal solution with real-time performance. By combining these two algorithms, the bidirectional RRT* (Bi-RRT*) algorithm is able to enhance the computing efficiency of the original RRT algorithm while ensuring optimality. In the paper published, the path generated from the Bi-RRT* algorithm is further smoothed using the Cantmull-Rom algorithm. Based on the result, the proposed Bi-RRT* algorithm can plan the avoidance path for UAV within 1s, hence making it suitable for real-time application.

Table 3. Obstacle avoidance algorithms for UAVs

Reference	Sensor(s)	Algorithm
Yu and Lu, 2021 [26]	-	Improved Artificial Potential Field (APF)
Yu et al., 2020 [14]	mmWave Radar, monocular camera	Bidirectional Rapidly Exploring Random Tree Star (Bi-RRT*) Algorithm
Krishnan and Manimala, 2020 [20]	Radar	Particle Swarm Optimization based Collision Avoidance (PSO-CA) Algorithm
Huang et al., 2021 [17]	mmWave Radar, monocular camera	Improved A* Algorithm
Aldao et al., 2022 [12]	3D LiDAR	Modified A* Algorithm
Guo et al., 2021 [27]	-	Circular Arc Trajectory Geometric Avoidance (CTGA) Algorithm
Chen and Lu, 2022 [23]	RGB-D Camera	Forbidden pyramid
Wessendorp et al., 2021 [15]	mmWave Radar	Velocity obstacle (VO)
Wakabayashi et al., 2023 [28]	Radar or depth camera	Chance-constraints based on obstacle velocity (CCOV)

On top of that, Krishnan and Manimala [20] presented a novel Particle Swarm Optimisation based Collision Avoidance (PSO-CA) algorithm to be applied in UAVs for secure navigation in the dynamic outdoor environment. In their work, the authors have considered both pop-up stationary and moving threats that can be encountered by a UAV during its flight. Besides, the need for a heuristic algorithm that is free from being trapped in a local minimum has been addressed. Other than that, the algorithm is also tested against scenarios with multiple collisions. Based on the results, the PSO-CA algorithm can obtain the optimised waypoint of the avoidance trajectory with the best safety criteria and shortest path length. It can detect obstacles and identify alternative paths well in advance whenever an unknown pop-up threat appears. Since the PSO-CA algorithm is simple and requires less computation time, it suits well in the obstacle sense and avoids application which has strict real-time constraints.

Besides, the A* algorithm is another popular AI-based path-planning algorithm for UAVs. The traditional A* algorithm requires numerous search nodes, leading to lower efficiency. Furthermore, in order to achieve the shortest path length, the traditional A* algorithm has more inflexion points, and that causes unsmooth and instability flight. Due to that, Huang et al. [17] have proposed an improved A* obstacle avoidance algorithm. In their work, the weight of the estimated cost is adjusted dynamically by using a dynamic heuristic function, according to the distance between the current point and the target point. Besides, they applied search point optimisation to minimise the number of search nodes. Meanwhile, they also optimise the number of inflexion points so that the turns can be reduced without increasing the avoidance path length. Based on the results, the improved A* achieved a significant reduction in data processing time.

Aldao et al. [12] have also developed a 3D path planning algorithm for UAVs by modifying the traditional A* algorithm. In this work, the modified A* algorithm is used as an obstacle avoidance algorithm for UAVs to navigate in a dynamic indoor environment. To speed up the computation process, the UAV is first loaded with a pre-processed model of the static indoor environment. Then, the dynamic avoidance manoeuvre will be performed during the flight based on the information gathered through the onboard 3D LiDAR sensor. Based on the results, the computed trajectories are optimally generated in terms of time deviation and position deviation from the planned route. Yet, this method does not optimise the avoidance path in terms of power consumption. Furthermore, the flight controller used in this case must also have the excellent memory capacity to store the entire pre-processed model of the static indoor environment.

Apart from the AI-based approach, there is also an obstacle avoidance algorithm developed based on a geometric approach. For a geometric-based obstacle avoidance algorithm, the location and velocity information of the UAV and the obstacles are used in simulating the obstacle-avoiding trajectories. It analyses the geometric attributes of the UAV and the obstacle to ensure that the minimum distances between them are not breached. Typically, this can be accomplished by computing the time to collision by utilising the distance between the UAV and the obstacles and their respective velocity. For instance, Guo et al. [27] proposed a geometric-based approach for obstacle avoidance in UAVs. In his proposed algorithm, the obstacles detected are modelled into the convex body, such as a cone, cylinder, and hemisphere. Then, an obstacle avoidance trajectory in the shape of a circular arc will be generated based on the geometrical attributes of the UAVs and the obstacle. According to them, the Circular Arc Trajectory Geometric Avoidance (CTGA) Algorithm proposed requires fewer computations, and it is able to satisfy the manoeuvrability constraints of the UAV.

On the other hand, Chen and Lu [23] have proposed the forbidden pyramid approach to compute the desired UAV velocity via an efficient iterative sampling-based method. By utilising the relative velocity between the UAV and the obstacle, the forbidden pyramids method is able to plan a safe desired velocity for the UAV so that it can avoid the obstacles it encountered. As its name implies, the forbidden pyramid refers to the set of velocities that is forbidden for the UAV since these velocities might result in a collision with the obstacles. In the proposed method, a sampling-based method is performed in the feasible space, and the sampled velocity with the lowest acceleration cost is selected as the desired velocity of the UAV. Based on the results, the proposed algorithm is proven to be computationally efficient, and it can avoid both stationary and moving obstacles.

Meanwhile, the obstacle avoidance method proposed for onboard MAV by Wessendorp et al. [15] is very similar to the forbidden pyramid method presented by Chen and Lu [23]. The obstacle avoidance method applied by Wessendorp et al. [15] is known as the Velocity Obstacle (VO) method. In fact, the VO method and the forbidden pyramid method are the same, whereby the algorithm will first obtain a set of velocity vectors of the MAV that will cause a collision. In their work [15], the VO method used is only considering the 2D space, where both the ego MAV and the detected obstacles are modelled as circles. Of course, the radii of both the obstacle and the MAV are taken into consideration when determining the desired velocity vector to avoid the obstacle

In conjunction with that, Wakabayashi et al. [28] have also presented a dynamic obstacle avoidance method for multirotor UAVs based on the VO method. In their work [28], the chance constraints based on the obstacle velocity (CCOV) method are proposed to solve the noise problem presented in the position and velocity information of all the obstacles detected and the ego UAV itself. In this work, the CCOV method is used together with positional chance constraints, so that the uncertainties present in both position and velocity data are considered. In their work, the UAV and the obstacles are treated as circles, and the collision avoidance manoeuvre is carried out only in a 2D plane, like the work presented by Wessendorp et al. [15]. On top of that, the work by Wakabayashi et al. [28] has also assumed that the avoidance targets are moving linearly in constant velocity. Nevertheless, the results show that the proposed CCOV algorithm can effectively avoid the collision of the ego UAV with other high-velocity obstacles, even if the environment is noisy.

5. Conclusion

To sum up, mmWave Radar is still a relatively unexplored sensor to be used on a UAV. In most cases, the mmWave Radar is used together with other state-of-the-art sensors like cameras to perform obstacle detection and avoidance tasks due to their complementary characteristics. It is undeniable that sensor fusion techniques can ensure better accuracy and performance. However, despite the recent research made in sensor fusion technology, there arises another problem with the maximum allowable payload when too many sensors are used on a UAV system. Due to that, more focus should be given to research works that study the use of only one perception sensor for DAA application in UAVs. Meanwhile, the works that are solely based on mmWave Radar are still relatively limited. Thus, more studies can be done in the future to implement the mmWave Radar sensor as a standalone perception sensor that can detect both static and dynamic obstacles in UAV applications.

In terms of obstacle state estimation techniques, the Kalman filter approach and its variation is the most preferred method to be used in UAV applications, as compared to other ways such as polynomial regression and cumulative moving average filter. In most works, the linear Kalman filter approach is used, assuming that the motion and measurement models are linear. Although there has been works that use non-linear models like extended Kalman Filter (EKF) and polynomial regression to forecast the future states of the obstacles detected, these methods, however, are computationally intensive and might not be appropriate for DAA application in a UAV. Hence, more studies should be done to develop a more computationally efficient algorithm to estimate the future states of the obstacles while considering the nonlinearity property of the UAV used.

For obstacle avoidance algorithms, it can be generally categorized into three main groups, namely the potential field approach, the AI-based approach, and the geometric-based approach, as discussed earlier. Based on the literature studied, there is work that addressed the non-optimality in the avoidance path generated by the traditional potential field approach, which models the ego UAV and the obstacles as a sphere. Yet, the work proposed does not tackle the local minimum problem in the traditional APF method. Thus, further work can be done to address both the optimality problem and local minima problem of the traditional APF method while enabling it to detect both stationary and moving obstacles simultaneously.

Meanwhile, the AI-based approach often uses optimization techniques to generate the optimized avoidance path for autonomous vehicles like UAVs. However, some of these methods only tackled static obstacles in the indoor environment. In some cases, the flight controller requires greater memory capacity to pre-load the data about the static indoor flight environment. For now, research has been actively done on the AI-based obstacle avoidance approach to extend it to both indoor and outdoor environments while enabling it to detect multiple static and dynamic obstacles.

Next, it is easier to implement a geometric-based obstacle avoidance approach in a UAV system that uses mmWave Radar since it can directly provide information such as range, relative velocity and angle of the obstacles detected. However, the length of the avoidance path generated via these geometric-based approaches is often not optimal. Methods like a forbidden pyramid, VO and CCOV have modelled the ego UAV and the obstacles as circles, causing the generated path to be less optimal since the shape of most obstacles does not fit exactly into a circle. Furthermore, these methods only perform the avoidance manoeuvre in the 2D plane, causing it to be less robust in a complex 3D flight environment. Thus, further studies can be made to optimize the avoidance path generated from geometric-based approaches and extend it to perform avoidance manoeuvres in 3D space.

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