Monocular Vision-Based Dynamic Moving Obstacles Detection and Avoidance

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Abstract. In this paper, we proposed an UAV system for obstacle avoidance depending of a ground station processing based on monocular vision. To accomplish detection, tracking, proximity estimation and dynamic obstacles avoidance that are approaching the UAV, a series of methods and techniques are implemented. To detect movement, frame differentiation was applied to consecutive frames, once the moving object is detected, we detect Shi-Tomasi feature points to track the object using optical flow method Lucas-Kanade. To make possible proximity estimation, a linear regression method based on the area covered by the object was used. A fuzzy logic controller was designed to avoid the moving object, we considered the approach rate and the area of the object to control UAV's position in relation to the object as fuzzy inputs.

Keywords: Obstacle avoidance · Proximity estimation · UAV-control

1 Introduction

UAVs (Unmanned Aerial Vehicles) [1, 2] cover a wide range of civil [3, 4] and military applications [5, 6] due to their ability to perform both outdoor and indoor [7] missions in challenging environments [8–10], often they equip various sensors and cameras to perform intelligence, surveillance [11, 12] and reconnaissance mission [13, 14]. Other applications comprehend search and rescue missions, environmental protection, mailing and delivery, mission to oceans or other planets and other diverse applications [15].

Nowadays, UAVs usage has had a remarkable growth in both research and commercial applications, for example, in precision agriculture a UAV can be useful for control and monitoring of crops. Exploration and rescue in places of difficult access such as caves, cliffs, surveillance, reconnaissance navigation, among others [16–18].

This paper is organized as follows: Sect. 2 presents a quick review of the literature about autonomous UAVs and different approaches to provide full autonomous navigation to UAVs. Section 3 presents our approach to give the UAV the capability to avoid dynamic moving obstacles that can compromise the integrity and stability of the

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UAV, in addition, results with different objects, distances and approaching rates are presented in Sect. 4. Conclusions and future work are presented in the last section.

2 Related Works

Design of autonomous UAVs requires an appropriate navigation system [19] for obstacle detection [20, 21], pose estimation [22–24] an environment perception [25, 26]. In [27, 28] the Inertial Measurement Unit (IMU) is described as a conventional navigation sensor, LIDAR in [29] is described as a suitable device for cartography and obstacle detection, since it measures environment range directly through a laser beam. Cameras stand out as a popular method for environment recognition [30, 31], since they are portable, passive and a compact sensor, providing extensive information about the movement of the vehicle and its relative pose.

Yilmaz et al. [32] describe several methods for detecting and tracking objects in the environment, object can be represented as geometric shapes, points, contours, in the case of person as an articulated model [33] of density probabilities, taking into consideration tracking characteristics such as color, texture, optical flow or edges.

Optical flow is a method often used to avoid collisions not based on stereoscopic vision. It can be understood as a visual phenomenon with daily experience when observing an object that moves at a speed different from that of the observer [34, 35]. The movement of the observed obstacle depends on the distance between the observer and the obstacle and its relative speed [36].

The detection algorithms based on feature points, such as SIFT [37] or SURF [38] detector being the most robust and resistant to image deformations but not the most efficient are commonly used for object tracking. Image segmentation algorithms are used to divide the image into perceptually similar regions as the exclusive method for real-time tracking Mean Shift [14].

Tendency of several research groups is navigation over known environments [39], that is, the place is previously explored, since the main problem is obstacle avoidance. Ritcher showed aggressive maneuvers for quadcopters flying in clogged indoor environments [40] path planning algorithm used was RRT*, but it was not implemented in real time. The planning phase was carried out offline, with an a priori map of obstacles, producing reference points that are at the minimum distance, not necessarily the minimum time to the final objective.

There are multiple solutions for obstacle avoidance, traditionally using active detection such as sonar, infrared LIDAR mentioned in Gageik et al. work [29], these sensors can be expensive, both in terms of real cost and payload, without neglecting power consumption. The common passive detection is stereo vision that is in charge of obtaining 3D information from 2 points of view (2 monocular cameras) [41] having as a limit the field of view of the cameras. Currently there is a navigation and obstacle avoidance system called S.L.A.M dunk on market that allows the development of autonomous UAVs.

3 Our Approach

When movement has been detected on the scene, it is possible to discriminate the object that is in movement. It should be mentioned that a defined template is not necessary to locate the object; the template will be defined automatically, once the movement of the object has occurred. That is, the object is not defined, it can be any that meets the minimum characteristics for detection.

3.1 Object Detection and Encapsulation

Let $I_{(x,y)}(t)$ be the actual frame that UAV sends to the ground station and $I_{(x,y)}(t-1)$ be the previous frame. Absolute difference between the actual and previous frame is defined as follows:

$$D_{(x,t)}(t) = |I_t - I_{t-1}|$$

Where $D_{(x,t)}(t)$ is a matrix which values are between 0 and 255, describing which pixels as different from the previous frame as a consequence of movement. Then a binary matrix is obtained from $D_{(x,t)}(t)$ as follows:

$$M_{(x,y)}(t)\begin{cases} 1, & D_{(x,y)}(t) \geq U(t) \\ 0, & D_{(x,y)}(t) < U(t) \end{cases}$$

Where:

$$U(t) = \overline{D}(t) + \sigma(t)$$

$U(t)$ is the threshold that a pixel must pass to be considered as an interest value. $\overline{D}(t)$ is the mean value of differences of all pixels in $D_{(x,t)}(t)$ and $\sigma(t)$ is the standard deviation. All this values are obtained in real time.

Once a binary image is ready, we consider that adjacent pixels that forms the images has similar colors, therefore these pixels can be excluded and divide the object in small parts. Canny border detection [42] was used to extract borders from the binary image, previous to that an opening morphological transformation was performed to handle noise present in the binary image (Fig. 1).

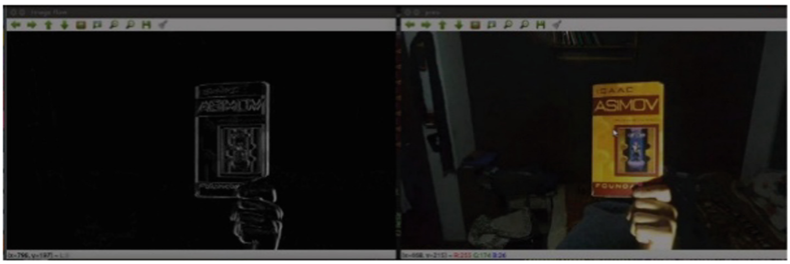

Fig. 1. Consecutive frames absolute difference

Border filtering is done discriminating area of quadrilaterals that are very large in comparison to movement objects. These areas appear due to UAVs positions is elevated and presents small variations when it is hovering, therefore, these areas should not be considered when encapsulating the object in a single geometric shape (Fig. 2).

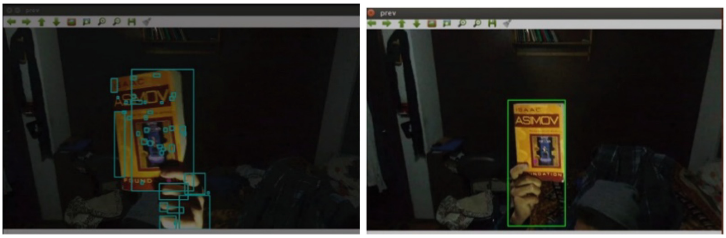

Fig. 2. Border detection on raw image from UAV's camera (left) – Moving object capture (right)

The moving object consists of several edges, which are represented by quadrilaterals of different sizes, it is necessary to integrate all these edges so that the object is represented by a single geometric shape. To achieve this, we considered the closest point to the upper left corner and closest to the lower right corner.

3.2 Object Tracking

It is important to know the approaching rate of the object to the UAV, Shi-Tomasi method was used to extract local characteristics giving good result when the feature points moves at fast velocities.

Optical flow allows us to estimate a vector field that describes the movement of each feature point, Lucas-Kanade method estimates this vector assuming that movement of the nearest neighbor pixels will have similar movement (Fig. 3).

Fig. 3. Tracking of Shi-Tomasi feature points

3.3 Approaching Rate

Approaching rate is the relation between distance and time; it describes the distance traveled by an object in a time unit. Taking this concept is possible to calculate velocity of each feature point in relation to the pixel's distance traveled in consecutive frames obtained from UAV's camera, this calculus depends on the shutter speed of the camera. In our case is 30 FPS. Table 1, describes how to calculate the distance by means of pixels per second.

Table 1. Approach to calculate velocity in pixels per second

Parameter	Formula	Description	Unit
Distance	$p1-p0$	Distance in pixels traveled by each point between consecutive frames	$[pixels]$
Time	1 Frame = 0.03 [s]	Distance can relate to the shutter speed by means of FPS, 30 Hz	$[second]$
Velocity	$\frac{p1-p0}{0.03}$	Pixels traveled in one frame at 30 FPS	$\left[\frac{pixels}{second}\right]$

The tracker loses feature points often. To solve that we assume that all points belonging to an object must move at the same speed.

Let

$$\overline{V}_p = \frac{1}{N}\sum_{i=0}^{N} V_p(i)$$

Be the mean velocity of every feature point and $V_p(i)$ velocity of each feature point. We can discard if a point loses track if the velocity of a feature point does not pass the threshold value, in this case the mean velocity. Threshold values are calculated as follows:

$$\boldsymbol{pv}(\boldsymbol{t}) = \begin{cases} V_p(i), & V_p(i) \geq \overline{V}_p - \sigma_p \\ V_p(i), & V_p(i) \leq \overline{V}_p + \sigma_p \\ 0, & out\ of\ threshold \end{cases}$$

Finally, kmeans method is used to ensure that a feature point does belong to the object; it is based on Euclidean distance for a set of points with correlated covariance and different variance in their axes.

3.4 Approaching of the Moving Object

To determine if the object is approaching to the UAV or moving away from it, area growth rate is calculated from a linear regression by means of the area present at the last 15 frames.

Let

$$Y = mX + b,$$

be the equation resulting of a linear regression, where Y is the area and X represents time, m suggest whether the object is approaching or moving away. If m grows the object is approaching and if m decreases the object is moving away. Figure 4 represents the linear regression obtained when an object is approaching the UAV. In Fig. 5 we show an example of an object approaching and moving away with speed, area and estimated position.

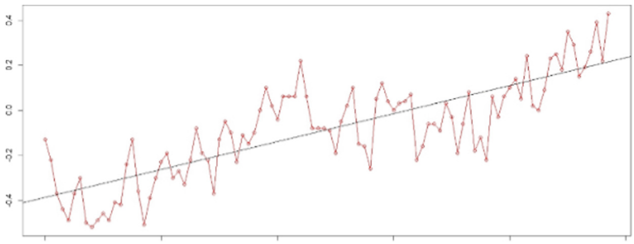

Fig. 4. Example of an approaching object

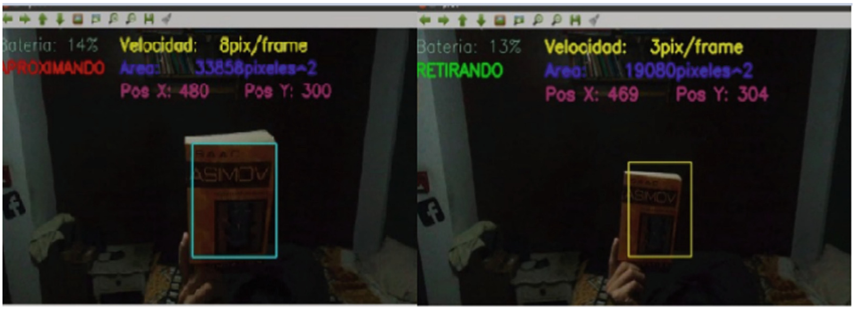

Fig. 5. Approaching (left) and withdrawal (right) of an object

3.5 Fuzzy Logic Controller

Fuzzy controller for moving object avoidance has two fuzzy inputs: (1) area of the moving object and (2) approaching rate. Its output corresponds to linear speed in x-axis showed in Fig. 6.

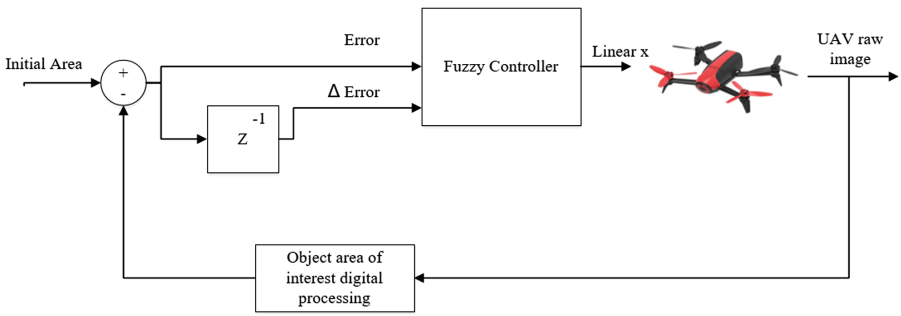

Fig. 6. Fuzzy control scheme for moving object avoidance

3.5.1 Membership Functions

Membership function for area input was determined so that we met the criterion of maintaining the moving object far from the UAV. Linguistic values are (Table 2, Fig. 7):

Table 2. Description of area membership function

Linguistic value	Value in universe of discourse	Description
Z: zero	[0, 0, 3]	There's no error
PC: little close	[2, 3, 5]	Object is not close
C: close	[3, 5, 7.5]	Object is close
MC: very close	[5, 7.5, 10]	Object is considerably close
SC: super close	[7.5, 10, 10]	Object is too close

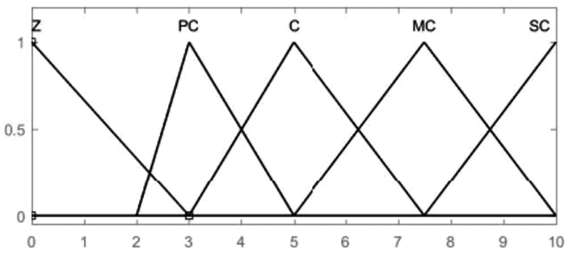

Fig. 7. Area membership function

Membership function for approaching rate was designed having in consideration to avoid a possible collision with the moving object. Linguistic values are (Table 3, Fig. 8):

Table 3. Description of approaching rate membership function

Linguistic value	Value in universe of discourse	Description
Z: zero	[0, 0, 2]	Object is not moving
PR: little fast	[1.5, 2, 3]	Object is approaching slowly
R: fast	[2, 3, 4]	Object is approaching
MR: very fast	[3, 4, 5]	Object is approaching considerably
SR: super fast	[4, 6, 6]	Object is approaching too fast

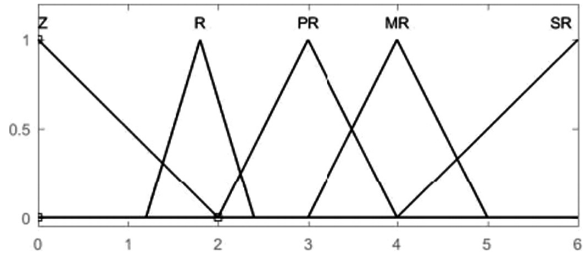

Fig. 8. Membership function for approaching rate

3.5.2 Fuzzy Output

The reaction speed that UAV must have directly depends on the approaching rate of the moving object. If the object approaches too fast UAV action must be as fast as possible, but if the object is too close and its approaching rate is not too fast, UAV must take a soft reaction to avoid the moving obstacle. Figure shows membership function for linear speed in x-axis (Fig. 9).

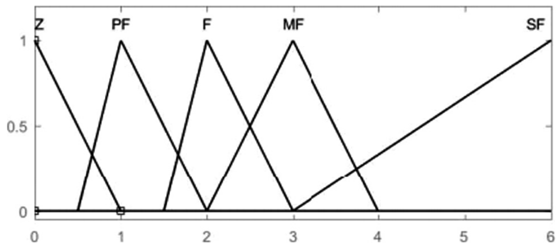

Fig. 9. Membership function for UAV linear speed in x-axis

3.5.3 Fuzzy Rules

In order to associate fuzzy sets of area and approaching rate it is necessary to establish fuzzy rules. Each fuzzy set is composed by 5 linguistic values therefore 25 rules are obtained in Table 4.

Table 4. Fuzzy rules

	Speed	Area				
		Z	PC	C	MC	SC
Approaching rate	Z	Z	Z	F	MF	MF
	PR	Z	F	F	MF	MF
	R	Z	F	MF	SF	SF
	MR	Z	MF	MF	SF	SF
	SR	Z	MF	SF	SF	SF

Output from the fuzzy controller when the object is approaching too fast is strong, but if its approaches moderately the UAV performs a soft evasion. This is shown in the fuzzy control surface in Fig. 10.

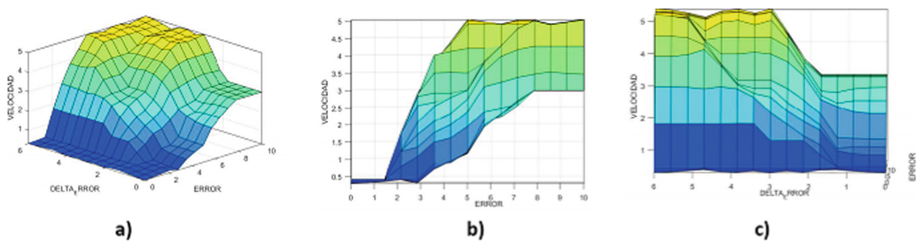

Fig. 10. Fuzzy control surfaces for UAV linear speed in x-axis (a) 3D view (b) Area-Speed view (c) Approaching rate-Speed

4 Results and Discussion

To measure the performance of our algorithms, we tested them under four evaluation criteria (Table 5).

Table 5. Evaluation criteria

Criteria	Description
Detection distance	Distance between the object and UAV's camera lens when it detects the moving object
Number of characteristics	Number of features point extracted with Shi-Tomasi method
Response time	Time in which UAV reacts to an event
Speed	Estimated approaching rate of the moving object

Objects used to test our approach were, 1 – Ballon, 2 – Book, 3 – Carton Box, 4 – hand.

4.1 Scenario: Maximum Detection Distance and Number of Characteristics

All the objects described above where placed and moved at different distances until UAV detects them, then the number of feature points was captured (Table 6).

Table 6. Number of feature points at different distances

Number of feature points	Distance 0.5 [m]	Distance 1 [m]	Distance 1.5 [m]	Distance 2 [m]
Object 1	74 ± 8	43 ± 13	35 ± 5	7 ± 4
Object 2	53 ± 7	45 ± 8	22 ± 7	2 ± 2
Object 3	38 ± 10	29 ± 5	15 ± 8	3 ± 4
Object 4	39 ± 15	28 ± 14	21 ± 11	8 ± 5

5 Conclusions and Future Work

There are several techniques and algorithms for feature point detection, to mention the most relevant SIFT, SURF, ORB and Shi-Tomasi. ORB algorithm detects considerable a larger set of feature points, but its response time exceeds and influence on transmission rate of UAV raw images.

Several trackers were tested in this project such as KCF, MOSSE and TLD, they all presented track loss due to change in luminosity caused by the moving object, optical flow approach lost feature points but did not lose track of the moving object.

Fuzzy controller is the one that fits the best to this approach, due to its instinctive nature it is possible to use imprecise expressions or events, for example, in the case that the object is approaching super-fast but is not near to the UAV, the avoidance reaction should be low in preparation for extreme avoidance. The parameters of the controller are adjusted to this type of eventualities.

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