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A Review on Method of Obstacle Detection and Avoidance Systems for Unmanned Aerial Vehicles: Monocular Camera

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Abstract

Unmanned Aerial Vehicles (UAVs) or known as drone is widely use by human as high risk and time-consuming task can be tackle by UAV. The usage of UAV includes the movement and path of the UAV to execute given tasks. However, any obstacles will restrict the movement of UAV thus various method is discovered and undergoes research specifically to detect and avoid any upcoming obstacles. This review paper will review vision sensor that include monocular and stereo camera sensor. Numerous researchers focus more on using monocular camera sensor as the main image input for image processing as it give benefits in terms of payload and power consume to the operational hours of the UAV. Therefore, this paper will focus on reviewing obstacle detection and avoidance method that use mainly monocular camera with respect to image cue to avoid obstacles. The method to extract cue from the image for this paper review will fall in the boundary of appearance-based, motion-based, depth-based, expansion-based of the input image. As a results from all techniques, texture-less, narrow, and small moving objects can be assumed as hard to detect and challenging that need to be tackled in future research particularly important for aerial vehicles.

1. Introduction

Vigorous expansion of Unmanned Aerial Vehicles (UAV) or drone technologies has contributed to its usage not only for military but also for commercial solutions [1]. The properties of UAVs that can be controlled remotely and may be flown at some different range of altitude and distance is the key point of why it is preferable for human to execute tasks using UAV. Numerous high risk and time-consuming inspection tasks [2], facilitates delivery [3], help save lives [4], variety of military applications [5], and excellent in recording videos and capturing images [6]. Obstacle sensing and avoidance plays a crucial role toward the development of UAV with respect to the execution of difficult tasks. The intelligence of the obstacle avoidance system of UAV must be upgraded to a higher level as the main component of the autonomous system is the navigation and system components. Detecting obstacles and free regions is one of the key technologies for obstacle avoidance [7]. The technique of obstacle detection and avoidance can be classified into three types which are range-based [8], vision-based [9] and hybrid [10]. Range-based method also known as active sensors is where the UAV is equipped with sensors such as radar [8], sonar [11], ultrasonic [12] and Kinect [13] to detect the obstacle.

2. Techniques of Obstacle Detection Using Image Input

Camera sensors can be further categorized into monocular camera sensor [19] and stereo camera sensor [20]. Various information about the surroundings may be captured through cameras [18], [21] such features of edges [14], [20], point [16] and grayscale values [15] to detect object. Each type of camera sensor has different techniques for obstacle detection that can be summarize as diagram below:

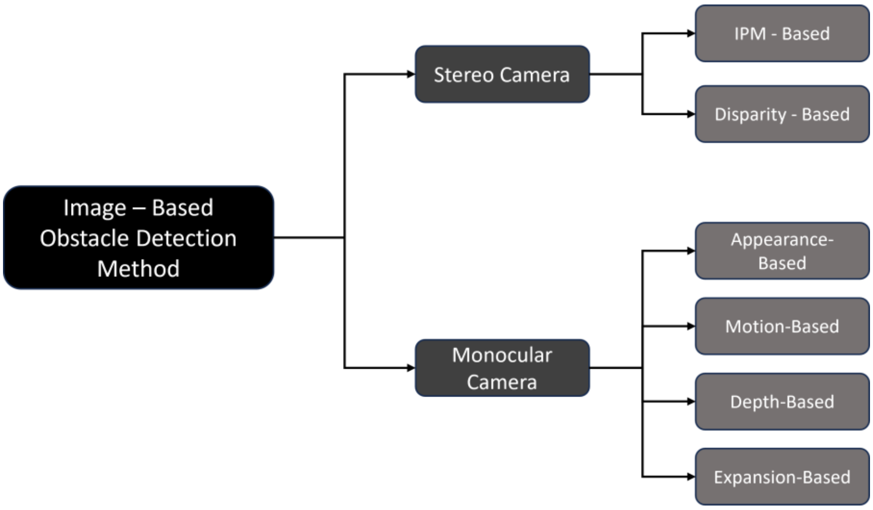

Fig. 1 *Categorization of obstacle detection techniques [22]*

Stereo cameras will utilize two cameras that will produce three-dimensional environments map from the image that has been captured in real-time then will be used to detect obstacles. Such methods have been developed to assist visually impaired people [23], Unmanned Aerial Vehicles (UAVs) [24] and MAVs [25]. Unluckily, these techniques are not computationally efficient for MAV microprocessors [26]. On other hand, monocular camera sensor only uses single that has camera been mounted at front of the unmanned vehicles to capture image [27]. In this review paper we will review obstacle detection techniques that fall within monocular camera sensor that is divided into four types [28]: appearance-based [29], motion-based [30], depth-based [31] and expansion-based [16].

2.1 Appearance – Based Method

With a consistent background (such as the ground or sky), these techniques treat an obstruction as a foreground object. They operate using elements like edges [30], colors [34], textures [56], or shapes [32] that represent past knowledge from the appropriate context. Using a camera situated in front of the robot, single pictures collected consecutively are used for obstacle detection. If the obtained picture does not match the characteristics of the sky or the ground, it is deemed to be an obstruction pixel. Every pixel in the picture is subjected to this procedure. The outcome is a binary picture in which obstacles are displayed in white pixels and the remaining pixels are black.

Previously, [32] had implement visual SLAM approaches where its "matches" camera pictures to known locations in a 3D-model of the environment to predict the status of the MAV (3D position and attitude) and optical flow approach by estimating the time-to-impact with an obstruction may be done using the flow of image points away from the Focus of Expansion (FoE). However, visual SLAM is expensive computationally and had issues with drifting while optical flow depends on the environment's texture and the need for precise optic flow measurements. Optical flow was also used by [33] which detected and avoided lateral impediments by employing twin cameras installed on a fixed-wing UAV, like biological flying insects.

However, this method has limitations in avoiding substantial barriers like walls occurred due to the detection's narrow emphasis on lateral obstructions. Moreover, if the UAV follows a straight path, the avoidance method is insufficient. In [34], Scale Invariant Feature Transform (SIFT) and Multi-scale Oriented Patches (MOPS) had been used by locating and matching the MOPS feature points of the corners, the 3D spatial information of the MOPS points is then retrieved, allowing the edges and corners of the object to be extracted using MOPS. The interior outline data is then discovered using SIFT. Unfortunately, this method is expensive computationally with (557ms) of time. For [35] use Canny edge and Hough transform to find straight line along corridors and detect intersections of paired lines with the maximum density for the UAV path, but the scope of this method was restricted to stairwells and hallways with uniform structure analyses. The Feature detection and Speed Up Robust Features (SURF) method used by [36] where they use a feature detection method along with template matching to identify obstacles that have grown. This method was only restricted to tree-like barriers and did not demonstrate desire result when tested on other forms.

Table 1 *Summary of Appearance-based techniques*

Method	Disadvantages	References
Visual SLAM / Optical flow	Method only works with detailed textures and limited to indoor environments	[32]
Optical flow method	limitations appeared in avoiding large obstacles like walls	[33]
SIFT and Multi-scale Oriented-Patches	Expensive computational time (577ms)	[34]
Edge detection	Experiments were limited to corridors and stairs areas.	[35]
Speed Up Robust Features (SURF) method	limited to tree-like obstacles and did not show results of other shapes.	[36]

2.2 Motion Based - Method

In motion-based techniques, it is expected that objects in close range move quickly, which can be retrieved up on by motion vectors in the picture. In a relatively little period, two consecutive pictures or frames are captured. On each frame, several match points are first extracted. The match points' displacement vectors are then calculated. Any point with a displacement value that exceeds a specific threshold is regarded as an obstacle pixel because objects closer to the camera have bigger displacements.

In this area, a lot of research has been done. [37] unique approach utilizes motion characteristics to identify obstacles apart from shadows and traffic signs. To achieve real-time obstacle recognition, they only relied on corners and Scale Invariant Feature Transform (SIFT) features, rather than all pixels. If the failure rate of features matching is high, such an algorithm may not succeed. Commonly, most motion-based methods primarily use optical flow as their source of data. Without a map of the surrounding area,[38] kept a mobile robot from colliding with objects. However, the position of looking downward camera may not suitable if the obstacle is higher than camera lens. To assist persons with visual impairments in navigating indoor spaces, [30] employed two consecutive frames to estimate the optical flow for obstacle identification on smartphones.

They computed the separation between two successive frames using a context-aware combination data approach. However, this method detects some incorrect points in lamps, floors, and reflective surfaces. [39] validate Speeded-up Robust Features (SURF) [40] point detector as locations obstacles, by using Support Vector Machine (SVM). In this study, the data needed to train the SVM were extracted using a dense optical flow technique. Then, they applied obstacle points and measures related to the spatial weighted saliency map to locate the obstacles. Their research method is applicable to mobile robots with cameras mounted at low elevations. Therefore, using it on UAVs that often fly at high altitudes would not be practical.

Table 2 *Summary of Motion-based techniques*

Method	Disadvantages	References
Scale Invariant Feature Transform (SIFT)	High number of mismatch features.	[37]
Optical flow	Downward looking camera (limited obstacle detection)	[38]
Optical flow and point track	Incorrect detection of some points on lamps, floors, and reflective surfaces	[30]
Optical Flow data for Support Vector Machine (SVM)	Not suitable for UAV	[39]

2.3 Depth – Based Method

Information taken for dept-based method are from images captured by single camera. To obtain depth, motion stereo or deep learning techniques can be implemented. In the former, two cameras are mounted on the sides of the robot, and two repeated photos are taken. Although only one camera was used to capture these images, they may be seen as a pair of stereo images that can extract the estimation depth of object points. A matching point will be implemented between the images and calculations of depth estimation will be used.

[31] use four fisheye cameras and motion stereo to produce depth maps and obstacles are denote as any object on the ground. However, this method cannot detect moving objects and is highly computational. Next, [41] implemented Inertial Measurement Unit (IMU) with fisheye camera in wide field of view (FOV) and depth estimation was based on keyframe for Micro UAV. Unfortunately, depth method cannot run as the MAV hovering and camera produce low image quality. In terms of artificial neural networks and deep learning, [42] applied a CNN and four single fisheye cameras on self-driving cars to determine the depth in every direction. However, this research requires further data training. [43] offers fast obstacle detection by producing the latest CNN framework that use image features through fine-tuning the VGG19 network to estimate depth and detect obstacles. Moreover, multi-hidden-layer neural networks that can predict the distance called (DisNet) were introduced by [44].

Table 3 *Summary of Depth-based techniques*

Method	Disadvantages	References
4 fisheye camera and depth motion	Highly computational	[31]
Fisheye camera and Inertial Measurement Unit (IMU)	Low image quality (not accurate)	[41]
CNN network	Appropriate data training needed	[42]
Image Features via fine-tuning the VGG19 network	Need adequate initial training	[43]
Hidden-Layer Neural Network (DisNet)	Limit obstacle detection by detecting inaccurate object bounding boxes	[44]

2.4 Expansion – Based Method

As objects become nearer, the size of the object will be larger compared to previous situations, same as human perception. This method will utilize the object expansion rate between consecutive images. Thus, this value or method can be calculated using homologous regions, distances, or even the acquired points from SIFT scales. When using expansion-based algorithms, an object is deemed an obstacle if its enlargement value surpasses a certain threshold. [36] applied the SURF algorithm's properties to find the initial locations of obstacles of various sizes. Despite having simple computations, this approach might fail because of slow reaction time to obstacles. [45] another research employed edge motion in two subsequent frames to detect incoming obstructions.

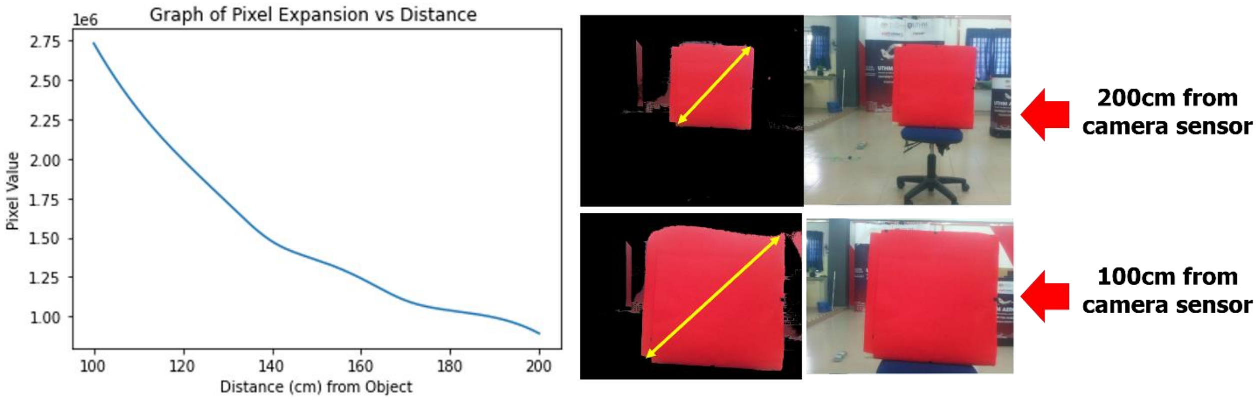

Fig. 2 *Expansion of pixel when object enlarge. [16]*

The object enlarges if its edge moves outwards (relative to its center in subsequent frames) and is applied to fixed and mobile robots. When the background is uniform, both stationery and mobile robots can use this method. This strategy only works for static items, and not suitable for complex background. [46] use compact

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UAV as platform to test obstacle detection method by implementing SURF method to detect some primary patterns as obstacles. Hence only specific obstacles can be detected, and the detection of obstacles is not robust. [16] compared and extracted points from subsequent frames using SIFT method [47]. He then created a convex hull with respect of the matching points. The points were regarded as obstacle points if the change in their SIFT scale values and the convex hull area exceeded a certain threshold.

Table 4 *Summary of Appearance-based techniques*

Method	Disadvantages	References
SURF algorithm	Slow reaction time to obstacle makes the calculation fail	[36]
Edge detection	Not suitable for complex background	[45]
SURF method	Cannot detect obstacles with different pattern.	[46]
Key points scale ratio and convex hull area ratio	Robot have limited maneuverability in complex situation	[16]

3. Conclusion

Generally, the obstacle detection and avoidance for visual based techniques consist of monocular and stereo camera sensor categories. Mainly, algorithms/systems for monocular camera sensor techniques were reviewed that falls in appearance-based, motion-based, depth-based, and expansion-based methods. Approaches for detecting obstacles with a monocular solely use one camera. They are quick and contain simple computations. As a result of this, researchers have widely used/researched these techniques for aerial and terrestrial robot navigation. Most research studies have employed monocular techniques because MAVs or small UAVs have small sizes, poor computing powers, and weight restrictions. Contrarily, stereo-based techniques involve a pair (or more) of synchronized cameras to take pictures while simultaneously creating a 3D map of the surroundings. These techniques are disappointingly not computationally economical. To overcome this problem, researchers often need a strong graphics processing unit (GPU) [46]. From this review, texture-less, narrow, and small moving objects are hard to detect and challenging that need to be tackled in future research particularly important for aerial vehicles.

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Conflict of Interest

This paper has no conflict of interest regarding the publication of the paper.

Author Contribution

The contribution for publishing this paper is as follow**, literature research and writing:** Muhamad Wafi bin Abdul Aziz, **review and supervision:** Muhammad Faiz bin Ramli.

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